An Ensemble-based Feature Selection Methodology for Case-Based Learning

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Doctor of Philosophy

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Abstract

Case-based learning (CBL) approach has been receiving a lot of attention in medical education, as an alternative to the traditional learning environment. This student-centric teaching methodology, exposes the medical students to practice the real-world scenarios. In order to support the learning outcomes of students, existing systems do not provide computer-based as well as experiential knowledge-based support for CBL practice. Medical literature contains textual knowledge, which can be used as a very beneficial source for the computer-based CBL practice. Therefore, designing and developing of an automated CBL approach is a challenging problem. In order, to solve this problem, the text mining domain provides the basic framework for constructing domain knowledge, where the feature selection is considered to be one of the most critical requirement to select the appropriate features.

Keeping in view these facts, this research, provides contribution, in the following areas: (1) Feature Ranking; where we propose, an innovative unified features scoring algorithm to generate a final ranked list of features, (2) Feature Selection; where we propose, an innovative threshold value selection algorithm to define a cut-off point for removing irrelevant features for the domain knowledge construction, and (3) CBL Platform; where we designed and developed, an interactive CBL system consisting of experiential as well as domain knowledge to nurture medical students for their professional learning and development. We perform both quantitative and qualitative evaluation of our proposed (1) methodology on benchmark datasets, and (2) CBL approach. The extensive experimental results show that our approach provides competitive accuracy and achieved (1) on average, more than 5% increase in f-
measure and predictive accuracy as compared to state-of-the-art methods, and (2) a success rate of more than 70% for students’ interaction, group learning, solo learning, and improving clinical skills.
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Chapter 1

Introduction

The main focus of this dissertation is on investigating the dynamics of case-based learning (CBL), leading to a proposal for an interactive medical learning approach to prepare medical students using real-world CBL case(s) for better clinical practice outside the class. For interactive and effective learning purposes, this dissertation includes a methodology to construct the domain knowledge (i.e. structured declarative knowledge) from unstructured text to facilitate and provide domain knowledge to medical students for solving the real-world clinical case(s) during CBL practice. For the domain knowledge construction, the feature selection task is considered to be one of the most critical problems in a text mining domain. This thesis proposed an efficient and comprehensive feature selection methodology for selecting appropriate features from a larger set of features. The opening chapter will contain the main motivations for this process in Section 1.1, the problem statement along with research questions in Section 1.2, key contributions of this research in Section 1.3, and finally, the summary of dissertation is outlined in Section 1.4.
1.1 Motivation

Medical education is an active area of research and has seen tremendous revolutionary measures in the past few decades. The main purpose of these educational programs is to: (1) develop educational leaders, (2) change the learners’ knowledge, skills, or attitudes, and (3) improve the educational structures [18]. Various teaching methodologies have been introduced in professional health education [19], with active learning gaining a lot of attention around the world [20]. In active learning, instructions are given to students to actively engage them [21]. Case-Based Learning (CBL) is one of the active learning approaches, which provides favorable circumstances to students in order to explore, question, discuss and share their experiential knowledge for improving their practical intelligence [20]. CBL is not a new term, from its introduction in the medical domain since 1912 [22]. It has proceeded in many forms, from simple hands-on, in-class exercises to semester long projects and/or case studies [23], CBL, has maintained its focus around clinical, communal, and scientific problems.

In terms of student-centric pedagogy, CBL is being widely used in various health-care training environments around the world [24–31]. In particular, this approach has been met with general acceptance in the fields of medicine, dentistry, pharmacology, occupational and physical therapy, nursing, allied health fields, and child development. Similarly, it is being used in clinical as well as non-clinical courses such as nursing courses, adult health, mental health, pediatric, and obstetrical nursing courses, pathophysiology, statistics, law, school affairs, physics education, and research [32, 33, 20]. In addition, this approach has been utilized in various departments such as medical education, information technology, and quality improvement [22], and has also been practiced in rural as well as underserved areas [22]. These findings validate the effectiveness and universal nature of CBL, which is especially useful for the curricula of medical and health professions [22].
In CBL practice, the clinical case is a key component in learning activities, which includes basic, social, and clinical studies of the patient [34]. In the medical domain, this component provides the foundation to understand the particulars of a disease. Recent trends have emphasized the use of real-life clinical case(s) for providing this much needed practice for the medical students [35–37]. These cases enable the students to use their experiential knowledge to interpret them easily [20]. In medical area, CBL facilitates students in learning the diagnosis and management of clinical cases [22], and prepares the participants to practice primary care and critical situations [38]. The CBL approach promotes learning outcomes and builds confidence in students, enabling them to practice real-life decisions [39, 28]. According to Thistlethwaite [34], “CBL promotes learning through the application of knowledge to clinical cases by students, enhancing the relevance of their learning and promoting their understanding of concepts”. CBL is also known to be an effective learning approach for small groups of medical students at undergraduate, graduate, postgraduate education levels as well as for professional development [34, 40, 35, 41, 22].

Besides the benefits of CBL approach, there are also a few shortcomings of this approach. For example, in professional education for health and social care domains, students feel that classroom CBL activities require a significant amount of time [42]. Sometimes, students feel uncomfortable while participating in group learning activities and they prefer to work alone [43]. Normally, formal learning activities are performed without a real patient case [34], where interactions are often unplanned and rely on the goodwill of patients. In specialized literature, medical education programs are considered to be complex due to their diverse interactions amongst participants and environments [18]. Discussion-based learning in a small group, like CBL, is considered to be a complex system [44]. In small-groups, multiple medical students are interacting and exchanging information with each other, where each student is also a complex system [45]. In health care professional education, students have to tackle uncertain situations due to the interplay of a number of problems [46]. In such
situations, each student has his/her own judgment, opinion, and feedback and will consider this integral as well as appropriate for that situation. In such situations, an experiential knowledge (EK) is thought-out as a resource [46] which can facilitate and provide lived knowledge to students. According to Willoughby [47], “Experiential knowledge is a knowledge of particular things gained by perception and experience”. Experiential knowledge enables individuals to capture practical experience for problem solving. It is considered as a valuable resource to enhance an individual’s participation and user empowerment [46].

For problem-based learning, humans and computers can play a key role in the medical domain. However, both have their own strengths and weaknesses [48, 49]. For example, In terms of their strengths, (1) Human judgment is considered as credible, (2) Humans have common sense and can determine new rules, off the shelf, (3) Humans can easily identify trends or abnormality in visualization data. However, Humans also suffer from severe weaknesses whereby they (1) cannot often accomplish complex computational decisions, (2) cannot perform fast reasoning computations, and (3) get easily tired and bored. These human weaknesses can be mitigated by using a computer, which can perform complex computation decisions relatively faster and will not suffer from tiredness or boredom.

Being a human, students are easily tired or bored, and tend to choose computer-based cases [34, 50] and opt for web-based cases as compared to lectures for their learning [51, 52]. Additionally, more attention is given to online/web-based learning environments [34]. In order to support the learning outcomes of students, a plethora of web-based learning systems have been developed [53–62]. A review of the literature shows that these systems either do not support computer-based interactive case authoring as well as its formulation, or without the support of acquiring real-world CBL cases or do not provide feedback to students. Currently, much less attention is given to the development mechanisms of real-world clinical cases using experiential knowledge and no support of domain knowledge while formulating the case. Case formulation means identification of a medical chart’s components (demographics, chief
1.1 Motivation

complaint, medical history, habits, family history, medicines, allergies, diagnosis, treatment, and recommendations) from a given clinical case and then writing personal observations for each component.

There exists plenty of textual data in the medical domain, which can be useful for medical education, especially for CBL purposes. This data is available in a variety of formats and with different semantics. This overwhelming data provides various opportunities to gain useful knowledge that reflects the depth of information that plays an important role in decision-making. Declarative knowledge (also called factual knowledge) is a type of knowledge expressed in the form of unstructured text, which can play an important role in health’s education, decision support, and wellness applications after structured transformation. According to the Simply Philosophy study [63], “Factual knowledge is a justified affirmation of something”. It combines the concepts to make an affirmation of something. For example, “Blood_disease” and “is a symptom” make an affirmation “Blood_disease is a symptom". The produced affirmation is either true or false; however, in declarative knowledge it is always true. Handling unstructured contents is the foundation to construct the domain knowledge (structured declarative knowledge) required for interactive learning, to prepare medical students for their clinical practice before and outside the class.

Text mining is the process of deriving high-quality information from an unstructured text. It involves the application of techniques from areas like information retrieval, natural language processing, information extraction, and data mining [64]. In the text mining domain, normally text preprocessing, text transformation, feature selection, term extraction, relation extraction, and model construction tasks are involved to construct domain knowledge from textual data. For constructing reliable domain knowledge, the feature selection (FS) task is considered one of the most critical problems for selecting appropriate features from a larger set of features [65–67].
Introduction

Feature selection performs a key role in the (so-called) process of ‘Knowledge Discovery’ [67]. Traditionally, this task is performed manually by a human expert; thereby making it more expensive and time-consuming, as opposed to an automatic FS which has become necessary for the fast-paced digital world of today [13]. Feature selection techniques are generally split into three categories: filters, wrappers, and hybrid, where each technique has capabilities and limitations [12–14]. Popular evaluation methods used for these techniques are information-theoretic measures, co-relational measures, consistency measures, distance-based measures and classification/predictive accuracy. A good feature selection algorithm can effectively filter out unimportant features [68]. In this regard, a significant amount of research has focused on proposing improved feature selection algorithms [69–73]; consequently, most of these algorithms use one or more of the aforementioned methods for performing feature selection. However, there is a lack of a comprehensive framework, which can select features from a given feature set.

1.2 Problem Statement

For an automated CBL, a structured knowledge construction from textual data is a challenging task [74]. In the text mining domain, normally text preprocessing, text transformation, feature selection, term extraction, relation extraction, and model construction tasks are involved, where the feature selection task is considered to be one of the most critical problems for selecting appropriate features from a larger set of features [65–67]. To design an effective CBL approach for better clinical competency, three major research questions must be answered:

1. How to rank the features without using any learning algorithm, high computational cost, and individual statistical biases of state-of-the-art feature ranking methods? In this case, the filter-based feature ranking approach is more suitable than the other two
approaches (wrapper, hybrid). Filter-based methods evaluate a feature’s relevance without using any learning algorithm [65, 12]. Filter-based feature ranking methods are further split into two subcategories: univariate and multivariate. Univariate filter methods are simple and have high performance characteristics as compared to other approaches [75]. Even though the univariate filter-based methods are considered to be much faster and less computationally expensive than wrapper methods [15, 12]; each method has its capabilities as well as its limitations. For example, Information Gain (IG) is a widely acceptable measure for ranking the features [76]; however, IG is biased towards choosing features with a large number of values [77]. Similarly, Chi Square (CS) determines the association between a feature and its target concept/class; however, CS is sensitive to sample size [77]. In addition, Gain Ratio and Symmetrical Uncertainty enhances the information gain; however, both are biased towards features with fewer values [78]. Therefore, designing an efficient feature ranking approach and overcoming the aforementioned limitations is our first target.

2. How to find a minimum threshold value for retaining important features irrespective of the characteristics of the dataset? In this case, for defining cut off points for removing irrelevant features, a separated validation set and artificially generated features approaches are used [70]; however, it is not clear how to find the threshold for the features’ ranking [79, 80]. Finding an optimal cut-off value to select important features from different datasets is problematic [79]. Therefore, designing an empirical method to specify a minimum threshold value for retaining important features and overcoming the aforementioned limitations is our second target.

3. How to fill the gaps between human-based and computer-based learning to innovate the CBL approach for better clinical proficiency? Both humans and computers have their own strengths and weaknesses [48, 49]. In the medical area, human (domain expert) judgment is considered as more credible than a computer; however, a human cannot
perform fast reasoning computations to work for extended periods and will get tired and feel bored. A computer has the advantage over a human of being able to perform fast reasoning computation without feeling bored. Being a human, students feel that classroom CBL activities require a significant amount of time; they get tired [42], and tend to choose computer-based cases [34, 50]. Similarly, students opt for web-based cases as compared to lectures for their learning [51, 52]. Additionally, more attention is given to online/web-based learning environments [34]. In order to support the learning outcomes of students, a plethora of web-based learning systems have been developed [53–62]. A review of the literature shows that these systems either do not support computer-based interactive case authoring as well as its formulation, or without the support of acquiring real-world CBL cases, or do not provide feedback to students. Currently, much less attention is given to fill the gaps between human-based and computer-based learning. Therefore, designing and developing an interactive and effective case-based learning approach to utilize the strength of both human (experiential knowledge) and computer (domain knowledge) and overcoming the aforementioned limitations is our third target.

1.3 Key Contributions

We summarize the main contributions of this thesis as below:

1.3.1 Novel feature ranking algorithm

For evaluating the feature-set in a comprehensive manner to generate a final ranked list of features, a unified features scoring (UFS) algorithm is introduced, which ranks the features without using any learning algorithm, without high computational cost, and without any of the individual statistical biases of state-of-the-art feature ranking methods.
1.3.2 Novel threshold value selection algorithm

For defining the cut-off point for removing irrelevant features, a threshold value selection (TVS) algorithm is introduced, which selects a subset of features that are deemed important for the domain knowledge construction. TVS finds a minimum threshold value for retaining important features irrespective of the characteristics of the dataset.

1.3.3 Improved feature selection

Proof-of-concept for the UFS and TVS techniques, after performing extensive experimentation which achieved (1) on average, a 7% increase in f-measure as compared to the baseline approach, and (2) on average, a 5% increase in predictive accuracy as compared to state-of-the-art methods.

1.3.4 Reliable domain knowledge construction

For interactive and effective learning purposes, this research includes a methodology to construct the domain knowledge (i.e. structured declarative knowledge) from unstructured text, to facilitate and provide computer-based domain knowledge to medical students for solving real-world clinical cases during CBL practice. With the evolution of knowledge stored in a database, the proposed system can hold better clinical competence and can provide intensive learning in the future. For effective transformation, controlled natural language is used, which constructs syntactically correct and unambiguous computer-processable texts.

1.3.5 Semi-automatic real-world clinical case creation technique

In professional education for health and social care domains, the clinical case is a key component in learning activities and provides a foundation to understand the nature of a disease. To innovate the case-based learning approach for better clinical proficiency, a
A semi-automatic technique for real-world clinical case creation is introduced. The proposed technique facilitates health care professionals (medical teachers) who are interconnected in common practice, to produce experiential knowledge for the purpose of developing clinical knowledge. This knowledge includes scientific knowledge and realistic experiences to provide responses in risky and uncertain situations.

1.3.6 An interactive and effective automated CBL system development

For an interactive as well as an effective case-based learning (CBL) approach, an interactive case-based learning system (iCBLS) is designed and developed, which utilizes the strength of both human (experiential knowledge) and computer (domain knowledge). The iCBLS enables medical teachers to create real-world CBL cases for their students with the support of their experiential knowledge and computer-generated trends, review students’ solutions, and give feedback and opinions to their students. It also facilitates medical students to do CBL rehearsal with a machine-generated domain knowledge support before attending an actual CBL class.

1.4 Thesis Organization

The dissertation aims to investigate an efficient feature selection methodology to construct reliable domain knowledge for case-based learning. Figure 1.1 shows the dissertation overview, and summarizes the structure and flow of the dissertation.

This dissertation is organized into chapters as following.

- **Chapter 1: Introduction.** Chapter 1 provides the introduction of the research work for feature selection to construct domain knowledge for an interactive and effective case-based learning. It focuses on the problems in areas, the goals to achieve these
problems, the objectives achieved in this research work, and finally the dissertation overview.

- **Chapter 2: Related work.** Chapter 2 reviews previous research for feature selection methodologies to filter out irrelevant features. This research focuses on presenting a comprehensive and flexible feature selection methodology based on an ensemble of univariate filter measures for constructing a reliable domain knowledge to innovate the case-based learning approach. Therefore, we present an overview of different methodological studies of feature selection as well as case-based learning approaches. Various research directions related to (1) feature selections like features ranking and ensemble approaches, (2) technologies used for the domain knowledge construction, and (3) case-based learning methodologies and related web-based learning systems
are discussed in each subsection. Finally, we summarize the related works that utilize feature selection, knowledge construction, and case-based learning methodologies.

- **Chapter 3: Univariate ensemble-based feature selection.** In this chapter, we present univariate ensemble-based feature selection (uEFS) methodology to select informative features from a given dataset. For the uEFS methodology, we first propose a unified features scoring (UFS) algorithm to generate a final ranked list of features after a comprehensive evaluation of a feature set. For defining a cut-off point to remove irrelevant features, we then propose a threshold value selection (TVS) algorithm to select a subset of features, which are deemed important for the domain knowledge construction. To evaluate the proposed uEFS methodology, we have performed two studies. Finally, for each study, we present the experiment setup, and then provide the corresponding experimental results for each study under different settings.

- **Chapter 4: Domain knowledge construction.** This chapter describes a methodology to construct the machine-generated domain knowledge (i.e. structured declarative knowledge) from an unstructured text. The proposed methodology constructs an ontology from unstructured textual resources in a systematic and automatic way using artificial intelligence techniques with minimum intervention of a knowledge engineer.

- **Chapter 5: Case-based learning.** This chapter presents an interactive and effective case-based learning approach for medical education, which utilizes the strength of both human (experiential knowledge) and computer (domain knowledge). In this chapter, we introduce (1) a semi-automatic technique for real-world clinical case creation, (2) case formulation technique with domain knowledge support, and (3) an IoT-based platform for supporting flipped case-based learning. To automate the proposed CBL approach, we design and develop an interactive case-based learning system (iCBLS). To evaluate the proposed approach, we have performed two studies. Finally, for each
study, we present the evaluation setup and then provide the corresponding evaluation results for each study under different settings.

- **Chapter 6: Conclusion and future directions.** This chapter concludes the thesis and provides future directions in this research area. It also describes the potential applications of the proposed methodology.
Chapter 2

Related Work

This chapter describes various existing studies related to each aspect of this research work. This research focuses on presenting a comprehensive and flexible feature selection methodology based on an ensemble of univariate filter measures for constructing a reliable domain knowledge, to innovate the case-based learning approach. Therefore, this section is split into three subsections to present an overview of different methodological studies of feature selection, domain knowledge construction, and case-based learning approaches. Various research directions related to (1) feature selections such as features ranking and ensemble approaches, (2) technologies used for domain knowledge construction, and (3) case-based learning methodologies and related web-based learning systems, are discussed in each subsection. Finally, we summarize the related works that utilize feature selection, knowledge construction, and case-based learning methodologies.

2.1 Overview of feature selection

This study includes a univariate ensemble-based feature selection (uEFS) methodology for selecting salient features from a dataset. This methodology is based on an empirical study of different univariate filter-based feature selection measures such as including information
gain, gain ratio etc. The following are some relevant feature selection (FS) studies from a methodological point of view, which contain:

- basic concepts and procedures of feature selection
- state-of-the-art feature selection approaches, and
- research surveys, comparative studies, and frameworks in the domain of FS

FS is an approach that chooses a subset of features from a given list of original features and filters the irrelevant features to speed up the processing of a machine learning algorithm for improving mining performance (predictive accuracy, result comprehensibility). Feature selection is an active area of research and has undergone significant revolution in the past few decades. Various research disciplines such as pattern recognition, machine learning, data mining, and text mining have applied FS techniques to many fields such as text categorization, image retrieval, customer relationship management, and intrusion detection [1]. The FS task is considered to be one of the most critical problems for selecting appropriate features from a larger set of features [65]. This approach becomes expensive and intractable (NP-hard), when the number of features N increases. It performs a key role in the so-called process of 'Knowledge Discovery' [67]. The FS task can also be performed manually by a human expert; however, in this case it is considered as an expensive and time-consuming task. In such cases, an automatic FS is necessary [13].

A review of applied FS methods for microarray datasets was performed by Bolón et al. [81]. Microarray data classification is a difficult task due to its high dimension and small sample sizes. Therefore, feature selection is considered the de-facto standard in this area [81]. Normally, a FS approach consists of four basic steps, namely, ‘subset generation’, ‘subset evaluation’, ‘stopping criterion’, and ‘result validation’ [82] as shown in Figure 2.1, which are described as follows.
2.1 Overview of feature selection

Fig. 2.1 Basic steps of feature selection [1].

- **Subset generation** is a searching process, which is based on a specific approach to evaluate a candidate subset. For this process, two basic criterion are defined. The first one is to decide the starting point of the search and the second one is about the search strategy. For the first criteria, the search can be started either from an empty set, or from a full set, or from both ends, or at random. Similarly, for the second criteria, the search strategy can be sequential, complete, or a random search.

- **Subset evaluation** is the second step for the feature selection procedure. In this step, each candidate subset, which is generated from the previous step, is compared against the previous best subset based on a certain evaluation criterion. In the case of better results, the new subset replaces the previous one, as it is considered the best subset. The goodness of a subset is evaluated either by an independent criterion (without involvement of mining algorithm such as filter method) or by a dependent criterion (reliant on mining algorithm such as wrapper and hybrid methods). For independent criteria, information-theoretic measures, co-relational or dependency-based measures, consistency-based measures, and distance-based measures are widely used in literature [1]. Most of the feature selection algorithms use one or more of the aforementioned measures for performing feature selection.

- **Stopping criterion** is the third step, in which the procedure of feature selection is stopped due to some stopping criteria. Following are some definitions of stopping
criteria, which are: (1) when the search is complete, (2) when a specific number (limit) is reached, (3) when addition or deletion of features are not improving the result, and lastly, (4) when the error rate is reduced for the given task [1].

- **Result validation** is the final step, where the selected subset is validated either by beforehand knowledge or by observing the change of mining performance using synthetic or real-world data sets [1].

A research taxonomy of feature selection approaches is shown in Figure 2.2; the components represented with bold text and highlighted background are covered in this study. This figure shows an abstract view of taxonomy for feature ranking methods.

![Fig. 2.2 Research Taxonomy - Dimensionality reduction and different feature selection approaches [2, 3].](image)

Feature selection approaches are generally split into three categories: filter, wrapper, and hybrid as shown in Figure 2.2, where each approach has capabilities and limitations as shown in Table 2.1.

Liu and Yu [1] proposed a categorizing framework to build an integrated system for automatic feature selection. This framework was based on a unifying platform and laid the important foundation for methodologically integrating different feature selection methods based on their shared characteristics. Chen et al. [83] performed a survey on FS algorithms
Table 2.1 Feature selection approaches [12, 1, 13–16].

<table>
<thead>
<tr>
<th>Capabilities</th>
<th>Filter approach</th>
<th>Wrapper approach</th>
<th>Hybrid approach</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>+ Performs simple and fast computation</td>
<td>+ Conducts a subset search with an optimal algorithm</td>
<td>+ Requires less computation than wrapper method</td>
</tr>
<tr>
<td></td>
<td>+ Not dependent on the classification algorithm</td>
<td>+ Better classification accuracy</td>
<td></td>
</tr>
<tr>
<td></td>
<td>+ Generally have less computational costs than wrapper and hybrid methods</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>+ Better suited to high dimensional datasets</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Limitations</td>
<td>– Decreases classification performance</td>
<td>– Higher risk of overfitting</td>
<td>– Specific to a learning machine</td>
</tr>
<tr>
<td></td>
<td></td>
<td>– High computational cost</td>
<td></td>
</tr>
<tr>
<td>Examples</td>
<td>Information Gain, Chi-Squared, ReliefF etc.</td>
<td>Sequential Forward or Backward Selection, Genetic Algorithm etc.</td>
<td>Information Gain + Genetic Algorithm etc.</td>
</tr>
</tbody>
</table>

for an intrusion detection system. Experiments were performed for different FS methods i.e. filter, wrapper, and hybrid. Since this study was not focused on comprehensible classifiers it did not study the effects of FS algorithms on the comprehensibility of a classifier. In addition to this, no unifying methodology was proposed which could categorize existing FS methods based on their common characteristics or their effects on classifiers.

With respect to ensemble feature selection studies, Rokach et al. [71] investigated an ensemble approach that could enhance feature selection; however, the researchers only considered non-ranking filters. Similarly, Jong et al. [72] proposed an ensemble feature ranking methodology that integrated various feature rankings from the same and artificial datasets to improve the stability of feature ranking. In addition, Slavkov et al. [73] conducted a study on various aggregation approaches of the feature rankings of public neuroblastoma microarrays using multiple ranking algorithms and datasets. They showed that aggregating feature rankings produced favorable outcomes compared to the use of a single feature ranking.
method. Prati [70] also proposed a general framework for the use of ensemble feature ranking to improve the quality of feature rankings, and was able to obtain better results than others. Belanche and Gonzalez [69] performed a thorough study of feature selection algorithms in synthetic problems to evaluate their performance. In this study, a scoring measure was devised to score the output of the feature selection methods, a solution that was considered to be optimal. In addition to this, a comprehensive survey of FS methods was also performed.

In the current study, we have used ensemble-based filter approach. A generalized filter approach is described in Algorithm-1.

**Algorithm 1: A generalized filter algorithm [1]**

```
Input : D = (f1, f2, ..., fn) // a training data set with N features
S0 // a subset from which to start the search
δ // a stopping criteria
Output : S_best // an optimal subset
initialization;
S_best ← S0
γ_best ← evaluate(S0, D, M);
while (δ is not reached) do
    S ← generate(D);
    γ ← evaluate(S, D, M);
    if (γ is better than γ_best) then
        γ_best ← γ;
        S_best ← S;
    end
end
return S_best
```

This algorithm takes a list of N features \((f_1, f_2, ..., f_n)\) from a given data set \(D\) as input and then sequentially passes through mandatory steps to produce best subset \(S_{\text{best}}\). \(S_0\) is a subset from which it starts the searching process. It can be either an empty set or a full set, or any random set. \(δ\) is a stopping criteria to stop the feature selection process as mentioned earlier. Initially, \(S_0\) is assumed as the best subset and represented by \(S_{\text{best}}\). Similarly, evaluate \(S_0\) using an independent measure \(M\) and store the result in \(γ_{\text{best}}\). Now based on stopping criteria \(δ\), generate subset \(S\) from a given data set \(D\). After subset generation, evaluate that
subset $S$ against measure $M$ and store the result in $\gamma$. After comparing $\gamma$ with $\gamma_{best}$, if $\gamma$ has a better result, consider $\gamma$ and $S$ as $\gamma_{best}$ and $S_{best}$. In each iteration, values are compared with the previous best one. This process is repeated until predefined $\delta$ stopping criteria is reached. Finally, the algorithm provides best subset $S_{best}$ as an output.

For ensemble-based feature selection studies, various combinations of univariate filter methods are used in the literature, including (i) IG, GR, CS, and SU [3, 65], (ii) IG, CS, and SU [84], and (iii) IG, GR, SU, CS, and OneR [70]. In literature, a hybrid approach by combining filter and wrapper methods is also presented that can eliminate unwanted features by using a ranking technique [85]. A similar concept to an EFS approach is also mentioned in [86, 67]. For ensemble feature ranking, two aggregate functions called arithmetic mean and median were used to rank features [3]. Authors obtained the ranking by arranging the features from the lowest to the highest. They assigned rank 1 to a feature with the lowest feature index and rank M to a feature with the highest feature index [3]. Similarly, authors aggregated several feature rankings to demonstrate the robustness of ensemble feature ranking that surges with the ensemble size [72]. Onan and Korukoğlu [75] presented an ensemble-based feature selection approach, where different ranking lists obtained from various FS methods were aggregated. Authors used the genetic algorithm (GA) for producing an aggregate ranked list, which is a relatively more expensive technique than a weighted aggregate technique. They performed experiments involving binary class problems; it is not clear how would the proposed method would deal with more complex datasets. Popular filter methods used for the ensemble-based feature selection approach are information gain, gain ratio, chi square, symmetric uncertainty, OneR, and ReliefF. Most of the feature selection methodologies use three or more of the aforementioned methods for performing feature selection [84, 3, 65, 70, 77, 80]. Finally, feature ranking approach is used in this study as it is considered an attractive approach due to its simplicity, scalability, and good empirical success [3, 87].
A good feature selection algorithm can effectively filter out unimportant features [68]. A feature selection algorithm assesses the usefulness of the features present in the dataset, based on some evaluation metrics. For this study, information-theoretic measures (information gain, gain ratio, and symmetric uncertainty) and co-relational or dependency-based or statistical measures (chi-squared and significance) are utilized. Statistical measures provide good performance in various domains [78] and information-theoretic measures such as entropy are good measures to quantify the uncertainty of features and provide good performance in various domains [2, 78], each of these measures is defined as follows:

**Information Gain (IG)** is an information theoretic as well as a symmetric measure, which is computed by the following equation [76]:

$$IG(A) = Info(D) - Info_A(D)$$

(2.1)

where $IG(A)$ is the IG of an independent feature or attribute $A$, $Info(D)$ is the entropy of the entire dataset, and $Info_A(D)$ is the conditional entropy of attribute $A$ over $D$.

**Gain ratio** is considered to be one of the disparity measures that provides normalized score to enhance the IG result. This measure utilizes the split information value that is given as follows [76]:

$$SplitInfo_A(D) = - \sum_{j=1}^{v} \frac{|D_j|}{|D|} \log_2 \frac{|D_j|}{|D|}$$

(2.2)

where $SplitInfo$ represents the structure of $v$ partitions. Finally, gain ratio is defined as follows [76]:

$$GainRatio(A) = \frac{IG(A)}{SplitInfo(A)}$$

(2.3)

**Chi-squared** is a statistic measure that computes the association between the attribute $A$ and its class or category $C_i$. It helps to measure the independence of an attribute from its class. It is defined as follows [76]:

$$CHI(A, C_i) = \frac{N * (F_1 F_4 - F_2 F_3)^2}{(F_1 + F_3) * (F_2 + F_4) * (F_1 + F_2) * (F_3 + F_4)}$$

(2.4)
2.1 Overview of feature selection

\[ CHI_{\text{max}}(A) = \max_i(CHI(A, C_i)) \]  

(2.5)

where \( F_1, F_1, F_3, \) and \( F_4 \) represent the frequencies of occurrence of both \( A \) and \( C_i \), \( A \) without \( C_i \), \( C_i \) without \( A \), and neither \( C_i \) nor \( A \), respectively, while \( N \) represents the total number of attributes. A zero value of CHI indicates that both \( C_i \) and \( A \) are independent.

**Symmetric uncertainty** is an information theoretic measure to assess the rating of constructed solutions. It is a symmetric measure and is expressed by the following equation [88]:

\[ SU(A, B) = \frac{2 \times IG(A|B)}{H(A) + H(B)} \]  

(2.6)

where \( IG(A|B) \) represents the IG computed by an independent attribute \( A \) and the class attribute \( B \). While \( H(A) \) and \( H(B) \) represent the entropies of the attributes \( A \) and \( B \).

**Significance** is a real-valued, two-way function used to assess the worth of an attribute with respect to a class attribute [89]. The significance of an attribute \( A_i \) is denoted by \( \sigma(A_i) \), which is computed by the following equation:

\[ \sigma(A_i) = \frac{AE(A_i) + CE(A_i)}{2} \]  

(2.7)

where \( AE(A_i) \) represents the cumulative effect of all possible attribute-to-class associations of an attribute \( A_i \), which are computed as follows:

\[ AE(A_i) = \left( \frac{1}{k} \sum_{r=1,2,...,k} \vartheta_i^r \right) - 1.0 \]  

(2.8)

where \( k \) represents the different values of the attribute \( A_i \).

Similarly, \( CE(A_i) \) captures the effect of change of an attribute value by the changing of a class decision and represents the association between the attribute \( A_i \) and various class...
decisions, which is computed as follows:

\[
CE + (A_i) = \left( \frac{1}{m} \right) \times \left( \sum_{j=1,2,...,m} A_{ij} \right) - 1.0
\]

(2.9)

where \( m \) represents the number of classes and \( + (A_i) \) depicts the class-to-attribute association of the attribute \( A_i \).

In order to identify an appropriate cut-off value studies for the threshold, Sadeghi and Beigy [2] proposed a heterogeneous ensemble-based methodology for feature ranking. Authors used the genetic algorithm to determine the threshold value; however, a \( \theta \) value is required to start the process. Moreover, the user is given an additional task of defining the notion of relevancy and redundancy of a feature. The proposed wrapper-based method is tightly coupled with the performance evaluation of a single classifier i.e. SVM; hence losing the generality of the method. Osanaiye et al. [80] combined the output of various filter methods; however, a fixed threshold value i.e. 1/3 of a feature set, is defined a priori irrespective of the characteristics of the dataset. Sarkar et al. [77] proposed a technique that aggregates the consensus properties of Information gain, Chi-Square, and Symmetric Uncertainty feature selection methods to develop an optimal solution; however, this technique is not comprehensive enough to provide a final subset of features. Hence, a domain expert would still need to make an educated guess regarding the final subset. To define cut-off points to remove irrelevant features, a separated validation set and artificially generated features approaches are used [70], however, it is not clear how to find the threshold for the features’ ranking [79, 80]. Finding an optimal cut-off value to select important features from different datasets is problematic [79].
2.2 Overview of domain knowledge construction

This section describes the important aspects of the data science (DS) process. It deals with: (1) DS background and the Cross Industry Standard Process for Data Mining (CRISP-DM) methodology, (2) methodological studies of knowledge construction approaches, and (3) controlled natural languages background and methodological studies for domain model construction.

The term DS was used in the early 1960s to cover six processes [90]—problem identification, data collection, data preprocessing, data analysis, data modeling, and product evaluation, in order to extract knowledge for decision-making. Text mining (TM) is a multidisciplinary research area, which derives high-quality information from textual data. TM includes information retrieval, natural language processing, data mining (DM), machine learning, and others [64]. Data mining is generally considered a sub-step of the DS process [90]. CRISP-DM, published in the year 2000, is a widely-used systematic methodology for developing DM/DS projects. It is considered to be the de facto standard [17] for executing a DM project systematically. Gupta [91] discussed software development and CRISP-DM, two different approaches to the data mining process. In the software development approach, the data mining process includes six steps: ‘requirement analysis,’ ‘data selection and collection,’ ‘cleaning and preparing data,’ ‘data mining exploration and validation,’ ‘implementation, evaluation, and monitoring,’ and ‘results visualization.’

According to Abacha and Zweigenbaum [6], “the medical knowledge is growing significantly every year. According to some studies, the volume of this knowledge doubles every five years, or even every two years”. Since most of the information available in digital format is unstructured [92], the information extraction problem has attracted wide interest in several research communities [93]. Rajni and Taneja [94] proposed a framework, called U-STRUCT that converts textual documents into an intermediate structured form; however, a knowledge engineer is required to convert that intermediate form into fully structured
form. Similarly, Friedman et al. [95] developed an approach, which maps the textual data into UMLS codes for translating them into a structured form (XML format); however, their approach does not support lexical ambiguity and requires a knowledge engineer as well as domain knowledge for structured translation. Leao et al. [96] proposed an ontology learning methodology using OntoUML. They converted unstructured text into structured form by utilizing WordNet lexicon to study word-sense disambiguation. Reuss et al. [97] proposed and implemented a semi-automatic methodology to extract knowledge from unstructured as well as semi-structured data. The proposed methodology does not support lexical ambiguity.

For knowledge construction, keyword extraction is a vital technique for textual data as well as information retrieval, automatic indexing, text summarization, text mining, text clustering, text categorization, topic detection, and question-answering [4, 98, 5]. Loh et al. [99] noted that concept extraction is a low cost process that helps to build a vocabulary for constructing/discovering domain knowledge. Haggag [4] described that both qualitative and quantitative techniques can be used for keywords extraction task. Qualitative techniques are considered reliable, while quantitative techniques are preferable due to handling multiple text processing tasks. According to Chen and Lin [100], machine learning approaches can be used for keyword extraction; however, as this approach is used in specific domains and for moving to other domains, re-learning is required to build that domain model. Zhu et al. [101] utilized supervised methods for extracting the term relations; however, they required human help to tag the data for learning an extractor. Wenchao et al. [102] presented a keyword extraction approach using a thesaurus; however, the man-made thesaurus are unable to follow the abrupt changes in textual information. In the literature various methodologies are used, which are represented in Figure 2.3.

Similarly, various technologies are used that help to construct the domain knowledge from textual data. Each method/technique/tool involved in knowledge construction process has advantages and disadvantages, which are illustrated in Tables 2.2, and 2.3.
2.2 Overview of domain knowledge construction

Keywords Extraction Methodologies

Quantitative
- Set of concordances
- Statistical relations
- Formal linguistic processing

- Word frequency
- TF-IDF
- Co-occurrence
- Bayesian
- K-Nearest Neighbor
- Expectation Maximization
- Genetic Algorithms
- Support Vector Machines
- Decision Tree

Qualitative
- Semantic relations
- Semantic analysis

- Lexical chains
- Thesaurus-based extraction
- web mining and statistical methods

Fig. 2.3 Keyword extraction methodologies [4–7]
<table>
<thead>
<tr>
<th>Reference</th>
<th>Method / Technique / Tool</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>[103]</td>
<td>Corpus dependent approach for keyword extraction</td>
<td>• Provides better performance</td>
<td>• Requires documents and fixed keywords to develop a prediction model for single domain.</td>
</tr>
<tr>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>[104, 100, 105, 4, 106, 5, 7]</td>
<td>Statistical approaches for keyword extraction</td>
<td>• Considered as simplest models,</td>
<td>• Does not always discover meaningful relations between words,</td>
</tr>
<tr>
<td>-</td>
<td>-</td>
<td>• Used for Complex terms extraction</td>
<td>• Does not always discover meaningful relations between words,</td>
</tr>
<tr>
<td>[107–109, 104]</td>
<td>Word Frequency Analysis - Term Frequency Inverse Domain Frequency (TF-IDF)</td>
<td>• Determines good candidate keywords,</td>
<td>• Requires manual annotation of texts for learning, requires models' target concept importance to identify relevant keywords,</td>
</tr>
<tr>
<td>-</td>
<td>-</td>
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<td>-</td>
</tr>
<tr>
<td>[92]</td>
<td>Co-occurrence strategy</td>
<td>• Constructs rules in fast manner</td>
<td>• Relatively low precision</td>
</tr>
<tr>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>[6]</td>
<td>MetaMap for medical entity recognition</td>
<td>• Maps medical text to UMLS concepts for identifying the precise concepts</td>
<td>• Recognizes some common words as medical terms,</td>
</tr>
<tr>
<td>-</td>
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<td>-</td>
<td>-</td>
</tr>
<tr>
<td>[102]</td>
<td>Naïve Bayes technique</td>
<td>• Simple technique to produce good results</td>
<td>• Requires manually assigned keywords for each document.</td>
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<td>-</td>
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</table>
### 2.2 Overview of domain knowledge construction

<table>
<thead>
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<th>Method / Technique / Tool</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>[6]</td>
<td>Domain-dependent relation extraction methods</td>
<td>• Extracts relations using meta-thesaurus and semantic network of UMLS</td>
<td>• Dependent on domain knowledge</td>
</tr>
<tr>
<td>[4, 110, 5]</td>
<td>WordNet</td>
<td>• Enables to calculate the similarity between noun as well as verb pairs, • Provides semantic features within words</td>
<td>• Supports limited vocabulary and not covers all domains</td>
</tr>
<tr>
<td>[99]</td>
<td>Word-sense disambiguation</td>
<td>• Natural language processing techniques help to solve the ambiguity problems</td>
<td>• Requires complex algorithms and time to analyze the text, • Requires knowledge models and rules</td>
</tr>
<tr>
<td>[111]</td>
<td>Restricted vocabulary or thesaurus</td>
<td>• Produce consistent results</td>
<td>• Construction and maintenance of thesaurus</td>
</tr>
<tr>
<td>[110, 107]</td>
<td>Lexical chains</td>
<td>• Widely used in text summarization, • Locate terms and their sequence in quick and accurate manner</td>
<td>• Not fully explored in keyword extraction problems, • Is an exhaustive method</td>
</tr>
</tbody>
</table>
Kuhn [8] described how controlled natural language (CNL) is similar to natural language and humans can easily understand it. CNL is a restricted language, which can be processed and interpreted by computers. This language preserves its essential properties, while restricting its syntax, semantic, and lexicon [112]. CNL was proposed to build knowledge bases (ontologies). Multiple CNLs have been developed to build semantic web ontologies such as Attempto Controlled English (ACE), Sydney OWL Syntax (SOS), Controlled Language for Ontology Editing (CLOnE), and Rabbit. In the literature, various categories of controlled natural languages are used, which are represented in Figure 2.4.

CNLs have been successfully used in various commercial applications such as machine translation, information management, mobile communication, and so on [113]. Shiffman et al. [114] translated a complete set of guideline recommendations into computer-interpretable statements using controlled natural language. Similarly, in GuideLines Into Decision Support (GLIDES) project, BRIDGE-Wiz used controlled natural language to formalize a process for writing implementable recommendations to improve guideline quality [115].

For computer processability, the CNL is written in formal logic. The basic purpose of defining CNL is to design computer-processable text for improving machine translation. Similarly, Safwat and Davis [116] noted that controlled natural languages (CNLs) facilitate non-expert users to develop ontologies of varying sizes in an easy-to-use manner. Williams et al. [117] described how CNLs are knowledge representation languages, which help non-expert users to translate their knowledge into a computer interpretable form without involvement of a knowledge engineer. Schwitter [118] worked on communication among humans with different native languages and used CNL to represent the formal notations. He concluded that CNL can improve human communication. In addition, Miyabe and Uozaki [113] described various features of CNL, namely that they:

- Enhance readability
- Improve the terms dis-ambiguity
• Are easy to understand
• Reduce misunderstanding
• Minimize the role of knowledge engineer
• Reduce the human translation cost, and
• Improve re-usability of knowledge

Kuhn [8] designed a CNL, called *Attempto Controlled English* (ACE), which is considered one of the most mature CNLs. ACE was developed in early 1995 and has been under development for more than 20 years. This language is most widely used in the academic domain. Its vocabulary is not fixed and varies based on the particular problem domain. ACE also covers all four design principles, as compared to other CNLs, which do not satisfy all principles. In addition, it is acknowledged to be an unambiguous language. Similarly, Denaux [119] also described some features of the ACE language; he noted that ACE can be used for ontology construction without knowing the knowledge of web ontology language (OWL). It supports all kinds of ontology expressiveness. In addition, it is easy to use for all domain experts.

One of the key problem of CNL is the writability problem, i.e. how to write statements that satisfy the restrictions of the language. Power et al. [120] defined that, “The domain expert can define a knowledge base only after training in the controlled language; and even after training, the author may have to try several formulations before finding one that the system will accept.” and similarly, Schwitter et al. [121] stated that, “It is well known that writing documents in a controlled natural language can be a slow and painful process, since it is hard to write documents that have to comply with the rules of a controlled language.” It is very difficult to write a syntactically correct statement without any external support. In order to resolve the writability problem of CNLs, Kuhn [8] has mentioned three approaches, namely *Error messages, Predictive editors, and Language generation.* He also designed the
predictive editor and described how the predictive editor is showing the most promise to resolve the writability problem. Schwitter [122] also mentioned that a predictive interface of an editor can help to write correct CNL sentences for building a knowledge base [122].

For evaluating the CNLs, ontographs are considered a simple and powerful approach [123, 124]. Kuhn described how ontographs are intuitive, represent the logic forms in simple manner, and help to understand the core logic [123, 124].

2.3 Overview of case-based learning

This section demonstrates pedagogical concepts, methodologies applied in case-based learning (CBL), and related web-based learning systems in medical education. It is further classified into: (1) a background subsection, which describes the basics of CBL with respect to background, features, its comparisons with problem-based learning (PBL), and role of experiential knowledge in CBL; (2) an evolutionary technologies subsection, which explains that how IoT technology was used in the medical domain, and how CBL with flip environment was applied in medical education; and (3) a review subsection, which overviews the existing web-based learning systems, and compares these with well-established CBL systems.

2.3.1 Background for case-based learning

CBL is one of the successful approaches in student-based pedagogy. Jones et al. [125] described that CBL arose from research that indicated that learners who commenced by tackling problems before attempting to understand underlying principles had equal or greater success that learners using a traditional approach. CBL is described as active learning that is focused around a clinical, community or scientific problem. Learning starts with a problem,
Related Work

CBL was introduced by pedagogy experts to improve knowledge exploration, emphasize critical thinking, achieve better collaboration, and increase opportunities for receiving feedback [126]. Research literature provides multiple features of CBL, such as: (i) it assists students to examine fact-based data, employ analytical tools, articulate their concerns, and draw conclusions for relating to new situations [127, 25], (ii) it offers an opportunity to realize theory in practice [25], and (iii) it develops students’ clinical skills in independent and group learning, as well as in communication and critical thinking, to acquire meaningful knowledge for improving students’ attitudes towards medical education [24–31]. Because of these features, there are several researchers who have applied CBL in medical education. Fish et al. [32] states Samford University received a grant to apply CBL in undergraduate education. CBL was integrated into the some of the nursing courses. This was successful and as a result CBL was implemented across the entire curriculum. CBL was effectively used in adult health, mental health, pediatric and obstetrical nursing courses. CBL was also used effectively in non-clinical courses such as pathophysiology, statistics and research. Moreover, students studying medicine at the University of Missouri who graduated from 1993 through to 1996 went through a traditional curriculum, whereas students graduating from 1996 through to 2006 went through a CBL curriculum [33]. As part of both curriculums students must pass a ’step 1’ test in their third year of study before progressing on to their fourth year. They must complete a ’step 2’ test in order to graduate. Since the introduction of the CBL curriculum, these scores have risen significantly and have remained significantly higher.

CBL is a teaching methodology that utilizes PBL principles. Scavarda et al. [128] and Thistlethwaite et al. [34] described CBL as more structured than PBL as it uses authentic cases for clinical practice. Similarly, Grauer et al. [129] noted that CBL methods require
less time and are more efficient in providing large amounts of material compared to PBL. Moreover, Umbrin [130] differentiated PBL from CBL and defined the steps for learning in both PBL as well as CBL. In PBL, the steps are: Problem → Explore problem → Self-learning → Group discussion, while in CBL, the steps are: Prior reading → Problem → Seeking out extra information → Interview with a knowledge expert. Furthermore, the researcher of [130] mentioned that in PBL, students improved their problem solving skills; while in CBL, students learned clinical skills. In addition, in PBL, the role of a facilitator is passive as opposed to CBL, where a facilitator’s role is active. Finally, the researcher of [130] concluded that CBL is a preferred methodology over PBL.

In specialized literature, medical education programs are considered to be complex due to their diverse interactions amongst participants and environments [18]. Discussion-based learning in a small-group, like CBL, is considered to be a complex system [44]. In small-groups, multiple medical students are interacting and exchanging information with each other, where each student is also a complex system [45]. In health care professional education, students have to tackle uncertain situations resulting from the accumulation of multiple problems [46]. In such situations, everyone has his/her own judgment, opinion, and feedback and will consider these integral as well as appropriate to the situation. Baillergeau and Duyvendak [46] relate this situation with bricolage, and investigated the ways to correlate the non-expert knowledge with other types of knowledge (expert knowledge). In such situations, experiential knowledge (EK) is considered a valuable resource [46, 131], which can facilitate and provide lived knowledge to students for enhancing individual’s participation and user empowerment [46].

According to Willoughby [47], “Experiential knowledge is a knowledge of particular things gained by perception and experience”. Similarly, Baillergeau and Duyvendak [46] noted that “Experiential knowledge is a type of knowledge that has the potential to enhance the understanding of the nature, causes and most effective responses to social problems”.

EK either recalled from experiences, or learned, or acquired [132] is mostly utilized for problem solving. Teachers, general practitioners, and social workers are the leading experts that provide experiential knowledge. These experts provide competent interventions utilizing their practical knowledge that is built up using experiential or lay knowledge. Experiential knowledge can be domain-specific as well as holistic and is mostly described in the form of statements [132]. The idea of experiential expertise was introduced in early 1980s [133]. Willoughby [47] observed that the brain has remarkable capacity for accumulating information and facts. She mentioned that an older brain has accumulated and stored vastly more information than a younger brain. So an older person has a well of information and experience to draw on. Therefore, age and experience are advantages in fields like coaching, journalism, law, and management. According to Storkerson [132], “The term experience refers to the interactions that humans have with their environments”. Similarly, Baillergeau and Duyvendak [46] stated that “Practical knowledge is a key element in clinical knowledge and clinicians build this up through face-to-face observations, screening and evaluation of persons”. Experiential knowing is an endless practice of perception and decision making, which is an important aspect for analyzing experiential knowledge [132]. Prior [134] explained the nature of experiential knowledge and considered it as a resource for individual deed. In health research, lay knowledge is widely used to deal with health issues; however, this knowledge is not considered as reliable as experiential knowledge, which helps to improve the quality of interactions. Baillergeau and Duyvendak [46] used a number of cases to analyze the role of experiential knowledge in uncertain situations of mental health and youth-related policy areas. They also analyzed the growth in identification of experiential expertise and highlighted important dimensions of experiential knowledge as a resource for action.
2.3 Overview of case-based learning

2.3.2 Evolutionary technologies for case-based learning

In this study, we have proposed *IoT-based Flip Learning Platform* (IoTFLiP) for medical education, especially, case-based learning; where IoT infrastructure is exploited to support flipped case-based learning in the cloud environment with state of the art security and privacy measures for potential personalized medical data. In order to propose the IoTFLiP, we conducted a literature review in IoT and flip learning research domains. This section covers (1) how IoT technology was used in the medical domain, and (2) how CBL with flip environment was applied in medical education.

IoT is no longer new to human and it has gained much attention in recent years [135]. According to the Gartner study\(^1\), 26 billion devices could be communicating with one another by 2020 with an estimated global economic value-add of $ 1.9 trillion. It has changed the concept of the virtual world for communication, information exchange, availability, and ease of use. The concepts of device-to-device connectivity is described by IoTivity. In healthcare, IoTivity has been exploited from wellness applications [136] for treatment and patient care, such as using sensors for monitoring and real-time status detection [137]. Apart from the wellness applications of IoT, it has been used for medical treatment, identification of diseases, complications, and prevention. IoTivity has been exploited to overcome the challenges of existing healthcare, hospital information and management systems [138, 139]. IoT offers great promise in healthcare fields especially in reducing the cost of care [140]. Due to its low cost and with reduced sensing device sizes, IoT can play an important role in boosting the learning capability of medical students by providing real-world CBL cases. In current practices, multiple IoT platforms exist with particular features. As health is the primary

\(^1\)Gartner says the Internet of things installed base will grow to 26 billion units by 2020, http://www.gartner.com/newsroom/id/2636073
concern for society and has strong impact on all stakeholders, IoT in healthcare domains not only improves healthcare in society but is also beneficial for macroeconomic conditions².

Aazam et al. [141] presented a resource management and pricing model for IoT through fog computing. The authors emphasized the usefulness and importance of customers’ history while determining the amount of resources required for each type of service. However, they did not discuss how their resource management can be mapped to flipped learning. This is also the case with another study the same authors presented in [142], where smart gateway architecture is discussed. The authors proposed that several type of services require smart and real-time decision making, which can be performed by a middleware gateway. Our proposed work integrates the features of [141, 142] and builds on those works, providing an architecture of how IoT resources and infrastructure can be used for medical education. In addition to that, various other platforms and systems have been applied to acquire real-time data through IoT devices such as Masimo Radical-7®, Freescale Home Health Hub reference platform, Remote Patient Monitoring [140], IoT-enabled mobile e-learning platform [143], Remote Monitoring and Management Platform of Healthcare Information (RMMP-HI) [144]. They have been proposed or implemented in specific domains for particular applications without flip learning, as well as CBL, for the purpose of medical education.

With the flipped learning environment, the effectiveness of CBL is surprisingly improved. The flipped classroom is a pedagogical framework in which the traditional lecture and assignment elements of a course are flipped or reversed [145]. Students can learn necessary knowledge before the class session, while in-class time is devoted to exercises and discussion by applying the knowledge. In comparing flip learning in CBL with traditional learning practices, Gilboy et al. [146] showed that students preferred flip learning over traditional pedagogical approaches. Similarly, according to Street et al. [147], “The flipped classroom could be a useful and successful educational approach in medical curricula”. With the

technologies available today, students learn more through active interactions as compared to passively watching the teacher do everything. Lack of such features is one of the main motivations of our proposed flip-based learning for medical education.

### 2.3.3 Review of existing web-based learning systems

In order to support the learning outcomes of students, a plethora of web-based learning systems have been developed [53–62]. A review of the literature shows that learning systems, *Design A Case* (DAC) [54] and *Extension for Community Healthcare Outcomes* (ECHO) [55] are well established CBL projects. The ECHO platform was developed for case-based learning in which primary and specialty care providers work together to provide care for patients using video conferencing and sharing electronic records. Similarly, the DAC provided an online educational tool, which is designed to supplement traditional teaching and allows for the development of health related virtual cases for medical students. Both ECHO and DAC projects support postgraduate medical students; however, they do not provide domain knowledge support for CBL practice, while ECHO does not support interactive case authoring and formulation.

Ali et al. [53] developed an online CBL tool, called *interactive case-based flip learning tool* (ICBFLT), which formulates the CBL case summaries (e.g., further history, examination, and investigations) of virtual patient through intervention of student as well as medical experts’ knowledge. This tool also provides learning services to medical students before attending an actual class. Boubouka [61] designed a case-based learning environment, called *CASes for Teaching and LLearning* (CASTLE) for supporting teaching as well as learning through cases. In CASTLE, a teacher can author the cases for their students and monitor the elaboration of scenarios interpreted by their students. In conclusion, ICBFLT and CASTLE lack the support of acquiring real-world patient cases and do not provide domain knowledge support for CBL practice. For medical training purposes, Dilullo et al. [58] created online
predefined case-based tutorials to provide clinical exposure to medical students without the support of acquiring real-world patient cases and without providing feedback to students.

Cheng et al. [57] adopted a web-based prototype system called *Health Information Network Teaching-case System* (HINTS) in practical training of medical students for clinical medicine. They also explained the development mechanism of teaching cases but with no support of providing feedback to students. Shyu et al. [56] established a platform, called *Virtual Medical School* (VMS) for problem-based learning. They utilized their online authoring tools to capture the patient cases from the *Hospital Information System* database. Suebnukarn and Haddawy [59] developed a problem-based learning system, called *Collaborative Medical Tutor* (COMET) for medical students to provide intelligent tutoring during problem solving tasks. The COMET generates tutorial hints to guide medical students in problem solving. Both VMS and COMET have been used for problem-based learning; however, they lacked tutor feedback and domain knowledge support. Sharples et al. [60] described a case-based training system called *MR Tutor* for learning purposes. This system provided computer-assisted training in radiology; it also provided feedback to users without considering tutors’ feedback for solved clinical cases. Chen et al. [62] developed a web-based learning system that followed the development of real clinical situations; however their system also lacked the support of feedback and domain knowledge.

### 2.4 Summary of literature

#### 2.4.1 Feature selection literature

The feature selection (FS) task is considered as one of the most critical problems for selecting appropriate features from a larger set of features [65]. Feature selection performs a key role in the (so-called) process of ‘Knowledge Discovery’ [67]. Traditionally, this task is performed manually by a human expert, thereby making it more expensive and time-consuming, as
opposed to an automatic FS, which has become necessary for the fast paced digital world of today [13].

Feature selection approaches are generally split into three categories: filters, wrappers, and hybrid, where each approach has capabilities and limitations [12–14]. The filter approach [15, 12]: (i) is generally much faster and have less computational cost than the wrapper approach, (ii) is better suited to high dimensional datasets, and (iii) provides better generalization. Both evaluate feature relevance without using any learning algorithm [65, 12].

The feature selection task requires two basic steps, ranking and filtering. Here the former step requires ranking of all features, while the later involves filtering out of irrelevant features based on some threshold value.

The ranking approach is considered an attractive approach due to its simplicity, scalability, and good empirical success [3, 87]; however, each feature ranking method has its own statistical biases and reveals different relative scales. For example, information gain (IG) is biased towards choosing features with a large number of values [77]. Similarly, chi square (CHI) is sensitive to sample size [77]. The ensemble feature selection (EFS) approach, has been examined recently by some researchers [86, 67], gives an improved estimation of ranks [3, 148, 67, 149]. The EFS, contains an intuitive concept of ensemble learning and obtains a ranked list of features by incorporating the outcomes of different feature ranking techniques [3, 65]. Popular filter methods used in the ensemble-based feature selection approach are information gain, gain ratio, chi square, symmetric uncertainty, OneR, and ReliefF. Most of the feature selection methodologies use three or more of the aforementioned methods for performing feature selection [84, 3, 65, 70, 77, 80]. In the literature, most of the ensemble-based feature ranking studies are wrapper-based or hybrid-based [75, 2, 3, 86, 67, 71–73, 70, 85], which are relatively more expensive approaches than the filter-based approach. The feature ranking task is important as it requires an optimal cut-off value to select important features from a list of candidate features. Finding an optimal
cut-off value to select important features from different datasets is problematic [79]. With respect to identifying an appropriate cut-off value for the threshold, some studies have been performed [2, 80, 77, 70, 79], which are either wrapper-based to determine the threshold value or domain expert needed to make an educated guess regarding the final subset; or a starting value is required to initiate the process or a fixed threshold value is defined; or a separated validation set and artificially generated features approaches are required, or it is not clear how to find the threshold value.

Taking into consideration the aforementioned discussion, a significant amount of research [72, 83, 71, 73, 69, 70, 2, 77, 80, 75] has focused on proposing improved feature selection methodologies; however, not so much consideration is given to how to select features from a given feature set in a comprehensive manner. The availability of a comprehensive feature ranking and filtering approach, which alleviates existing limitations and provides an efficient mechanism for achieving optimal results, is a major problem. State-of-the-art feature selection methodologies have either used relatively more expensive techniques to select the features or required an educated guess to specify a minimum threshold value for retaining important features.

2.4.2 Domain knowledge construction literature

Knowledge is the wisdom of information that plays an important role in decision making [150]. There exists an enormous amount of textual data in a medical domain, which can be useful for medical education, especially for CBL purposes. This overwhelming data provides various opportunities to obtain useful knowledge that reflects the wisdom of information. Declarative knowledge (also called factual knowledge) is a type of knowledge expressed in the form of unstructured text, which can play an important role in health education, decision support, and wellness applications after structured transformation. According to the Simply Philosophy study [63], “Factual knowledge is a justified affirmation of something”. It
combines the concepts to make an affirmation of something. For example, “Blood_disease” and “is a symptom” make an affirmation “Blood_disease is a symptom”. The produced affirmation is either true or false; however, in declarative knowledge it is always true. Handling unstructured content is the foundation to construct the domain knowledge (structured declarative knowledge) required for interactive learning to prepare medical students for their clinical practice before and outside the class. One way to represent declarative knowledge is ontology, which has been considered as a common way to represent a real-world machine interpretable knowledge and is not constructed systematically [151].

According to Abacha and Zweigenbaum [6], “the medical knowledge is growing significantly every year. According to some studies, the volume of this knowledge doubles every five years, or even every two years”. Since most of the information available in digital format is unstructured [92] the information extraction problem has attracted wide interest in several research communities [93]. Text mining (TM) is a multidisciplinary research area, which derives high-quality information from textual data. TM involves the application of techniques from areas such as information retrieval, natural language processing, information extraction, and data mining [64]. In text mining domain, normally text preprocessing, text transformation, feature selection, term extraction, relation extraction, and model construction tasks are involved to construct domain knowledge from textual data. For reliable knowledge construction, keywords as well as their relations are the key elements for knowledge representation, which are mostly extracted from given data using machine learning approaches and a thesaurus [100–102].

In the literature, most of the systems/methodologies [94–96] require a knowledge engineer to translate unstructured text into fully structured form and most of the systems have been proposed or implemented in narrow domains for particular applications using natural language processing techniques and without support of controlled natural language [152, 153, 95]. Regarding structured knowledge construction, some studies do not support lexical ambigu-
ity [94, 97]. We have responded to these deficiencies by including a methodology to construct the domain knowledge (i.e. structured declarative knowledge) from unstructured text. For effective transformation, controlled natural language is used, which constructs syntactically correct and unambiguous computer-processable texts [8].

2.4.3 Case-based learning literature

Case-based learning (CBL) is an active learning approach, which focuses around clinical, community and scientific problems. CBL is a teaching methodology that utilizes problem-based learning (PBL) principles and is preferred over PBL methodology [128, 34, 129]. In CBL, the role of the facilitator is active and authentic cases for clinical practice are used [130, 34]. The CBL approach is one of the successful approaches in student-based pedagogy and it is widely applied in medical education [24–31]. CBL has been used in clinical as well as non-clinical courses such as nursing courses, adult health, mental health, pediatric, and obstetrical nursing courses, pathophysiology, statistics and research [32, 33]. In professional education for health and social care domains, the clinical case is a key component in learning activities, which includes basic, social, and clinical studies of the patient. Normally, formal learning activities are performed without a real patient case, where interactions are often unplanned and rely on the goodwill of patients [34]. Furthermore, students also feel that classroom CBL activities require a significant amount of time [42]. Sometimes, students feel uncomfortable while participating in group learning activities and they prefer to work alone [43]. In specialized literature, medical education programs are considered to be complex due to their diverse interactions amongst participants and environments [18]. Discussion-based learning in a small-group, like CBL, is considered to be a complex system [44]. In health care professional education, students have to tackle the uncertain situations due to the accumulation of a diverse range of problems [46]. In such situations, everyone has his/her own judgment, opinion, and feedback and will consider this
integral as well as appropriate for the situation. In such situations, an experiential knowledge is thought-out as a valuable resource [46, 131], which can facilitate and provide lived knowledge to students for enhancing individual’s participation and user empowerment [46].

In the medical area, human (domain expert) judgment is considered as more credible than a computer; however, a human cannot perform fast reasoning computation to work for long periods and they fatigue, as well as feel bored. A computer has the advantage over a human of being able to perform fast reasoning computations, while not experiencing boredom. Being human, students feel that classroom CBL activity requires a significant amount of time and they report tiredness [42]. Medical students tend to choose computer-based cases [34, 50] and opt for web-based cases as compared to lectures for their learning [51, 52]. Additionally, more attention is given to online/web-based learning environments [34] while real-life clinical case(s) are increasingly emphasized in medical students’ practice [34, 154, 155].

In order to support the learning outcomes of students, a plethora of web-based learning systems have been developed [53–62]. A review of the literature shows that these systems either do not support computer-based interactive case authoring as well as its formulation, or without the support of acquiring real-world CBL cases or do not provide feedback to students. Currently, very less attention is given to fill the gaps between human-based and computer-based learning. In addition, very little attention is given to the development mechanisms of real-world clinical cases using experiential knowledge and no support of domain knowledge while formulating the case.

Recent trends show that increasing attention is being paid to flipped learning approaches for boosting learning capabilities [156, 146]. As defined by Kopp [157], "Flipped learning is a technique in which an instructor delivers online instructions to students before and outside the class and guides them interactively to clarify problems. While in class, the instructor imparts knowledge in an efficient manner". Currently, CBL is typically performed without
exploiting the advantages of the flipped learning methodology, which has significant evidence supporting it over traditional learning methods [146, 147, 53, 158].
Chapter 3

Univariate Ensemble-based Feature Selection

This chapter covers the solutions of the first two research questions/challenges mentioned in the problem statement section of chapter 1 and explains the proposed Univariate Ensemble-based Feature Selection (uEFS) methodology, which includes two innovative Unified Features Scoring (UFS) and Threshold Value Selection (TVS) algorithms to select informative features from a given data for constructing a reliable domain knowledge. The uEFS methodology is evaluated using standard text as well as nontext benchmark datasets and achieved (1) on average, a 7% increase in F-measure as compared to the baseline approach, and (2) on average, a 5% increase in predictive accuracy as compared to state-of-the-art methods.

3.1 Introduction

In the domain of data mining and machine learning, one of the most critical problems is the Feature Selection (FS) task, which pertains to the complexity of appropriate feature selection from a larger set of features [65]. Feature selection performs a key role in the (so-called) process of ‘Knowledge Discovery’ [67]. Traditionally, this task is performed manually by
a human expert, thereby making it more expensive and time-consuming, as opposed to an automatic FS which has become necessary for the fast paced digital world of today [13]. Feature selection techniques are generally split into three categories: filters, wrappers, and hybrid, where each technique has capabilities and limitations [12–14]. Popular evaluation methods used for these techniques are information-theoretic measures, co-relational measures, consistency measures, distance-based measures and classification/predictive accuracy. A good feature selection algorithm can effectively filter out unimportant features [68]. In this regard a significant amount of research has focused on proposing improved feature selection algorithms [69–73]; consequently most of these algorithms use one or more of the aforementioned methods for performing feature selection. However, there is a lack of a comprehensive framework, which can select features from a given feature set.

This chapter introduces an efficient and comprehensive feature selection methodology, called Univariante Ensemble-based Feature Selection (uEFS), which includes two innovative Unified Features Scoring (UFS) and Threshold Value Selection (TVS) algorithms to select informative features from a given dataset. The uEFS is a consensus methodology for appropriate features’ selection in order to generate a useful feature subset for the domain knowledge construction task.

The main intention of the UFS algorithm is to evaluate the feature-set in a comprehensive manner, which is based on different filter-based feature selection measures. In this algorithm, univariate filter measures are employed to assess the usefulness of a selected feature subset in a multi-dimensional manner. The UFS algorithm generates a final ranked list of features after a comprehensive evaluation of a feature set without (a) using any learning algorithm, (b) high computational cost, and (c) without any individual statistical biases of state-of-the-art feature ranking methods. The current version of the UFS has been plugged into a recently developed tool, called data-driven knowledge acquisition tool (DDKAT) [159] to assist the domain expert in selecting informative features for the data preparation phase of
cross-industry standard process for data mining (CRISP-DM). The DDKAT supports an end-to-end knowledge engineering process for generating production rules from a dataset and covers all major phases of the CRISP-DM [159]. The current version of the UFS code and its documentation is open-source and can be downloaded from GitHub [160, 161].

Research shows that the ranking of variables, or ensemble features’ selection does not suggest any cut-off point to select only important features [79]. For defining cut off points for removing irrelevant features, a separated validation set and artificially generated features approaches are used [70]; however, it is not clear how to find the threshold for the features’ ranking [79]. Finding the optimal value of this threshold for different datasets is problematic. In this regard, an algorithm called threshold value selection (TVS), is proposed for feature selection that is empirically based on the data-sets considered in this study. The TVS provides an empirical algorithm to specify a minimum threshold value for retaining important features irrespective of the characteristics of the dataset. It selects a subset of features that are deemed important for the domain knowledge construction.

The motivation behind the uEFS is to design and develop an efficient feature selection methodology for evaluating a feature subset through different angles and produce a useful reduced feature set for constructing a reliable domain knowledge. In order to accomplish this aim, this study is undertaken with the following objectives: (1) To design a comprehensive and flexible features ranking methodology to compute the ranks without (a) using any learning algorithm, (b) high computational cost, and (c) without any individual statistical biases of state-of-the-art feature ranking methods (see Section 3.2.2), and (2) To identify an appropriate cut-off value for the threshold to select a subset of features irrespective of the characteristics of the dataset with reasonable predictive accuracy (see Section 3.2.3).

The key contributions of this research are as to:

1. Present a flexible approach, called UFS for incorporating state-of-the-art univariate filter measures for feature ranking.
2. Propose an efficient approach, called TVS for selecting a cut-off value for the threshold in order to select a subset of features.

3. Provide proof-of-concept for the aforementioned techniques, after performing extensive experimentation which achieved (1) on average, a 7% increase in f-measure as compared to the baseline approach, and (2) on average, a 5% increase in predictive accuracy as compared to state-of-the-art methods.

This chapter is organized as follows: Section 5.2 covers the methodology of the proposed uEFS approach; the experimental results of the TVS algorithm is discussed in Section 3.3. Section 3.4 provides the details of the uEFS evaluations performed along with results, while Section 5.7 concludes the chapter with a summary of the research findings.

3.2 Materials and methods

This section first explains the process of uEFS methodology. Second, the UFS algorithm is explained through algorithms. Third, the TVS algorithm is presented. Fourth, state-of-the-art feature selection methods for comparing the performance of the proposed uEFS methodology and, lastly, the statistical measures, used for evaluating the performance of the proposed uEFS methodology, are explained.

3.2.1 Univariate ensemble-based features selection methodology

In the feature selection process, normally two steps are required [79]. In the first step, normally features are ranked, whereas in the second step, a cut-off point is defined to select important features and to filter out the irrelevant features. In this regard, the proposed UFS algorithm [159] covers the first step of feature selection, while the TVS algorithm covers the second step.
Figure 3.1 shows the functional details of the proposed uEFS methodology, which consists of three major components, called the *Unified Features Scoring*, *Threshold Value Selection*, and *Select Features*. The *Unified Features Scoring* component evaluates the feature-set in a comprehensive manner and generates a final ranked list of features. For example, feature $f_2$ has the highest priority, then feature $f_4$ and so on as shown in Figure 3.1. Similarly, the *Threshold Value Selection* component defines a cut-off point for selecting important features. Finally, the *Select Features* component filters out the irrelevant features from the final-ranked list of features based on a cut-off point, and selects a subset of features which are deemed important for the classifier construction. For example, $f_2, f_4, f_1, \ldots, f_{n-45}$ are the list of features that were selected by the proposed uEFS methodology as shown in Figure 3.1.

![Univariate Ensemble-based Features Selection](image)

**Fig. 3.1 uEFS methodology.**

### 3.2.2 Unified features scoring

*Unified Features Scoring*, called UFS is an innovative feature ranking algorithm that attempts to unify different feature selection measures. The intention of the UFS algorithm is to evaluate the feature-set in a comprehensive manner, which is based on different filter-based feature selection measures. In this algorithm, univariate filter measures are employed to assess the usefulness of a selected feature subset in a multi-dimensional manner. It uses an
intuitive approach to ensemble learning and produces a final ranked list by combining the results of various feature ranking techniques [3, 65].

The following is a rationale for the approaches used in UFS. The feature selection methods are generally split into three categories: filters, wrappers, and hybrid [12–14]. The UFS focuses on filter-based methods, which evaluates feature’s relevance in order to assess its usefulness without using any learning algorithm [65, 12]. The filter methods [15, 12]: (i) are generally much faster and have less computational costs than wrapper methods, (ii) are better suited to high dimensional datasets, and (iii) provide better generalization. They evaluate feature’s relevance without using any learning algorithm [65, 12]. Filter-based feature selection methods are further split into two subcategories: univariate and multivariate. UFS focuses on univariate filter measures due to simplicity and high performance characteristics [75]. The UFS algorithm uses the ensemble feature selection (EFS) approach, which has been examined recently by some researchers [86, 67]. The EFS, an intuitive concept of ensemble learning obtains a final ranked list by combining the outcomes of various feature ranking techniques [3, 65]. Generally, the purpose of the EFS approach is to reduce the risk of selecting an irrelevant feature, yield more robust feature subsets, give an improved estimation to the most favorable subset of features, and finally to improve classification performance [3, 148, 67, 149]. As mentioned in [3], fewer studies have focused on the EFS approach to enrich feature selection itself. Although ensemble-based methodologies have additional computational costs, these costs are affordable due to offering an advisable framework [162]. As mentioned in [3], there are three types of filters’ approaches: ranking, subset evaluation, and a new feature selection framework that decouples the redundancy analysis from relevance analysis. The UFS uses a ranking approach as it is considered an attractive approach due to its simplicity, scalability, and good empirical success [3, 87]. Feature ranking measures the relevancy of the features (i.e. independent attributes) by their correlations to the class (i.e. dependent attribute) and ranks independent attributes according
3.2 Materials and methods

to their degrees of relevance [65]. These values may reveal different relative scales. To avoid the impact of multiple relative scales, the UFS rescales the values to the same range (i.e. between 0 and 1) using min-max normalization (MMN) to make it scale insensitive. The MMN is defined as follows:

\[
\text{MMN} = \frac{\text{value} - \text{min}}{\text{max} - \text{min}}
\]  

(3.1)

For rescaling, the UFS assigns rank 1 to a feature with the highest feature index, as opposed to [3], which assigned rank 0 to a feature with the highest feature index. After features rescaling, the UFS uses an ordered-based ranking aggregation approach as it is easy to implement, scale insensitive, and elegant as well as being an effective technique [70]. The ordered-based ranking aggregation method combines the base rankings and considers only the ranks for ordering the attributes [70]. Finally, the UFS applies an arithmetic mean as an aggregate function to compute relative feature weights and their ranking priorities.

UFS is explained through Algorithm 2. This algorithm takes a data set (i.e., \(D\)) as input and sequentially passes this through mandatory steps of the algorithm to compute ranks (scores) of the features. UFS is based on \(n\) univariate filter-based measures. The key rationale for \(n\) filter measures is to evaluate a feature through different considerations.

In Algorithm 2, the first step was to compute the number of features from a given dataset. In the second step, each feature in a data set was ranked using \(n\) number of univariate filter-based measures as shown in line-4 to line-7 of Algorithm 2. After that, Algorithm 3 was used to scale (normalize) all computed ranks using the first filter measure. This process was replicated for other \((n - 1)\) measures as well as shown in line-9 to line-12. Once each feature is evaluated and scaled according to different filter measures then different ranks of feature were combined as shown in line-18 of Algorithm 2. Later, the comprehensive score of each feature was assessed as shown in line-25 of Algorithm 2. Moreover, the attribute weight was also calculated based on features individual score and combined scores of all the features.
Algorithm 2: UFS (D)

Input: D: Input data set (data)
Output: FR ← Features Ranks

1 noOfAttrs ← numAttributes(data) // compute the number of attributes;
2 /* Consider n attribute evaluation measures, also called
univariate filter measures
(AttrEv_1, AttrEv_2, AttrEv_3,..., and AttrEv_n) */;
3 /* Compute the ranks using each selected measure */;
4 CR_1[] ← computeRanks(data, AttrEv_1) //where CR represents computed ranks;
5 CR_2[] ← computeRanks(data, AttrEv_2);
6 CR_3[] ← computeRanks(data, AttrEv_3);
7 CR_n[] ← computeRanks(data, AttrEv_n);
8 /* Compute the scaled ranks of each computed ranks using
Algorithm 3 */;
9 scaledRanks_1[] ← scaleRanks(CR_1) // invoke Algorithm 3;
10 scaledRanks_2[] ← scaleRanks(CR_2);
11 scaledRanks_3[] ← scaleRanks(CR_3);
12 scaledRanks_n[] ← scaleRanks(CR_n);
13 /* Compute the combined sum of all computed ranks */;
14 combinedranksSum ← 0;
15 combinedRanks[];
16 for ∀ noOfAttrs ∈ D do
17 /* For each attribute, compute the combined rank by adding
all computed scaled ranks */;
18 combinedRanks_i ← \sum_{j=1}^n scaledRanks_{ji} //where n represents the number of filter
measures;
19 combinedranksSum = combinedranksSum + combinedRanks_i;
20 end
21 /* Rank the list in ascending order */;
22 sortedRanks[] ← sort(combinedRanks);
23 /* Compute the score, weight, and priority of each attribute
*/;
24 for ∀ noOfAttrs ∈ D do
25 attrScores_i ← combinedRanks_i / n //where n represents number of filter measures;
26 attrWeights_i ← combinedRanks_i / combinedranksSum;
27 attrPriorities_i ← attrScores_i * attrWeights_i;
28 /* Assign an index (Rank ID) on ascending order to each
attribute based on its priority value */;
29 FR[] ← assignRank(attrPriorities_i);
30 end
31 return FR : features ranks
3.2 Materials and methods

**Algorithm 3:** Scaling the Computed Ranks (CR)

```plaintext
Input : CR: Input computed ranks (ranks)
Output : SR – Scaled Ranks

1. smallest ← ranks0;
2. largest ← ranks0;
3. for ∀ noOfAttrs ∈ CR do
   4. if ranki > largest then
      5. largest ← ranki
   6. else
      7. if ranki < smallest then
         8. smallest ← ranki
   9. end
10. end
11. min ← smallest;
12. max ← largest;
13. SR[] ← (ranks – min)/(max – min);
14. return SR: scaled ranks
```

present in the data set. Finally, attribute priority was computed based on contributions of a feature in terms of its individual measure score (line-25) and its relative weightage (line-26) in a data set. This priority value of a feature was further utilized for ranking and feature subset selection.

For the proof of concept, five univariate filter-based measures, namely information gain, gain ratio, symmetric uncertainty, chi-square and significance [159, 3, 65, 84, 70] were used to explain the process of the proposed unified features scoring algorithm. With each of these filter measures, the features are evaluated under various considerations. The rationale for choosing each is as follows:

- **Information gain**, one of the popular feature selection measures, measures how much information a feature provides about the target class [76].

- **Gain ratio** is a disparity measure that enhances the information gain result [76].

- **Symmetrical uncertainty** performs well for highly imbalanced feature sets [88].
• **CHI-square** is a statistical measure that determines the association of a feature with its target class [76].

• **Attribute significance** is a probabilistic measure that assesses an attribute’s worth. It is a two-way function that computes the attribute’s significance, or association with a class attribute [89].

Using above-mentioned five univariate filter-based measures, the process of the UFS is depicted in Figure 3.2.

![Fig. 3.2 UFS algorithm.](https://archive.ics.uci.edu/ml/machine-learning-databases/pima-indians-diabetes/)

This process is also explained through a diabetes dataset example, as shown in Figure 3.3. In Figure 3.3, \(f_1, f_2, f_3, \ldots, f_n\) represent the features (such as `preg`, `plas`, `pres`, `age`) of the diabetes dataset, and \(M_1, M_2, \ldots, M_n\) represent the five aforementioned univariate filter-based measures. Ranks are computed using each filter measure. For example, using \(M_1\) (information gain), the computed ranks of each feature are:

1. rank of `attribute preg` = 0.0392
2. rank of `attribute plas` = 0.1901
3. rank of `attribute pres` = 0.014
4. rank of `attribute skin` = 0.0443

\(\ldots\)

---

3.2 Materials and methods

3.2.2 Numerical instability and measures biasness problems

3.2.3 Threshold Value Selection

The process of feature selection starts once features are ranked. In order to select a subset of features a threshold value is required. This threshold value specifies those attributes which are deemed important for domain knowledge construction. Those attributes which score
less than the minimum threshold value can be discarded without significantly affecting the reliability of knowledge. Hence, specifying the value of a threshold is an important task.

Research shows that finding an optimal cut-off value to select important features from different datasets is problematic [79] and also it is not clear how to find the threshold for the features’ ranking [79, 80]. Moreover existing methodologies [77, 80] required an educated guess to specify a minimum threshold value for retaining important features.

Keeping in view these facts, a threshold value selection (TVS) algorithm is introduced, which provides an empirical approach for specifying a minimum threshold value. The proposed algorithm is implemented in Java language using WEKA API. TVS is explained through Algorithm 4. This algorithm takes \( n \) data sets (i.e., \( D \)) as input and sequentially passes these through mandatory steps of the algorithm to find the cut-off value from a predictive accuracy graph.

In Algorithm 4, first consider the \( n \) number of benchmark datasets having varying complexities. After that for each dataset, compute the feature ranks using ranker search mechanism and then sort them in an ascending order as shown in line-3 and line-4 of Algorithm 4. Then partition each dataset into different chunks (filtered dataset) from 100% to 5% features retained. Once filtered datasets are created then consider \( m \) number of classifiers from various classifiers category/family having varying characteristics ( where \( m << n \) ) and feed each filtered dataset to these classifiers as shown in line-6 and line-11 of Algorithm 4. Following this, record predictive accuracies of these classifiers to each chunk of dataset partitioning using 10-fold cross validation approach (line-12). Later compute the average predictive accuracy of all classifiers as well as datasets against each chunk of dataset partitioning (line-15). Finally, plot all computed average predictive accuracies against each chunk of dataset partitioning (line-16) and identify the cut-off value from the plotted graph (line-20).
Algorithm 4: TVS \((D, C)\)

\begin{verbatim}
Input : \(D = (d_1, d_2, ..., d_n)\) // set of \(n\) datasets with varying complexities 
\(C = (c_1, c_2, ..., c_m)\) // set of \(m\) machine learning classifiers 

Output: \(V\) - cut off value

1 initialization;
2 for \(d_i \leftarrow \text{in } D\) do
3     \(d_i \leftarrow \text{computeFeatureRank}(d_i)\) // rank each feature ;
4     \(d_i \leftarrow \text{sortByRankASC}(d_i)\) // sort features by rank in ASC ;
5 end
6 \(P \leftarrow 100;\)
7 for \(d_i \leftarrow \text{in } D\) do
8     while \(P \geq 5\) do
9         \(k \leftarrow \text{sizeOf}(d_i) \times (p/100)\) // compute partition size ;
10        \(\text{Acc} \leftarrow \text{newSet}()\) // initialize empty set ;
11        for \(c_i \leftarrow \text{in } C\) do
12            \(P_{\text{acc}} \leftarrow \text{predictiveAccuracy}(c_i, \text{topKFeatures}(d_i, k));\)
13            \(\text{Acc}.\text{add}(P_{\text{acc}})\) // add accuracy to set ;
14        end
15        \(\text{AVG}_{\text{acc}} \leftarrow \text{computeAVG}(\text{Acc})\) // compute average accuracy ;
16        \(G \leftarrow \text{Plot}(\text{AVG}_{\text{acc}}, k)\) // plot the average point ;
17        \(P \leftarrow P - 5\) // decrease the partition size by 5 ;
18    end
19 end
20 \(V \leftarrow \text{getCutOffValue}(G);\)
\end{verbatim}
For the proof of concept, eight datasets of varying complexities, were used, to explain the process of the proposed threshold selection algorithm. The process of threshold value selection is depicted in Figure 3.4.

As depicted in the Figure 3.4, each dataset (Cylinder-bands, Diabetes, Letter, Sonar, Waveform, Vehicle, Glass, Arrhythmia) was fed to the Information Gain filter measure for computing attributes’ ranks; then all measured ranks of attributes of each dataset were sorted in ascending order. Afterwards, each dataset was partitioned into different chunks (filtered dataset) from 100% to 5% features retained e.g. in case of 80% chunk, dataset retains nearly 80% highly ranked features while 20% features, which are below the rank, were discarded. Each filtered dataset was fed to 5 well-known classifiers from various classifiers category/family having varying characteristics (Naive Bayes from Bayes category, J48 from Trees category, kNN from Lazy category, JRip from Rules category, and SVM from Functions category) and then using 10-fold cross validation approach [70], predictive accuracies of these classifiers were recorded to each chunk of dataset partitioning as illustrated in Tables 3.3, 3.4, and 3.5. Finally, an average predictive accuracy of all classifiers as well as datasets against each chunk of dataset partitioning was computed. The main purpose of this process is to identify an appropriate chunk value, which provides reasonable predictive accuracy and considerably reduces the dataset as well. Through empirical evaluation, it was found that
45% chunk provided a reasonable threshold value of feature subset selection (see Figure 3.5 in Section 3.3).

3.2.4 State-of-the-art feature selection methods for comparing the performance of the proposed univariate ensemble-based feature selection methodology

In this study, both single-feature selection (FS) methods—namely, information gain, gain ratio, symmetric uncertainty, chi-squared, significance, OneR, Relief, ReliefF, and decision rule-based FS (DRB-FS)—and ensemble-based feature selection method such as gain-ratio–chi-squared (GR-\(\chi^2\)) method was used as state-of-the-art FS methods for comparing the performance of the proposed uEFS methodology [159, 3, 65, 84, 70]. Each of the FS methods is defined as follows:

**Information gain** (IG) is an information theoretic as well as a symmetric measure and is one of the popular measures for FS. It is calculated based on a feature’s contribution in enhancing information about the target class label. An equation for IG is given as follows [76]:

\[
IG(A) = Info(D) - Info_A(D)
\]  

(3.2)

where \(IG(A)\) is the IG of an independent feature or attribute \(A\), \(Info(D)\) is the entropy of the entire dataset, and \(Info_A(D)\) is the conditional entropy of attribute \(A\) over \(D\).

**Gain ratio** is considered to be one of the disparity measures that provides normalized score to enhance the IG result. This measure utilizes the split information value that is given as follows [76]:

\[
SplitInfo_A(D) = - \sum_{j=1}^{v} \frac{|D_j|}{|D|} \log_2 \frac{|D_j|}{|D|}
\]  

(3.3)
where \( \text{SplitInfo} \) represents the structure of \( v \) partitions. Finally, gain ratio is defined as follows [76]:

\[
\text{GainRatio}(A) = \frac{\text{IG}(A)}{\text{SplitInfo}(A)} \tag{3.4}
\]

\( \text{Chi-squared} \) is a statistic measure that computes the association between the attribute \( A \) and its class or category \( C_i \). It helps to measure the independence of an attribute from its class. It is defined as follows [76]:

\[
\text{CHI}(A, C_i) = \frac{N \ast (F_1F_4 - F_2F_3)^{2}}{(F_1 + F_3) \ast (F_2 + F_4) \ast (F_1 + F_2) \ast (F_3 + F_4)} \tag{3.5}
\]

\[
\text{CHI}_{\text{max}}(A) = \max_i(\text{CHI}(A, C_i)) \tag{3.6}
\]

where \( F_1, F_3, \) and \( F_4 \) represent the frequencies of occurrence of both \( A \) and \( C_i \), \( A \) without \( C_i \), \( C_i \) without \( A \), and neither \( C_i \) nor \( A \), respectively, while \( N \) represents the total number of attributes. A zero value of \( \text{CHI} \) indicates that both \( C_i \) and \( A \) are independent.

\( \text{Symmetric uncertainty} \) is an information theoretic measure to assess the rating of constructed solutions. It is a symmetric measure and is expressed by the following equation [88]:

\[
\text{SU}(A, B) = \frac{2 \ast \text{IG}(A|B)}{H(A) + H(B)} \tag{3.7}
\]

where \( \text{IG}(A|B) \) represents the IG computed by an independent attribute \( A \) and the class-attribute \( B \). While \( H(A) \) and \( H(B) \) represent the entropies of the attributes \( A \) and \( B \).

\( \text{Significance} \) is a real-valued, two-way function used to assess the worth of an attribute with respect to a class attribute [89]. The significance of an attribute \( A_i \) is denoted by \( \sigma(A_i) \), which is computed by the following equation:

\[
\sigma(A_i) = \frac{AE(A_i) + CE(A_i)}{2} \tag{3.8}
\]
3.2 Materials and methods

where $AE(A_i)$ represents the cumulative effect of all possible attribute-to-class associations of an attribute $A_i$, which are computed as follows:

$$AE(A_i) = \left( \frac{1}{k} \sum_{r=1}^{k} \vartheta_i^r \right) - 1.0$$  \hspace{1cm} (3.9)

where $k$ represents the different values of the attribute $A_i$.

Similarly, $CE(A_i)$ captures the effect of change of an attribute value by the changing of a class decision and represents the association between the attribute $A_i$ and various class decisions, which is computed as follows:

$$CE + (A_i) = \frac{1}{m} \left( \sum_{j=1}^{m} A_{ij}^j \right) - 1.0$$  \hspace{1cm} (3.10)

where $m$ represents the number of classes and $+(A_i)$ depicts the class-to-attribute association of the attribute $A_i$.

OneR is the rule-based method to generate a set of rules, which test one particular attribute. The details of this method can be found elsewhere [163].

Relief [11] and ReliefF [164] are distance-based methods to estimate the weightage of a feature. The original Relief method deals with discrete and continuous attributes; it does not support attempts to deal with incomplete data and is limited to application in two-class problems. ReliefF is an extension of the Relief method that covers the limitations of the Relief method. The details of these methods can be found elsewhere [11, 164].

DRB-FS is a statistical measure to eliminate all irrelevant and redundant features. It allows one to integrate domain-specific definitions of feature relevance, which are based on high, medium, and low correlations that are measured using Pearson’s correlation coefficient, which is computed as follows [9, 2]:

$$r_{XY} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{(n-1)S_X S_Y}$$  \hspace{1cm} (3.11)
where $\bar{x}$ and $\bar{y}$ represent the sample means and $S_X$ and $S_Y$ are the sample standard deviations for the features $X$ and $Y$, respectively. Here, $n$ represents the sample size.

$GR-\chi^2$ is an ensemble ranking method that simply adds together the computed ranks of the gain ratio and chi-squared methods [2].

### 3.2.5 Statistical measures for evaluating the performance of the proposed univariate ensemble-based feature selection methodology

In this study, precision, recall, f-measure, and the percentage of correct classification were used as evaluation criteria for feature selection accuracy [2]; second for processing speed; and a non-exhaustive $k$-fold cross-validation technique (i.e. rotation estimation) for predictive accuracy to measure and assess the performance of machine learning methods or schemes [165, 166]. Furthermore, a 10-fold cross-validation (i.e. $k = 10$) technique was selected for computing predictive accuracy [167, 70].

In order to compute the statistical measures (precision, recall, f-measure, and percentage of correct classification), the following four measures are required:

- **True Positives** (TP) represents the correctly predicted positive values (actual class = yes, predicted class = yes)

- **True Negatives** (TN) represents the correctly predicted negative values (actual class = no, predicted class = no)

- **False Positives** (FP) represents contradictions between actual and predicted classes (actual class = no, predicted class = yes)

- **False Negatives** (FN) represents contradicts between actual and predicted classes (actual class = yes, predicted class = no)

Joshi [168] defined these measures as follows:
3.3 Experimental results of the threshold value selection algorithm

Accuracy is a ratio of correctly predicted observation to the total observations, which is computed as follows:

\[
Accuracy = \frac{TP + TN}{TP + FP + FN + TN}
\]  

(3.12)

Precision is the ratio of correctly predicted positive observations to the total predicted positive observations, which is computed as follows:

\[
Precision = \frac{TP}{TP + FP}
\]  

(3.13)

Recall (Sensitivity) is the ratio of correctly predicted positive observations to the all observations in actual class - yes, which is computed as follows:

\[
Recall = \frac{TP}{TP + FN}
\]  

(3.14)

F-measure is the weighted average of Precision and Recall, which is computed as follows:

\[
F - measure = \frac{2 \times (Recall \times Precision)}{(Recall + Precision)}
\]  

(3.15)

3.3 Experimental results of the threshold value selection algorithm

This section first describes the characteristics of classifiers used in explaining the process of the proposed threshold selection algorithm, and then demonstrates the results of the proposed TVS algorithm. The purpose is to interpret as well as comment on the results obtained from experimentation.

In order to explain the process of the proposed threshold selection algorithm, five well-known classifiers from various classifiers category/family as shown in Tables 3.1 and 3.2,
including Naive Bayes, J48, kNN, JRip, and SVM of varying characteristics were considered. Tables 3.1 and 3.2 show the characteristics of each classifier.

Tables 3.3, 3.4, and 3.5 record predictive accuracies of eight datasets (Cylinder-bands, Diabetes, Letter, Sonar, Waveform, Vehicle, Glass, Arrhythmia) against five classifiers (Naive Bayes, J48, kNN, JRip, SVM) with varying threshold values from 100 to 5. In these tables, predictive accuracies are recorded in percentages, which were determined by the 10-fold cross validation technique; whereas each threshold value represents the percentage of features retained. After recording the predictive accuracies, an average predictive accuracy of all classifiers as well as datasets against each threshold value was computed, which is shown in Figure 3.5. This figure depicts the summarized effects of different threshold values on the predictive accuracy of the datasets present in the Tables 3.3, 3.4, and 3.5.

![Predictive accuracy graph](image)

**Fig. 3.5** An average predictive accuracy graph using the 10-fold cross validation technique for threshold value identification.

Furthermore, predictive accuracies using training examples of these eight datasets were also recorded against the same five classifiers with varying threshold values from 100 to 5 as illustrated in Tables 3.6, 3.7, and 3.8. In these tables, predictive accuracies are recorded in percentages, which were determined by considering each dataset as training dataset without any data partitioning; whereas each threshold value represents the percentage of features
Table 3.1 Selected classifiers characteristics.

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Parameters</th>
<th>Description</th>
<th>Classifiers category</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naïve Bayes</td>
<td>useKernelEstimator = False</td>
<td>- Use a kernel estimator for numeric attributes rather than a normal distribution.</td>
<td>Bayes</td>
</tr>
<tr>
<td></td>
<td>useSupervisedDiscretization = False</td>
<td>- Use supervised discretization to convert numeric attributes to nominal ones.</td>
<td></td>
</tr>
<tr>
<td>J48</td>
<td>binarySplits = False</td>
<td>- Whether to use binary splits on nominal attributes when building the trees.</td>
<td>Trees</td>
</tr>
<tr>
<td></td>
<td>confidenceFactor (C) = 0.25</td>
<td>- The confidence factor used for pruning (smaller values incur more pruning).</td>
<td></td>
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<tr>
<td></td>
<td>minNumObj (M) = 2</td>
<td>- The minimum number of instances per leaf.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>subtreeRaising = True</td>
<td>- Whether to consider the subtree raising operation when pruning.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>unpruned = False</td>
<td>- Whether pruning is performed.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>useMDLcorrection = True</td>
<td>- Whether MDL correction is used when finding splits on numeric attributes.</td>
<td></td>
</tr>
<tr>
<td>kNN</td>
<td>KNN (K) = 1</td>
<td>- The number of neighbors to use.</td>
<td>Lazy</td>
</tr>
<tr>
<td></td>
<td>distanceWeighting = No distance weighting</td>
<td>- Gets the distance weighting method used.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>searchAlgorithm = LinearNNSearch</td>
<td>- The nearest neighbour search algorithm to use.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>distanceFunction = EuclideanDistance</td>
<td>- Implementing Euclidean distance (or similarity) function.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>attributeIndices (R) = first-last</td>
<td>- Specify range of attributes to act on.</td>
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</tr>
<tr>
<td></td>
<td>windowSize (W) = 0</td>
<td>- Gets the maximum number of instances allowed in the training pool. A value of 0 signifies no limit to the number of training instances.</td>
<td></td>
</tr>
<tr>
<td>Classifiers Category</td>
<td>Classifier</td>
<td>Parameters</td>
<td>Description</td>
</tr>
<tr>
<td>----------------------</td>
<td>------------</td>
<td>------------</td>
<td>-------------</td>
</tr>
<tr>
<td>Functions</td>
<td>JRip</td>
<td>checkErrorRate = True, folds (F) = 3, minNo (N) = 2.0, optimizations (O) = 2, randomSeed (W) = 1</td>
<td>Whether pruning is performed, whether pruning is performed for error rate, the number of folds for pruning, the number of optimizations, the random number seed</td>
</tr>
<tr>
<td>Rules</td>
<td>SVM</td>
<td>c (C) = 1.0, kernel (K) = PolyKernel, cacheSize (C) = 25007, exponent (E) = 1.0, seed (S) = 1</td>
<td>Whether check for error rate = 1/2 is included in the stopping criterion, the exponent, the kernel type, the cache size, whether check for error rate</td>
</tr>
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</table>

Table 3.2 Selected classifiers characteristics (cont.)
Table 3.3 Predictive accuracy (in %age) of classifiers using the 10-fold cross validation technique.

<table>
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<th>%age of Features Retained</th>
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<th>J48</th>
<th>kNN</th>
<th>JRip</th>
<th>SVM</th>
<th>Naive Bayes</th>
<th>J48</th>
<th>kNN</th>
<th>JRip</th>
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<th>kNN</th>
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Table 3.4 Predictive accuracy (in %) of classifiers using the 10-fold cross validation technique.
3.3 Experimental results of the threshold value selection algorithm

Table 3.5 Predictive accuracy (in %age) of classifiers using the 10-fold cross validation technique.

<table>
<thead>
<tr>
<th>%age of Features Retained</th>
<th>Naive Bayes</th>
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<th>kNN</th>
<th>JRip</th>
<th>SVM</th>
<th>Naive Bayes</th>
<th>J48</th>
<th>kNN</th>
<th>JRip</th>
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retained. After recording the predictive accuracies, again an average predictive accuracy of all classifiers as well as datasets against each threshold value was computed, which is shown in Figure 3.6. This figure also depicts the summarized effects of different threshold values on the predictive accuracy of the training datasets present in the Tables 3.6, 3.7, and 3.8.

Fig. 3.6 An average predictive accuracy graph using training datasets for threshold value identification.

It can be observed from Figures 3.5 and 3.6 that the average predictive accuracy remained consistent from the 100% feature set retained i.e. no feature selection, to 45% features retained. After reducing the dataset from 45% retained features to 5% retained features, the predictive accuracy started to decline as well. Therefore, a threshold value of 45 is selected and top 55% features were selected. This chunked value (i.e. 45%) was utilized in experimentation for evaluating the uEFS methodology.

Lastly, in order to check the performance of each model at the selected threshold value (i.e. 45%), receiver operating characteristic (ROC) areas using training examples of these eight datasets were computed against the same five classifiers. Table 3.9 records ROC area values of the Arrhythmia dataset against five classifiers with the selected 45% as a threshold value. A weighted average values of ROC area were also computed against the same five classifiers as illustrated in Table 3.10. It can be observed from Tables 3.9 and 3.10 that most
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Table 3.7 Predictive accuracy (in %age) of classifiers using training datasets.
Table 3.8 Predictive accuracy (in %age) of classifiers using training datasets.

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<td>96.68</td>
<td>75</td>
<td>71.9</td>
</tr>
<tr>
<td>20</td>
<td>35.98</td>
<td>68.22</td>
<td>92.99</td>
<td>54.67</td>
<td>35.51</td>
<td>74.34</td>
<td>88.27</td>
<td>90.93</td>
<td>76.33</td>
<td>70.35</td>
</tr>
<tr>
<td>15</td>
<td>35.98</td>
<td>68.22</td>
<td>92.99</td>
<td>54.67</td>
<td>35.51</td>
<td>73.45</td>
<td>89.16</td>
<td>85.18</td>
<td>77.43</td>
<td>68.14</td>
</tr>
<tr>
<td>10</td>
<td>35.51</td>
<td>35.51</td>
<td>35.51</td>
<td>35.51</td>
<td>35.51</td>
<td>71.24</td>
<td>88.5</td>
<td>72.12</td>
<td>75.88</td>
<td>64.82</td>
</tr>
<tr>
<td>5</td>
<td>35.51</td>
<td>35.51</td>
<td>35.51</td>
<td>35.51</td>
<td>35.51</td>
<td>67.26</td>
<td>86.73</td>
<td>96.46</td>
<td>71.24</td>
<td>63.5</td>
</tr>
</tbody>
</table>
of the ROC area values as well as weighted average values of the training datasets are near to 1, which indicates that the performance of each model is reliable at 45% chunked value.

Table 3.9 ROC area values of well-known classifiers using Arrhythmia dataset.

<table>
<thead>
<tr>
<th>Class</th>
<th>Naive Bayes</th>
<th>J48</th>
<th>kNN</th>
<th>JRip</th>
<th>SVM</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.878</td>
<td>0.96</td>
<td>0.991</td>
<td>0.848</td>
<td>0.817</td>
</tr>
<tr>
<td>2</td>
<td>0.894</td>
<td>0.951</td>
<td>0.955</td>
<td>0.726</td>
<td>0.865</td>
</tr>
<tr>
<td>3</td>
<td>0.998</td>
<td>0.999</td>
<td>1</td>
<td>0.994</td>
<td>0.999</td>
</tr>
<tr>
<td>4</td>
<td>0.999</td>
<td>0.998</td>
<td>1</td>
<td>0.97</td>
<td>0.997</td>
</tr>
<tr>
<td>5</td>
<td>0.973</td>
<td>0.992</td>
<td>0.995</td>
<td>0.925</td>
<td>0.978</td>
</tr>
<tr>
<td>6</td>
<td>0.964</td>
<td>0.995</td>
<td>0.999</td>
<td>0.973</td>
<td>0.948</td>
</tr>
<tr>
<td>7</td>
<td>0.999</td>
<td>0.918</td>
<td>0.999</td>
<td>0.895</td>
<td>0.949</td>
</tr>
<tr>
<td>8</td>
<td>1</td>
<td>0.998</td>
<td>1</td>
<td>0.818</td>
<td>0.999</td>
</tr>
<tr>
<td>9</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.999</td>
<td>1</td>
</tr>
<tr>
<td>10</td>
<td>0.966</td>
<td>0.977</td>
<td>1</td>
<td>0.885</td>
<td>0.956</td>
</tr>
<tr>
<td>11</td>
<td>1</td>
<td>0.993</td>
<td>1</td>
<td>0.756</td>
<td>0.997</td>
</tr>
<tr>
<td>12</td>
<td>1</td>
<td>0.995</td>
<td>1</td>
<td>0.998</td>
<td>1</td>
</tr>
<tr>
<td>13</td>
<td>0.817</td>
<td>0.951</td>
<td>1</td>
<td>0.725</td>
<td>0.809</td>
</tr>
<tr>
<td>Weighted Avg.</td>
<td><strong>0.908</strong></td>
<td><strong>0.967</strong></td>
<td><strong>0.991</strong></td>
<td><strong>0.856</strong></td>
<td><strong>0.869</strong></td>
</tr>
</tbody>
</table>

Table 3.10 Weighted average values of ROC area of well-known classifiers using benchmark datasets.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Naive Bayes</th>
<th>J48</th>
<th>kNN</th>
<th>JRip</th>
<th>SVM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cylinder-Bands</td>
<td>0.961</td>
<td>0.5</td>
<td>1</td>
<td>0.744</td>
<td>0.997</td>
</tr>
<tr>
<td>Diabetes</td>
<td>0.805</td>
<td>0.747</td>
<td>1</td>
<td>0.7</td>
<td>0.692</td>
</tr>
<tr>
<td>Letter</td>
<td>0.71</td>
<td>0.85</td>
<td>0.999</td>
<td>0.696</td>
<td>0.5</td>
</tr>
<tr>
<td>Sonar</td>
<td>0.794</td>
<td>0.993</td>
<td>1</td>
<td>0.821</td>
<td>0.795</td>
</tr>
<tr>
<td>Waveform</td>
<td>0.957</td>
<td>0.993</td>
<td>1</td>
<td>0.94</td>
<td>0.936</td>
</tr>
<tr>
<td>Vehicle</td>
<td>0.747</td>
<td>0.973</td>
<td>1</td>
<td>0.904</td>
<td>0.836</td>
</tr>
<tr>
<td>Glass</td>
<td>0.815</td>
<td>0.993</td>
<td>1</td>
<td>0.93</td>
<td>0.744</td>
</tr>
<tr>
<td>Arrhythmia</td>
<td><strong>0.908</strong></td>
<td><strong>0.967</strong></td>
<td><strong>0.991</strong></td>
<td><strong>0.856</strong></td>
<td><strong>0.869</strong></td>
</tr>
</tbody>
</table>
After recording the ROC areas, ROC curves of all classifiers for the *Arrhythmia*) dataset were also plotted, which are shown in Figure 3.7. This figure depicts the quality of the classifiers, which is good in most of the cases except the *kNN* classifier.

![ROC curves using each classifier for the Arrhythmia dataset.](image)

**Fig. 3.7 ROC curves using each classifier for the Arrhythmia dataset.**

### 3.4 Evaluation of the univariate ensemble-based feature selection methodology

The evaluation phase of any methodology has a key role to investigate the worth of any proposed method. This section describes the evaluation setup and compares the proposed feature selection methodology with state-of-the-art feature selection methods. The purpose is to check the impact of the proposed methodology on features’ selection suitability in terms of features’ ranking on the precision, recall, f-measure, and predictive accuracy performance measure factors.
3.4.1 Experimental setup

For holistic understanding, two studies were performed to evaluate the uEFS methodology by involving non-text and text benchmark datasets. In each study, the methodology is compared with the state-of-the-art feature selection methods using precision, recall, f-measure, and predictive accuracy performance measure factors. The motivation behind comparing the results achieved with the text and non-text datasets was to check the scalability of the proposed uEFS methodology from small- to high-dimensional data, where dimension represents the number of attributes or features.

For the Study-I, four text datasets of varying complexity were selected, namely MiniNews-Groups\(^2\), Course-Cotrain\(^3\), Trec05p-I\(^4\), and SpamAssassin\(^5\).

These datasets are in text form and to apply the features ranking algorithms on these datasets, there is need to preprocess the text data into structured form. In order to perform text preprocessing, the following tasks were performed:

1. Remove HTML tags from web documents, sender as well as receiver information from e-mail documents, urls and etc.

2. Eliminate pictures and e-mail attachments from the documents.

3. Tokenize the documents.

4. Remove the non-informative terms like stop-words from the contents.

5. Perform the term stemming task.

6. Eliminate the low length terms whose length is less than or equal to 2.

\(^2\)http://kdd.ics.uci.edu/databases/20newsgroups/20newsgroups.html
\(^3\)http://www.cs.cmu.edu/afs/cs.cmu.edu/project/theo-51/www/co-training/data/course-cotrain-data.tar.gz
\(^4\)https://plg.uwaterloo.ca/ gvcormac/treccorpus/
\(^5\)http://csmining.org/index.php/spam-assassin-datasets.html
3.4 Evaluation of the univariate ensemble-based feature selection methodology

7. Finally, generate the feature vectors representing document instances by computing the Term Frequency–Inverse Document Frequency (TF-IDF) weights.

Table 3.11 shows the characteristics of structured form of text datasets. Our selected datasets are comprised of small to medium size datasets. Both binary and multi-class problems were considered for this study.

Table 3.11 Selected text datasets’ characteristics.

<table>
<thead>
<tr>
<th>Text Dataset</th>
<th>No. of Features</th>
<th>No. of Documents</th>
<th>No. of Distinct Classes</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>MiniNewsGroups</td>
<td>27419</td>
<td>1600</td>
<td>4</td>
<td>• Is a 10% subset of 20NewsGroups dataset, • Consider four equal sized categories, namely computer, politics, society and sport</td>
</tr>
<tr>
<td>Course-Cotrain</td>
<td>13919</td>
<td>1051</td>
<td>2</td>
<td>• Is a subset of 4Universities dataset, • Consists of web pages, • Consider two categories of pages, namely course and non-course</td>
</tr>
<tr>
<td>Trec05p-1</td>
<td>12578</td>
<td>62499</td>
<td>2</td>
<td>• Consists of e-mail documents, • Consider two categories of emails, namely spam and ham</td>
</tr>
<tr>
<td>SpamAssassin</td>
<td>9351</td>
<td>3000</td>
<td>2</td>
<td>• Consists of e-mail documents, • Consider two categories of emails, namely spam and ham</td>
</tr>
</tbody>
</table>

For the Study-II, eight non-text benchmark datasets of varying complexity (i.e., small to medium size and binary to multi-class problems) were chosen, namely Cylinder-bands, Diabetes, Letter, Sonar, Waveform, Vehicle, Glass, and Arrhythmia as shown in the Table 3.12. These datasets were collected from the openML\(^6\) repository.

To select a suitable classifier for assessing the proposed uEFS methodology, initially, five well-known classifiers were used: naive Bayes, J48, kNN, JRip, and SVM [77, 80, \(^6\)http://www.openml.org/]
Table 3.12 Selected nontext datasets’ characteristics.

<table>
<thead>
<tr>
<th>Nontext Dataset</th>
<th>No. of Instances</th>
<th>No. of Attributes</th>
<th>No. of Distinct Classes</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cylinder-bands</td>
<td>540</td>
<td>40</td>
<td>2</td>
<td>• Contains the process delay information of engraving printing for decision tree induction.</td>
</tr>
<tr>
<td>Diabetes</td>
<td>768</td>
<td>9</td>
<td>2</td>
<td>• Consists of diagnostic measurements, • Consider two prediction categories of patient, namely has diabetes (YES) and not diabetes (NO)</td>
</tr>
<tr>
<td>Letter</td>
<td>20000</td>
<td>17</td>
<td>2</td>
<td>• Consists of black-and-white character image features, • Identify English capital alphabet letter (from A to Z).</td>
</tr>
<tr>
<td>Sonar</td>
<td>208</td>
<td>61</td>
<td>2</td>
<td>• Contains signals information, • Consider two bounced off categories of signals, namely “bounced off a metal cylinder” and “bounced off a roughly cylindrical rock”</td>
</tr>
<tr>
<td>Waveform</td>
<td>5000</td>
<td>41</td>
<td>3</td>
<td>• Contains 3 waves classes, which are produced by integrating 2 of 3 base waves.</td>
</tr>
<tr>
<td>Vehicle</td>
<td>846</td>
<td>19</td>
<td>4</td>
<td>• Consists of silhouette features, • Consider/classify four categories of vehicle</td>
</tr>
<tr>
<td>Glass</td>
<td>214</td>
<td>10</td>
<td>6</td>
<td>• Consists of oxide content, • Consider/classify six categories of glass</td>
</tr>
<tr>
<td>Arrhythmia</td>
<td>452</td>
<td>280</td>
<td>13</td>
<td>• Consists of ECG records, • Consider two prediction categories of cardiac arrhythmia, namely presence of cardiac arrhythmia (YES) and absence of cardiac arrhythmia (NO), • Consider/classify sixteen categories of group</td>
</tr>
</tbody>
</table>

169, 170, 75, 2, 70, 171]. Using each classifier, predictive accuracy was measured with a varying percentage of features retained values from 100 to 5, as illustrated in Figure 3.8.
3.4 Evaluation of the univariate ensemble-based feature selection methodology

The pictorial results show that, of the five classifiers, SVM and kNN tended to perform best with regard to the above-mentioned datasets. Figure 3.8 shows the four datasets—namely \textit{Cylinder-bands}, \textit{Diabetes}, \textit{Waveform}, and \textit{Arrhythmia}—on which SVM performed better. Likewise, Figure 3.8 shows the three datasets (\textit{Letter}, \textit{Sonar}, and \textit{Glass}) on which kNN performed best. In recent years, the SVM classifier has been considered as a dominant tool for dealing with classification problems in a wide range of applications [170] and is largely preferred over other classification methods [171].

Keeping in view with the Figure 3.8 results and state-of-the-art classifier considerations, finally, the SVM classifier was used to assess the proposed uEFS methodology, as it tends to outperform the F-measures and predictive accuracies for the benchmark datasets [170, 2]. Further, the \textit{SMOreg} function (SVM with sequential minimum optimization) of the SVM classifier was used, which is an improved version of the SVM [172]. Table 3.13 shows the parameters of the selected classifier.
Table 3.13 Selected classifier parameters.

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Function</th>
<th>Kernel Type</th>
<th>Epsilon</th>
<th>Tolerance</th>
<th>Exponent</th>
<th>Random Seed</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>SMO</td>
<td>Polynomial</td>
<td>1.0E-12</td>
<td>0.001</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

For comparison purposes, a standard open source implementation of this classifier was utilized as provided by the *Waikato Environment for Knowledge Analysis* (WEKA\(^7\)). Using open source implementation, a method in Java language was written, which computes precision, recall, f-measure, and predictive accuracy of this classifier using the 10-fold cross-validation technique.

Finally, to compare the computational cost, the performance speed of the proposed methodology as well as state-of-the-art methods was measured on a system having the following specifications:

- Processor: Intel (R) Core (TM) i5-2500 CPU @ 3.30GHz 3.30 GHz
- Installed memory (RAM): 16.0 GB
- System type: 64-bit Operating System

### 3.4.2 Experimental execution

For the *Study-I*, a comparison of the proposed uEFS methodology with state-of-the-art feature selection methodologies was performed. The proposed methodology outperforms most of the existing algorithms and individual feature selection measures in terms of f-measure as well as predictive accuracy. It can be observed from Figures 3.9 and 3.10 that the average f-measure and predictive accuracy results of the proposed uEFS methodology on multiple text datasets are higher than existing techniques.

\(^7\)http://weka.sourceforge.net/doc.dev/
3.4 Evaluation of the univariate ensemble-based feature selection methodology

Fig. 3.9 Comparisons of F-measure with existing feature selection measures [2, 9–11].

Fig. 3.10 Comparisons of predictive accuracy with existing feature selection measures [2, 9–11].

On the other hand, the individual numeric values of precision against each dataset are shown in Table 3.14. On SpamAssassin benchmark; the uEFS outperformed the existing algorithms with the precision of 0.858. Similarly, the uEFS achieved an average of 0.669 precision on Course-Cotrain data, which is close enough to the Relief algorithm with a difference of 0.004, which achieved the highest precision against the existing algorithms. On the other hand, while comparing the average classifier recall, shown in Table 3.15, it was
noticed that the proposed uEFS methodology outperforms all of the existing algorithms with the recall of 0.850, 0.864 on Trec05p-1 and SpamAssassin benchmarks respectively.

Table 3.14 Comparisons of average classifier precision with existing feature selection methods [2, 9–11].

<table>
<thead>
<tr>
<th>Text Dataset</th>
<th>Feature Selection Algorithms</th>
<th>Proposed Methodology</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>IG</td>
<td>Relief</td>
</tr>
<tr>
<td>Course-Cotrain</td>
<td>0.668</td>
<td><strong>0.673</strong></td>
</tr>
<tr>
<td>Trec05p-1</td>
<td>0.836</td>
<td>0.375</td>
</tr>
<tr>
<td>MiniNewsGroups</td>
<td>0.730</td>
<td>0.708</td>
</tr>
<tr>
<td>SpamAssassin</td>
<td>0.708</td>
<td>0.710</td>
</tr>
</tbody>
</table>

Table 3.15 Comparisons of average classifier recall with existing feature selection methods [2, 9–11].

<table>
<thead>
<tr>
<th>Text Dataset</th>
<th>Feature Selection Algorithms</th>
<th>Proposed Methodology</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>IG</td>
<td>Relief</td>
</tr>
<tr>
<td>Course-Cotrain</td>
<td>0.717</td>
<td>0.711</td>
</tr>
<tr>
<td>Trec05p-1</td>
<td>0.731</td>
<td>0.410</td>
</tr>
<tr>
<td>MiniNewsGroups</td>
<td>0.669</td>
<td>0.636</td>
</tr>
<tr>
<td>SpamAssassin</td>
<td>0.766</td>
<td>0.778</td>
</tr>
</tbody>
</table>

For the Study-II, a comparison was made between the proposed uEFS methodology and the five aforementioned univariate filter measures, which were used for the proof of concept. Figure 3.11 illustrates the difference of the f-measure of the proposed uEFS methodology with each feature selection measure, which is used in the uEFS methodology. It can be deduced from the results, shown in Figure 3.11, that the proposed methodology provides competitive results as compared to state-of-the-art feature selection measures.

For comparison purposes, computed precision and recalls were also used, as recorded in Tables 3.16 and 3.17. The results of these two tables also reveal that the proposed methodology provides competitive results as compared to state-of-the-art feature selection
Method Comparison on Average F-measure

<table>
<thead>
<tr>
<th>Non-text Datasets</th>
<th>F-measure</th>
<th>Gain Ratio</th>
<th>Chi Squared</th>
<th>Symmetrical Uncert.</th>
<th>Significance</th>
<th>uEFS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cylinder-bands</td>
<td>0.795</td>
<td>0.799</td>
<td>0.79</td>
<td>0.795</td>
<td>0.805</td>
<td>0.81</td>
</tr>
<tr>
<td>Diabetes</td>
<td>0.93</td>
<td>0.94</td>
<td>0.95</td>
<td>0.96</td>
<td>0.97</td>
<td></td>
</tr>
<tr>
<td>Letter</td>
<td>0.785</td>
<td>0.79</td>
<td>0.795</td>
<td>0.8</td>
<td>0.805</td>
<td></td>
</tr>
<tr>
<td>Sonar</td>
<td>0.6</td>
<td>0.62</td>
<td>0.64</td>
<td>0.66</td>
<td>0.68</td>
<td></td>
</tr>
<tr>
<td>Waveform</td>
<td>0.87</td>
<td>0.866</td>
<td>0.864</td>
<td>0.867</td>
<td>0.872</td>
<td></td>
</tr>
<tr>
<td>Vehicle</td>
<td>0.7</td>
<td>0.65</td>
<td>0.64</td>
<td>0.62</td>
<td>0.64</td>
<td></td>
</tr>
<tr>
<td>Glass</td>
<td>0.6</td>
<td>0.55</td>
<td>0.55</td>
<td>0.55</td>
<td>0.55</td>
<td></td>
</tr>
<tr>
<td>Arrhythmia</td>
<td>0.4</td>
<td>0.45</td>
<td>0.45</td>
<td>0.45</td>
<td>0.45</td>
<td></td>
</tr>
</tbody>
</table>

Fig. 3.11 Comparisons of F-measure with existing feature selection measures.
measures. The proposed uEFS methodology yields significant precision and recall on all nontext benchmarks except the Glass dataset, against all existing feature selection measures. On recall comparison, the closest competitors to the uEFS methodology were information gain, gain ratio and symmetrical uncertainty measures, which achieved similar recall of 0.869 on the Waveform dataset. While on the other datasets, the existing measures achieved much lower recall as compared to the uEFS. Similarly, on the precision comparison, the chi-squared and symmetrical uncertainty remained the closest competitors to the uEFS on the Glass dataset. While on the rest of the datasets, the uEFS outperformed the existing feature selection measures with a significant difference.

Table 3.16 Comparisons of average classifier precision with existing feature selection measures.

<table>
<thead>
<tr>
<th>Nontext Dataset</th>
<th>Feature Selection Measures</th>
<th>Proposed Methodology</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>IG</td>
<td>GR</td>
</tr>
<tr>
<td>Cylinder-bands</td>
<td>0.805</td>
<td>0.801</td>
</tr>
<tr>
<td>Diabetes</td>
<td>0.753</td>
<td>0.753</td>
</tr>
<tr>
<td>Letter</td>
<td>0.920</td>
<td>0.962</td>
</tr>
<tr>
<td>Sonar</td>
<td>0.789</td>
<td>0.791</td>
</tr>
<tr>
<td>Waveform</td>
<td>0.869</td>
<td>0.869</td>
</tr>
<tr>
<td>Vehicle</td>
<td>0.586</td>
<td>0.604</td>
</tr>
<tr>
<td>Glass</td>
<td>0.477</td>
<td>0.484</td>
</tr>
<tr>
<td>Arrhythmia</td>
<td>0.640</td>
<td>0.647</td>
</tr>
</tbody>
</table>

*IG: Information Gain, GR: Gain Ratio, CS: Chi Squared, SU: Symmetrical Uncertainty, S: Significance*

A comparison was also made between the predictive accuracies of the uEFS methodology and the five aforementioned univariate filter measures. Table 3.18 illustrates the comparison of the predictive accuracy of the uEFS methodology with the five FS measures that are used in the uEFS methodology. It can be observed from the Table 3.18 results that the proposed methodology provides competitive results as compared with existing feature selection methods.
Table 3.17 Comparisons of average classifier recall with existing feature selection measures.

<table>
<thead>
<tr>
<th>Nontext Dataset</th>
<th>Feature Selection Measures</th>
<th>Proposed Methodology</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>IG</td>
<td>GR</td>
</tr>
<tr>
<td>Cylinder-bands</td>
<td>0.806</td>
<td>0.802</td>
</tr>
<tr>
<td>Diabetes</td>
<td>0.759</td>
<td>0.759</td>
</tr>
<tr>
<td>Letter</td>
<td>0.959</td>
<td>0.961</td>
</tr>
<tr>
<td>Sonar</td>
<td>0.788</td>
<td>0.789</td>
</tr>
<tr>
<td>Waveform</td>
<td><strong>0.869</strong></td>
<td><strong>0.869</strong></td>
</tr>
<tr>
<td>Vehicle</td>
<td>0.617</td>
<td>0.632</td>
</tr>
<tr>
<td>Glass</td>
<td>0.579</td>
<td>0.584</td>
</tr>
<tr>
<td>Arrhythmia</td>
<td>0.719</td>
<td>0.723</td>
</tr>
</tbody>
</table>

selection measures. Similarly, it can also be seen from the results shown in Figure 3.11 and Tables 3.16, 3.17, and 3.18, respectively, that, in terms of f-measure, precision, recall, and predictive accuracy, the proposed methodology did not perform better than existing FS measures on the Glass dataset due to having a small size of data, multiple classes, and imbalanced class characteristics.

The result of one-sample test with and without bootstrapping technique is also illustrated in Table 3.18. The purpose of performing this test was to determine whether the values obtained from the proposed uEFS methodology were significantly different to the values obtained from existing feature selection measures. For performing this test against each dataset, feature selection measures’ values were considered as sample data, and the uEFS value as a test value, which is a known or hypothesized population mean. For example, in the case of the Cylinder-bands dataset, 81.11 (value generated by the uEFS) was considered a test value, while 80.56, 80.19, 79.81, 80.37, 80.19 (values generated by Info. Gain, Gain Ratio, Chi Squared, Symmetrical Uncert., Significance) were used as sample data. The null hypothesis ($H_0$) and (two-tailed) alternative hypotheses ($H_1$) of this test will be:
Table 3.18 Comparisons of predictive accuracy (in %age) of the uEFS with existing feature selection measures using the 10-fold cross validation technique.

<table>
<thead>
<tr>
<th>Nontext Dataset</th>
<th>Feature Selection Measures</th>
<th>Proposed Methodology</th>
<th>One-Sample Test p (Sig. (2-tailed))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>IG</td>
<td>GR</td>
<td>CS</td>
</tr>
<tr>
<td>Cylinder-bands</td>
<td>80.56</td>
<td>80.19</td>
<td>79.81</td>
</tr>
<tr>
<td>Diabetes</td>
<td>75.91</td>
<td>75.91</td>
<td>75.91</td>
</tr>
<tr>
<td>Letter</td>
<td>95.94</td>
<td>96.08</td>
<td>95.94</td>
</tr>
<tr>
<td>Sonar</td>
<td>78.85</td>
<td>78.86</td>
<td>78.85</td>
</tr>
<tr>
<td>Waveform</td>
<td>86.88</td>
<td>86.88</td>
<td>86.86</td>
</tr>
<tr>
<td>Vehicle</td>
<td>61.7</td>
<td>63.24</td>
<td>65.48</td>
</tr>
<tr>
<td>Glass</td>
<td>57.94</td>
<td>58.41</td>
<td><strong>58.88</strong></td>
</tr>
<tr>
<td>Arrhythmia</td>
<td>71.9</td>
<td>72.35</td>
<td>71.68</td>
</tr>
</tbody>
</table>

- $H_0$: 81.11 = $\bar{x}$ (“the mean predictive accuracy of the sample $\bar{x}$ is equal to 81.11”)
- $H_1$: 81.11 $\neq$ $\bar{x}$ (“the mean predictive accuracy of the sample $\bar{x}$ is not equal to 81.11”)

In this case, the mean feature selection measures score for Cylinder-bands dataset (M = 80.22, SD = 0.28) was lower than the normal uEFS score of 81.11, a statistically significant mean difference of 0.89, 95% CI [0.54 to 1.23], $t(4) = -7.141$, $p = .002$. Since $p < .05$, we reject the null hypothesis due to mean predictive accuracy of sample $\bar{x}$ is equal to 81.11 and conclude that the mean predictive accuracy of sample is significantly different from existing methodologies result. It can be observed from Table 3.18 that most of significance (i.e. $p$) values are less than 0.05 (i.e. $p < .05$), which shows that the proposed uEFS methodology results are statistically significantly different from the results of existing methodologies.

Cross validation and out-of-sample bootstrap sampling techniques are often utilized for approximating the predictive performance of a classification model [173]. The results reported in Table 3.18 for performing a t-test, are computed using 10-fold cross validation.
Table 3.19 Comparisons of predictive accuracy (in %age) of the uEFS with existing feature selection measures using the out-of-sample bootstrapping technique.

<table>
<thead>
<tr>
<th>Nontext Dataset</th>
<th>Feature Selection Measures</th>
<th>Proposed Methodology</th>
<th>Bootstrap for One-Sample Test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>IG</td>
<td>GR</td>
<td>CS</td>
</tr>
<tr>
<td>Cylinder-bands</td>
<td>77.49</td>
<td>77.81</td>
<td>77.34</td>
</tr>
<tr>
<td>Diabetes</td>
<td>76.27</td>
<td>76.24</td>
<td>76.39</td>
</tr>
<tr>
<td>Letter</td>
<td>96.56</td>
<td>96.56</td>
<td>96.74</td>
</tr>
<tr>
<td>Sonar</td>
<td>77.29</td>
<td>76.97</td>
<td>77.27</td>
</tr>
<tr>
<td>Waveform</td>
<td>86.79</td>
<td>86.68</td>
<td>86.48</td>
</tr>
<tr>
<td>Vehicle</td>
<td>61.46</td>
<td>62.75</td>
<td>65.28</td>
</tr>
<tr>
<td>Glass</td>
<td>51.4</td>
<td>51.3</td>
<td>51.63</td>
</tr>
<tr>
<td>Arrhythmia</td>
<td>70.14</td>
<td>70.29</td>
<td>70.21</td>
</tr>
</tbody>
</table>

The result of the t-test depends on the independent samples, otherwise, t-tests may yield misleading results. In 10-fold cross-validation, each test set is independent of the others. However, this test still suffers from the problem that the training sets overlap and produced optimistically biased results. This overlap may prevent the t-test from obtaining a good estimate. In order to obtain good estimation of t-test and to remove the biased results, out-of-sample bootstrap sampling was also performed in this study.

Bootstrap is a statistical estimation technique, where a mean is estimated from multiple random samples of data. It provides more robust estimation of a statistical quantity. Out-of-sample bootstrap sampling technique is different from general bootstrap sampling, in which \( N \) number of random samples \( (B_1, B_2, \ldots, B_N) \) are drawn from original training sample \( (T) \), where each drawn sample \( (B_i, \text{ where } i = 1, 2, \ldots, N) \) has the same size as original training sample \( (T) \). In out-of-sample bootstrapping technique, each drawn sample \( (B_i) \) is considered as training data, while remaining data \( (T - B_i) \) is used as a test data. After creating \( N \) number of training as well as testing datasets, average performance estimation is computed.
Table 3.19 reports the mean predictive accuracy results of the uEFS and existing feature selection measures, which are computed using out-of-sample bootstrapping technique. For example, in the case of the Cylinder-bands dataset ($T$), 540 random samples or training datasets ($B_1, B_2, \ldots, B_{540}$) were drawn, which is based on number of instances in a dataset (see Table 3.12). Similarly, 540 test datasets were created. Finally, mean predictive accuracy of existing feature selection measures as well as the proposed methodology is computed. For example, the value 77.49 in Table 3.19, represents the mean predictive accuracy using the IG feature selection measure for the Cylinder-bands dataset. It can be observed from Table 3.19 results that the proposed methodology provides competitive results as compared to existing feature selection measures. Table 3.19 also reports the result of one-sample t-test. It can be observed from Table 3.19 that most of significance (i.e. $p$) values are less than 0.05 (i.e. $p < .05$), which shows that the proposed uEFS methodology results are statistically significantly different from the results of existing methodologies.

For evaluating the computation cost of the proposed feature selection methodology, the performance speed was also computed, as shown in Table 3.20. The results show that on average, the proposed methodology takes 0.37 sec more time than state-of-the-art filter measures.

Proposed feature selection methodology is also compared with other well-known feature selection methods (i.e. OneR and ReliefF) as illustrated in Table 3.21. The results of Table 3.21 also show that the proposed methodology provides competitive results as compared to existing feature selection methods.

In the proposed uEFS methodology, computed feature ranks are without any given weightages. In order to validate this consideration, the proposed uEFS methodology is compared with and without giving weightage to features. For computing weightage of each attribute, a borda method [77, 169] is used, where a pre-defined score is assigned to each position in a list produced from each univariate filter measure [77]. In this method,
3.4 Evaluation of the univariate ensemble-based feature selection methodology

Table 3.20 Comparisons of time measure (in seconds) with existing feature selection measures.

<table>
<thead>
<tr>
<th>Nontext Dataset</th>
<th>Feature Selection Measures</th>
<th>Proposed Methodology</th>
<th>ATSM(^a)</th>
<th>TD(^b)</th>
<th>ATD(^c)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>IG</td>
<td>GR</td>
<td>CS</td>
<td>SU</td>
<td>S</td>
</tr>
<tr>
<td>Cylinder-bands</td>
<td>4.12</td>
<td>3.28</td>
<td>3.82</td>
<td>3.79</td>
<td>3.59</td>
</tr>
<tr>
<td>Diabetes</td>
<td>0.14</td>
<td>0.11</td>
<td>0.12</td>
<td>0.12</td>
<td>0.12</td>
</tr>
<tr>
<td>Letter</td>
<td>4.60</td>
<td>4.12</td>
<td>4.63</td>
<td>4.28</td>
<td>4.60</td>
</tr>
<tr>
<td>Sonar</td>
<td>0.06</td>
<td>0.05</td>
<td>0.08</td>
<td>0.06</td>
<td>0.06</td>
</tr>
<tr>
<td>Waveform</td>
<td>1.11</td>
<td>1.12</td>
<td>1.12</td>
<td>1.09</td>
<td>1.12</td>
</tr>
<tr>
<td>Vehicle</td>
<td>0.33</td>
<td>0.28</td>
<td>0.30</td>
<td>0.28</td>
<td>0.30</td>
</tr>
<tr>
<td>Glass</td>
<td>0.36</td>
<td>0.36</td>
<td>0.33</td>
<td>0.34</td>
<td>0.33</td>
</tr>
<tr>
<td>Arrhythmia</td>
<td>2.67</td>
<td>2.68</td>
<td>2.54</td>
<td>2.70</td>
<td>2.64</td>
</tr>
</tbody>
</table>

\(^a\) ATSM: Average Time of State-of-the-art Measures, \(^b\) TD: Time Difference, \(^c\) ATD: Average Time Difference

Table 3.21 Comparisons of predictive accuracy (in %age) with existing feature selection methods.

<table>
<thead>
<tr>
<th>Nontext Dataset</th>
<th>Feature Selection Methods</th>
<th>Proposed Methodology</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OneR</td>
<td>ReliefF</td>
</tr>
<tr>
<td>Cylinder-bands</td>
<td>79.63</td>
<td>80.37</td>
</tr>
<tr>
<td>Diabetes</td>
<td>75.39</td>
<td>75.52</td>
</tr>
<tr>
<td>Letter</td>
<td>97.14</td>
<td>96.91</td>
</tr>
<tr>
<td>Sonar</td>
<td>77.88</td>
<td>75.96</td>
</tr>
<tr>
<td>Waveform</td>
<td>86.76</td>
<td>86.90</td>
</tr>
<tr>
<td>Vehicle</td>
<td>64.89</td>
<td>63.83</td>
</tr>
<tr>
<td>Glass</td>
<td>49.07</td>
<td>57.01</td>
</tr>
<tr>
<td>Arrhythmia</td>
<td>71.02</td>
<td>71.46</td>
</tr>
</tbody>
</table>

A position-based scoring mechanism is used to compute score of a feature [77], where a final score of each feature is computed by summing all positional scores of that particular feature from all produced lists. After generating a final score list, weightage of each feature is computed using the following equation:
Weightage = 1 - \frac{(value - \min)}{(\max - \min)} \quad (3.16)

Where the value is a final score of feature, while the min and max are minimum and maximum values in a final score list.

This process is explained through a diabetes dataset\(^8\) example, as illustrated in Table 3.22.

<table>
<thead>
<tr>
<th>Univariate Filter-based Measure</th>
<th>Position</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Information Gain</td>
<td>(f_2)</td>
</tr>
<tr>
<td>Gain Ratio</td>
<td>(f_2)</td>
</tr>
<tr>
<td>Chi Squared</td>
<td>(f_2)</td>
</tr>
<tr>
<td>Symmetrical Uncertainty</td>
<td>(f_2)</td>
</tr>
<tr>
<td>Significance</td>
<td>(f_2)</td>
</tr>
</tbody>
</table>

In Table 3.22, \(f_1, f_2, f_3, f_4, f_5, f_6, f_7, f_8\) represent the features (such as \(\text{preg}, \text{plas}, \text{pres}, \text{skin}, \text{insu}, \text{mass}, \text{pedi}, \text{age}\)) of the diabetes dataset. Scaled ranks were computed using each filter measure. For example, using information gain, the computed scaled ranks of each feature were:

1. scaled rank of \(@\text{attribute preg} = 0.1431\)
2. scaled rank of \(@\text{attribute plas} = 1.0\)
3. scaled rank of \(@\text{attribute pres} = 0.0\)
4. scaled rank of \(@\text{attribute skin} = 0.1721\)
5. scaled rank of \(@\text{attribute insu} = 0.2584\)
6. scaled rank of \(@\text{attribute mass} = 0.3458\)
7. scaled rank of \(@\text{attribute pedi} = 0.0386\)
8. scaled rank of \(@\text{attribute age} = 0.3322\)

\(^8\)https://archive.ics.uci.edu/ml/machine-learning-databases/pima-indians-diabetes/
3.4 Evaluation of the univariate ensemble-based feature selection methodology

After calculating the scaled ranks of each feature using information gain, all features were sorted in a descending order such as \( f_2, f_6, f_8, f_5, f_4, f_1, f_7, f_3 \) and then assigned a pre-defined score to each position in a list as shown in first row of Table 3.22; for example, here \( f_2 \) (plas feature) had the highest priority and is assign score 1. Similarly, \( f_6 \) (mass feature) had the second highest priority and is assign score 2, and so on. Table 3.22 records all position-based scores of features using each filter measure.

Once each feature has been scored according to each filter measure, a combined position score (final score) of the individual feature is calculated, as illustrated in Table 3.23. Finally, weightage of each feature is computed based on the contribution of a feature in terms of its individual final score, minimum, and maximum values of final scores using each filter measure; for example, in Table 3.23 the \( f_1 \) had the final score of 25, while 5 and 40 are the minimum and maximum values. Therefore, weightage of the \( f_1 \) feature will be \( 1 - ((25 - 5)/(40 - 5)) = 0.429 \).

<table>
<thead>
<tr>
<th>Features</th>
<th>( f_1 )</th>
<th>( f_2 )</th>
<th>( f_3 )</th>
<th>( f_4 )</th>
<th>( f_5 )</th>
<th>( f_6 )</th>
<th>( f_7 )</th>
<th>( f_8 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Combined Position Score</td>
<td>25</td>
<td>05</td>
<td>40</td>
<td>30</td>
<td>22</td>
<td>11</td>
<td>33</td>
<td>14</td>
</tr>
<tr>
<td>Weightage</td>
<td>0.429</td>
<td>1</td>
<td>0</td>
<td>0.286</td>
<td>0.514</td>
<td>0.829</td>
<td>0.2</td>
<td>0.743</td>
</tr>
</tbody>
</table>

After computing a weightage value of the individual feature, multiply this value to each scaled ranks value to generate a new scaled value of the individual feature that will be used for computing the combined sum of all computed ranks step (line-13 of Algorithm 2). After applying weighting mechanism, the predictive accuracy and F-measures of the proposed uEFS methodology were computed, as shown in Table 3.24. The results of Table 3.24 show that the proposed methodology (without considering weighting mechanism) provides competitive results as compared to giving weightage to features.
Table 3.24 Comparisons of predictive accuracy and F-measure with weightage mechanism.

<table>
<thead>
<tr>
<th>Nontext Dataset</th>
<th>Predictive Accuracy (%) of uEFS</th>
<th>F-measure of uEFS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Without weightage</td>
<td>With weightage</td>
</tr>
<tr>
<td>Cylinder-bands</td>
<td>81.11</td>
<td>82.59</td>
</tr>
<tr>
<td>Diabetes</td>
<td>76.04</td>
<td>76.04</td>
</tr>
<tr>
<td>Letter</td>
<td>96.97</td>
<td>96.35</td>
</tr>
<tr>
<td>Sonar</td>
<td>80.29</td>
<td>78.37</td>
</tr>
<tr>
<td>Waveform</td>
<td>86.9</td>
<td>80.46</td>
</tr>
<tr>
<td>Vehicle</td>
<td>65.84</td>
<td>65.84</td>
</tr>
<tr>
<td>Glass</td>
<td>58.41</td>
<td>58.41</td>
</tr>
<tr>
<td>Arrhythmia</td>
<td>72.79</td>
<td>67.04</td>
</tr>
</tbody>
</table>

### 3.5 Conclusions

Features’ selection is an active area of research for the data mining and text mining research community. In this study, we present a *univariate ensemble-based feature selection* (uEFS) methodology to select informative features from a given dataset. For the uEFS methodology, we first propose a *unified features scoring* (UFS) algorithm to evaluate the feature-set in a comprehensive manner for generating a final-ranked list of features. For defining a cut-off point to remove irrelevant features, we then propose a *threshold value selection* (TVS) algorithm to select a subset of features, which are deemed important for the domain knowledge construction. Extensive experimentation was performed in order to analyze the proposed uEFS methodology in different facets. The uEFS methodology was evaluated using standard nontext as well as text benchmark datasets and achieved (1) on average, a 7% increase in F-measure as compared to the baseline approach, and (2) on average, a 5% increase in predictive accuracy as compared to state-of-the-art methods. The current version of the UFS has been plugged into a recently developed tool, the *data-driven knowledge acquisition tool* (DDKAT), to assist the domain expert in selecting informative features [159].
The current version of the UFS code and its documentation is open-source and can be downloaded from GitHub [160, 161].
Chapter 4

Domain Knowledge Construction

This chapter briefly describes a methodology to construct the machine-readable domain knowledge (i.e. structured declarative knowledge) from unstructured text. The proposed methodology constructs an ontology from unstructured textual resources in a systematic and automatic way, using artificial intelligence techniques with minimum intervention from a knowledge engineer.

4.1 Introduction

Knowledge is the wisdom of information that plays an important role in decision-making. It is able to distinguish between facts and information that is gained through experience and education. Declarative knowledge, also known descriptive knowledge, is a type of knowledge expressed in the form of unstructured sentences. An unstructured document is defined as a document having information in unexpected places [174], for example a hand written note or a dictation etc. In the health-care domain there exists a large volume of heterogeneous unstructured declarative knowledge in the form of medical progress notes, hospital discharge summaries, and clinical guidelines [175, 176].
Handling unstructured contents is the foundation to construct the declarative structured knowledge required for decision support as well as health and wellness systems. The unstructured forms of knowledge resources are important aspects to enable us to comprehend the contents and relationships of knowledge. This declarative knowledge can play an important role in real life applications for better analysis if the unprocessed text is transformed into structured contents (i.e. explicit knowledge). A huge amount of valuable textual data is available on the web, which has led to a corresponding interest in technology for automatically extracting relative information from open data, to convert it into declarative knowledge, and to represent it in a way, which is machine interpretable. One way to represent this knowledge is the ontology, which represents a machine-readable reality using a restriction-free framework, where you can explicitly define, share, reuse, and or distribute information. An ontology has been considered as a common way to represent a real-world declarative knowledge [151].

For knowledge construction, various knowledge systems have come a long way, from manual knowledge curation to automatic data-driven knowledge generation. The major drivers of this transition were the size and complexity of data. Since large datasets cannot be efficiently analyzed manually, the automation process is essential [177]. Initially in this process of knowledge automation, knowledge engineers followed ad-hoc procedures [178]. Later on, more systematic methodologies were devised, which can be referred to as data-driven knowledge acquisition systems. To gain insights from unstructured data, data science (DS) was created, supporting both automatic and semi-automatic data analysis [179]. Data science is similar to Knowledge Discovery in Databases and is intricately linked to data-driven decision-making concepts [180]. It employs techniques and theories drawn from many fields such as data mining, machine learning, cluster analysis, classification, visualization, and databases [90]. The CRoss-Industry Standard Process for Data Mining (CRISP-DM) is a widely used systematic methodology for DS system development. According to a poll
conducted in 2014, CRISP-DM was regarded as the leading methodology for data science projects, data mining, and analytics [181].

Considering the above discussion and the rapid increase in textual data rates, it is almost impossible to extract/construct machine-readable knowledge using manual approaches. The research community prefers to use natural language processing (NLP) techniques to resolve this problem. In the literature, most of the systems/methodologies [94–96] require high intervention of a knowledge engineer to translate unstructured text into a structured form and to resolve the construction of unambiguous machine-readable knowledge. We have responded to these deficiencies by including a methodology to construct the machine-readable domain knowledge (i.e. structured declarative knowledge) from unstructured text. The main motivation for proposing this approach is to automate the ontology development process without requiring extensive training in knowledge engineering, to reduce the human resource cost. The proposed methodology constructs an ontology from unstructured textual resources in a systematic and an automatic way using artificial intelligence techniques with minimum intervention from a knowledge engineer. In addition, the proposed methodology covers all major phases of CRISP-DM to explain the end-to-end knowledge engineering process. For effective transformation, controlled natural language (CNL) is used, which constructs syntactically correct and unambiguous computer-processable texts.

## 4.2 Materials and methods

To construct the machine-readable domain knowledge from unstructured text, this section briefly describes (1) the proposed methodology and modules details, and (2) functional mapping of the proposed methodology to the phases of CRISP-DM. Each of these items is explained in the following subsections.
4.2.1 Proposed knowledge construction methodology

This section describes the workflow of the proposed methodology, as shown in Fig. 4.1, as well as the functionality of each module.

Text mining is the process of deriving high-quality information from an unstructured text. It involves the application of techniques from areas like information retrieval, natural language processing, information extraction, and data mining [64]. For constructing machine-readable domain knowledge from textual data, a workflow is shown in Figure 4.1, which consists of six modules, namely text preprocessing, text transformation, feature selection, terms extraction, relations extraction, and model construction.

![Fig. 4.1 A workflow for domain knowledge construction methodology](image)

The brief description of each module is described as follows:

**Text preprocessing**

The *Text Preprocessing* module applies various basic preprocessing techniques to prepare the textual data. This module consists of four components, namely *Tokenization* for chopping the given text into pieces (tokens), *Filtration* for removing the non-informative terms (such as the, in, a, an, with, etc.), *Tagging* for assigning each token with a parts-of-speech tag, such as noun, verb, etc., and *Normalization* for identifying the root/stem of a word. i.e. the words “connected” and “connecting” are stemmed to “connect”.
4.2 Materials and methods

Text transformation

This module computes the *Term Frequency – Inverse Document Frequency* (TF-IDF) of the extracted tokens to generate the feature vectors (tabular form) representing document instances.

Feature selection

This module applies the proposed feature selection methodology, uEFS to select the important features for domain knowledge construction.

Terms extraction

A concept expresses more concrete and accurate meanings than keywords do. For identifying concept relationships and building a domain ontology, there is need to extract concepts (i.e. named entities) from the given textual data. The Terms Extraction module configures an external thesaurus (i.e. Princeton’s WordNet) to identify the concepts by mapping all nouns of the processed textual data with the concepts defined in a thesaurus. This module is responsible for identifying relevant terms.

Relations extraction

For generating concepts hierarchy to build a domain ontology, identification of concept relationships is needed, which can be achieved by using an external semantic lexicon. The Relations Extraction module extracts relations based on linguistic patterns using external semantic lexicons. This module performs the semantic analyses to define the meanings of words and unambiguous relationships among concepts by mapping with standard or domain vocabularies. Finally, this module validates the generated knowledge from the domain expert before model construction.
Model construction

This module constructs syntactically correct and unambiguous machine processable text and then transforms the relations into structured ontological model, called as domain model, using controlled natural language (CNL). The CNL is preferred to construct the ontological model. As according to [119, 182, 183], CNL can transform the declarative unstructured knowledge into machine interpretable knowledge and can consume less memory as well as computing power.

In order to construct domain knowledge each above-mentioned module has performed some task(s) and used method(s) as illustrated in Table 4.1. For Text Preprocessing, Text Transformation, Terms Extraction, and Relation Extraction modules, the RapidMiner Studio was used [184], whereas the ACE View was used for the Model Constructing module. The ACE View is an ontology editor that uses Attempto Controlled English (ACE) to view and edit OWL ontology [185].

4.2.2 Functional mapping of the proposed knowledge construction methodology with phases of the CRISP-DM

CRISP-DM consists of six well-defined phases: business understanding, data understanding, data preparation, modeling, evaluation, and deployment [188]. The major goal of developing CRISP-DM was to establish a process model for end-to-end application execution.

This section gives a description of the functional mapping of the proposed methodology to the phases of CRISP-DM, as shown in Table 4.2, which details the tasks performed by the proposed methodology for each phase.
Table 4.1 Methods used for constructing domain knowledge.

<table>
<thead>
<tr>
<th>Process</th>
<th>Task</th>
<th>Method</th>
<th>Reason</th>
</tr>
</thead>
<tbody>
<tr>
<td>Text preprocessing</td>
<td>Tokenization</td>
<td>English tokenizer</td>
<td>1. TF-IDF provides a good heuristic for determining likely candidate keywords [107].</td>
</tr>
<tr>
<td></td>
<td>Filtration</td>
<td>Stopword removal</td>
<td>2. It is one of the best-known and most commonly used keyword extraction algorithms currently in use [108] when a document corpus is available.</td>
</tr>
<tr>
<td></td>
<td>Normalization</td>
<td>Porters stemmer</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Tagging</td>
<td>POS tagger</td>
<td></td>
</tr>
<tr>
<td>Text transformation</td>
<td>Technique used</td>
<td>Term Frequency – Inverse Document Frequency (TF-IDF)</td>
<td></td>
</tr>
<tr>
<td>Feature selection</td>
<td>Features ranking</td>
<td>UFS algorithm</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Subset selection</td>
<td>TVS algorithm</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Filtration</td>
<td>Label filter</td>
<td></td>
</tr>
<tr>
<td>Terms extraction</td>
<td>Process</td>
<td>Nouns, Verbs, Adjectives, and Adverbs Identification</td>
<td>Penn Treebank [186] provides distinct coding for all classes of words having distinct grammatical behavior.</td>
</tr>
<tr>
<td></td>
<td>Thesaurus used</td>
<td>Penn Treebank</td>
<td></td>
</tr>
<tr>
<td>Relations extraction</td>
<td>Technique used</td>
<td>Lexical chaining and heuristics</td>
<td>Lexical chain is a well known technique for text connectivity [187] that locate terms and their sequence in accurate manner [107].</td>
</tr>
<tr>
<td></td>
<td>Thesaurus used</td>
<td>Princeton’s WordNet</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Process</td>
<td>Hyponyms identification</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Keep original tokens</td>
<td>True</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Multiple meanings per word policy</td>
<td>Take all meanings per token</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Multiple synset words</td>
<td>Take only first synset word</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Validation</td>
<td>Domain expert</td>
<td></td>
</tr>
<tr>
<td>Model construction</td>
<td>Language used</td>
<td>Attempto Controlled English (ACE)</td>
<td>ACE [8] is a logic-based knowledge representation language. 2. It uses the syntax of a subset of English.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>3. It provides automatic and unambiguous translation of text into first-order logic.</td>
</tr>
</tbody>
</table>
Table 4.2 CRISP-DM phases and tasks performed in the proposed methodology [17].

<table>
<thead>
<tr>
<th>Business understanding</th>
<th>Data understanding</th>
<th>Data preparation</th>
<th>Modeling</th>
<th>Evaluation</th>
<th>Deployment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Understand application domain</td>
<td>Search domain documents</td>
<td>Text tokenization</td>
<td>Select features</td>
<td>Evaluate the results of uEFS methodology</td>
<td>Plan deployment</td>
</tr>
<tr>
<td>Identify application goal</td>
<td>Collect initial documents</td>
<td>Remove stopwords</td>
<td>Extract terms</td>
<td>Evaluate the extracted terms</td>
<td>Monitor application impact</td>
</tr>
<tr>
<td>Identify application objectives</td>
<td>Analyze documents</td>
<td>Terms stemming</td>
<td>Extract relations</td>
<td>Evaluate the extracted relations</td>
<td>Maintain application</td>
</tr>
<tr>
<td>Analyze resource specification (software, hardware)</td>
<td>Remove irrelevant documents</td>
<td>POS tagging</td>
<td>Convert to ACE</td>
<td>Determine next steps</td>
<td>Prepare final report</td>
</tr>
<tr>
<td>Prepare application development plan</td>
<td>Store required documents</td>
<td>Text transformation</td>
<td>Construct model</td>
<td>Review application</td>
<td></td>
</tr>
</tbody>
</table>

### 4.3 Realization of the domain knowledge construction methodology

In this section, a diabetes scenario is described to illustrate the proposed methodology. The scenario is explained below based on the above-mentioned modules.

The steps for realization of the domain knowledge construction methodology are:

1. Load the clinical documents of diabetes and non-diabetes domains.

2. Perform the text preprocessing task, including text tokenization, stopwords removal, tokens filtration, terms stemming, and POS tagging, on loaded documents.
Table 4.3 A partial view of feature vectors.

<table>
<thead>
<tr>
<th>action</th>
<th>agonist</th>
<th>.....</th>
<th>blood</th>
<th>bloodstream</th>
<th>bmi</th>
<th>.....</th>
<th>label</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0000</td>
<td>0.0044</td>
<td>.....</td>
<td>0.0119</td>
<td>0.0000</td>
<td>0.0155</td>
<td>.....</td>
<td>diabetes</td>
</tr>
<tr>
<td>0.0020</td>
<td>0.0005</td>
<td>.....</td>
<td>0.0510</td>
<td>0.0000</td>
<td>0.0079</td>
<td>.....</td>
<td>diabetes</td>
</tr>
<tr>
<td>0.0029</td>
<td>0.0204</td>
<td>.....</td>
<td>0.0323</td>
<td>0.0025</td>
<td>0.0247</td>
<td>.....</td>
<td>diabetes</td>
</tr>
<tr>
<td>0.0009</td>
<td>0.0039</td>
<td>.....</td>
<td>0.0306</td>
<td>0.0000</td>
<td>0.0000</td>
<td>.....</td>
<td>diabetes</td>
</tr>
<tr>
<td>0.0021</td>
<td>0.0008</td>
<td>.....</td>
<td>0.0530</td>
<td>0.0000</td>
<td>0.0055</td>
<td>.....</td>
<td>diabetes</td>
</tr>
<tr>
<td>0.0025</td>
<td>0.0025</td>
<td>.....</td>
<td>0.0816</td>
<td>0.0000</td>
<td>0.0066</td>
<td>.....</td>
<td>diabetes</td>
</tr>
<tr>
<td>0.0015</td>
<td>0.0042</td>
<td>.....</td>
<td>0.0431</td>
<td>0.0000</td>
<td>0.0190</td>
<td>.....</td>
<td>diabetes</td>
</tr>
<tr>
<td>0.0016</td>
<td>0.0042</td>
<td>.....</td>
<td>0.0437</td>
<td>0.0000</td>
<td>0.0192</td>
<td>.....</td>
<td>diabetes</td>
</tr>
<tr>
<td>0.0032</td>
<td>0.0023</td>
<td>.....</td>
<td>0.0303</td>
<td>0.0000</td>
<td>0.0000</td>
<td>.....</td>
<td>diabetes</td>
</tr>
<tr>
<td>0.0013</td>
<td>0.0000</td>
<td>.....</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>.....</td>
<td>non-diabetes</td>
</tr>
<tr>
<td>0.0000</td>
<td>0.0000</td>
<td>.....</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>.....</td>
<td>non-diabetes</td>
</tr>
<tr>
<td>0.0007</td>
<td>0.0000</td>
<td>.....</td>
<td>0.0013</td>
<td>0.0000</td>
<td>0.0000</td>
<td>.....</td>
<td>non-diabetes</td>
</tr>
<tr>
<td>0.0006</td>
<td>0.0000</td>
<td>.....</td>
<td>0.0007</td>
<td>0.0000</td>
<td>0.0000</td>
<td>.....</td>
<td>non-diabetes</td>
</tr>
<tr>
<td>0.0010</td>
<td>0.0000</td>
<td>.....</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>.....</td>
<td>non-diabetes</td>
</tr>
<tr>
<td>0.0007</td>
<td>0.0000</td>
<td>.....</td>
<td>0.0006</td>
<td>0.0000</td>
<td>0.0000</td>
<td>.....</td>
<td>non-diabetes</td>
</tr>
<tr>
<td>0.0017</td>
<td>0.0000</td>
<td>.....</td>
<td>0.0021</td>
<td>0.0000</td>
<td>0.0000</td>
<td>.....</td>
<td>non-diabetes</td>
</tr>
<tr>
<td>0.0006</td>
<td>0.0000</td>
<td>.....</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>.....</td>
<td>non-diabetes</td>
</tr>
<tr>
<td>0.0022</td>
<td>0.0000</td>
<td>.....</td>
<td>0.0019</td>
<td>0.0000</td>
<td>0.0000</td>
<td>.....</td>
<td>non-diabetes</td>
</tr>
<tr>
<td>0.0000</td>
<td>0.0000</td>
<td>.....</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>.....</td>
<td>non-diabetes</td>
</tr>
</tbody>
</table>

3. Compute the TF-IDF of each term to generate the feature vectors for transforming the text into structured form as shown in Table 4.3.

4. Compute the ranks of each feature using proposed uEFS methodology, and then select the important features (words) of diabetes domain only as shown in Table 4.4.

5. Extract terms (words) after identification of nouns, verbs, adjectives, and adverbs using Penn Treebank as shown in Table 4.5.

6. Extract and identify all entities relations using the lexical chain technique and a heuristic approach. For example, lexical chain extracts 'symptom/'
Table 4.4 Top diabetes domain words extracted from clinical documents.

| Diabetes domain words | action | prevention | child | beverage | triglyceride | agonist | sick | cholesterol | bmi | unstable | antidiabetic | stage | dietary | mellitus | reduce | blood | type | eat | diagnose | condition | bodyweight | critical | education | diastolic | woman | chest | cycle | excretion | dietitian | adult | diabetes | drug | glucagon | episode | judgment | diabetic | energy | obese | fat | gestational | diet | external | overweight | foot | height | fatness | failure | plasma | glycemia | cough | glucose | food | pressure | hemoglobin | fatigue | glargine | goal | protection | hemoprotein | breakfast | hormone | healthy | urine | hospitalization | syndrome | insulin | level | complication | hypertension | vital | lifestyle | medication | exercise | injection | avoid | lower | substance | tired | intake | problem | monitor | yield | metformin | intensive | indicator | nutrition | activity | vision | habit | frequent | obesity | aged | hdl | goal | coma | visualize | influenza | hyperglycemia | disease | lispro | amount | adult | hypoglycemia | regular | hyper | walk | breathless | metabolic | pregnancy | thirst | drink | feet | protein | repeat | glimepiride | growth | person | weight | sugar | high | prevent | serum | training | systolic | loss |
4.3 Realization of the domain knowledge construction methodology

Table 4.5 Selected words for domain model construction.

<table>
<thead>
<tr>
<th>Diabetes domain words along-with their weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;weight name=&quot;blood&quot; value=&quot;0.998&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;diabetes&quot; value=&quot;0.998&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;diabetic&quot; value=&quot;0.998&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;diet&quot; value=&quot;0.998&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;glucose&quot; value=&quot;0.998&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;glargine&quot; value=&quot;0.998&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;insulin&quot; value=&quot;0.998&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;obesity&quot; value=&quot;0.998&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;level&quot; value=&quot;0.751&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;feet&quot; value=&quot;0.743&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;person&quot; value=&quot;0.743&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;serum&quot; value=&quot;0.743&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;pressure&quot; value=&quot;0.743&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;metformin&quot; value=&quot;0.743&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;vision&quot; value=&quot;0.743&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;hdl&quot; value=&quot;0.743&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;hyperglycemia&quot; value=&quot;0.743&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;weight&quot; value=&quot;0.587&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;glycemia&quot; value=&quot;0.587&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;hypertension&quot; value=&quot;0.587&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;disease&quot; value=&quot;0.485&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;regular&quot; value=&quot;0.485&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;fatigue&quot; value=&quot;0.388&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;indicator&quot; value=&quot;0.373&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;frequent&quot; value=&quot;0.373&quot;/&gt;</td>
</tr>
<tr>
<td>&lt;weight name=&quot;coma&quot; value=&quot;0.362&quot;/&gt;</td>
</tr>
</tbody>
</table>

- blood_disease’ and ‘symptom/feeling/somesthesia/unpleasant_person/
negative_stimulus/hurt’ relations of ’symptom’ word.

7. Finally, for the model construction process, first construct the correct controlled natural language text for each identified relation between words as shown in Table 4.6.
Table 4.6 Identified relations of diabetes domain.

<table>
<thead>
<tr>
<th>Attempto Controlled English (ACE) text</th>
</tr>
</thead>
<tbody>
<tr>
<td>feeling is a symptom.</td>
</tr>
<tr>
<td>somesthesia is a feeling.</td>
</tr>
<tr>
<td>unpleasant_person feels somesthesia.</td>
</tr>
<tr>
<td>unpleasant_person has negative_stimulus.</td>
</tr>
<tr>
<td>negative_stimulus is a hurt.</td>
</tr>
<tr>
<td>blood_disease is a symptom.</td>
</tr>
<tr>
<td>glycemia is glucose_level.</td>
</tr>
<tr>
<td>hyper_tension is bloodpressure.</td>
</tr>
<tr>
<td>weightlost is a symptom.</td>
</tr>
<tr>
<td>frequent_urination is a symptom.</td>
</tr>
<tr>
<td>high_thirst is a symptom.</td>
</tr>
<tr>
<td>high_fatigue is a symptom.</td>
</tr>
<tr>
<td>high_obesity is a symptom.</td>
</tr>
<tr>
<td>over_weight is a symptom.</td>
</tr>
<tr>
<td>edema is a symptom.</td>
</tr>
<tr>
<td>blood_serum is an indicator.</td>
</tr>
<tr>
<td>hdl is an indicator.</td>
</tr>
<tr>
<td>hyperglycemia is an indicator.</td>
</tr>
<tr>
<td>metformin is a medicine.</td>
</tr>
<tr>
<td>regular_insulin is a medicine.</td>
</tr>
<tr>
<td>swallow_feet is a symptom.</td>
</tr>
<tr>
<td>glimepiride is a medicine.</td>
</tr>
<tr>
<td>lispro is a medicine.</td>
</tr>
<tr>
<td>glargine is a medicine.</td>
</tr>
</tbody>
</table>

8. Write the correct controlled natural language text into the ACE editor (see Figure 4.2) to construct the domain model as shown in Figure 4.3.

Fig. 4.2 Domain model generation through ACE controlled natural language
Once the ontological models are built, they can be accessible and useable by the mapping process [189] for decision-support system as well as education, health and wellness applications.

4.4 Conclusions

Declarative knowledge is one of the crucial component in the medical domain and constitutes unstructured representation. In current practices, it is very difficult, time-consuming, and costly to construct machine-readable declarative knowledge from domain documents. In this study, we present a methodology to construct the machine-readable domain knowledge (i.e. structured declarative knowledge) from unstructured text that can serve a broad range of applications such as decision support systems, as well as education, health, and wellness applications. The proposed methodology constructs an ontology from unstructured textual resources in a systematic and automatic way using artificial intelligence techniques with minimum intervention from a knowledge engineer.
Chapter 5

Case-Based Learning

This chapter covers the solution of the third set of research questions/challenges mentioned in the problem statement section of chapter 1. In this chapter, an interactive and effective case-based learning (CBL) approach is presented, which enables the medical teacher to create real-world CBL cases for their students with the support of their experiential knowledge and computer generated trends; review the student solutions, and give feedback and opinions to their students. This approach facilitates medical students to undertake CBL rehearsal with machine-generated domain knowledge support before attending an actual CBL class. In this chapter, a semi-automatic real-world clinical case creation, and case formulation techniques with domain knowledge support are introduced. To automate the proposed approach, an interactive case-based learning system (iCBLS) was designed and developed. To evaluate the proposed CBL approach, two studies were performed. The proposed approach was evaluated under the umbrella of the context/input/process/product (CIPP) model and achieved a success rate of more than 70% for student interaction, group learning, solo learning, and improving clinical skills. To exploit the IoT infrastructure for supporting flipped case-based learning in the cloud environment with state-of-the-art security and privacy measures, this chapter also presents an IoT-based Flip Learning Platform, called IoTFLiP and working scenario for the case-base flip learning using IoTivity.
5.1 Introduction

Medical education is an active area of research and has undergone significant revolution in the past few decades. In health education, the purpose of medical education programs is to: (1) develop educational leaders, (2) change the learners’ knowledge, skills, or attitudes, and (3) improve educational structures [18]. Various teaching methodologies have been introduced in professional health education [190], where active learning has gained a lot of attention around the world [20]. In active learning, instructions are given to students to actively engage them [21]. Case-Based Learning (CBL) is an active learning approach, which provides favorable circumstances to students in order to explore, question, discuss and share their experiential knowledge for improving their practical intelligence [20]. The term CBL was introduced in the medical area in 1912 [22] and proceeds in many forms, from simple hands-on, in-class exercises to semester long projects and/or case studies [23]. It focuses around clinical, community or scientific problems. According to McLean [22], “CBL is a tool that involves matching clinical cases in health care-related fields to a body of knowledge in that field, in order to improve clinical performance, attitudes, or teamwork”.

The CBL approach is one of the successful approaches in student-based pedagogy and it is a widely used approach in various health-care training settings around the world [24–31]. This approach is used in different fields of medicine, namely medicine, dentistry, pharmacology, occupational and physical therapy, nursing, allied health fields, and child development. Similarly, it has been used in clinical as well as non-clinical courses such as nursing courses, adult health, mental health, pediatric, and obstetrical nursing courses, pathophysiology, statistics, law, school affairs, physics education, and research [32, 33, 20]. In addition, this approach has been utilized in various departments such as medical education, information technology, and quality improvement [22], and has also been practiced in rural as well as underserved areas [22]. These findings validate that CBL is used throughout
the world across multiple fields, and is considered to be effective for medical and health profession’s curricula [22].

In CBL practice, the clinical case is a key component in learning activities, which includes basic, social, and clinical studies of the patient [34]. In the medical domain, the clinical case provides a foundation to understand the situation of a disease and in recent trends; the real-life clinical case(s) are more emphasized for the practice of medical students [35–37]. In medical education, these cases enable the students to use their experiential knowledge to interpret them easily [20]. In the medical area, CBL facilitates students to learn the diagnosis and management of clinical cases [22], and prepares the participants to practice basic primary care and in critical situations [38]. The CBL approach promotes learning outcomes and builds confidence in students while they are making decisions to practice in real life [39, 28]. According to Thistlethwaite [34], “CBL promotes learning through the application of knowledge to clinical cases by students, enhancing the relevance of their learning and promoting their understanding of concepts”. CBL is also known to be an effective learning approach for a small group of medical students at undergraduate, graduate, postgraduate education levels as well as for professional development [34, 40, 35, 41, 22].

Besides the benefits of CBL approach, there are also a few shortcomings of this approach. For example, in professional education for health and social care domains, students feel that classroom CBL activities require a significant amount of time [42]. Sometimes, students feel uncomfortable while participating in group learning activities and they prefer to work alone [43]. Normally, formal learning activities are performed without a real patient case [34], where interactions are often unplanned and rely on the goodwill of patients. In the specialized literature, medical education programs are considered to be complex due to their diverse interactions amongst participants and environments [18]. Discussion-based learning in a small-group like CBL, is considered to be a complex system [44]. In small-groups, multiple medical students are interacting and exchanging information with each other, where each
student is also a complex system [45]. In health care professional education, students have to tackle uncertain situations due to the accumulation of diverse problems [46]. In such situations, everyone has their own judgment, opinion, and feedback and will consider this integral as well as appropriate for that situation. In such situations, experiential knowledge (EK) is thought-out as a resource [46], which can facilitate and provide lived knowledge to students. According to Willoughby [47], “Experiential knowledge is a knowledge of particular things gained by perception and experience”. Experiential knowledge enables the individuals to capture practical experience for problem solving. It is considered a valuable resource for enhanced individual participation and user empowerment [46].

For problem-based learning, both human and computer can play a key role in the medical domain. Both of these have their own strengths and weaknesses [48, 49]. For example, (1) human judgment is considered credible, (2) a human have common sense and can determine new rules ‘off the shelf’, (3) a human can easily identify trends or abnormality in visualization data. However, a human (1) cannot accomplish complex computation decisions, (2) cannot perform fast reasoning computations, (3) easily gets tired and bored. These weaknesses of humans can be mitigated by collaborating with a computer. A computer has advantages over a human for these weaknesses. A computer can perform complex computation decisions, supported by fast reasoning computation, and does not tire.

Being a human, students are easily tired or bored, and tend to choose computer-based cases [34, 50] and opt for web-based cases as compared to lectures for their learning [51, 52]. Additionally, more attention is given to online/web-based learning environments [34]. In order to support the learning outcomes of students, a plethora of web-based learning systems have been developed [53–62]. A review of the literature shows that these systems either do not support computer-based interactive case authoring as well as its formulation, or without the support of acquiring real-world CBL cases or do not provide feedback to students.
Currently, less attention is given to fill the gaps between human-based and computer-based learning.

Case-Based Learning (CBL) has become an effective pedagogy for student-centered learning in medical education, which builds its foundation on accumulated patient cases. Flip learning and Internet of Things (IoT) concepts have gained much attention in recent years. These concepts with CBL can improve learning capabilities by providing real and evolutionary medical cases. The concepts also enable students to build confidence in decision-making, and to enhance teamwork environment efficiently.

Recent trends show that increasing attention is being paid to flipped learning approaches for boosting learning capabilities [156, 146]. Currently, CBL is typically performed without exploiting the advantages of the flipped learning methodology, which has significant evidence supporting it over traditional learning methods [146, 147, 53, 158]. As defined by Kopp [157], "Flipped learning is a technique in which an instructor delivers online instructions to students before and outside the class and guides them interactively to clarify problems. While in class, the instructor imparts knowledge in an efficient manner".

In order to support healthcare improvement, much work has been done to acquire information through IoT devices. However, there is still a lack of systems and frameworks to efficiently exploit IoT data and use it for the purpose of extracting knowledge, creating knowledge with partial involvement of the field expert, and using the acquired knowledge for providing real-time patient care and treatment. When designing any system, keeping the privacy of information, providing on-demand services, and knowledge sharing among organizations are important parameters [146, 191]. For knowledge creation and acquisition, various learning models exist that need to be used for the real-time extraction of meaningful information from IoT devices and to make it shareable among caregivers, patients, and doctors/experts [137, 192]. Currently, the CBL lacks a development mechanism for real-world clinical cases using IoT infrastructure, and there is need to exploit existing IoT resources and
Case-Based Learning infrastructure for boosting medical education. Very little attention is given to the development mechanisms of real-world clinical cases and most of the stakeholders, including learners, teachers, administrators, and other health professionals are interested in change [18].

Keeping in view all aforementioned facts, we focused on designing and developing an interactive computational e-learning platform by using CBL concepts so that medical students are can be provided with the following learning activities: (1) practicing real-world case(s) before and outside the class to determine the treatment of patients in an easy to use manner, (2) identifying the components of a medical chart (such as demographics, chief complaint, medical history, etc.) from a given clinical case, (3) constructing appropriate interpretations about a patient’s problems to create a significant medical story using identified components within the context of his or her life, and (4) implanting clinical knowledge to obtain professional experience for effective learning purposes. In order to achieve these goals and expectations, this study was undertaken with the following objectives: (1) create a real-world online and computer-based clinical case using an experiential knowledge (see Sections 5.2.2 and 5.3.2); (2) identify basic science information relevant to patient data for their practice with a support of machine-generated domain knowledge (see Sections 5.2.3 and 5.3.3); and (3) design an IoT-based platform that can be used for medical, as well as other domains for effective and enriched learning (see Section 5.5).

In this chapter, an interactive Case-Based Learning System (iCBLS) based on the current CBL practices in the School of Medicine, University of Tasmania, Australia was designed and developed. The proposed iCBLS provides features such as: an online learning environment, interactivity, flexibility, display of the entire collection of data at one place, a paging facility, and support for in-line reviewing to edit and delete the displayed data. The iCBLS consists of three modules: (i) system administration (SA), (ii) clinical case creation (CCC), and (iii) case formulation (CF). The SA module manages multiple types of users and it maintains the hierarchy of courses, their units, and clinical cases for each unit. Similarly,
the CCC module is based on an innovative semi-automatic approach that consists of three steps. First, graphs are generated from a patient’s vital signs with a single click. In the second step, a clinical case is generated automatically by integrating basic, history, and vital signs information. Finally, in the third step, the medical teacher utilizes his/her experiential knowledge and refines the generated case in order to create the real-world clinical case.

The CF module is based on identification of the medical-chart’s components in order to formulate the summaries of CBL cases through the intervention of medical students’ as well as teachers’ knowledge, as well as the provision of feedback from the teacher. In addition, the CF module enables the students to practice real-world case(s) with machine-generated domain knowledge support before and outside the class.

This study also introduced an IoT-based Flip Learning Platform, called IoTFLiP, that integrates the features of existing IoT resources. The IoTFLiP exploits the IoT infrastructure to support flipped case-based learning in the cloud environment with state-of-the-art security and privacy measures for potentially personalized medical data. It also provides support for application delivery in private, public, and hybrid approaches. Due to the low cost, reduced sensing devices’ size, support of IoTs, and recent flip learning concepts can enhance medical students’ academic and practical experiences. To demonstrate the working scenario of the proposed IoTFLiP platform, a real-time data through IoTs gadgets is collected to generate a real-life situation case for a medical student using iCBLS.

The key contributions of this research are as follows:

1. This work focuses on developing an intelligent computational e-learning platform for CBL in medicine that enriches and enhances the learning experience for medical students.

2. The chapter shows the design and development of an interactive CCC module that supports an innovative method to real-world clinical case creation using a semi-automatic approach.
3. The chapter shows the design and development of an interactive CF module that provides a flexible case formulation environment.

This chapter is organized as follows: Section 5.2 covers the methodology of the proposed CBL approach; the iCBLS along with a case study scenario is discussed in Section 5.3. Section 5.4 provides the details of evaluations performed along with results, while Section 5.5 presents the IoTFLiP architecture and working scenario for the case-base flip learning using IoTivity. Section 5.6 discusses the significance, challenges and limitations of the proposed system. Section 5.7 concludes the chapter with a summary of the research findings.

5.2 Materials and Methods

To develop an interactive CBL system to prepare medical students for their real-world clinical practice before and outside the class, this section describes the architecture of the proposed system and detailed methodologies used for Clinical Case Creation and Case Formulation modules.

5.2.1 Proposed system architecture

The functional architecture of the proposed system is described as shown in Figure 5.1, which consists of four modules, namely Graphical User Interface, System Administration, Clinical Case Creation, and Case Formulation. Three types of users - administrator, medical teacher, and medical students interact with the iCBLS through the Graphical User Interface module.

The functionalities of the iCBLS are illustrated in Figure 5.2. Using this system, the Administrator manages courses by specifying course details, modules, and allotments. The Medical teacher manages CBL cases and their model solutions, evaluates student solutions, and provides feedback to students. The Medical student formulates case summaries (history, examination, and investigations) with the help of domain knowledge to solve the CBL case,
views other available solutions, and receives feedback from the medical teacher. The detailed role description of each user is shown pictorially in Section 5.3 Figure 5.6.

The functionality of each aforementioned module of the proposed architecture is described as follows:
The functionality of the Graphical User Interface module

The Graphical User Interface module provides an interface to all users to interact with the other three aforementioned modules. This module provides a flexible environment by facilitating: (1) an easy and user-friendly paging facility, (2) a display of the entire collection of data, and (3) support for inline editing to edit and delete the displayed data.

The functionality of the System Administration module

The iCBLS provides support for managing numerous courses, where each course consists of multiple units e.g. 'CBL Cases' is one course that includes two units, namely 'Fundamentals of Clinical Science' and 'Functional Clinical Practice'. Multiple students are able to enrol in each unit. The administrator is assumed to be the coordinator that manages the CBL administration and interacts with System Administration module, as shown in Figure 5.2. The administrator manages the hierarchy of courses, their units, and users’ relations with units by using the Course Manager, Unit Manager, and User Manager components to store the information into the System Database. Moreover, the administrator manages two types of users, namely medical teacher and medical student. In addition to this, the administrator assigns the courses’ units to the individual medical teacher and enrols the medical students to each unit. All aforementioned information is stored and managed in System Database. The detailed flow diagram of System Administration module is described and shown in Figure 5.3.

The functionality of the Clinical Case Creation module

The Clinical Case Creation module is used to create real-world clinical cases. The medical teacher who interacts with this module is assumed to be a medical expert that interacts with patients either at private clinics or at hospitals. This module consists of five components as follows: Patient Information Manager for managing patient’s basics and history information, Vital Sign Manager for managing the categories and measurement information of patient’s
vital signs, *Graph Generator* for generating and visualizing vital signs, both individual and average values, *Clinical Case Generator* for auto-generating a clinical case by integrating basic information, patient history, vitals’ (a.k.a. vital signs) information and finally, *Clinical Case Refiner* for refining the auto integrated case. This module also requires real-world patients’ and vital signs reference rules’ information (see Table 5.3 in Section 5.2.2) that is obtained from *External Data Source*, which includes *Patient, Patient History Document, Vitals’ Measurements*, and *Reference Rules’ Documents* as data sources.

**The functionality of the Case Formulation module**

The *Case Formulation* module is intended for (1) identifying the components of a medical chart (such as demographics, chief complaint, medical history etc.) from a given clinical case, (2) allowing the medical students to write their observations for each component by utilizing domain knowledge and finally, (3) receiving feedback from the medical teacher. This module helps medical students to understand the causes of patient behaviors and symptoms, to formulate summaries of CBL cases and to get feedback about self-formulated cases from their medical teacher. The *medical students* as well as *medical teacher* interact with this module. This module is comprised of two components: *Case Formulation Manager* for loading the ontological model (domain knowledge) to practice the CBL cases and for
managing formulated cases that are created by students as well as teachers, and Feedback Manager for providing teachers’ feedback to individual students. This module obtains the ontological model from the External Data Source, which includes Domain Knowledge as knowledge source.

5.2.2 Clinical case creation methodology

This section briefly describes the procedure for creating a real-world clinical case in the proposed system (iCBLS) using an innovative semi-automatic approach as shown in Figure 5.4. As mentioned in some studies [57, 193, 194], a clinical case is generally written as a problem which includes basic personal information, reported complaints, history and physical examinations, imaging studies, vital signs, clinical signs and symptoms, laboratory results, findings, diagnoses, discussions, comments, and learning points. In this study, patient basic information, patient history, and vital signs information are considered as components of a real-world clinical case.

Five steps are involved for real-world clinical case creation, which are shown in Figure 5.4. First, the medical teacher converses with the patient and records the patient’s basic information such as the patient’s name, gender and age. Following this, the patient’s history is recorded, this covers medical history, family history, symptoms review and food habits etc. This information is stored in the Patient Database. In the second step, the patient’s vital signs are recorded in the Vital Signs Database. In this study, body temperature, blood pressure, blood glucose, and heart rate vital signs categories are considered, which are helpful for patient treatment and disease diagnosis [144, 195]. These vital signs are measured by traditional devices such as thermometers for body temperature, sphygmomanometers for blood pressure, blood glucose meters for blood glucose, and stethoscopes for heart rate. However, this vital signs information can also be captured with the help of RFID technology.
Fig. 5.4 Real-world clinical case creation steps

and sensors through wearable devices [196, 197]. Multiple IoT gadgets are available to measure these vitals; they are presented in Table 5.1.

Table 5.1 IoT gadgets for collecting vital signs.

<table>
<thead>
<tr>
<th>Vital sign</th>
<th>Available devices</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Blood Glucose</td>
<td>iHealth’s Blood Glucose Monitor, iHealth Align, iBG Star, etc</td>
</tr>
<tr>
<td>2. Blood Pressure</td>
<td>iHealth Wireless Blood Pressure Monitors, Omron BP786, Microlife WatchBP home A, QardioArm Blood Pressure Monitor, etc</td>
</tr>
<tr>
<td>3. Heart Rate</td>
<td>LG gear watch, Wellograph, Polar V800, Mio LINK, Epson Pulse Watch, Spree Headband, etc</td>
</tr>
</tbody>
</table>
Weekly graphs are generated from a patient’s vital signs data in the third step. For visualization, line and bar graphs are used, and the weekly average value for each vital sign’s category is computed and a separate graph is generated. In addition, reference ranges, as defined in Table 5.3, for each vital sign category, are shown in each graph in order to assist with interpretation. In the fourth step, the patient’s basic information along-with history and vital signs’ data are integrated to create the system-generated clinical case. Finally, in the fifth step, the medical teacher visualizes the system-generated case as well as all auto-generated graphs. After visualization and analysis, the medical teacher refines the auto-generated case as shown in Table 5.2 and stores this in the Clinical Case Base for medical students’ practice.

Table 5.2 Example real-world CBL case.

<table>
<thead>
<tr>
<th>Case Outline</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mr. X, a 65 years old corporate sector worker, came to a medical expert with a few complaints. He said that he is providing financial consulting to various clients. He added that his office hours are 8:30 am to 6:00 pm. Since his job is related to office work, he has little physical activity. He used to drink regularly and likes to eat fatty and oily foods. He says he has become exhausted very easily for the last few weeks. He feels fatigued and breathless after walking only 100 m. He reported experiencing blurry vision and weight-loss. He said that he has never experienced these problems before. He was on no medications. He was 183 cm tall and weighed 196 lbs. He had a family history of hypertension and hyperglycemia. The expert was worried about his health and cautioned him to be more conscious of his health. In order to observe his vital signs, the expert suggested that he use wearable devices to measure his blood pressure, glucose level, and heart-rate. On examination, the results were: Systolic Blood Pressure = 135.24 mmHg, Diastolic Blood Pressure = 89.33 mmHg, Glucose Level in fasting = 145.43 mg/dL, Glucose Level in random = 247.36 mg/dL, Heart Rate = 90.14 bpm, Body Temperature = 98.69</td>
</tr>
</tbody>
</table>

The aforementioned process of real-world clinical case creation for multiple patients is briefly described in Algorithm-5. This algorithm takes basic information (i.e., BI), patient’s history (i.e., PH), and vitals’ information (i.e., VI) as input and then sequentially passes through mandatory steps to create the multiple real-world clinical cases. The output of this algorithm is used as input for Algorithm-6, which is described in following subsection.
Algorithm 5: Creation of Real-World Clinical Case\((D = BI, PH, VI)\)

**Input:** \(D = BI, PH, VI\): Input dataset (basic information, patient history, vitals’ information)

**Output:** \(CC\) – Real-world clinical case

1. \(/* D = p_1, p_2, p_3, \ldots, p_n \) where \(D\) represents data for \(n\) patients */;
2. for \(\forall p_i \in D\) do
3.   /* Get the basic information e.g. gender, age; and patient’s history e.g. medical history, family history, symptoms for each patient \(p_i\) */;
4.     \(BI_i \leftarrow \text{getBasicInformation}(D, p_i)\);
5.     \(PH_i \leftarrow \text{getPatientHistory}(D, p_i) : p_i = ph_1, ph_2, \ldots, ph_n\);
6.     /* Vitals’ information \(VI_i\) consists of vital’s category and its measurements. Firstly, select the vital sign category e.g. systolic blood pressure for each patient \(p_i\) */;
7.     \(selectVitalSign(VS) : VS = vs_1, vs_2, vs_3, \ldots, vs_n\);
8.     for \(\forall vs_j \in VS\) do
9.       \(M_k = m_1, m_2, m_3, \ldots, m_n\) // no. of measurements for \(vs_j\);
10.      for \(\forall m_i \in M_k\) do
11.         /* Get vital sign measurements for each vital sign category \(vs_j\) */;
12.          \(m_i \leftarrow \text{getVSMeasurement}(D, p_i, vs_j)\);
13.     end
14.     /* Compute the average values for each vital sign category \(vs_j\) */;
15.     \(vsmAvg_i \leftarrow \sum_{i=1}^{size(M_k)} m_i / size(M_k)\);
16.     /* Plot the individual and average graph for each category \(vs_j\) */;
17.     \(trendgraph \leftarrow \text{plotVSMeasurementGraph}(D, p_i, vs_j)\);
18.     \(meangraph \leftarrow \text{plotVSMeasurementAverageGraph}(vsmAvg_i)\);
19. end
20. /* Generate the case by integrating \(BI_i\), \(PH_i\), and \(vsmAvg_i\) for each patient \(p_i\) */;
21. \(SGC_i \leftarrow \text{generateCase}(BI_i, PH_i, vsmAvg_i)\);
22. /* Analyze the patient auto generated graphs */;
23. \(AG_i \leftarrow \text{analyseGraphs}(meangraph, trendgraph)\);
24. /* Refine the generated case based on the personal knowledge and graphical analytic */;
25. \(CC_i \leftarrow \text{refineCase}(SGC_i, AG_i)\);
26. return \(CC_i : \text{clinical case}\)
27. end
### Table 5.3 Vital signs reference ranges with interpretations

<table>
<thead>
<tr>
<th>Vital Sign (units)</th>
<th>Categories</th>
<th>Reference Range</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blood Pressure (mmHg) [198]</td>
<td>Systolic Blood Pressure (SBP)</td>
<td>SBP ≤ 119</td>
<td>normal</td>
</tr>
<tr>
<td></td>
<td></td>
<td>120 ≤ SBP ≤ 139</td>
<td>prehypertension</td>
</tr>
<tr>
<td></td>
<td></td>
<td>140 ≤ SBP ≤ 159</td>
<td>hypertension stage 1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>160 ≤ SBP ≤ 180</td>
<td>hypertension stage 2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SBP ≥ 181</td>
<td>hypertensive crisis</td>
</tr>
<tr>
<td></td>
<td>Diastolic Blood Pressure (DBP)</td>
<td>DBP ≤ 79</td>
<td>normal</td>
</tr>
<tr>
<td></td>
<td></td>
<td>80 ≤ DBP ≤ 89</td>
<td>prehypertension</td>
</tr>
<tr>
<td></td>
<td></td>
<td>90 ≤ DBP ≤ 99</td>
<td>hypertension stage 1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>100 ≤ DBP ≤ 110</td>
<td>hypertension stage 2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DBP ≥ 111</td>
<td>hypertensive crisis</td>
</tr>
<tr>
<td>Blood Glucose (mg/dL) [198, 199]</td>
<td>Fasting Blood Glucose (FBG)</td>
<td>FBG ≤ 69</td>
<td>hypoglycemia</td>
</tr>
<tr>
<td></td>
<td></td>
<td>70 ≤ FBG ≤ 99</td>
<td>normal</td>
</tr>
<tr>
<td></td>
<td></td>
<td>100 ≤ FBG ≤ 126</td>
<td>pre-diabetic</td>
</tr>
<tr>
<td></td>
<td></td>
<td>FBG ≥ 127</td>
<td>diabetic</td>
</tr>
<tr>
<td></td>
<td>Random Blood Glucose (RBG)</td>
<td>RBG ≤ 139</td>
<td>normal</td>
</tr>
<tr>
<td></td>
<td></td>
<td>140 ≤ RBG ≤ 199</td>
<td>pre-diabetic</td>
</tr>
<tr>
<td></td>
<td></td>
<td>RBG ≥ 200</td>
<td>diabetic</td>
</tr>
<tr>
<td>Heart Rate (bpm) [200, 201]</td>
<td>Resting Heart Rate (RHR)</td>
<td>RHR ≤ 59</td>
<td>bradycardia</td>
</tr>
<tr>
<td></td>
<td></td>
<td>60 ≤ RHR ≤ 100</td>
<td>normal</td>
</tr>
<tr>
<td></td>
<td></td>
<td>RHR ≥ 101</td>
<td>tachycardia</td>
</tr>
<tr>
<td></td>
<td>Sleeping Heart Rate (SHR)</td>
<td>40 ≤ SHR ≤ 50</td>
<td>normal</td>
</tr>
<tr>
<td></td>
<td>Irregular Heart Rate (IHR)</td>
<td>IHR == true</td>
<td>arrhythmia</td>
</tr>
<tr>
<td>Body Temperature (°F) [201]</td>
<td>Body Temperature (BT)</td>
<td>97.7 ≤ BT ≤ 99.5</td>
<td>normal</td>
</tr>
</tbody>
</table>

#### 5.2.3 Case formulation methodology

Case formulation is a commonly taught clinical skill and it is the foundation for balanced treatment planning that develops with practice and clinical experience [202–204]. In case formulation, clinicians determine the treatment of their patients and treatment of each particular patient is different from that of other patients [202]. Case formulation has a vital role in clinical decision-making [203] which is emphasized in many published documents [204]. It is frequently emphasized to practitioners to develop professional competency in case
formulation for their professional training as well as continuing medical education. Case formulation has multiple definitions and contents in various approaches [202]. As described by Godoy and Haynes [204], "Case formulation is an individualized integration of multiple judgements about a patient’s problems and goals, the casual variables that most strongly influence them, and additional variables that can affect the focus, strategies, and results of treatment with a patient". Formulating a clinical case involves constructing appropriate interpretations about a patient’s problem to create a significant medical story within the context of his or her life [203].

As case formulation has multiple definitions, in this study case formulation means identification of a medical-chart’s components from a given clinical case and then writing personal observations for each component. As mentioned in some studies [57, 205], demographics, chief complaint, medical history, habits, family history, medicines, allergies, physical exam, tests ordered, initial diagnosis, differential diagnosis, test results, final diagnosis, treatment, recommendations, and prognosis are considered as the components of medical-chart.

As described in Figure 5.5, the authorized medical student views the allotted courses. For case formulation, the student first selects the CBL case. After clinical assessment of the selected case, the student conceptualizes the information and identifies the components of the medical chart. Following this, the student then gets the domain knowledge to record his/her personal observations. During the formulation process, the student can also get help from available formulated cases that are completed by other medical students. After case formulation, students get feedback from their teacher in order to improve their concepts and knowledge.

The process of case formulation briefly is described in Algorithm-6. This algorithm takes a clinical case (i.e., CC) as an input and sequentially passes this through mandatory steps to resolve the clinical case in terms of creating a medical-chart.
5.3 Simulation of iCBLS

The design of the iCBLS is based on the current CBL practices whose working principle is explained with the help of a *Glycemia* case study. Using this system, the medical teacher can create cross-domain clinical case(s) and then students can formulate summaries of cases before attending the actual CBL class for practice. Moreover, the teacher can review the students’ formulated summaries and can provide feedback on their solutions. The output of this system is the course’s information, real-world cases, health records, formulated cases, and the teacher’s feedback.

The iCBLS is an interactive as well as flexible online software system, which manages multiple types of users according to their roles and privileges. It has been implemented in *C#* using *SQL Server 2008 R2* and *Bootstrap* as the front-end framework. In this system, nested *GridView* controls are used to manage the hierarchies of courses or cases. Similarly, *Stored Procedures* are created to decrease roundtrip response times and avoid code redundancy, as well as to simplify maintenance and enhancement. Both *GridView* and *Stored Procedure* techniques allow for increased system flexibility.
5.3 Simulation of iCBLS

Algorithm 6: Case Formulation($D = CC$[Ref. Algorithm 1])

Input: $D = CC$: Input dataset (clinical case)
Output: $CF$ — Case Formulation

1. if Verify($D$) then
   2. /* For creating the medical charts, add the components of medical charts e.g. presenting complaints, previous medications for $D$ cases */
   3. $MCC \leftarrow \text{addMedicalChartComponent} (D): D = mcc_1, mcc_2, mcc_3, ..., mcc_n$
   4. for $\forall mcc_m \in D$ do
      5. /* Get domain knowledge to add observations e.g. felt fatigue, breathlessness of each chart component $mcc_m$ */
      6. $Obs \leftarrow \text{addObservations}(mcc_m)$
   7. end
   8. /* Case formulation includes information of medical charts component and observations */
   9. $CF \leftarrow \text{caseFormulation} (MCC, Obs)$
 10. return $CF$ : case formulation
11. else
12.    Error(message);
13. end

The role description of this system is shown in Figure 5.6, it depicts types of system users, main options available in iCBLS for each user, and detailed functionalities of each main option.

5.3.1 Case study: Glycemia case

For in-depth study or analysis of real-world or imagined scenarios, the case study is used as a training tool to explain development factors in the case. In this case study, a Glycemia patient was monitored regularly, who visits a hospital for clinical check-ups. The medical teacher interacts directly with the patient to obtain his demographics, daily routine activities, medication history (if any), and family history information. The medical expert obtains the patient’s basic information and initial history through dialogue and available patient records.

The medical teacher requires the log of vital signs to understand the severity of disease; therefore, it is advisable that the patient’s vital signs such as body temperature, blood pressure,
Fig. 5.6 iCBLS role descriptor

[Diagram showing the roles and responsibilities of different individuals in a case-based learning setting, including Medical Student and Medical Teacher.]
glucose level, and heart rate are recorded on a regular basis. The teacher also suggests that the patient’s blood glucose level should be monitored in the morning with fasting as well as measured 2 hours after lunch and dinner. The patient then records their vital signs information three times a day for one week, based on the teacher’s instructions.

5.3.2 Clinical case creations

The process of real-world clinical case creation is described through the steps that are explained as follows.

Step-1: Record basic information and history information for the patient

In order to execute the scenario for creating a CBL case, the medical teacher uses the patient’s basic information e.g. patient name, gender, age. This information is added into the system after clicking the Add Patient link as shown in Figure 5.7(1a). After successful addition, the system refreshes the patient pane as shown in Figure 5.7(1b). Similarly, after adding a patient record, the system displays the history pane to enable history details to be added, by clicking the Add Patient History link as shown in Figure 5.7(2a). The system then refreshes the history pane as shown in Figure 5.7(2b). Once patient information is added, the teacher can easily modify or delete the record at any time using the Edit or Delete links as shown in Figure 5.7.

Step-2: Record patient’s vital signs information

For inclusion of vital signs information, the medical teacher uses the Add Vital Sign Info. link shown in Figure 5.7(3a). After doing this, the system displays the list of vital signs as shown in Figure 5.8(a). The teacher clicks the ’+’ icon to see a child grid that provides options for adding a vital sign measurement as shown in Figure 5.8(a). In the expanded grid view, the ’+’ icon is changed to ’–’ icon. For a better view, a paging concept is also implemented as shown
in Figure 5.8(a). The teacher enters the vital signs data into iCBLS. To enter date and time information, the system provides a calendar to the teacher for user-friendliness as shown in Figure 5.8(b). When modifying existing measured values, the teacher clicks the *Edit* link. The system then shows the relevant data in an editable form as shown in Figure 5.8(c). After modification, the teacher clicks the *Update* link. The system then updates the existing data and refreshes the grid.
Step-3: Generate and visualize the vital signs graphs

Visualization is the presentation of data in a format, which is easily understandable. It is a key feature used to analyse and interpret measured data. Once the Vital Signs Graph link icon, as shown in Figure 5.7(3b) is clicked, the system generates auto-scaled trend charts for each vital sign category using their measured values and then visualizes them as shown in Figure 5.9. Moreover, charts are also auto divided into different areas based on the previously mentioned reference ranges. In Figure 5.9, each vital sign graph is divided into different areas depending on their reference ranges. Each range has its own interpretation in each vital sign category. For example, in Figure 5.9(a), the Systolic Blood Pressure (SBP) graph shows three areas having ranges $\leq 119$ (Normal Range), $120–139$ (Pre-hypertension), and $140–159$ (Hypertension Stage-1) as defined in Table 5.3. These ranges help medical teachers to analyse and interpret any vital signs trends easily. The system computes the average of each vital sign and generates the average trend chart for each vital sign category as shown in Figure 5.10.

Fig. 5.9 Weekly trends of patient’s vital signs information
Step-4: Generate clinical case

Once the basic information, patient history, and vital signs information are recorded into iCBLS, the system generates the clinical case when the *Generate Clinical Case* link icon is selected as shown in Figure 5.7(4). The system integrates all this information as described in Step-1 and Step-3 to generate the new clinical case labelled (2) that is shown in Figure 5.11.

Step-5: Refine clinical case

After generating a new clinical case, the medical teacher interacts with the iCBLS and loads the system generated case, as shown in Figure 5.11(2), by clicking the *Load Case* link as shown in Figure 5.11(1). Once the case is loaded, the medical teacher enters *Case Title* and selects *Case Domain, Unit Title, and Difficulty Level* of the case as shown in Figure 5.11(3)-(6). Following this, the teacher utilizes his/her experiential knowledge and enriches the system generated case, as shown in Figure 5.11(7), based on the personal knowledge and graphical trends’ information shown in Figures 5.9-5.10. In Figure 5.11, labels 2 and 7 show the comparison between the system generated and teacher-enriched case. After enriching the clinical case description, the teacher clicks the *Add Case* link, as shown in Figure 5.11(8), in order to store newly created CBL case into *Case Base.*
5.3 Simulation of iCBLS

5.3.3 Case formulation

After the medical teacher creates the CBL case, the system automatically updates the list of cases available to students for their practice along with related information. In order to start the case formulation, the student loads the interface, which is shown in Figure 5.12. A timer starts at the back-end of this interface until the submission of this formulation. The timer helps the teacher to assess the future difficulty level of a case for that particular group of students.

As depicted in Figure 5.12, the interface is divided into three sections. The first section provides the description of real-world CBL case, while the second section shows the medical chart that includes students’ entered chart-components such as Previous Medication and their observations such as No medicine mention. In addition, it also display the partial view of ontological model (domain knowledge) as illustrated in Figure 5.12. Initially this section is blank. As students add chart components this section updates and expands dynamically. This section allows medical students to add chart components and then loads the ontological model that enables medical students to view the domain knowledge to record their personal observations of each component during their CBL practice. For example, when students add the word "Medicine/Medication" as a chart component, the system displays the Medicine...
parent concept and its child concepts such as *Glargine, Glimepiride, Lispro, Metformin, Regular Insulin* from ontological model as depicted in Figure 5.12. Finally, the third section shows the list of students who already formulated that particular case. After formulating a CBL case, students submit their data to get feedback from their teachers. During the submission process, the system records the total time taken by each student.

Once students have submitted their solutions the teacher reviews the medical chart and analyses student capabilities by considering their submitted solution along with the time taken to construct it. After reviewing the submitted formulation, the teacher enters their opinions and feedback for each student in each case through the feedback interface as shown in Figure 5.13. This feedback enables students to improve their learning conceptualization and increase their understanding, which contributes to their evolution of knowledge [206].
Once experiential experts induce their practical knowledge through feedback, the students are empowered to utilize this knowledge for better clinical competency [46].

![Fig. 5.13 Tutor view for providing feedback](image)

### 5.4 System Evaluation

In specialised literature, medical education programs are considered to be complex due to their diverse interactions amongst participants and environment [18]. Discussion-based learning in a small-group, like CBL, is considered to be a complex system [44]. In small-groups, multiple medical students are interacting and exchanging information with each other, where each student is also a complex system [45]. For evaluation of complex systems, the CIPP (context/input/process/product) model is most widely used in the literature [207–211]
and is considered as a powerful approach [18]. This model is used for evaluating as well as improving ongoing medical education programs; it is also consistent with system theory, and to some degree, with complexity theory [18, 211]. For holistic understanding, the proposed system is evaluated under the umbrella of the CIPP model.

The evaluation phase of any system involves studying, investigating and judging the importance of the information for making a decision about the worth of an education program [18, 212]. In the health profession education field new developments in system evaluation are evolving, which are not yet ready for mainstream approaches [213]. Developments are still based on outcome-based evaluation, which is considered not to be sufficient for evaluating the health profession [213]. Furthermore, predicting the outcome of an education program is limited if we have an incomplete view of a program [18]. For evaluation of health professionalism, the program’s context and process elements of the CIPP model are widely used factors for assessing health professionalism using surveys and informal interviews [210, 213].

For holistic understanding, the proposed system is evaluated in heterogeneous environments by involving multiple stakeholders and using multiple methods such as quantitative methods (e.g. surveys) and qualitative methods (e.g. interviews and focus groups) under the umbrella of the CIPP model. Medical students varying from 1st to 5th year from medical schools in the University of Tasmania and Melbourne metropolitan hospital, and professionals had participated in the evaluation of CBL system in year 2016. The students and professionals worked as a user and the system was used during the tutorial for one semester. The functional mapping of the evaluation approach used in iCBLS’s evaluation, with each element of CIPP model are illustrated in Table 5.4. In the first element of the CIPP model, heterogeneous environments, surveys, interviews, and focus groups are considered for context study, while for input study, literature review, other learning projects visitation, and expert consultation are performed in the second element. In the third element, the establishment of
evaluation questions, data collection as well as participant interviews are covered for analysis purposes as to whether iCBLS is delivered in the manner in which we intended. Finally, the last element is used for assessing the outcome of the proposed system through positive or negative feedback and it also assesses the degree to which the target is achieved.

Table 5.4 CIPP elements and tasks performed in iCBLS [18]

<table>
<thead>
<tr>
<th>Context</th>
<th>Input</th>
<th>Process</th>
<th>Product</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heterogeneous environments</td>
<td>Literature review</td>
<td>Establish the evaluation questions</td>
<td>Judgements of the system</td>
</tr>
<tr>
<td>Surveys</td>
<td>Visiting standard learning programs</td>
<td>Collect the data</td>
<td>Assessment of achieved targets</td>
</tr>
<tr>
<td>Interview</td>
<td>Consulting expert</td>
<td>Participant interviews</td>
<td>Interviews about system’s outcomes</td>
</tr>
<tr>
<td>Focus groups</td>
<td></td>
<td></td>
<td>Surveys</td>
</tr>
</tbody>
</table>

In this study, the product element of the CIPP model is responsible for investigating the impact of the proposed CBL system usability in terms of students’ interaction and the system effectiveness for students’ learning, which is explained in the following subsections. For both environments, survey-based as well as interview-based system evaluations are selected after performing beta testing on a given scenario with control information. In each survey, multiple evaluation questions are selected and prepared as shown in Figures C.1, C.2, and C.3 in Appendix C. The questions are considered as important factors for system evaluation, to help understand the success or shortcomings of the system [18]. A CBL case is created through iCBLS and made available to all users to assess the impact of the developed system. Moreover, in each environment, the system is first introduced and demonstrated before the survey and interview are completed. The evaluation setup for both environments is illustrated in Table 5.5.
Table 5.5 Evaluations setup for the iCBLS

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Primary hypothesis</td>
<td>Flexible and easy to learn</td>
<td>System appropriateness with respect to students’ learning</td>
</tr>
<tr>
<td>Secondary hypothesis</td>
<td>Minimum memory load and efficiency (minimum actions required)</td>
<td>System suitability with respect to students’ level and user friendly system</td>
</tr>
<tr>
<td>Variables</td>
<td>System capability, Operation learning, Screen flow, Interface consistency, Interface interaction, Minimal action, Memorization</td>
<td>Appropriate for group learning, Appropriate for solo learning, Useful for improving clinical skills, Performing tasks straightforward</td>
</tr>
<tr>
<td>Options and weights set for each question</td>
<td>Excellent (10), Good (8), Above Average (6), Average (4), Poor (2)</td>
<td>Five options from 1 to 5 representing poor to excellent and quantified in multiple of 20</td>
</tr>
<tr>
<td>Survey method</td>
<td>Google docs (Online), 1-on-1</td>
<td>Google docs (Online), 1-on-1, small groups at the hospital</td>
</tr>
<tr>
<td>Number of users</td>
<td>209 (different years students and professionals)</td>
<td></td>
</tr>
</tbody>
</table>

5.4.1 Users interaction evaluation

This subsection describes the system evaluation in terms of interaction [214]. We compiled the feedback provided by the users to draw the holistic picture of the system, which is illustrated in Table 5.6. Overall, we found that interaction of the system through the interface was generally valued by the users, whereas, load on the users’ memory was criticized as experiential knowledge of students relies on memory and recognition [215] and due to scattered knowledge, it is difficult to obtain [46]. The results, as illustrated in Table 5.6, clearly show that users were quite satisfied with the system capabilities, operating learning, screen flow, and interface interaction, which were greater than 70%. The area of consistency and load on user memory due to surplus steps needs improvement as the system’s interface was not able to satisfy the users. It was also inferred that the display of error and support message windows has further room for improvement.
### Table 5.6 Summarized response with respect to categories results

<table>
<thead>
<tr>
<th>Evaluation Criteria</th>
<th>Sub-categories</th>
<th>Categories Response</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sub-categories</td>
<td>(Average) (%)</td>
</tr>
<tr>
<td>Categories</td>
<td>System Capability</td>
<td></td>
</tr>
<tr>
<td></td>
<td>System reliability</td>
<td>7.5555 78.15</td>
</tr>
<tr>
<td></td>
<td>Designed for all levels of users</td>
<td>8.0740</td>
</tr>
<tr>
<td></td>
<td>Operation Learning</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Learning to operate the system</td>
<td>7.2963 72.04</td>
</tr>
<tr>
<td></td>
<td>Reasonable Data grouping for easy learning</td>
<td>7.1111</td>
</tr>
<tr>
<td></td>
<td>Screen Flow</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Reading characters on the screen</td>
<td>6.9629 70.56</td>
</tr>
<tr>
<td></td>
<td>Organization of information</td>
<td>7.1481</td>
</tr>
<tr>
<td></td>
<td>Interface Consistency</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Consistency across the label format and location</td>
<td>7.1111 66.85</td>
</tr>
<tr>
<td></td>
<td>Consistent symbols for graphic data standard</td>
<td>6.2592</td>
</tr>
<tr>
<td></td>
<td>Interface Interaction</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Flexible data entry design</td>
<td>8.0000 81.48</td>
</tr>
<tr>
<td></td>
<td>Zooming for display expansion</td>
<td>8.2962</td>
</tr>
<tr>
<td></td>
<td>Minimal Action</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Wizard-based information management</td>
<td>6.7407 60.19</td>
</tr>
<tr>
<td></td>
<td>Provision of default values</td>
<td>5.2962</td>
</tr>
<tr>
<td></td>
<td>Memorization</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Highlighted selected information</td>
<td>4.8148 48.15</td>
</tr>
</tbody>
</table>

We classify our users into 3 groups on the basis of their responses which are; those who evaluated the system as poor; those who evaluated it as average and above average; and those who evaluated it as good and excellent. In order to assess an evaluation criteria of the system,
the comparison of evaluation for various categories is depicted in Figure 5.14. The details of these results are given in Tables 5.7 and 5.8.

Fig. 5.14 iCBLS interaction evaluation - response comparison chart

As represented in Figure 5.14, the confidence on *system capabilities* and *interface interaction* was measured as about 70% from all users. Approximately 50% of users considered the *interface consistency*, *screen flow* and *operation learning* aspect as an appealing factor. Moreover, less than 40% of users were satisfied with the factors like *load on human memory* and with the *number of actions performed*, in order to achieve a particular task. Finally, for the evaluation of the system, on average, 42% of users responded with their level of satisfaction as medium level.

Tables 5.7 and 5.8 present the detailed results of the proposed system’s interaction, where results with bold size are depicted in Figure 5.14.
Table 5.7 Interaction evaluations results.

<table>
<thead>
<tr>
<th>Evaluation criteria</th>
<th>Poor (%)</th>
<th>Average (%)</th>
<th>Above average (%)</th>
<th>Good (%)</th>
<th>Excellent (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Categories</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>System capability</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>System reliability</td>
<td>2</td>
<td>14</td>
<td>14</td>
<td>45</td>
<td>25</td>
</tr>
<tr>
<td>Designed for all levels of users</td>
<td>2</td>
<td>7</td>
<td>15</td>
<td>35</td>
<td>41</td>
</tr>
<tr>
<td>Average</td>
<td>2</td>
<td>10.5</td>
<td>14.5</td>
<td>40</td>
<td>33</td>
</tr>
<tr>
<td>Range average</td>
<td>2</td>
<td>25</td>
<td></td>
<td>73</td>
<td></td>
</tr>
<tr>
<td>Operation learning</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Learning to operate the system</td>
<td>4</td>
<td>12</td>
<td>23</td>
<td>36</td>
<td>25</td>
</tr>
<tr>
<td>Reasonable Data grouping for easy learning</td>
<td>2</td>
<td>8</td>
<td>43</td>
<td>34</td>
<td>13</td>
</tr>
<tr>
<td>Average</td>
<td>3</td>
<td>10</td>
<td>33</td>
<td>35</td>
<td>19</td>
</tr>
<tr>
<td>Range average</td>
<td>3</td>
<td>43</td>
<td></td>
<td>54</td>
<td></td>
</tr>
<tr>
<td>Screen flow</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reading characters on the screen</td>
<td>4</td>
<td>15</td>
<td>27</td>
<td>38</td>
<td>16</td>
</tr>
<tr>
<td>Organization of information</td>
<td>4</td>
<td>8</td>
<td>32</td>
<td>32</td>
<td>24</td>
</tr>
<tr>
<td>Average</td>
<td>4</td>
<td>11.5</td>
<td>29.5</td>
<td>35</td>
<td>20</td>
</tr>
<tr>
<td>Range average</td>
<td>4</td>
<td>41</td>
<td></td>
<td>55</td>
<td></td>
</tr>
<tr>
<td>Interface consistency</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Consistency across the label format and location</td>
<td>4</td>
<td>15</td>
<td>23</td>
<td>38</td>
<td>20</td>
</tr>
<tr>
<td>Consistent symbols for graphic data standard</td>
<td>12</td>
<td>19</td>
<td>27</td>
<td>33</td>
<td>9</td>
</tr>
<tr>
<td>Average</td>
<td>8</td>
<td>17</td>
<td>25</td>
<td>35.5</td>
<td>14.5</td>
</tr>
<tr>
<td>Range average</td>
<td>8</td>
<td>42</td>
<td></td>
<td>50</td>
<td></td>
</tr>
<tr>
<td>Interface interaction</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flexible data entry design</td>
<td>5</td>
<td>6</td>
<td>23</td>
<td>37</td>
<td>29</td>
</tr>
<tr>
<td>Zooming for display expansion</td>
<td>1</td>
<td>3</td>
<td>20</td>
<td>25</td>
<td>51</td>
</tr>
<tr>
<td>Average</td>
<td>3</td>
<td>4.5</td>
<td>21.5</td>
<td>31</td>
<td>40</td>
</tr>
<tr>
<td>Range average</td>
<td>3</td>
<td>26</td>
<td></td>
<td>71</td>
<td></td>
</tr>
</tbody>
</table>
Table 5.8 Interaction evaluations results (cont.).

<table>
<thead>
<tr>
<th>Evaluation criteria</th>
<th>Poor (%)</th>
<th>Average (%)</th>
<th>Above average (%)</th>
<th>Good (%)</th>
<th>Excellent (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Categories</td>
<td>Sub-categories</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minimal action</td>
<td>Wizard-based information management</td>
<td>0</td>
<td>14</td>
<td>35</td>
<td>45</td>
</tr>
<tr>
<td></td>
<td>Provision of default values</td>
<td>16</td>
<td>32</td>
<td>29</td>
<td>23</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>8</td>
<td>23</td>
<td>32</td>
<td>34</td>
</tr>
<tr>
<td></td>
<td>Range average</td>
<td>8</td>
<td>55</td>
<td>32</td>
<td>34</td>
</tr>
<tr>
<td>Memorization</td>
<td>Highlighted selected information</td>
<td>20</td>
<td>41</td>
<td>24</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>20</td>
<td>41</td>
<td>24</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>Range average</td>
<td>20</td>
<td>65</td>
<td>24</td>
<td>12</td>
</tr>
</tbody>
</table>

5.4.2 Learning effectiveness evaluation

This evaluation captures educational viewpoints and highlights the aspects that are technically inclined. We compiled the feedback from users as shown in Figure 5.15 and found that system appropriateness with respect to group learning was mostly appreciated by the users.

Fig. 5.15 System effectiveness summary chart
Figure 5.15 clearly represents that users were quite satisfied with the *system appropriateness* for group as well as solo learning, *system usefulness* with respect to enhancing clinical skills, and *user friendliness* of the system, which were greater than 70%. We also evaluated our system to check *suitability* and *appropriateness* for different course-year levels of medical students. The system achieved votes for year-levels 2 or 3 that showed confidence on system suitability for these students, which is the stage where students begin to do placements at hospitals.

We also conducted an open-ended survey evaluation in order to analyse whether the proposed online interactive CBL system contributed to effective medical knowledge and skill learning. All 155 first-year medical students in the *University of Tasmania* used the system for one semester and were asked to provide information on their learning experiences and perceptions through an open-ended survey with 3 different questions. Open-ended questions normally aim to collect more detailed information and actionable insights since they allow the freedom and space to answer in as much detail as the respondents would like to give. The aim of the conducted survey was to encourage students to share their medical skill learning experience by using the proposed CBL system. The table 5.9 shows the open-ended survey questions for learning efficiency evaluation.

<table>
<thead>
<tr>
<th>Q. #</th>
<th>Open-ended Survey Questions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>What did you like most about the computer-based tutorial preparation module?</td>
</tr>
<tr>
<td>2</td>
<td>What did you like least about the computer-based tutorial preparation module?</td>
</tr>
<tr>
<td>3</td>
<td>Are there any areas where you think the Case-Based Learning tutorial program can improve?</td>
</tr>
</tbody>
</table>

Responses to our survey evaluation with 155 students can be summarized as follows:

(Q1) Key phrases from answers to the first question were ‘self-learning’, ‘independent thinking’, ‘gaining more professional knowledge’ and ‘distance learning’. The majority
of students felt that CBL encouraged them to be active learners, and to use logic to think and learn with real-world cases. The system also allowed students to access the learning materials (real-world problems observation, problem-solving skill learning, and teachers’ feedback) in rural settings, and students felt this sort of online system could help support this lack of resources.

(Q2) The key phrase from answers to the second question was ‘senior level education’. Further to that, some students felt this system is not suitable for very junior students (i.e. first-years) as they have not had the exposure to clinical environments to understand what sort of content they were given in such a system format without some guidance. However, other students thought that it was great opportunity to review their learned knowledge and skills as first-year students.

(Q3) Key phrases from answers to the third question were ‘time consuming work’, ‘tutor engagement’, ‘improvement of feedback interface’. Some students mentioned that it would be better to have more tutor support or feedback on their answers through the system interface in real time.

The evaluation of any medical education program can be affected by participants’ characteristics, the domain knowledge, and the environment in which the system operates [216]. As it is an initial concept, we do believe that with increased usage of the system this efficiency may increase for complicated scenarios and it will help students to understand the real world’s patient-medical scenario in an efficient and accurate manner [193].

5.5 IoT-based Flip Learning Platform (IoTFLiP)

To exploit the IoT infrastructure for supporting flipped case-based learning in the cloud environment with state-of-the-art security and privacy measures for potentially personalized
medical data, this section describes the IoTFLiP architecture and working scenario for the case-base flip learning using IoTivity.

5.5.1 Proposed platform architecture

This section describes the architecture of the proposed IoT-based platform, called IoTFLiP, as shown in Fig. 5.16, and the functionalities of its layers. The IoTFLiP integrates the features of existing individual platforms and can be used for medical as well as other domains.

Figure 5.16 is composed of eight layers, which are abstractly divided into 2 blocks on the basis of communication and resources, called local and cloud processing blocks. The first four layers, namely Data Perception, Data Aggregation and Preprocessing, Local Security, and Access Technologies Layers deal with communication and resources locally, while the remaining four layers, namely Cloud Security, Presentation, Application and Service, and Business Layers deal at the cloud level. These layers cover important features including data interoperability for handling data heterogeneity, smart gateway communication for reducing network traffic burden, fog computation for resource management to avoid delayed information sharing, multiple levels of storage and communication securities, error handling while transcoding, application delivery policies, and business policies. Moreover, these layers provide state-of-the-art security as well as privacy measures for potentially personalized data, and give support for application delivery in private, public, and hybrid approaches. Further details for each layer are given below.

Data perception layer

In this layer, the identification of devices is performed, where devices are used to monitor, track, and store patients’ vital signs, statistics or medical information. The devices include
Fig. 5.16 IoT-based flip learning platform (IoTFLiP) architecture

Google Gear\(^1\), Google Glass\(^2\), patient monitoring sensors, smart meters, wearable health monitoring sensors, video cameras, and smart phones.

\(^1\)https://store.google.com/product/samsung_gear_live
\(^2\)https://en.wikipedia.org/wiki/Google_Glass
Data aggregation and preprocessing layer

This layer is divided into Data Aggregation and Data Preprocessing modules. The Data Aggregation module deals with heterogeneous data interoperability, load balancing, and smart data communication issues i.e. communicating only when required, by either storing the data locally, temporarily, or discarding it when not required. This data aggregation & preprocessing requires resources, which are not available in relatively less rich sensor nodes and other perception layer devices. Therefore, fog is incorporated here. Fog computing is a small cloud that acts as an extended cloud to the edge of the network [141]. In order to perform the rich tasks and filtering of communication, which sensors and light IoTs are not capable of doing, smart gateways are used [142]. Similarly, the Data Preprocessing module filters the irrelevant data for faster communication and then transcodes it by encoding, decoding, and translation.

Local security layer

Security is the degree of protection from unauthorized users and attacks. Security of patient information is the most ethical issue. Patient always remains cautious about sharing personal medical information with others. In order to secure the temporary storage and for fog to cloud communication, a Local Security Layer is introduced. This layer addresses where security is required and which security technique is needed. Also, security policies are defined in this layer, in which decision of operations e.g. whether to be encrypted or not, are made. In order to assess where security is required, if the communication is local, temporary storages are used which require local security. Similarly, based on application requirement, it has been decided whether fast communication will be feasible or slow. For example, for the case of patient monitoring urgency, security may not be affordable. In that case, we need fast communication. For answering which security technique for storage or protocol for communication are chosen, it has been decided based on the application requirement.
For storage security, *Message-Digest* algorithm (MD5), *Rivest-Shamir-Adleman* algorithm (RSA), *Digital-Signature-Algorithm* (DSA), and so on, while for communication security, *Wireless Application Protocol* (WAP), *Wi-Fi Protected Access* (WPA), and *Transport Layer Security* (TLS) can be used.

**Access technologies layer**

Various access networks exist for communication with cloud resources like WiFi, WiBro, GPRS, LTE, etc. This layer selects the access technology based on the requirement and availability of services.

**Cloud security layer**

Once data moves from local processing blocks to cloud processing blocks, security of data storage is an important aspect in order to secure it from various types of cloud-users. *Secured User* profiling can also be an important fact. This layer deals with storage security and user profiling. Security techniques are chosen based on user profiling.

**Presentation layer**

The main purpose of this layer is to deal with encoding, decoding, and error handling during data transformation. This layer converts data into a proper, understandable format e.g. ECG graph, pulse rate, angiography, prescription text, picture, video etc.

**Application and service layer**

In this layer, *Application Delivery Policies* are defined in terms of private, public or hybrid access. Based on the service scope, delivery policies are chosen. Also, services are categorized based on the requirements from ordinary user access to admin user access. For example, one service is categorized into two parts. One part is accessible to everyone, while other part is
restricted. The same categorization can be applicable for medical center administration and medical institutes.

**Business layer**

This layer deals with the business policies and services packages in terms of free or subscribed rates. The packages offerings are according to the usage.

### 5.5.2 Working scenario

In this section, the working scenario for case-base flip learning using IoTivity is described through steps as shown in Fig. 5.17. This scenario covers CBL case creation, case formulation, case evaluation, case feedback, and storing medical knowledge. In Fig. 5.17, the steps 1 to 5 belong to *Data Perception, Data Aggregation and Preprocessing, Local Security, and Access Technologies layers* of the IoTFLiP, while steps 6 to 10 belong to *Cloud Security, Presentation, Application and Service, and Business layers* of the IoTFLiP.

![Fig. 5.17 Working scenario for case-based flip learning](image)

In this study, for generating a realistic CBL case scenario, a patients’ dataset was prepared with the help of a medical expert and a knowledge engineer, as illustrated in Table 5.10. This
Table 5.10 Patients’ vital signs data

<table>
<thead>
<tr>
<th>ID</th>
<th>Age</th>
<th>Gender</th>
<th>Systolic BP&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Diastolic BP</th>
<th>GL&lt;sup&gt;b&lt;/sup&gt; at Fasting</th>
<th>GL at Random</th>
<th>Heart Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>65</td>
<td>M</td>
<td>135</td>
<td>89</td>
<td>145</td>
<td>247</td>
<td>90</td>
</tr>
<tr>
<td>2</td>
<td>57</td>
<td>F</td>
<td>130</td>
<td>87</td>
<td>110</td>
<td>160</td>
<td>95</td>
</tr>
<tr>
<td>3</td>
<td>54</td>
<td>M</td>
<td>139</td>
<td>92</td>
<td>90</td>
<td>130</td>
<td>89</td>
</tr>
<tr>
<td>4</td>
<td>16</td>
<td>M</td>
<td>136</td>
<td>85</td>
<td>85</td>
<td>120</td>
<td>79</td>
</tr>
<tr>
<td>5</td>
<td>9</td>
<td>M</td>
<td>123</td>
<td>75</td>
<td>80</td>
<td>125</td>
<td>130</td>
</tr>
<tr>
<td>6</td>
<td>35</td>
<td>F</td>
<td>125</td>
<td>84</td>
<td>90</td>
<td>125</td>
<td>80</td>
</tr>
<tr>
<td>7</td>
<td>3</td>
<td>F</td>
<td>110</td>
<td>78</td>
<td>70</td>
<td>125</td>
<td>130</td>
</tr>
<tr>
<td>8</td>
<td>35</td>
<td>M</td>
<td>110</td>
<td>78</td>
<td>85</td>
<td>115</td>
<td>63</td>
</tr>
<tr>
<td>9</td>
<td>45</td>
<td>M</td>
<td>123</td>
<td>85</td>
<td>80</td>
<td>130</td>
<td>85</td>
</tr>
<tr>
<td>10</td>
<td>43</td>
<td>M</td>
<td>127</td>
<td>85</td>
<td>130</td>
<td>180</td>
<td>84</td>
</tr>
</tbody>
</table>

<sup>a</sup> Blood Pressure, <sup>b</sup> Glucose Level

dataset can be easily generated by available IoT gadgets, which are mentioned in Step-3. For the patients’ dataset, over the period of one week, three times a day, data is prepared by considering the valid ranges and important facts from available online resources<sup>3,4,5</sup>. The expert built 10 CBL case scenarios based on the prepared patient data shown in Table 5.10, in which the one shown with bold text is considered as an example in this study. These scenarios were of primary level difficulty and related to the general medicine domain.

The process of creating a real-life situation case for medical students is described through steps, as shown in Figure 5.17, that are explained as follows.

**Step-1:**

The expert interviews with patient to get the basic information such as patient name, gender, age, etc. Patients’ names are not revealed in the Table 5.10 but we collected

---

<sup>3</sup>Categories for Blood Pressure Levels in Adults, http://www.nhlbi.nih.gov/health/health-topics/topics/hbp


that in order to distinguish the patients. The exact age and gender will be used in clustering them into a specific age and gender group.

**Step-2:**

During the interview, experts note down the patient’s history information, including review of symptoms, medication history, and family history.

**Step-3:**

After advice from the expert, the patient uses the wearable devices to record his vital signs of *blood pressure*, *glucose level*, and *heart rate*. These vitals are helpful for treatment and for disease diagnosis [144, 195]. To measure these vitals, multiple IoT gadgets are available, which are illustrated in Table 5.1.

**Step-4:**

Once vital signs are collected, the medical expert analyzes the patient’s data by viewing through the graphical interfaces that are shown in Figure 5.10.

**Step-5:**

With analysis and processing of this data, the medical expert interprets the vital signs information, which are one-week average values such as *Systolic Blood Pressure* = 135.24 mmHg and other vitals shown in Figure 5.10.

**Step-6:**

The expert integrates patient history and vital signs to generate a new real-world CBL case as represented in Table 5.3.

**Step-7:**

Medical students solve the new real-world created case by interpreting the patient’s problems. They create a significant medical story within the context of his or her life and then submit their interpretations.
Step-8:

The expert evaluates student interpretations and provides feedback to each student.

Step-9:

The iCBLS stores student interpretations along with tutor opinions; these will be helpful for computerized feedback in the future [217, 218].

Step-10:

Students receive the expert’s feedback to improve their concepts and learning for their evolving knowledge.

5.6 Discussion about Significance, Challenges and Limitations of the Work

This study addresses an issue of great interest to many readers who have an interest in teaching and learning in medicine with regard to how to foster medical trainees’ collaborative learning skills as a lifelong learning endeavour, using advanced technology. The main aim of every medical student is to interact with patients and to experience a variety of cases during their clinical practice period. The proposed system, iCBLS, provides the facilities for creating a real-life situation clinical case, practicing that case before and outside the class, and finally getting feedback from experts to evolve their knowledge. This system supports distance learning and provides maximum time management flexibility to each student. In addition, this system has the capability to generate useful information as well as knowledge which is then stored in a continuous manner that can be helpful in future for computerized feedback, intensive learning, better clinical competence, and transferring expertise among experts and students. Based on the aforementioned system’s characteristics, we do believe that the iCBLS will be effective in professional learning.
During the real-time implementation of our proposed system, we encountered several challenges. Some of the key challenges we attempted to resolve were the hierarchical management of data, abstraction of logic, avoidance of code redundancy, and analysis of the vital signs data. To manage the addition, modification, deletion, paging and nested hierarchy of data, we have used data grids. Similarly, for abstraction or obscuration of logic and to avoid code redundancy, we have used the stored procedures. Moreover, for analyses of vital signs data, we have generated individual as well as average graphs based on reference ranges.

Limitations of the proposed approach include lack of real-time integration systems due to the .NET framework; no user interface was created for the administrator to manage course allotments and enrolments; no connection with IoT devices to collect vital signs data was developed, nor did the system perform data validation for invalid values. Finally, the real-world clinical case creation process currently does not include image support.

5.7 Conclusions

This study describes how to foster medical trainees’ collaborative learning skills as a lifelong learning endeavor using advanced technology with the support of online learning and real-world clinical cases. Practicing real-world clinical cases before and outside the class can promote learning capabilities, save class time for effective discussion, and enhance the academic experience of medical students. For this purpose, we have developed a CBL system, iCBLS, which fills the gaps between human-based and computer-based learning and utilizes the strength of both human (experiential knowledge) and computer (domain knowledge). The iCBLS creates real-world clinical cases using a semi-automatic approach with the support of their experiential knowledge, gets the domain knowledge to formulate the summaries of CBL cases and provides feedback for formulated cases. The iCBLS is developed based on the current CBL practices in Australia. iCBLS formulates the summaries of CBL cases through synergies of students as well as medical expert knowledge. This
system manages multiple types of users according to their roles and privileges. In addition, this system also supports a number of features such as displaying the entire collection of data at one place, a paging facility, and support for in-line reviewing to edit and delete the displayed data. The working principle of the iCBLS is explained with the help of a *Glycemia* case study. Two types of evaluations under the umbrella of the CIPP model have been performed in heterogeneous environments. The iCBLS achieves a success rate of more than 70% for students’ interaction, group learning, solo learning, and improving clinical skills. This success rate indicates that iCBLS effectively supports the learning of medical students. In addition to that, the system is most likely recommended for the year level 2-3 medical students.

Due to low cost and with reduced sensing devices size, support of IoTs for providing real and evolutionary medical cases, as well as support of recent flip learning concepts can enhance medical students’ academic and practical experience. To exploit the IoT infrastructure to support flipped case-based learning in the cloud environment, an *IoT-based Flip Learning Platform*, called IoTFLiP is also presented in this study, with state-of-the-art security and privacy measures for potentially personalized medical data. It also provides the support for application delivery in private, public, and hybrid approaches. The proposed platform integrates the features of existing individual platforms and can be used for medical as well as other domains.
Chapter 6

Conclusion and Future Direction

This chapter concludes the thesis and provides future directions in this research area. It also describes the potential applications of the proposed methodology.

6.1 Conclusion

The case-based learning (CBL) approach has been receiving attention in medical education, as it is a student-centered teaching methodology that exposes students to real-world scenarios that need to be solved using their reasoning skills and existing theoretical knowledge. Being human, students feel that traditional CBL activities require a significant amount of time and they get tired. In recent trends, more attention is given to e-learning environments for clinical practice of medical students as compared to lectures for their learning. In order to support the learning outcomes of students a plethora of web-based learning systems have been developed; however, most of them either do not support computer-based interactive case authoring as well as its formulation, without the support of acquiring real-world CBL cases, or do not provide feedback to students. Currently, very little attention is given to fill the gaps between human-based and computer-based learning. Medical literature contains a lot of useful knowledge in textual form, which can be beneficial for computer-based CBL
practice. For an automated CBL, a structured knowledge construction is a challenging task. The key challenge in this regard is to select appropriate features from a larger set of features. The feature selection task requires two basic steps, ranking and filtering. Here the former step requires ranking of all features, while the latter involves filtering out irrelevant features based on some threshold value. In this regard, several feature selection methods with well-documented capabilities and limitations have already been proposed. Similarly, a feature ranking task is also important as it requires optimal cut-off value to select important features from a list of candidate features. However, the availability of a comprehensive feature ranking and filtering approach, which alleviates the existing limitations and provides an efficient mechanism for achieving optimal results, is a major problem.

Keeping in view all above-mentioned facts and to take care of the students’ learning systems, this research investigated case-based learning and proposed an interactive medical learning framework to utilize the strength of both human (experiential knowledge) and computer (domain knowledge) for preparing medical students for clinical practice. For effective and enriched learning purposes, this research includes a method to construct the domain model that will provide domain knowledge to medical students for intensive learning in the future. Finally, to construct a reliable domain model, this research investigated a feature selection methodology and proposed an efficient and comprehensive ensemble-based feature selection methodology to select informative features from a larger set of features. The key contributions of this research are as follows:

1. Introduced an efficient and comprehensive Univariate Ensemble-based Feature Selection (uEFS) methodology to select informative features from a larger set of features. For the uEFS methodology:
   (a) Proposed an innovative Unified Features Scoring (UFS) algorithm to generate a final ranked list of features after a comprehensive evaluation of a feature set. The UFS algorithm ranks the features without using any learning algorithm,
high computational cost, and any individual statistical biases of state-of-the-art feature ranking methods. The current version of the UFS code and its documentation are freely available and can be downloaded from the GitHub open source platform [160, 161].

(b) Proposed an innovative Threshold Value Selection (TVS) algorithm to define a cut-off point for removing irrelevant features and selecting a subset of features, which are deemed important for domain knowledge construction.

(c) Performed extensive experimentation to evaluate the uEFS methodology using standard benchmark datasets; the results show that the uEFS methodology provides competitive accuracy and achieved (1) on average around a 7% increase in f-measure, and (2) on average around a 5% increase in predictive accuracy as compared to state-of-the-art methods.

2. Introduced an interactive and effective Case-Based Learning (CBL) approach to utilize the strength of both experiential knowledge and domain knowledge. The proposed approach enables the medical teacher to create real-world CBL cases for their students with the support of their experiential knowledge and computer-generated trends, review the student solutions, and give feedback and opinions to their students. This approach facilitates medical students to do CBL rehearsal with a machine-generated domain knowledge support before attending actual CBL classes. For an automated CBL:

(a) Introduced semi-automatic real-world clinical case creation, and case formulation techniques.

(b) Designed and developed an interactive Case-Based Learning System (iCBLS) to automate the proposed approach.

(c) Performed two studies to evaluate the proposed CBL approach under the umbrella of the Context/Input/Process/Product (CIPP) model and achieved a success rate
of more than 70% for student interaction, group learning, solo learning, and improving clinical skills.

(d) Introduced an IoT-based Flip Learning Platform (IoTFLiP) to exploit the IoT infrastructure for supporting flipped case-based learning in a cloud environment with state-of-the-art security and privacy measures.

6.2 Future Direction

This research investigated feature selection methodologies to construct reliable domain knowledge for case-based learning and proposed an ensemble-based feature selection methodology for an automated CBL approach. Possible future directions include:

1. Currently, the proposed methodology incorporates state-of-the-art univariate filter measures to consider the relevance aspect of feature ranking and ignores the features’ redundancy aspect that is also an important factor for selecting informative features from a larger set of features. In the future, we will extend the methodology for incorporating multi-variate measures to consider the redundancy aspect of features subset selection.

2. Similarly, the proposed methodology does not evaluate the suitability of a measure, or it’s precision. In order to consider that factor, we will also investigate the application of fuzzy-logic for determining the cut-off threshold value in the future.

3. Furthermore, the proposed methodology takes 0.37 sec more time than state-of-the-art filter measures on a Intel (R) Core (TM) i5-2500 CPU @ 3.30GHz 3.30 GHz machine. The proposed algorithm is written in JAVA language, which has multiple packages dependencies and increases the computation time due to the cold start problem (NP-hard). In the future, we can reduce the cold start problem by optimizing the code and
its dependencies. To measure the scalability of the proposed algorithm, our plan is to perform this methodology in a parallel execution environment.

4. Finally, the proposed CBL approach does not support an interactive question-answering technique. In the future, we will extend the current CBL approach towards a QA-based (Question-Answer) learning environment.

6.3 Potential Applications

In this section, we briefly describe the overall advantages of the proposed methodology and two real-world potential applications where the advantage of features ranking is highlighted.

Based on empirical as well as experiment analysis of the proposed methodology, the advantages of our proposed uEFS methodology for feature selection include that it:

- Provides competitive accuracy and achieved (1) on average around a 7% increase in f-measure, and (2) on average around a 5% increase in predictive accuracy as compared to state-of-the-art methods.
- Performs simple and fast computation
- Is not dependent on the classification algorithm
- Generally have less computational costs than wrapper and hybrid methods
- Is better suited to high dimensional datasets
- Computes rank of the features without any individual statistical biases of state-of-the-art feature ranking methods.

The proposed uEFS methodology contributes to feature selection, which is the key step in many decision support systems. The following are two real-world applications, where the proposed methodology is utilized.
1. One of the applications of features ranking is the data understanding phase of the data mining process, where data is closely inspected, which is crucial for the next phase, data preparation. For realization, the current version of the proposed UFS algorithm has been plugged into a recently developed tool, called data-driven knowledge acquisition tool (DDKAT) \[159\] to assist the domain expert in selecting informative features for the data preparation phase of cross-industry standard process for data mining (CRISP-DM). The DDKAT supports an end-to-end knowledge engineering process for generating production rules from a dataset.

2. A huge amount of valuable textual data is available on the web, which has led to a corresponding interest in technology for automatically extracting relative information from open data, which can then be converted into domain knowledge. In order to construct reliable domain knowledge, appropriate feature selection is another application of the proposed methodology. The feature selection (FS) task can also be performed manually by a human expert; however, this is considered as an expensive and time-consuming task; thus an automatic FS is necessary. The proposed methodology selects the important features for domain knowledge construction.
Bibliography


Appendix A

List of Acronyms

Acronyms

In alphabetical order:

ACE  Attempto Controlled English
CBL  Case-Based Learning
CIPP  Context/Input/Process/Product
CNL  Controlled Natural Language
CRISP-DM  Cross Industry Standard Process for Data Mining
CS  Chi-Square
DDKAT  Data-Driven Knowledge Acquisition Tool
DM  Data Mining
DS  Data Science
EFS  Ensemble Feature Selection
**FS** Feature Selection

**GR** Gain Ratio

**iCBLS** Interactive Case-Based Learning System

**IG** Information Gain

**IoT** Internet of Things

**IoTFLiP** IoT-based Flip Learning Platform

**kNN** k-Nearest Neighbors

**PBL** Problem-Based Learning

**POS** Part of Speech

**S** Significance

**SVM** Support Vector Machine

**SU** Symmetric Uncertainty

**TF-IDF** Term Frequency - Inverse Domain Frequency

**TM** Text Mining

**uEFS** Univariate Ensemble-based Feature Selection

**TVS** Threshold Value Selection

**UFS** Unified Features Scoring

**WEKA** Waikato Environment for Knowledge Analysis
Appendix B

UFS Algorithm - Source Code

/**
 * Copyright [2017] [Maqbool Ali]
 *
 * Licensed under the Apache License, Version 2.0 (the "License");
 * you may not use this file except in compliance with the License.
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 * http://www.apache.org/licenses/LICENSE-2.0
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 * distributed under the License is distributed on an "AS IS" BASIS,
 * WITHOUT WARRANTIES OR CONDITIONS OF ANY KIND, either express or implied.
 * See the License for the specific language governing permissions and
 * limitations under the License.
 */

import java.io.File;
import java.util.ArrayList;
import org.apache.commons.io.FileUtils;
import org.apache.wink.json4j.JSONArray;
import org.apache.wink.json4j.OrderedJSONObject;
import weka.attributeSelection.ChiSquaredAttributeEval;
import weka.attributeSelection.GainRatioAttributeEval;
import weka.attributeSelection.InfoGainAttributeEval;
import weka.attributeSelection.Ranker;
import weka.attributeSelection.SignificanceAttributeEval;
import weka.attributeSelection.SymmetricalUncertAttributeEval;
import weka.core.Instances;
import weka.core.converters.CSVLoader;

// TODO: Auto-generated Javadoc
/**
 * This class computes the features’ scores.
 */
public class FeatureEvaluator {

    /** The features titles list */
    private ArrayList<String> featureTitles;

    /** The features scores list */
    private ArrayList<Double> featureScores;

    /** The features weights list */
    private ArrayList<Double> featureWeights;

    /** The features priorities list */
    private ArrayList<Double> featurePriorities;


/** base directory to store resource data files */
private static final String BASE_DIR = System.getProperty("user.home") +
"/resources/";

/**
 * Constructor to instantiate a new FeatureEvaluator object.
 *
 * @param json the data string
 * @param data the data set
 * @throws Exception the exception
 */

public FeatureEvaluator(String json, Instances data) throws Exception {

    this.featureTitles = new ArrayList<String>;
    this.featureScores = new ArrayList<Double>;
    this.featureWeights = new ArrayList<Double>;
    this.featurePriorities = new ArrayList<Double>;

    OrderedJSONObject jsonObject = new OrderedJSONObject(json.toString());
    JSONArray jsontokenArray = jsonObject.getJSONArray("unprocessed_data");
    String csvString = "";
    String str;
    for (int i=0;i<jsontokenArray.length();i++){
        str = jsontokenArray.get(i).toString();
        str = str.substring(1, str.length()-1);
        csvString += str +"\n";
String filePath = BASE_DIR + "InputDataSet.csv";
File file = new File(filePath);

// if file does not exists, then create it
if (!file.exists())
    file.createNewFile();

FileUtils.writeStringToFile(file, csvString);

CSVLoader loader = new CSVLoader();
loader.setSource(new File(filePath));
data = loader.getDataSet();

if (data.classIndex() == -1)
    data.setClassIndex(data.numAttributes() - 1);

int numUnlabeledAttributes = data.numAttributes() - 1;
double[] minmaxValues = new double[2];
double min, max;

String[] options = new String[1];
options[0] = "-T -1.7976931348623157E308 -N -1";
Ranker atrank = new Ranker();
atrank.setOptions(options);

weka.attributeSelection.AttributeSelection atsel = new weka.attributeSelection.AttributeSelection();
// Information Gain Attribute Evaluator
InfoGainAttributeEval infoGainAttrEval = new InfoGainAttributeEval()
atsel.setEvaluator(infoGainAttrEval);
atsel.setSearch(atrank);
atsel.SelectAttributes(data);
double[] infoGainRanks = new double[numUnlabeledAttributes];
for (int i = 0; i < numUnlabeledAttributes; i++) {
  infoGainRanks[i] = Math.round(10000 * infoGainAttrEval.evaluateAttribute(i)) / 10000d;
}
minmaxValues = computerMinMaxValues(infoGainRanks);
min = minmaxValues[0];
max = minmaxValues[1];
double[] scaledInfoGainRanks = new double[numUnlabeledAttributes];
for (int i = 0; i < numUnlabeledAttributes; i++) {
  scaledInfoGainRanks[i] = Math.round(10000 * (((infoGainRanks[i]−min)/(max−min))) / 10000d;
}

// Gain Ratio Attribute Evaluator
GainRatioAttributeEval gainRatioAttrEval = new GainRatioAttributeEval();
atsel.setEvaluator(gainRatioAttrEval);
atsel.setSearch(atrank);
atsel.SelectAttributes(data);
double[] gainRatioRanks = new double[numUnlabeledAttributes];
for (int i = 0; i < numUnlabeledAttributes; i++) {

gainRatioRanks[i] = Math.round(10000 * gainRatioAttrEval.evaluateAttribute(i)) / 10000d;
}
minmaxValues = computerMinMaxValues(gainRatioRanks);
min = minmaxValues[0];
max = minmaxValues[1];
double[] scaledGainRatioRanks = new double[numUnlabeledAttributes];
for (int i = 0; i < numUnlabeledAttributes; i++) {
scaledGainRatioRanks[i] = Math.round(10000 * ((gainRatioRanks[i] - min) / (max - min))) / 10000d;
}

// Chi Squared Attribute Evaluator
ChiSquaredAttributeEval chiSquaredAttrEval = new ChiSquaredAttributeEval();
atsel.setEvaluator(chiSquaredAttrEval);
atsel.setSearch(atrank);
atsel.SelectAttributes(data);
double[] chiSquaredRanks = new double[numUnlabeledAttributes];
for (int i = 0; i < numUnlabeledAttributes; i++) {
    chiSquaredRanks[i] = Math.round(10000 * chiSquaredAttrEval.evaluateAttribute(i)) / 10000d;
}
minmaxValues = computerMinMaxValues(chiSquaredRanks);
min = minmaxValues[0];
max = minmaxValues[1];
double[] scaledChiSquaredRanks = new double[numUnlabeledAttributes];
for (int i = 0; i < numUnlabeledAttributes; i++) {
scaledChiSquaredRanks[i] = Math.round(10000 *
((chiSquaredRanks[i]−min)/(max−min))) / 10000d;
}

// Symmetrical Uncert Attribute Evaluator
SymmetricalUncertAttributeEval symmetricalUncertAttrEval = new
SymmetricalUncertAttributeEval();
at.sel .setEvaluator(symmetricalUncertAttrEval);
at.sel .setSearch(at.rank);
at.sel .SelectAttributes(data);
double[] symmetricalUncertRanks = new double[numUnlabeledAttributes];
for (int i = 0; i < numUnlabeledAttributes; i++) {
symmetricalUncertRanks[i] = Math.round(10000 *
    symmetricalUncertAttrEval.evaluateAttribute(i)) / 10000d;
}
minmaxValues = computerMinMaxValues(symmetricalUncertRanks);
min = minmaxValues[0];
max = minmaxValues[1];
double[] scaledSymmetricalUncertRanks = new double[numUnlabeledAttributes];
for (int i = 0; i < numUnlabeledAttributes; i++) {
scaledSymmetricalUncertRanks[i] = Math.round(10000 *
    ((symmetricalUncertRanks[i]−min)/(max−min))) / 10000d;
}

// Significance Attribute Evaluator
SignificanceAttributeEval significanceAttrEval = new
SignificanceAttributeEval();
at.sel .setEvaluator(significanceAttrEval);
atset . setSearch( atrank );
atset . SelectAttributes( data );

double[] significanceRanks = new double[numUnlabeledAttributes];
for ( int i = 0; i < numUnlabeledAttributes; i++) {
    significanceRanks[i] = Math.round(10000 *
    significanceAttrEval . evaluateAttribute (i)) / 10000d;
}
minmaxValues = computerMinMaxValues(significanceRanks);
min = minmaxValues[0];
max = minmaxValues[1];
double[] scaledSignificanceRanks = new double[numUnlabeledAttributes];
for ( int i = 0; i < numUnlabeledAttributes; i++) {
    scaledSignificanceRanks[i] = Math.round(10000 *
    (( significanceRanks[i]−min)/(max−min))) / 10000d;
}

double attributeSum;

double[] combinedRanks = new double[numUnlabeledAttributes];
double combinedranksSum = 0;

for ( int i = 0; i < numUnlabeledAttributes; i++) {
    attributeSum = scaledInfoGainRanks[i] + scaledGainRatioRanks[i] +
    scaledChiSquaredRanks[i] + scaledSymmetricalUncertRanks[i] +
    scaledSignificanceRanks[i];
    combinedRanks[i] = Math.round(10000 * attributeSum ) / 10000d;
    combinedranksSum = combinedranksSum + combinedRanks[i];
}
double[][] tempArray = new double[numUnlabeledAttributes][2];
String[] attributesTitles = new String[numUnlabeledAttributes];
double[] attributesScores = new double[numUnlabeledAttributes];
double[] attributesWeights = new double[numUnlabeledAttributes];
double[] attributesPriorities = new double[numUnlabeledAttributes];

for (int j = 0; j < numUnlabeledAttributes; j++) {
    tempArray[j][0] = j;
    tempArray[j][1] = combinedRanks[j];
}

double temp;
for (int i=0; i < numUnlabeledAttributes; i++){
    for (int j=1; j < (numUnlabeledAttributes−i); j++){
        if (combinedRanks[j−1] < combinedRanks[j]){
            // swap the elements!
            temp = combinedRanks[j−1];
            combinedRanks[j−1] = combinedRanks[j];
            combinedRanks[j] = temp;
        }
    }
}

for (int j = 0; j < numUnlabeledAttributes; j++) {
    for (int k = 0; k < numUnlabeledAttributes; k++) {
        if (combinedRanks[j] == tempArray[k][1]){
            attributesTitles[j] = data.attribute((int)tempArray[k][0]).toString();
        }
    }
}
String res[] = attributesTitles[j].split("\s+"�);
        attributesTitles[j] = res[1];

        this.featureTitles.add(attributesTitles[j]);
        break;
    }
}

attributesScores[j] = Math.round(10000 * (combinedRanks[j]/9)) / 100d;
attributesWeights[j] = Math.round(10000 * (combinedRanks[j]/combinedranksSum)) / 100d;
this.featureScores.add(attributesScores[j]);
this.featureWeights.add(attributesWeights[j]);
this.featurePriorities.add(attributesPriorities[j]);
}

public ArrayList<String> getFeatureTitles() {
    return featureTitles;
}

public void setFeatureTitles(ArrayList<String> featureTitles) {
    this.featureTitles = featureTitles;
}

public ArrayList<Double> getFeatureScores() {
public void setFeatureScores (ArrayList<Double> featureScores) {
    this.featureScores = featureScores;
}

public ArrayList<Double> getFeatureWeights() {
    return featureWeights;
}

public void setFeatureWeights (ArrayList<Double> featureWeights) {
    this.featureWeights = featureWeights;
}

public ArrayList<Double> getFeaturePriorities () {
    return featurePriorities;
}

public void setFeaturePriorities (ArrayList<Double> featurePriorities) {
    this.featurePriorities = featurePriorities;
}

protected double[] computerMinMaxValues(double dataArr[]) throws Exception {
    // assign first element of an array to largest and smallest
    double smallest = dataArr[0];
    double largest = dataArr[0];
    }
for (int i=1; i< dataArr.length; i++){
    if (dataArr[i] > largest)
        largest = dataArr[i];
    else if (dataArr[i] < smallest)
        smallest = dataArr[i];
}

double minmaxArr[] = new double[2];
minmaxArr[0] = smallest;
minmaxArr[1] = largest;

return minmaxArr;
}
Appendix C

Survey Forms for Evaluating the iCBLS

C.1 Users Interaction Evaluation

Fig. C.1 Instructions on how to use and evaluate the iCBLS.
Fig. C.2 Users interaction survey form.
C.2 Learning Effectiveness Evaluation

![Interactive CBL System Survey](image)

Fig. C.3 Learning effectiveness survey form.
Appendix D

List of Publications

D.1 International Journal Papers [8]


3 Maqbool Ali, Hafiz Syed Muhammad Bilal, Muhammad Asif Razzaq, Jawad Khan, Sungyoung Lee, Muhammad Idris, Mohammad Aazam, Taebong Choi, Soyeon Caren Han, and Byeong Ho Kang, “IoTFLiP: IoT-based Flip Learning Platform for Medical


D.2 Domestic Journal Paper [1]


D.3 International Conference Papers [10]


5 Maqbool Ali, Sungyoung Lee, and Byeong Ho Kang, “UDeKAM: A Methodology for Acquiring Declarative Structured Knowledge from Unstructured Knowledge Re-


## D.4 Domestic Conference Papers [5]


## D.5 Patents [3]
