Socially Interactive Clinical Decision Support System (CDSS)

by

CDSS Team

Technical Report

Ubiquitous Computing Lab
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ABSTRACT

Socially Interactive Clinical Decision Support System (CDSS)

by CDSS Team

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Clinical decision support system (CDSS) is designed to aid in clinical decision making. There are several benefits to use CDSS, such as accurate diagnoses, disease prevention, and alerting adverse drug events. Although many CDSS systems have been developed, most of them do not support social interaction, such as the feedback from normal users or patients.

The integration of knowledge from the clinical domain expert and the experience of the user (e.g., patients) is a key framework to develop more realistic and intelligent CDSS. Such multiple-knowledge-sources-based CDSS may offer social interaction which enhances its decision making capacity by manipulating the dynamic social knowledge.

CDSS supports knowledge authority component which captures and manipulates data from the society. In addition, since input data might be incorrect, this component supports data cleaning function and provides reliable data to the inference engine. Secondly, to efficiently handle dynamic data from user feedback, we design the rough set based reasoning engine with the goal of providing stable and incremental learning ability..With the support of the rough set engine, dynamic rules can be automatically generated with less effort from experts. To fully take advantages of the generated dynamic rules, we propose to utilize a hybrid solution of rough set and rule-based inference engines.

CHAPTER I

Introduction to Clinical Decision Support System

- Computer systems have long been promoted for their potential to improve the quality of health care, including their use to support clinical decisions.
- Computer-based decision support systems (CDSSs) are defined as softwares designed to directly aid in clinical decision making in which characteristics of individual patients are matched to a computerized knowledge base for the purpose of generating patient-specific assessments or recommendations that are presented to clinicians for consideration.
- For example, imagine the following scenario: While his doctor is out-of-town, an elderly asthma patient who has developed severe knee pain sees another physician in his doctor's office. An EMR provided documentation of the last visit, including recent laboratory results and a list of the patient's medications. This information easily brought the doctor up to date on the patient's condition. The doctor entered an order for medicine for the knee pain into the system, printed out a (legible) prescription for the patient, and sent him on his way. Unfortunately, within 2 months, the patient wound up in the emergency room with a bleeding ulcer caused by interaction of the pain medicine with the patient's asthma medicine. Problems of this kind occur frequently, as documented in reports from the Institute of Medicine [1-3].
- Any of several types of CDS tools could have prevented this patient's drug interaction. Examples include a pop-up alert to the potential drug interaction when the doctor prescribed the new medicine; clinical prediction rules to assess the risks of the pain medication for this patient; clinical guidelines for treatment of asthma; or reminders for timely follow up. It is pointed out in [4] that more than 40% of adverse drugs are now preventable.
- The most common use of CDS is for addressing clinical needs, such as ensuring accurate diagnoses, screening in a timely manner for preventable diseases, or averting adverse drug events [5].
- However, CDS can also potentially lower costs, improve efficiency, and reduce patient inconvenience. In fact, CDS can sometimes address all three of these areas simultaneously; for example, by alerting clinicians to potentially duplicative testing.
- For more complex cognitive tasks, such as diagnostic decision making, the aim of CDS is to assist, rather than to replace, the clinician [6-7], whereas for other tasks (such as presentation of a predefined order set) the CDS may relieve the clinician of the burden of reconstructing orders for each encounter [8].
- The CDS may offer suggestions, but the clinician must filter the information, review the suggestions, and decide whether to take action or what action to take. Table 1 below provides examples of CDS that address a range of target areas.

Table 1: Examples of CDS interventions by target area of care

Target Area of Care	Example
Preventive care	Immunization, screening, disease management guidelines for secondary prevention
Diagnosis	Suggestions for possible diagnoses that match a patient's signs and symptoms
Planning or implementing treatment	Treatment guidelines for specific diagnoses, drug dosage recommendations, alerts for drug-drug interactions
Follow-up management	Corollary orders, reminders for drug adverse event monitoring
Hospital, provider efficiency	Care plans to minimize length of stay, order sets
Cost reductions and improved patient convenience	Duplicate testing alerts, drug formulary guidelines

- The impacts on care process and patient health outcomes of CDSSs
    - In 2001, Trowbridge and Weingarten summarized the results of several systematic reviews or meta-analyses of CDS RCTs [9-12]. Since that paper, several new reviews and additional RCT studies have shown similar results [5, 13-14]. The meta-analyses of studies of alerts and reminders for decision support have been fairly consistent in showing that they can alter clinician decision making and actions, reduce medication errors, and promote preventive screening and use of evidence-based recommendations for medication prescriptions.
    - The data on how those decisions affect patient outcomes are more limited, although a number of studies have shown positive effects [15-16]. Overall, the results indicate the potential of CDS to improve the quality of care.
    - In addition, studies comparing CDS diagnostic suggestions with expert clinicians' analyses of challenging clinical cases have shown that the diagnostic CDS can remind even expert physicians of potentially important diagnoses they did not initially consider [17-18].
- Factors that facilitate broader utilization of CDSSs in US
    - There are a number of factors that can facilitate adoption and more extensive use of CDS. These include (1) Federal or other payer initiatives that provide incentives for CDS deployment and (2) technological developments, including more widespread use of EMRs with CDS capabilities, increased capabilities of systems, development of technologies for health care providers to share information across entities, and cheaper, faster or more flexible technology. In both of these areas in recent years, there has been movement to facilitate the adoption and use of CDS.
    - Payer Initiatives To Increase Incentives for Use of CDS
        - Recently passed legislation related to pay for performance and e-prescribing shift payment incentives to make use of CDS more attractive [19].
        - In addition, as recommended in a recent report from the National Research Council, health care facilities should be offered incentives to deploy health IT that provides "cognitive support for health care providers," [20] that is, well-designed CDS that truly support clinicians' cognitive tasks.

- Technological Developments
  - There have been funding and policy initiatives that are likely to lead to both improved systems and standardization across systems. These changes will lead to more "interoperable" systems that can communicate with each other.
  - The Commission for Certification of Healthcare Information Technology (CCHIT) has developed requirements for ambulatory and inpatient systems and is beginning to develop standards for CDS [21].
  - In addition, standards development organizations are developing technical and functional standards for CDS [22].

- Taxonomy of CDSSs
  - To provide a general view of the existing researches in CDSSs, which greatly vary in design as well as function, we provide a taxonomic view of the existing works as in the table below.

Table 2: A taxonomic view of existing CDSSs

Category and axis	Description
Context Clinical setting Clinical task Decision maker	Setting where CDSS operates (inpatient, outpatient) Clinical task CDSS supports (prevention, diagnosis, etc) Person whose actions the CDSS is designed to influence
Knowledge and Data Source Clinical knowledge source Data source Data coding	Source for the clinical knowledge used to generate recommendations Source for the patient data used to generate recommendations (paper chart, EMR) Format of data entered into the CDSS
Decision Support Reasoning method	Method employed by reasoning engine to generate CDSS recommendation (rule-based, neural network) - Rule based reasoning - Machine learning based reasoning

  - Table 3 provides some information about the surveyed systems in [13] regarding to their targeted clinical tasks and decision makers.

Table 3: Clinical task by target decision maker

	Patient	Clinician
Prevention/Screening	52% (of the surveyed system)	17% (of the surveyed system)
Diagnosis	0%	20%
Treatment	6%	17%
Drug dosing	15%	46%
Test ordering	0%	22%
Chronic disease management	9%	26%
Health-related behaviours	27%	0%

  - In addition, as pointed out in [13], EMR and paper chart are the two methods for inputting data into the systems. However, when consider a socially interactive system, which allows patient to interact with the system, EMR and paper chart are not available from the patient's side. It is therefore necessary to develop more user friendly input method.

- Last but not least, the problem of standardization is still not completely solved by the existing systems, the clinical data can be coded with different terms making inter-cooperation among different CDSSs difficult or even impossible.

Existing Clinical Decision Support Systems CDSS

- After analyzing recently published CDSSs (see Table 4) based on the above taxonomy, we realize that even though the existing CDSSs cover many clinical tasks such as prevention/screeing, drug dosing, chronic disease management, they were designed particularly for a group of users (physician or patient). It is surprising that there has been no comprehensive system targeting both groups of users [13].

Table 4: Representative works of CDSSs

Author	Date	CDSS Description / Characteristics	Outcome
Ageno [23]	2000	Computer-based dosage program (DAWN AC) to monitor oral anti-coagulant therapy in inpatients initiating anti-coagulation	Standard manual dosing
Bennett [24]	2003	Computer-generated consumer product information and computer generated timetable of medication administration for patients	No computer generated materials
Bogusevicius [25]	2002	Computer-aided diagnosis of small bowel obstruction	Contrast radiography-based diagnosis of small bowel obstruction
Boukhors [26]	2003	Insulin dosing calculator for patients with Type 1 diabetes mellitus	Paper-based algorithms for insulin dosing
Branston [27]	2002	Online cancer pathology reporting with structured data-entry	Free text data-entry of cancer pathology reporting
Filippi [28]	2003	EMR with online reminders encouraging use of anti-platelet drugs in patients with diabetes + letter (to physician) summarizing benefits of anti-platelet drugs in patients with diabetes	Letter (to physician) summarizing benefits of anti- platelet drugs in patients with diabetes
Nieminen [29]	2003	Neural network program designed to identify irregular cervical cells in pap smear	Standard, non-neural network guided cytotechnician screening
Lesourd [30]	2002	CDSS to guide decisions regarding timing of ovarian stimulation in fertility treatment	Standard, clinician guided fertility treatment
Lipkus [31]	2000	Telephone counseling using a computer-based protocol and computer-generated, personalized letters to remind/encourage patients to schedule mammogram appointment	Usual care involving generic postal reminders to patients
Kuperman [32]	2000	EMR with online alerts of critical lab values	Standard alerting procedure using phone call from lab to unit secretary
Safren [33]	2003	Pager reminders for patients with HIV to take anti-retroviral medications + monitoring of medication adherence via electronic pill cap	Monitoring of medication adherence via electronic pill cap

Problem with the Clinical Decision Support System

Lack of social interaction

- To the best of our knowledge, the current clinical decision support systems [23-33] utilize a knowledge base from experts or national guideline and do not consider the direct feedbacks from the patient, which are the direct object of any clinical treatment.
- The reason lies under the difficulties of the following issues.

Inflexible data input processing

- Since the current systems were designed for a specific group of users. Input data is often from well-formatted documentation such as: EMR, paper chart [13].
- However, allowing users (including patients) to interact with system for example providing feedbacks about the effect of medication, requires the system to be more robust in processing unformatted input data like: email, short messages.
- Therefore, to develop a socially interactive CDSS, smart and flexible data mining techniques are required to process different type of data.

Lack of dynamic knowledge based & reasoning method support

- Different from the conventional CDSSs [23-33], a socially interactive system continuously gain knowledge not only from the experts but also from user feedbacks.
- Hence, the knowledge base of the systems is updated frequently. Because of this simple reasoning method like rule based techniques are not suitable because transferring massive and unformatted data into clearly-defined rules is impossible.
- Therefore, more robust techniques in machine learning area should be utilized (neural network, bayes, rough set).
- Among those methods, neural network and bayes are commonly used.
- However, one limitation of those methods is the black-box nature of them.
- Hence, recently rough set model is exploited because it allows extracting explicit and human-understandable rules from complicated input data [34].
- Even though, since the existing systems utilize a well defined knowledge base, it may require a lot of effort to retrain with an updated knowledge base.

Lack of standardization

- In addition to the above problems, standardization is a must-have for interacting among different CDSSs.
- From our survey, it is surprising that a standard vocabulary (like SNOMED) is not commonly used in the current systems [13].

CHAPTER 2

Our proposed Solution Socially Interactive Clinical Decision Support System (CDSS)

- While many research groups are developing clinical decision support systems (CDSS), they are lack of social interaction support.
- For existing CDSSs, only the domain experts contribute to build and supply the knowledge base providing the domain expertise.
- In addition to domain experts, we believe that social interaction is the other important information sources of knowledge base.
- By utilizing social input information, the knowledge base of CDSS is self evolutionary and augmented, consequently, CDSS will be more realistic and intelligent which is able to provide user customized services.
- To support social interaction in CDSS, mainly three components will be developed
  1. **Inference engine.**
     It is the brain of CDSS. We plan to use rough set theory as the inference algorithm since its generated knowledge is represented by rules which could are human understandable. Hence, our rough set engine is not only capable of working independently but also in co-operation with conventional rule-based inference engines to enhance the accuracy of the overall system. By social interaction, the data repository is dynamic. To handle the dynamic data repository more efficiently, we will propose the stable rough set based feature selection algorithm and rough set based incremental learning algorithm.
  2. **Clinical knowledge authority module.**
     In this module, we will design the interface for capturing social and clinical data; we will design the scheme to transfer the raw clinical data into system understandable forms; we will design clinical data cleaning and verification schemes.

Importance Solution Socially Interactive Clinical Decision Support System (CDSS)

- This research will contribute both technologically and economically.
- From the technological point of view, the research proposes a novel framework for a socially interactive CDSS.
- From the economical point of view, the proposed system not only helps physician to avoid risky decision in diagnosis and treatment as well, but also provide patients a robust tool for interact with the physician (provide feedback, receive up-to-date recommendation for health problems) to improve the quality of the health-related services. Those capabilities potentially reduce the cost for health care systems.

Technological point of view

- A socially interactive CDSS requires much more complicated issues to be solved than do the conventional CDSSs. To overcome those difficulties, we propose our novel techniques to deal with
    - Clinical data mining: we introduce our robust data mining algorithm to deal with both well-formatted material from physician (like EMR, paper chart) and massive unformatted inputs from different users.
    - Dynamic knowledge base and incremental learning: since the knowledge is updated frequently based on both the expert knowledge and users' feedback, we proposed a robust architecture of our knowledge base to store those updated information efficiently. Furthermore, we present a novel learning strategy for the rough set model to avoid time-consuming and resource-demanding retraining of the systems.

Economical point of view

- Our CDSS not only plays an important role in improving the health-related service quality but also bring much benefits regarding to the economic aspects
- Reduction in costs related to storage of paper records
- Reduction in prescription drug costs:
    - Cost savings from changes in type of medications prescribed, for example: use of generics or lower-tier drugs when applicable.
    - Substantial reductions in pharmacy costs due to dose recommendations for selected high-cost medications [24]
- Significant reduction in medical costs associated with adverse drug events: It is worth to note that adverse drug events may cost a huge amount of money. For example, in U.S. the figure is about $5.6 million each year per hospital. In addition, U.S. Department of Health & Human Services highlighted some important facts about the drug adverse [25]
    - Patients who experienced adverse drug events (ADEs) were hospitalized an average of 8 to 12 days longer than patients who did not suffer ADEs, and their hospitalization cost $16,000 to $24,000 more.
    - Anywhere from 28 percent to 95 percent of ADEs can be prevented by reducing medication errors through computerized monitoring systems.
    - Computerized medication order entry has the potential to prevent an estimated 84 percent of dose, frequency, and route errors.
    - Hospitals can save as much as $500,000 annually in direct costs by using computerized systems.

CHAPTER 3

Proposed Clinical Decision Support System Architecture

- Clinical decision support system (CDSS) is designed to aid in clinical decision making. There are several benefits to use CDSS, such as accurate diagnoses, disease prevention, and alerting adverse drug events. Although many CDSS systems have been developed, most of them do not support social interaction, such as the feedback from normal users or patients, see Figure 1.

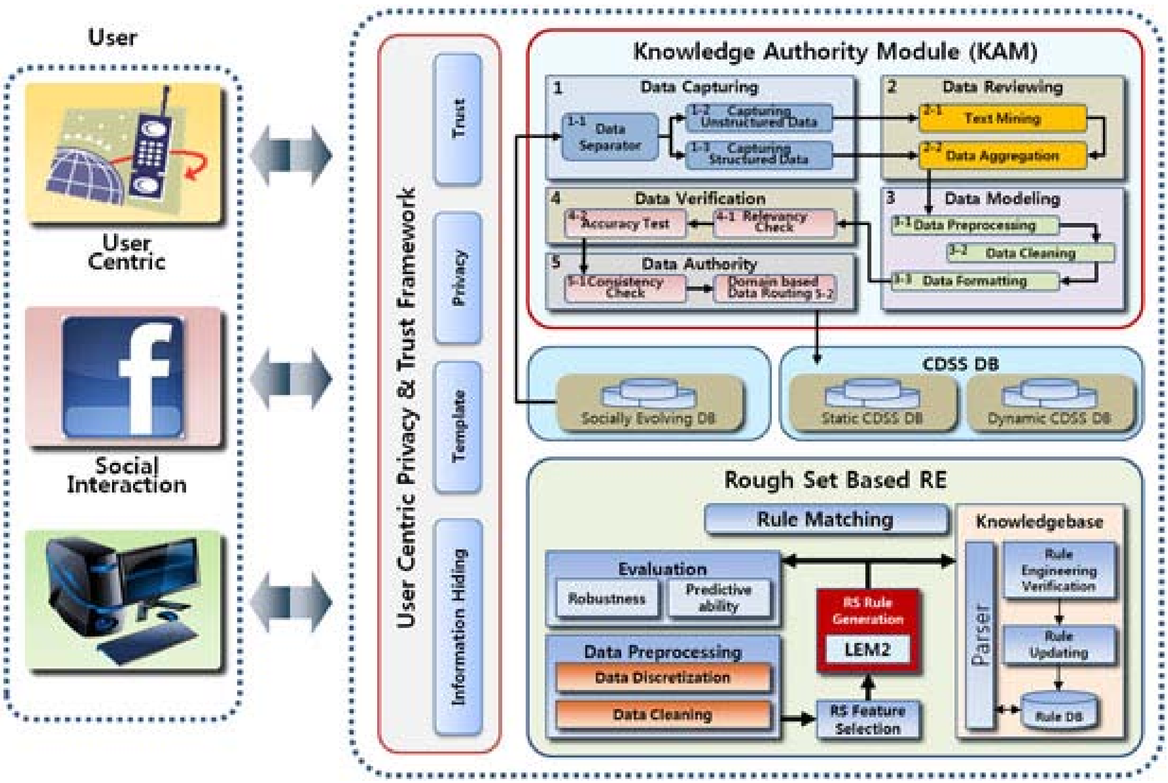


Figure 1 - Proposed CDSS System

- The proposed MCAR is composed of various sub-components such as Knowledge authority module: to capture and manipulate social data which also supports data cleaning and data verification.
- One reason for data cleaning and verification is that there might be case that users might enter fake data, so expert will stop this fake data from entering in the repository.
- Secondly, user may provide data in different formats not necessary in structured format, so in that case the data will be preprocessed and aggregated and then logged in the main repository.
- Rough set based inference engine is used to utilize rough set theory and provide rule-based, stable and incremental inference learning.
- As the knowledge will keep on increasing in the repository, that will be used by rough set based inference engine to construct new rules and use these rules later for decision making.
- The flow of information is that for every activity (i.e., storing social data or decision making) with the system.
- The social data will first be stored in socially evolving DB and then filtered by KAM. The filtered

data will then be logged the dynamic database.

- The information from database is then used by inference engine (based on user request) for rule generation as well as decision making.

Proposed Components of Clinical Decision Support System

Inference engine in our proposed CDSS

- Inference Engine in CDSS
  - The "brain" that CDSS uses to reason about the information in the knowledge base for the ultimate purpose of formulating new conclusions.
  - As shown in Fig. 2, typically inference engine consists of knowledge base and a reasoning algorithm.
  - Categorized by the type of knowledge base, existing work of reasoning engine in CDSS can be classified into two main categories.
    - Rule-based approach [38-39]
    - Machine learning approach [40-41]

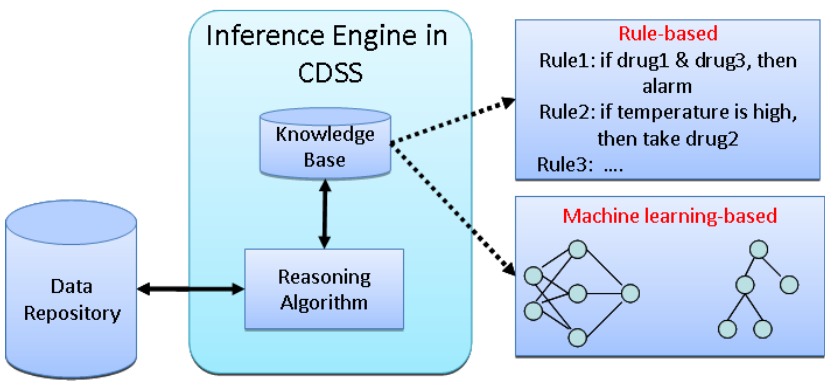


Fig. 2 Reasoning engine in CDSS

  - Rule-based approach:
    - The knowledge base contains the rules and associations of compiled data which most often take the form of IF-THEN rules.
    - If this was a system for determining drug interactions, then a rule might be IF drug X is taken AND drug Y is taken THEN alert user.
    - Using another interface, an advanced user could edit the knowledge base to keep it up to date with new drugs.
    - The inference algorithm combines the rules from the knowledge base with the patient's data.
    - Advantages:
      - It is easy to store a large amount of information
      - Rules will help to clarify the logic used in the decision-making process

        - Experts prefer rule-based CDSS since they understand the behavior of system
    - Disadvantages:
        - It is difficult for an expert to transfer their knowledge into distinct rules
        - Many rules can be required for a system to be effective. It usually time-consuming since most rules are generated by the experts manually
  - Machine learning approach:
    - Machine learning allows computers to learn from past experiences and/or find patterns in clinical data.
    - Typical machine learning approaches for CDSS include:
        - Artificial neural networks
        - Bayesian network
        - Causal probabilistic network
        - Genetic algorithms
    - Advantages:
        - It eliminates the need to write the rules and for expert input.
        - It derives their knowledge from patient data automatically.
    - Disadvantages:
        - Since the system cannot explain the reason it uses the data the way it does, most clinicians don't use them for reliability and accountability reasons
        - It often focuses on a narrow list of symptoms like ones for a single disease as opposed to the rule based approach which cover many different diseases to diagnosis
- Understanding the requirements of inference engine in our CDSS

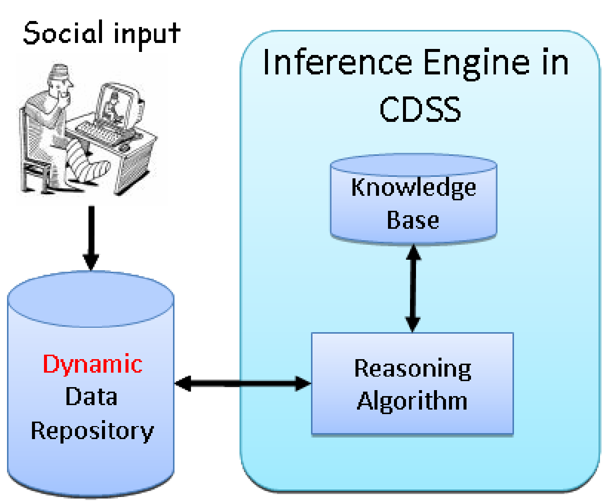


Fig. 3 Inference engine in our proposed CDSS

- Traditionally inference engine mainly deals with relative static data. While, the purpose of our proposed CDSS is to utilize the social feedback (such as patient) which are usually dynamic. Therefore, we need an inference engine will can efficiently handle dynamic data.
    - Machine learning reasoning is required since we cannot frequently ask the experts to analyze the data which are dynamic added
    - Rule-based knowledge base is required since experts could validate the knowledge and remove some unreasonable rules. It is important because usually patient's input data is not very reliable due to their knowledge limitation in medical area.

- Limitations of inference engines in traditional CDSS
    - Most rule-based CDSS generates the rules by the experts manually. It is not suitable for our dynamic data base since dynamic data base requires more efforts from experts.
    - Most machine learning-based CDSS generates the knowledge which are not understandable by human. It is not suitable for our CDSS because usually the input from social is not very reliable and understandable knowledge is preferred so that the unreasonable knowledge could be removed by experts.
- Our solution: using rough set [34] in our CDSS inference engine
    - Rough set is a machine learning algorithm
    - Its output is human understandable rules
    - Rough set can process imprecision and uncertainty information
    - Rough set will select the most informative attributes/features and then make rules based on the refined features. Therefore, the rules generated by rough set are concise and correct
    - Rough set does not require any prior information which is normally required by other machine learning algorithms. For example, prior probability is often needed by probability related algorithms.

Rough set based reasoning engine

- Data preprocessing sub-module: preprocesses the data to meet the requirement of rough set algorithm
    - Firstly, if the input is the continuous value, it need to be converted to discrete value since traditional rough set only works with discrete data. For examples, in the case of Fever, we discrete it into three values so that "0" means temperature below 37.5°C, "1" represents temperature between 37.5°C and 38°C, and "2" is temperature above 38°C.
    - Secondly, some obvious noises will be removed by data cleaning function.
    - data discretization algorithm used: CAIM algorithm [51]
        - Minimize the number of discretization intervals
        - Minimize the information loss
        - Automatically selects the number of discrete intervals without any user supervision

- Architecture of rough set based reasoning engine is shown in Fig. 8.

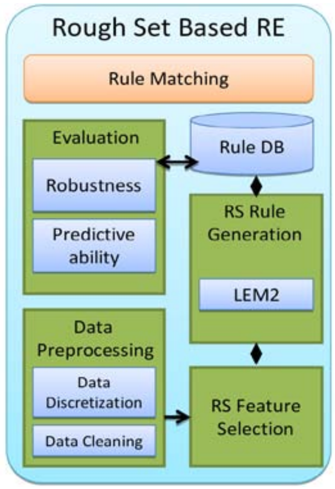


Fig. 8 Rough set inference engine

- Rough set feature selection sub-module: removes redundant and irrelevant information.
  - For example, a number of patients who suffer from high blood sugar input their experiences about how to control blood sugar level (BSL). Patient A feels that the combination of drugs 1, 2, 10 is very effective. Patient B feels that the combination of drugs 3, 4, 10 is better.
  - In this case, if without feature selection, the rules which represent the knowledge of these patients might suffer from two main problems: Firstly, the number of rules is big. Secondly, the knowledge of the rule is not reliable since many useless information exist in the rules. This sub-module can solve these two problems.
  - Limitation of existing rough set based inference engine in CDSS
    - Lack of stability support. A variety of rough set feature selection methods have been developed. Most of these methods try to extract a set of features, as small as possible, that accurately classifies the learning examples. A relatively neglected issue in the work of feature selection is the stability of the feature selection methods. Stability, defined as the sensitivity of a method to variations in the training set. Stability is an important issue when selected feature subsets are subsequently analyzed by domain experts to gain more insight into the problem modeled.
    - We investigate the use of ensemble feature selection techniques, where multiple feature selection methods are combined to yield more robust results. In real applications, it is often reported that several different feature subsets may yield equally optimal results, and ensemble feature selection may reduce the risk of choosing an unstable subset. Furthermore, different feature selection algorithms may yield feature subsets that can be considered local optima in the space of feature subsets, and ensemble feature selection might give a better approximation to the optimal subset or ranking of features. Finally, the representation power of a particular feature

selector might constrain its search space such that optimal subsets cannot be reached. Ensemble feature selection could help in alleviating this problem by aggregating the outputs of several feature selectors.

- Two steps. The first step involves creating a set of different feature selectors, each providing their output, while the second step aggregates the results of the single models. Variation in the feature selectors can be achieved by various methods: choosing different feature selection techniques, instance level perturbation, feature level perturbation, stochasticity in the feature selection. Aggregating the different feature selection results can be done by weighted voting, e.g. in the case of deriving a consensus feature ranking, or by counting the most frequently selected features in the case of deriving a consensus feature subset. In this work, we focus on ensemble feature selection techniques that work by aggregating the feature rankings provided by the single feature selectors into a final consensus ranking. Consider an ensemble E consisting of s feature selectors, $E = \{F_1, F_2, ..., F_s\}$, then we assume each F_i provides a feature ranking $f_i = \{ f_i^1, ..., f_i^N \}$, which are aggregated into a consensus feature ranking f by weighted voting: $f^l = \sum_{i=1}^{s} w(f_i^l)$ where $w(\cdot)$ denotes a weight function. If a linear aggregation is performed using $w(f_i^l) = f_i^l$, this results in a sum where feature contribute in a linear way with respect to their rank. By modifying $w(f_i^l)$, more or less weight can be put to the rank of each feature. This can be e.g. used to accommodate for rankings where top features can be forced to influence the ranking significantly more than lower ranked features.

- Rough set rule generation. Following feature selection sub-module, rough sets can generate decision rules automatically. The syntax of a decision rule can be expressed as follows:
  - If (conjunction of conditions) then (disjunction of decisions).
  - A rule is associated with a strength, which means the number of records satisfying the condition part of the rule and belonging to the decision class. Stronger rules are more general, i.e., their condition parts are shorter.
  - To induce a set of decision rules, we propose to use LEMS [52] algorithm. The LEM2 algorithm generates the minimum set of rules, i.e., the set does not contain any redundant rules. Let K be a nonempty lower or upper approximation of a concept, c is an elementary condition, and C is a conjunction of such conditions being a candidate for the condition part of the decision rule, C(G) denotes the set of conditions currently considered to be added to the conjunction C. Rule r is characterized by its condition part R. The LEM2 algorithm can be described as follows:

- The main limitation of existing rule generation methods in CDSS is lack of incremental learning support. The incremental technique is a way to solve the issue of added-in data without re-implementing the original algorithm in a dynamic database. It often occurs in using the RS theory that there are millions of data records, and the number of records increases dynamically in the database. To obtain new decision rules from the changed data set obviously consumes a huge amount computation time and memory space, and therefore the efficiency of these algorithms is very low. An efficient incremental rough set based approach is required. In this proposal, we adopt the following traditional method: deal with the new added data set by using the same reduction algorithm, and merge these new rules obtained from the incremental data set with those existing rules extracted from the original data set. In this part, we need to define the RuleMerge() function which could merge the existing rules and new generated rules. In this proposal, we propose to use the technique published in [53].

- Evaluation sub-module: evaluates the generated rules by using some validation data. This sub-module is required to overcome the potential over-fitting of the rules. It means some rules might meet the requirement of rule strength, rule length, and so on. However those rules might too data specific, they might not work well with other data.
- Rule matching sub-module: matches the new information with the rules in the knowledge and makes decisions based on the matched rules.

Rule based reasoning engine

As we pointed out above that, to fully utilize the advantage of automatic rule generation provided by rough set based engine, we propose to combine a rule-based reasoning engine with the rough set so that the overall accuracy can be enhanced. In the below paragraphs, we first briefly review the commonly used rule-based architecture then identify our suitable selection. After that we introduce the detail process or our rule-based inference engine.

Current Knowledgebase (Rules) in CDSS systems

- Facts represent what we know at any time about the problem we are working at, Rules represent relationships among the Facts, and Inference Engine is a program that activates the knowledge in the knowledgebase [54].

- A rule-based expert system is an expert system which works as a production system in which rules encode expert knowledge [55]. Most expert systems are rule-based. Alternatives are [56]:

    1. Frame-based - knowledge is associated with the objects of interest and reasoning consists of confirming expectations for slot values. Such systems often include rules too.

2. Model-based, where the entire system models the real world, and this deep knowledge is used to e.g. diagnose equipment malfunctions, by comparing model predicted outcomes with actual observed outcomes.

3. Case-based - previous examples (cases) of the task and its solution are stored. To solve a new problem the closest matching case is retrieved, and its solution or an adaptation of it is proposed as the solution to the new problem.

❖ **<u>Data-driven Rule-based Expert Systems</u>**

1. Use Forward Chaining:

2. Given a certain set of facts, use the rules to generate new facts until the desired goal is reached.

3. To forward chain the inference engine must:

   3.1. Match the condition patterns of rules against facts in working memory.

   3.2. If there is more than one rule that could be used (that could "fire"), select which one to apply (this is called conflict resolution)

   3.3. Apply the rule, maybe causing new facts to be added to working memory.

   3.4. Halt when some useful (or goal) conclusion is added to WM (or until all possible conclusions have been drawn.)

❖ **Data-driven search is suggested if:**

1. All or most of the data is given in the problem statement (interpretation problems)

2. Large number of potential goals but few achievable in a particular problem instance.

3. It is difficult to formulate a goal or hypothesis.

❖ **Goal-driven Rule-based Expert Systems**

1. Use Backward Chaining:

2. Work backwards from a hypothesised goal, attempting to prove it by linking the goal to the initial facts.

3. To backward chain from a goal in WM the inference engine must:

   - Select rules with conclusions matching the goal.

   - Replace the goal by the rule's premises. These become sub-goals.

   - Work backwards till all sub-goals are known to be true - either they are facts (in WM) or the user provides the information.

❖ **Goal-driven search is suggested if:**

1. A goal or hypothesis is given in the problem statement or can be easily formulated (theorem-proving, diagnosis hypothesis testing).

2. There are a large number of rules that match the facts, producing a large number of conclusions - choosing a goal prunes the search space.

3. Problem data are not given (or easily available) but must be acquired as necessary (e.g. medical tests).

❖ Rule-based systems can be designed to answer questions like

  - WHY do you want to know this fact? (i.e., where is the reasoning going?)
  - HOW did you deduce this fact? (i.e., how did we get here?)

Explanation facilities are useful for debugging a rule base but also for instilling confidence in users of the Expert System (ES).

❖ Knowledgebase is one of the main components of proposed CDSS that store and manipulate Decision Rules based on user request.

❖ Then Inference Engine need to take a decision then for decision making Knowledgebase is contacted and corresponding Rules are extracted for decision making.

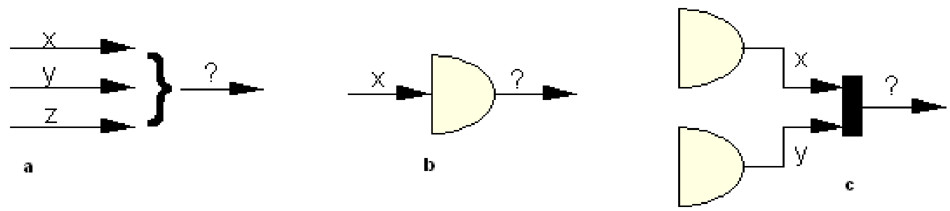
❖ These rules are mainly composed based on expert (Doctors) knowledge [3], but in our proposed system we also incorporate the patient experience that further help in decision making and also making suggestions

❖ To achieve better healthcare services, recommendations, and decision makings, we need to provide more sophisticated and exhaustive list of rules.

❖ With the passage of time, the advancement in expert knowledge and user experience may introduce some new rules as well as some changes in the existing rules. So these all need to be accommodating appropriately in the rule base.

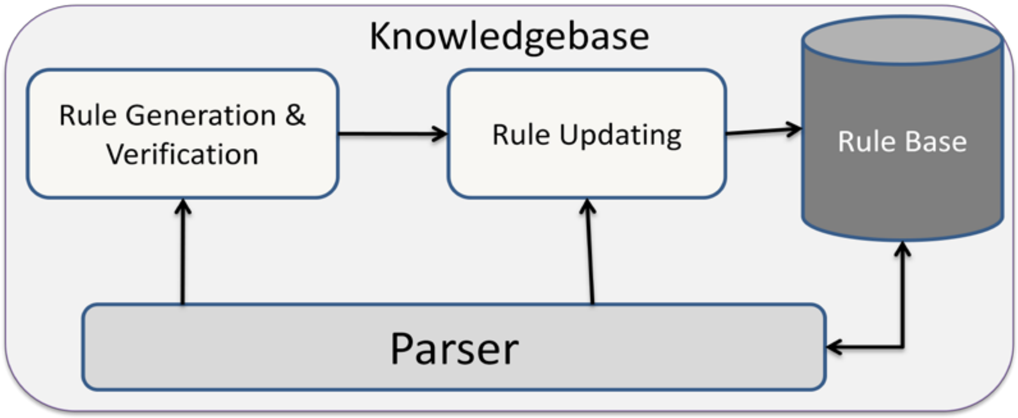
❖ Change in rules based on patient's experience is very sensitive. For this reason, the rules will only be generated from those experiences that are verified by the expert and allowed to be stored in the repository.

❖ We use the notion of social as the system is more interactive and also use patient's experience for recommendations and decision makings.

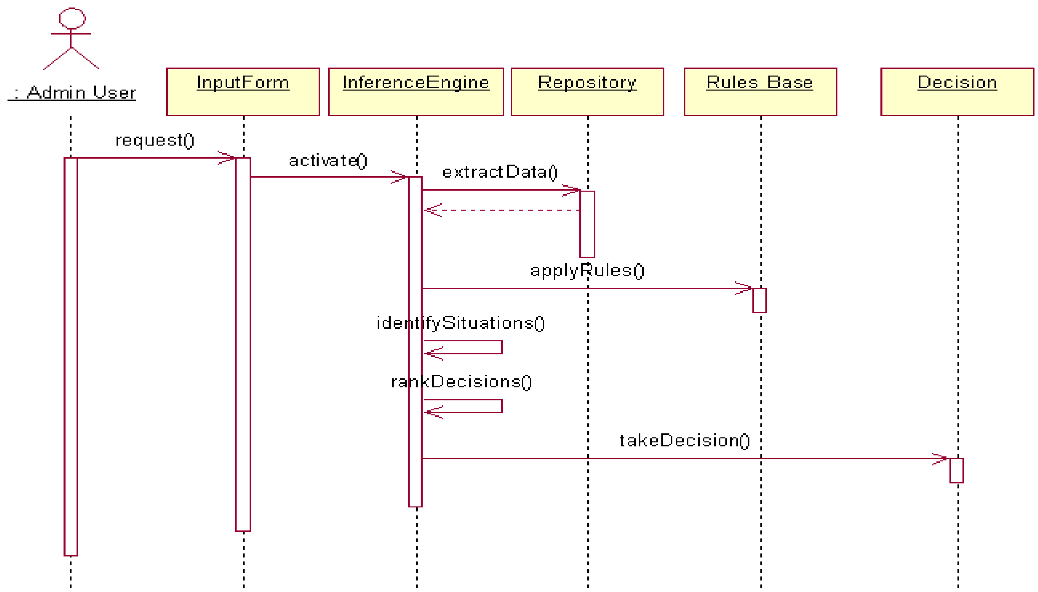


❖ In the above figure, (a) shows that what is the consequence of combination of 3 rules, (b) shows that what is the confidence of particular rule in given situation, and (c) represents that what is the consequent effects of confidence of two rules on the argument suggested.

❖ The rules are used by inference engine for decision making or analysis, so its main interaction point id the inference engine. The updates in rules and rule base will all happen through inference engine.



- Knowledgebase consistent of mainly four components as shown in the above figure.
  - Rule Base is basically a repository that store the rules used during decision making process by Inference Engine. Currently the rules are in if-then-else structure. As we are introducing ontologies for storing and managing information, so in that case we are converting rules to Horn Clauses and Description Logic Rules
  - Parser is the contact point of Knowledgebase with the other module of the overall system. Inference Engine communicate with parser for extraction different rules from the Rule Base. Parser is also responsible for activating the Rule Generation & Verification module for new rules to be generated and added in the Rule Base based on the new information found in the Repository
  - Rule Generation & Verification: Based on new discoveries in the field, new symptoms, new knowledge in the repository, and suggestions from the experts, new rules are generated in this module. After rule is drafted then it is verified with the help of an expert for its verification against the domain knowledge. Once it is verified then send to the next module for logging in Rule Base
  - Rule Updating: When a new rule is received from the Rule Generation & Verification module then this module simply logs that in the Rule Base. During Inference if some rules are found incorrect or expert want to make some changes in particular rule(s) then all these changes are communicated using Parser and these changes are made in this module
- Information provided by the patients and the rules, will be used by the system to suggest or make more appropriate decisions for improving patients health, and providing better healthcare services. An example of a simple rules are given below:
  - If alcohol per week consumption are >= 20 AND <= 40 THEN alcohol consumption is average
  - If alcohol consumption per week is high AND Salt intake is high AND blood pressure is high THEN Risk of Heart failure is high
- The use of rules in Decision making process is shown in the below sequence diagram.



- A set of scenarios will be selected and rules will be engineered to fulfill the requirements of these scenarios. As per system overall objective, the scenarios will be taken from medical domain.
- The focus will also be on providing the evidence for better performance of the proposed algorithm and the accuracy of overall results of the Rules. Theoretical verification is important and will deliver its proof.
- Testing of system on existing datasets and on real time information to verify and validate. The system implementation testing will be at both levels; component level as well as overall testing.

Knowledge Authority Module in CDSS

- Necessity of Research
  - Clinical decision support systems (CDSS) are being used increasingly in medical practice. CDSSs have been employed effectively for a wide variety of purposes, including preventive health, quality assurance and computer-aided diagnosis [42]. Assemble all relevant patient information at one place is core requirement of the CDSS systems. Uncertainty exists in almost every stage of a clinical decision making process. Sources of uncertainties may include that patients cannot describe exactly what has happened to them or how they feel; doctors and nurses cannot tell exactly what they observe; laboratories report results may be with some degrees of error; physiologists do not precisely understand how the human body works; medical researchers can not precisely characterize how diseases alter the normal functioning of the body; pharmacologists do not fully understand the mechanisms accounting for the effectiveness of drugs; and no one can precisely determine one's prognosis [43][44].
  - One of the main challenges in representation and management of social dynamic data repository knowledge is how to rationally handle above uncertainties so that a CDSS can support clinicians to make correct and reliable diagnosis and treatment decisions [45]. The potential approach is to continuously evolve the CDSS by manipulating the feedback from the users (i.e., patient, doctors, nurses, physiologists etc.). Therefore, long-term maintenance of the dynamic information/data repository of such systems

becomes important. To quantify changes that occur as a data repository evolves long-term maintenance of a dynamic data repository for a CDSS requires significant changes over time and requires creation of new portions of a data repository as well as modification of extant portions [46]. It is informative to note which sections of the data repository changed most frequently. In order of importance, these were the logic slot, action slot, database queries and the data slot exclusive of queries.

- Major challenges in dynamic data repository in CDSS
  - In recent CDSS studies, database management systems (DBMS) are frequently used to store and manage structural knowledge. Most CDSSs use relational database to record patient history data and clinical signs and symptoms [47]. Some CDSSs use object-oriented database management systems (OODBMS) to store medical knowledge, which are limited by data types in relational databases. DBMS is good at storing declarative and procedural medical knowledge with or without uncertainty. However, DBMS has a major drawback [48]. Although its structured query language (SQL) can manipulate “query”, “add”, “update” and “delete” to its stored objects, it lacks a specific knowledge inference mechanism to reason and draw logic conclusions from the data. There are special knowledge representation schemes developed to represent temporal and spatial medical knowledge [49].
  - With the rapid development of networking and database technologies, the problem of developing an adequate database which can store both declarative and procedural knowledge may not be difficult to overcome [50]. However, it is not easy to model uncertain clinical domain knowledge and structure the knowledge base so that the knowledge can be easily accessed, expanded, updated and maintained. Because of the uncertain knowledge in providing informative, clinical decision support is still one of the weaknesses in most, if not all, implemented CDSSs [42].
- Our proposed research: capturing and manipulating data from the society
  - Social data acquisition is a very important starting procedure for the construction of dynamic data repository in CDSS. The first step of social data acquisition is to select the targeted clinical area and select expert clinicians to gain domain specific knowledge. The next step is then to transfer the knowledge into computer interpretable form on the designed data representation schemes. The main focus is on the review of the social data acquisition to acquire clinical domain knowledge from experts. Therefore, development of a knowledge authority module (KAM) that can handle both data acquisition and authentication has become crucial. The KAM will capture user feedback, convert it in the system understandable form, verify its integrity and relevance, and finally store it in a formatted form in the dynamically evolving part of the central CDSS database. The schematic diagram of the proposed KAM is presented in Figure 4.

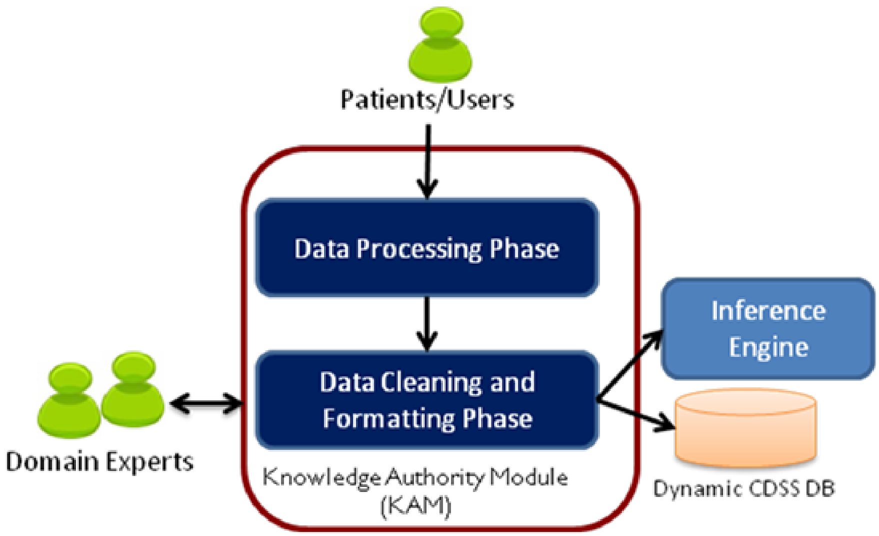


Fig. 4 Overall architecture of KAM

- Goal
  - Providing an open platform to acquire/share clinical knowledge from the society
  - Reflecting user experiences in clinical knowledge management for the CDSS
  - Incorporating dynamism in clinical knowledge management in CDSS
  - Increasing accuracy in clinical decision making

- Overall architecture is shown in Fig. 5

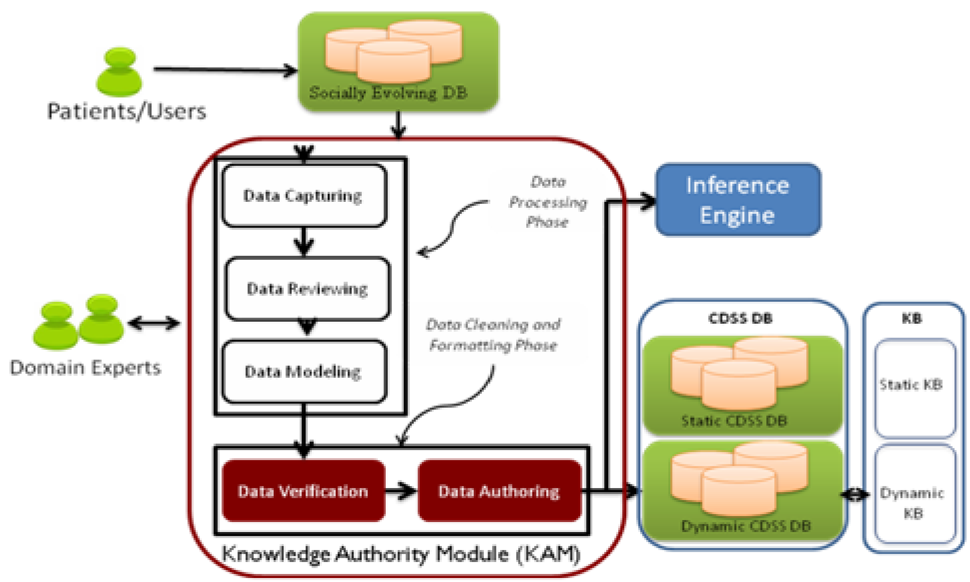


Fig. 5 Architecture of KAM

Data capturing module

- Capture raw data from the user.

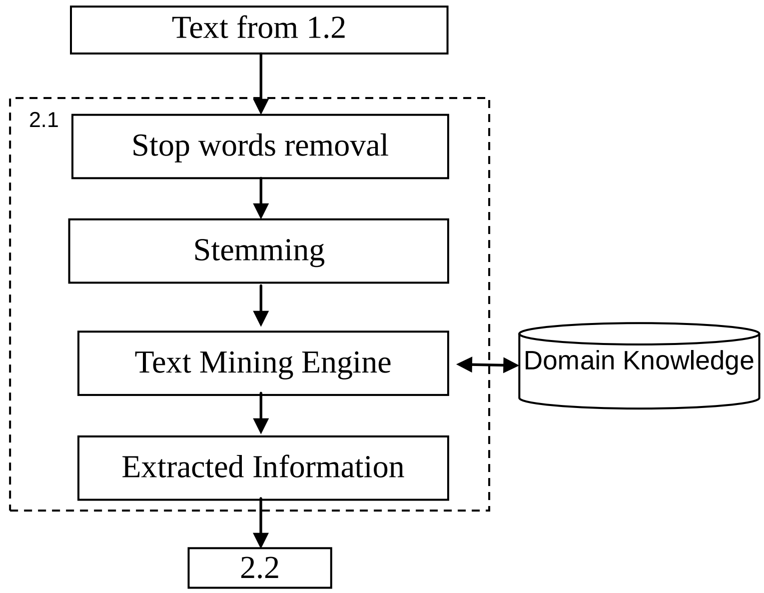
- Implement the data interface adaptor.

- Module 1.1 : Data Separator
  - To offer a high quality, fast, and general data capturing service, the data provided by the user are captured based on two types: structured and unstructured. The part of the data captured through pre-formatted input forms are structured data, while user provide unstructured information without any data entry form or guidance. These two types of data are required to be separated for efficient processing of information and extracting knowledge. This module separates the structured and unstructured data.
  - Once data are separated they are distributed among 1.2 and 1.3.
- Module 1.2 : Capturing Unstructured Data
  - The purpose of this step is to store the unstructured data temporarily in a standard fast-accessed data storing device.
  - In other words, it acts as an input data buffer for the Text mining module.
- Module 1.3 : Capturing Structured Data
  - In order to avoid data loss the captured structured data are also necessary to be stored in a temporary storage.
  - Therefore, this data capturing module acts as the underlying data repository for the data to be aggregated with the result from 2.1.

Data Reviewing module

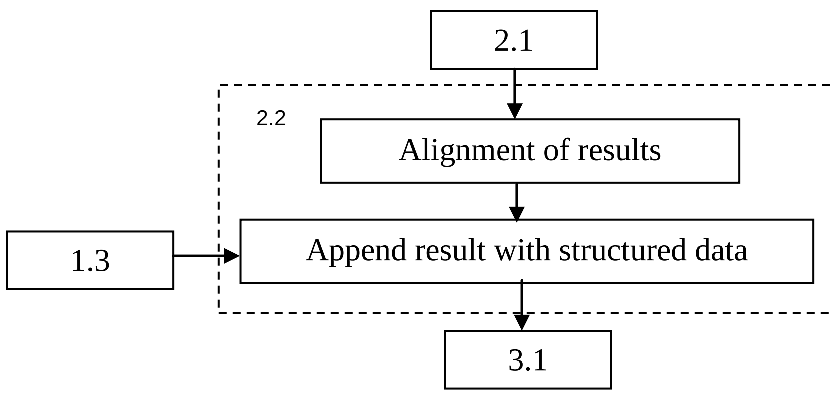
- Capture data from the data modeling module.
- Implement the data reviewing module that will provide a summarized view of the user feedback.
- The summarized and accumulated data are passed to the Data Modeling module.

- Module 2.1 : Text Mining
  - To extract clinical knowledge and information from the unstructured data we apply efficient text mining technique. The technique is highly supervised and influenced by the knowledge of the domain expert. The proposed text mining approach provides a new efficient text mining engine along with other typical text mining processing steps such as ‘stop word removal’ and ‘stemming’.



- The mining result is forwarded to the next Data Aggregation unit for further processing and accumulating with the structured data.

- Module 2.2 : Data Aggregation
  - Depending on the requirement to be aggregated with structured data, the result obtained from the



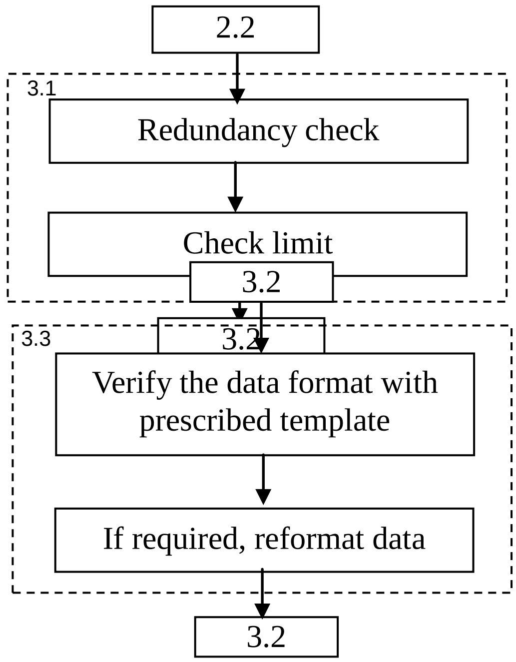
text mining step might not be appropriately arranged. Hence, the first task of this module is to align the results extracted from 2.1.

  - Once both the data types are commonly aligned, next step is to append the results from 2.1 with the captured structured data obtained from 1.3.

Data Modeling module

- Capture data from the data capture adaptor.
- Implement the data modeling module that is responsible to model the data to make them suitable for review by the domain expert.

- Module 3.1 : Data Preprocessing



  - It might be quite possible that, user provides same information through the structured and the unstructured method. Identifying and eliminating such redundancy from data increases the data processing efficiency and accuracy as well. Because of this, data obtained from 2.2 are passed through redundancy check.
  - Again, there may a set of limits for specific data defined by the system. Accommodating the data within the preferred limit is another major part of the tasks of this module.

- Module 3.2 : Data Cleaning
  - Because there may be different types of error in the data provided by the user, data cleaning is an essential step in populating and maintaining data in CDSS. Such types of errors are required to be defined. The preprocessed data then are to be checked of determining whether there exist any of such errors.
  - Once errors are identified exact error correction measures are taken to correct them. At the same time for future reference the error instances, types, and the correction measures are documented.
  - Since the user might not be expert in data inputting, the data may contain significant amount of noise. Removing such noise from data is another major task of the module.
  - To reduce future error and noise, the data entry procedure is modified.

- Module 3.3 : Data Formatting
  - Verification of the format of the data captured from 3.2 is essential for further processing.

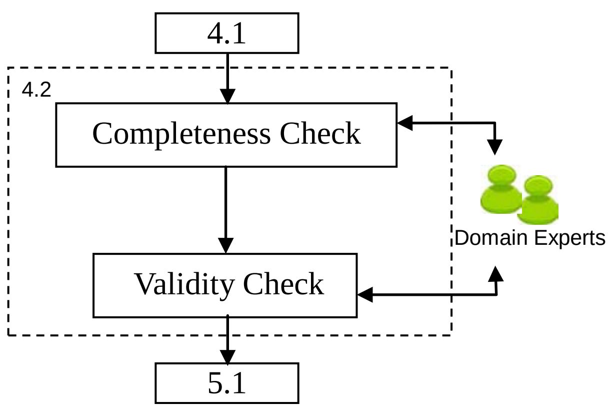
- If required, reformat the data to make it understandable for the next module of 4.1.

- Implementation of Data cleaning and Formatting phase components

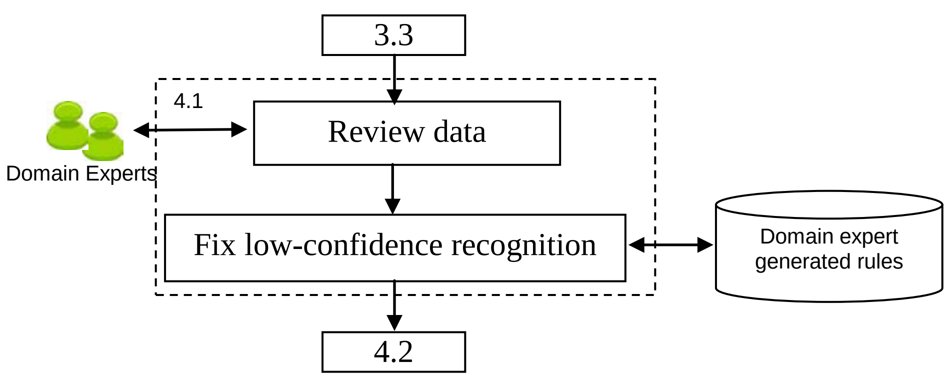
Data Verification module

- Capture summarized data from the data processing phase.
- Implement the data verification module which will apply clinical domain knowledge for ensuring the completeness, relevancy, accuracy, and validity of the data.

- Module 4.1 : Relevancy Check
    - Data verification maximizes accuracy. Data verification is the process wherein the data are check for accuracy and relevancy after data formatting is done. To identify any irrelevant information, in this step data are reviewed by a domain expert.
    - The review is performed based on a predefined scale of confidence appropriately set by the clinical domain expert. The degree of relevancy of data is tested against the prescribed scale.
    - To broaden the scope of the knowledge to be processed, the relevancy check is performed based on the preset fixed low-confidence.
- Module 4.2 : Accuracy Check



- Even though the data are relevant to the addressed issue, it might not be as complete as required for further processing. Hence, for appropriately processing data by the knowledge base it is very important to check whether user provided complete data or there are any missing parts. To test this completeness we need to consult with a clinical domain expert.

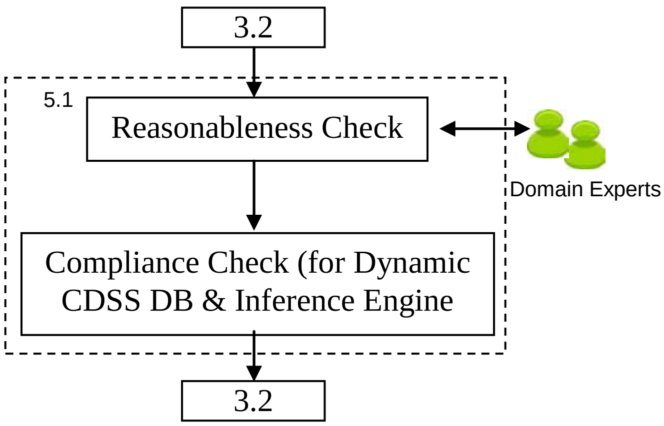


- Data passed from both relevancy test and completeness test still may carry invalid information for the specific subject matter the user is focusing on. Therefore, under the supervision of appropriate expert further validity check on the data is essential.

Data Authoring module

- Capture verified data from the data verification module.
- Implement the data authoring module for checking (with the help of clinical domain expert) the correctness, consistency, and compliance of the user feedback.

- Module 5.1 : Consistency Check
  - The accurate data obtained from 4.2 still may suffer from a number of limitations. For example,



the data may consist of information which is not at all reasonable keeping in mind the addressed issue and/or the person providing it. An expert in the domain can identify the reasonableness of the captured information.

  - Again, it is also necessary to test whether the data produced by the knowledge authority module is compatible against the next interface part of the system (i.e., the Dynamic CDSS DB and the Inference Engine). A predefined compliance check is, therefore, performed on data before sending them to the next step.

- Module 5.2 : Domain based Data Routing
  - The processed data then will be stored in dynamically evolving database for the CDSS. They will also be fed to the inference engine for generating underlying rules and using in machine learning technique. Depending on the format and compatibility issues data obtained from 5.1 are required to be routed towards either the Dynamic CDSS database or the Inference Engine.

A. Evaluation of the KAM

- After successful implementation, the whole module of KAM will be evaluated with synthetically generated and real-life data.

CHAPTER 4

CDSS Component Integration

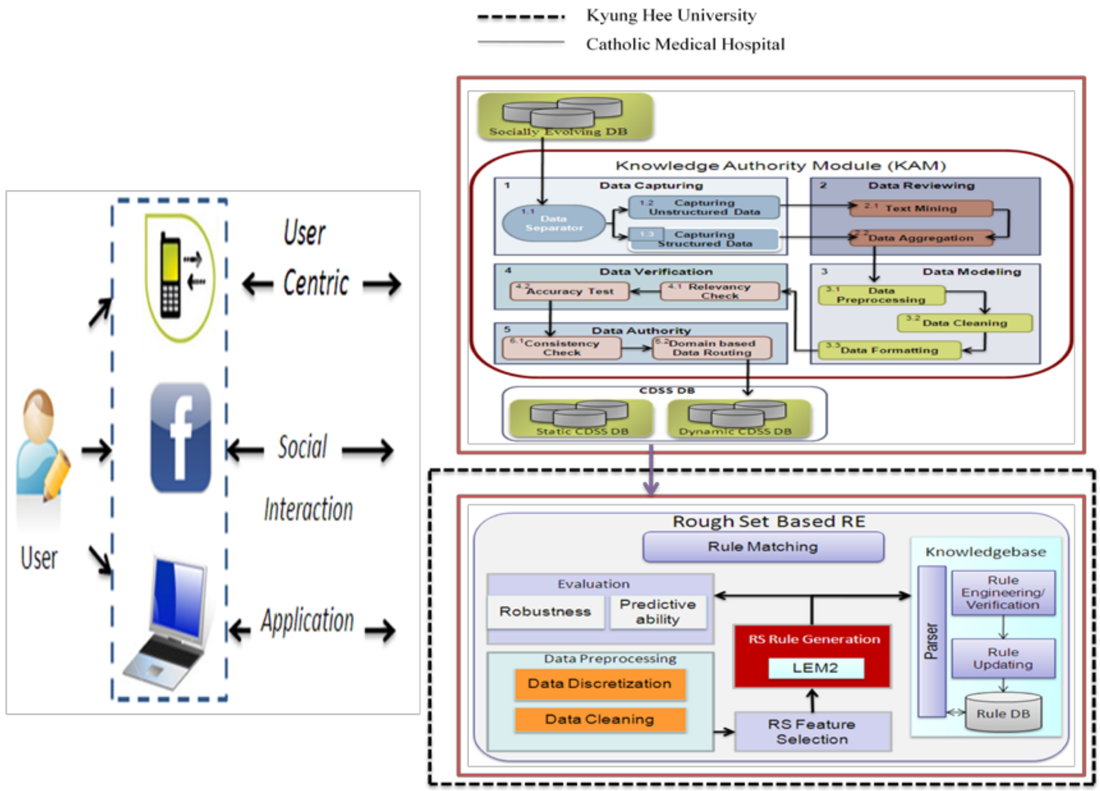


Fig. 12 System architecture of our proposed CDSS

In the third year, the focus is on how to integrate the overall system components presented in system architecture to make it applicable in real time environment. To achieve the objective of system integration and smooth functioning of overall system we need to define different criteria as discussed below.

- Input to each component, its internal processing, and its output needs to be formally defined.
- The types of input parameters, the intermediate inputs among different individual components, the interaction of these components, components configuration, and the output.
- Integration process of intra components of each different component needs to be formalized. Intra interaction of internal components, sequence of interaction, flow of information, and type of information exchange.
- Inter component integration and interaction is important to know and specify for proper working of overall proposed CDSS. Here the integration of how all the components like, KAM, and Rough Set Based RE are tightly integrated together to achieve the end objective of proposed CDSS (i.e., socially interactive, decision support system for healthcare.
- The interaction of different components with one another is also important, it is to specify the sequence and activation of components for their operation (see Figure [13] for the activation of different components and input-output flow).

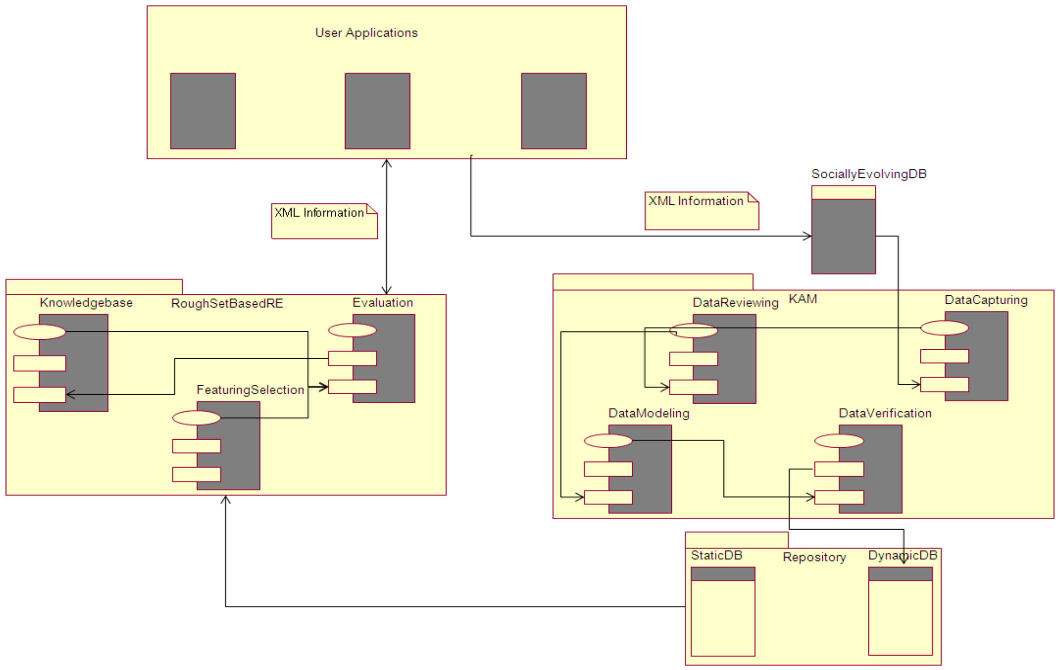


Figure 13. Integration of inter components and sequence of information flow.

- It is important to specify the interfaces among all the components that which modules will be available as public for the other modules and which will remain private. Specification of hooks for available interfaces and specification of configuration parameters to make these modules communicate with one another.
- Specification of information exchange format is a kind of requirement to fulfill before integrating the overall system. The reason is that different components have focus that contributes to the same end objective. For this reason these components might be working on data in different format, to cope this issue a prior specification of information exchange format is necessary.
- Interaction with the Repository is required by almost all the components of proposed CDSS. The basic restriction on all of them is not to change the structure of the Repository but only have particular credentials for manipulation of user information.
- Overall workflow of the system will be checked for robustness and accuracy in integration with other components.
- Complete integrated system will be tested with different set of sample scenarios, with available dataset, against existing systems, and in real-time environment.
- Documentation on system integration will be delivered at end of 3rd year

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