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Improving Intensive Care Surveillance Protocols

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***Abstract*— The Intensive Care Unit (ICU) plays a central and pivotal role in the processes of critical care decision-making. Patients in the ICU require immediate critical care regardless of ICU care processes and infrastructure facilities available. Existing clinical evidence and the research gaps suggest that the interchange between the two processes; clinical decision making and protocols are defectively managed. The reasons for this are unclear despite the existence of the critical clinical information integration for a considerable period of time. It is understood that in-effective of the information provided and disconnection between hierarchical structures of the clinical decision makers are a crucial factor for the ICU. The physicians as hierarchical decision makers are playing a vital role in ICU units congested with information from different sources, including clinical notes and reports, flow charts, bedside monitors and laboratory results. Integration between this flows of information is, therefore challenging and useful. Consequently, past research evidence suggests that clinicians with several decades of experience are unable to integrate the information consistently for unknown reasons. Hence, a literature review was undertaken to examine existing solutions. A conceptual model which consists of the components of input case, interface, case library, decision maker, classification, system tuner and knowledge miner was discussed. This is ongoing research which emerges with a conceptual framework of expert clinical decision making processes. Finally the requirements of the case in line with the accessibility, modification and addition modelled using the UPPAAL tool are presented.**

***Keywords*— Intensive Care Unit (ICU), Case Base Reasoning (CBR), Rule Base Reasoning (RBR), Clinical Decision Support System, UPPAAL.**

I. INTRODUCTION

The working environment of the Intensive Care Unit (ICU) is trans-disciplinary and deals with general scientific issues based on different academic and professional backgrounds. Hence, to get a clear picture it is important to understand the working domain, knowledge contributions, skill sharing, product use, technology and tools utilized and developed, and physiological and socio technical factors of team members' success [1].

Healthcare Information Technology (HIT) offer tools with the capacity to improve the quality of life when augmented with the process of clinical decision-making. The ICU being a central point of critical care decision-making in the clinical setting [2], provides its patients critical care. For that reason, ICU clinicians are reliant on available care processes and infrastructure facilities [3], to make timely clinical decisions. As an example, the Neonatal Intensive Care Unit (NICU) [4] provides care for newborns with severe clinical conditions; prematurity and conditions requiring immediate attention [4]. The neonatal mortality rate (per 1000 live births) is 5.90 in Sri Lanka according to World Bank reporting [5]. A research report (Jill, 2013) identifies nearly 40% of deaths occur in the hospital in the United States and more than half of that occurs in the ICU including NICU [6]. Available clinical evidence and the research gap suggests that the crucial factors are the timely communication between the processes of clinical decision making and protocols, lack of accuracy in the information provided and disconnection between hierarchical structures of the clinical decision makers, at the ICU [7]. The physicians, the hierarchical decision makers who play a vital role in the ICU unit are exposed to information overloaded from different sources which includes clinical notes and reports, flow charts, bedside monitors and laboratory results. The flow of integrated information is, to a great extent broken.

Evidence from past research suggests that there are still clinicians with several decades of experience who are unable to consistently integrate the information [8]. This scenario serves as a classic example for the complication of the situation with several variables for information processing at a given time at the ICU unit but disconnected for some reason when the process of ICU critical decision making demand timely, accurate and quality decisions [8]. One noticeable strategic research approach is to manage the shared healthcare decision-making and healthcare information exchange protocols through the selection of optimal treatment for a patient assisted by clinical decision demanding expert systems [9].

As such, this paper has been organized as follows. Section 2 is a review of related work in this area, section 3 lists the materials and methods and section 4 presents preliminary results and future work, followed by limitations of the study.

II. BACKGROUND

NICU with its 18% characteristic rates of Heath Care-Associated Infections (HAI) is in need of strict surveillance. It is affected by the increasing number of medical staff, frequent changes in healthcare staff positions, inefficiency in the process of decision making. Consequently, through a process of effective decision-making, there is a possibility to decrease HAI rates [10]. So the solution is a shared decision support system. The literature review was carried out to identify available models in the health care scenario. For reference, some of the early decision support models are included here. MYCIN (1976): MYCIN, a rule-based expert system has been designed to diagnose and recommend treatment for certain blood infections and it was later extended to handle other infectious diseases. Clinical knowledge in MYCIN is represented as a set of IF-THEN rules with certainty factors attached to diagnoses [11].

Rule-based classification systems have performed well on many occasions in the health care scenario, but one disadvantage is the qualitative and causal knowledge readily available in medicine, which is ineffective when using rule based classification.

The model (Kumar et al., 2009) components were Case Base Reasoning (CBR) system, Rule Base Reasoning (RBR) module, data entry module, system tuner, ICU scoring expert and knowledge miner. CBR and RBR have been used for implementation and modelling of the decisions made and ID3 knowledge mining algorithms have been introduced in knowledge miner [9].

EXiTCDSS framework has also been introduced to support workflow oriented decision support with CBR module of three models: workflow editor, results navigator and CBR engine. This framework facilitates the interaction with physicians in a more user friendly manner. The engine compares the stored cases with the current patient data, and selects the most similar cases from the case base [12].

A dynamic Bayesian network (Charitos et al., 2009) diagnoses ventilator associated pneumonia in ICU and assists the clinician to diagnose ventilator associated pneumonia [13].

The model (Reilly et al., 2015) uses fuzzy logic mythologies which enables real time alerts to the intensive care team for decision making [14] but remains difficult to expand to a different domain.

A probabilistic decision theoretical approach also introduced decision making process in ICU but it is difficult to acquire probabilistic information integrated with the qualitative knowledge available in rules [15].

Extant clinical decision support systems (CDSS) are generally based on RBR systems while domain dependent CDSS employs the MYCIN model which provides support for diagnosis of blood diseases. For this reason, the opportunity to construct a generic CDSS that will meet the needs of multidisciplinary clinical settings should be explored.

III. MATERIALS AND METHODS

It is understood that the implementation of such an expert system with clinical decision making capabilities has the potential to enhance the quality of clinical decisions and improve efficiency of the flow of information between hierarchical structures of the processes of clinical decision making in the Neonatal Intensive Care Unit (NICU). This hints at the demand for a review of the clinical care information model. As such, this analysis was undertaken by referring to published literature.

The published scientific papers were analysed in order to select a suitable model. It was identified that an EXiTCDSS framework that uses CBR, can easily be extended to different domains but not supported with Rule Base Reasoning. Some medical knowledge can be easily built using rule based reasoning presenting a disadvantage in this model [11].

Reilly et al offer a model using fuzzy logic methodologies which cannot be easily extended to different domains and takes years to build a knowledge base for a single domain [12]. The use of a dynamic Bayesian network becomes too difficult to be implemented here since their properties are hard to define in a medical scenario.

From the existing models, the model (Kumar et al., 2009) that was capable of handling different domains of medical knowledge using CBR and RBR was selected. According to the model, existing decisions (cases, rules) are extracted using the Redcap software with a case library, which is a repository of cases, yet to be developed. Case Based Reasoning and Rule Based Reasoning are used to implement and model decisions. Knowledge mining algorithms are implemented to identify new patterns of treatments using the existing case library [Fig.1].

With the available resources at the NICU, a clinical decision making framework was designed and presented in the following subsections.

A. Framework Model

Models of clinical decision making (Original Source: Kumar et al 2009) was used for the initial experiment.

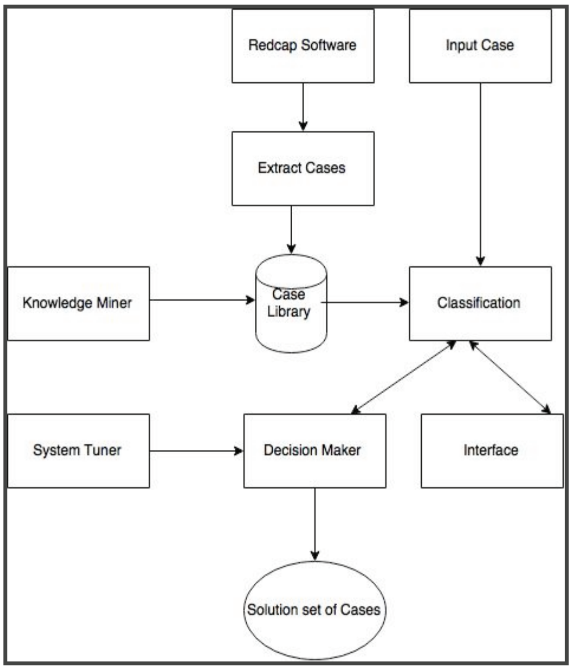

Fig. 1. Framework of Clinical Decision Making

1) *Input Case*: Here, the input Case contains the CBR agent which marks the functionality of driving the system in the beginning of each CBR cycle. At the initial stage, with partial information of the new patient's case as input, the CBR agent searches the past cases from case library through the classification component and picks the most relevant matches for the given input case information [9].

2) *Interface:* This component is a user-interface in which the user can enter the data values of observations and investigations of the patient for the period of 24 hours. The

data is temporarily stored in XML file. When the user is satisfied with the results, the data of that patient is then permanently entered into the case library. If the user finds difficulty in entering the values for 24 hours, this component can then be configured to take data automatically from the patient health monitoring devices [Fig.2] [9].

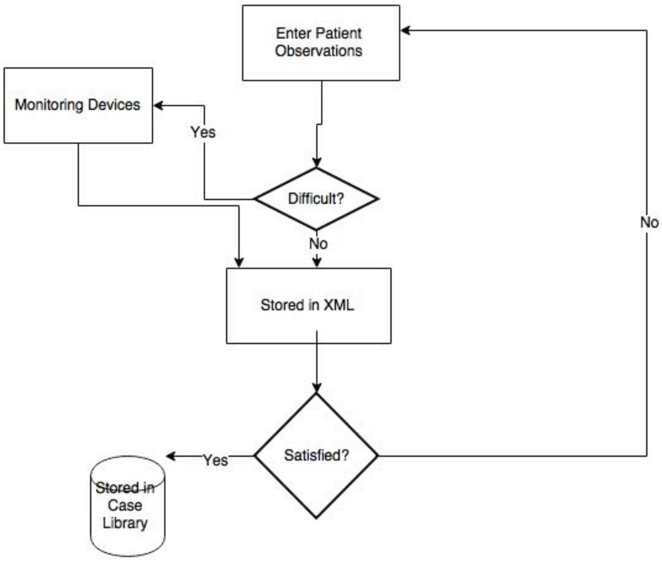

Fig. 2. Process of the Interface

3) Case Library: Case Library was developed using existing cases which will extract information using an existing database.

4) *Decision Maker:* This component takes the cases retrieved as input, then analyses these retrieved cases using RBR and CBR. Subsequently, the component decides on the observations to be made and investigations are performed with a certain level of confidence. After making a decision, it offers suggestions to the user about the observations to be made and investigations to be performed. This component is connected to the data entry system component for entering values collected after performing the investigations suggested by this component. This component also contains the RBR module. In this module, the declarative knowledge collected from the opinions of the domain experts is embedded with taxonomy of production rules, fired through a forward chaining mechanism. For each rule, this module performs an action. Rules are in red in XML format and generalize all the existing domains handled by ICU [9] [Fig.3].

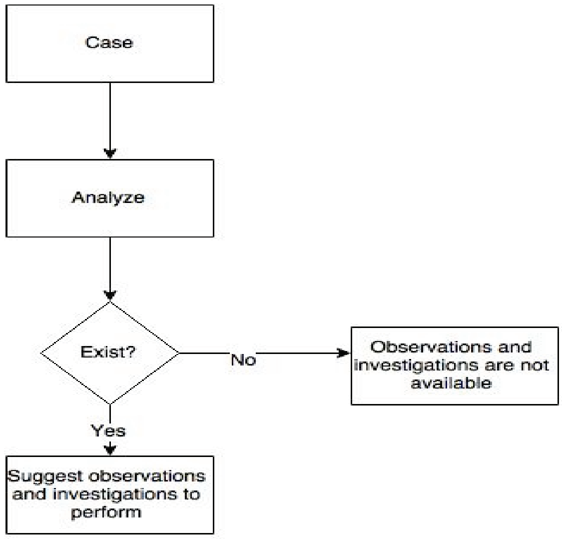

Fig. 3. Process of the Decision Maker

5) *Classification:* Classification was in accordance with the decision maker.

6) *System Tuner:* This means tuning the system. The user is able to tune the system to ensure its accurate performance through this module. This will be implemented when the user rectified the system is filtering a set of cases incorrectly or moving in wrong direction [9].

7) *Knowledge Miner:* ICU data often contains hidden information and patterns. These prove to be very useful for doctors when for effective treatment of the patients. The knowledge Miner identifies the new patterns of treatments which will assist doctors for their treatments [9].

8) *Knowledge Miner:* ICU data often contains hidden information and patterns. These prove to be very useful for doctors when for effective treatment of the patients. The knowledge Miner identifies the new patterns of treatments which will assist doctors for their treatments [9]. To ensure that end-users are able to obtain decision support services in time using the model, verification of the model with UPPAAL [16] is required. UPPAAL is a tool for modelling, simulation and verification of real time systems.

B. Valid Access to Cases

Within the model, the case can only be viewed, added or modified by a limited number of users. The following is a breakdown of the users: Healthcare Professionals (HP) and Healthcare Administrator (HA), and the definition provided by each.

Healthcare Professionals: The HP should not be able to add or modify cases, but can only view cases and new treatment patterns.

Healthcare Administrator: The HA should have the ability to add and modify cases into the case library in order to provide quality services to the patients.

C. Modelling

The requirements of the case in line with the accessibility, modification and addition were next modelled. This first checks the user for the current role (HA, HP) allowing HA to access, modify and add cases. The user requesting the data is then verified, relating to the cases assisted by the metadata of the entry to see whether they have access to the cases. If the user is not the HA, and required to justify the action taken, in the case of HPs, in case of role interchange as an "actor" this action is recorded and identified.

This system was modeled using UPPAAL. UPPAAL is a model-checker jointly developed by Uppsala University in Sweden and Aalborg University in Denmark enabling the verification of real-time systems that could be modeled as networks of timed automata. Its main components are a system editor to create models, the simulator to simulate the behavior of the system, and the verifier to analyze the behavior of the model [16].

The following scenarios of UPPAAL are identified here for the purpose of validation.

***Algorithm*-1**

If the current role access level =HA AND HP
If the input data = Cases in the library
View the case
Else
Display indicates 'case does not exit'
If the current role access level =HA
Save the Case and Tune the system
Else
The Input Case doesn't match with the Case Library
Else if
Display you are not allowed to view

***Algorithm*-2**

If the current role access level allowed =HA
If the input data = Cases in the library
View the case
User Modify the case
Save
Else
Display "the case does not exit'
Else if
Display you are not allowed to modify

***Algorithm*-3**

If the current role access level allowed =HA
If the input data = Cases in the library
Display "Case already exit"
Else
Save the case and tune the system
Else if
Display you are not allowed to add case details

***Algorithm*-4**

If current role access level allowed =HA AND HP
If View new patterns of treatments are available
Display the pattern
Else
Display: "New treatment patterns are not available"
Else if
Display "You are not allowed to view new patterns of treatments"

IV. RESULTS

A simple model of the algorithm for accessing the cases is depicted in figures4, 5, 6, and Fig. 7. Using the verifier on this model, it can be seen whether the defined access requirements are satisfied. As in Fig. 4, in order to test that a user is able to view a case for their health record the following query is in use:

E<> (userIsOwner && CaseAccessControl.CaseDisplayed)

This query tests if there is a path through the model where the case is displayed to the access user of the case. The result from the verifier is "Property is satisfied", meaning our requirement is met. To test the requirement that only the user, HA, or the HP who performed the actions can view the case, we first verify that there is a path in the model where a user who is not related to the cases can receive an access denied result using the following query:

E<> (!userIsOwner && !userIsHA && !userIsActor && CaseAccessControl.CaseAccessDenied)

This results in the statement "Property is satisfied", which was
the desired outcome. Next, to verify that there isn't a path through the model that would allow a user who is not related to the cases to view it, we use this query:

E<> (!userIsOwner && !userIsHA&& !userIsActor && CaseAccessControl.CaseDisplayed)

This query results in the statement "Property is not satisfied", verifying that there is no such path in the model and our requirement is met.

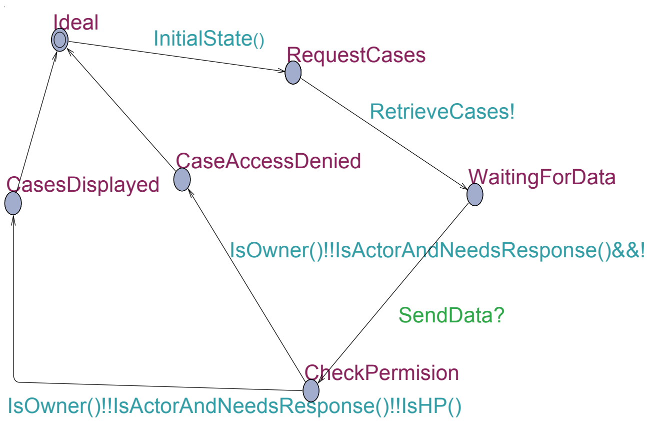

Fig. 4. Model of view Cases

As in Fig.5and Fig.6, in order to test that a user is able to modify and add a case for their health record we can use the following query:

E<> (userIsOwner && CaseAccessControl.CaseDisplayed)

This query tests if there is a path through the model where the case is displayed to the access user of the case. The result from the verifier is "Property is satisfied", which means that our requirement is met. To test the requirement that only the user, HA or the HP who performed the action can add or modify the case, we first verify that there is a path in the model where a user who is not related to the cases can receive an access denied result using the following query:

E<> (!userIsOwner && !userIsHP && !userIsActor && CaseAccessControl.CaseAccessDenied)

This results in "Property is not satisfied", which was the desired outcome. Next we verify that the HP cannot add and modify cases.

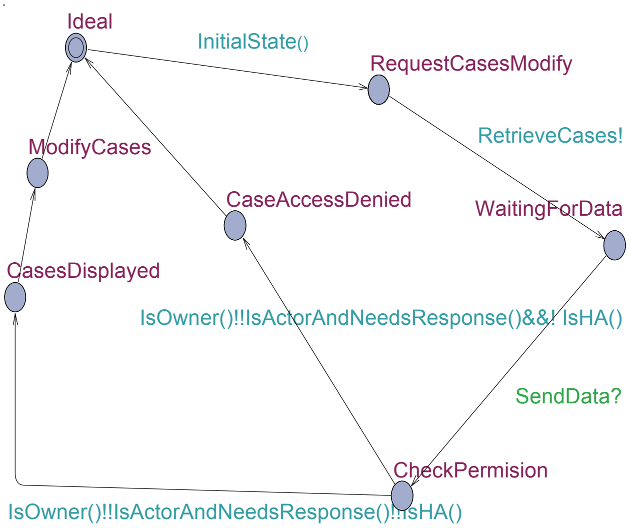

Fig. 5. Model of Modify Cases

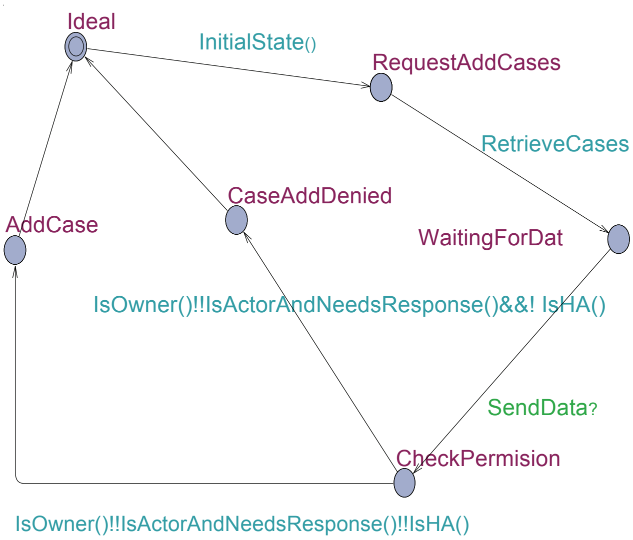

Fig. 6. Model of Add cases

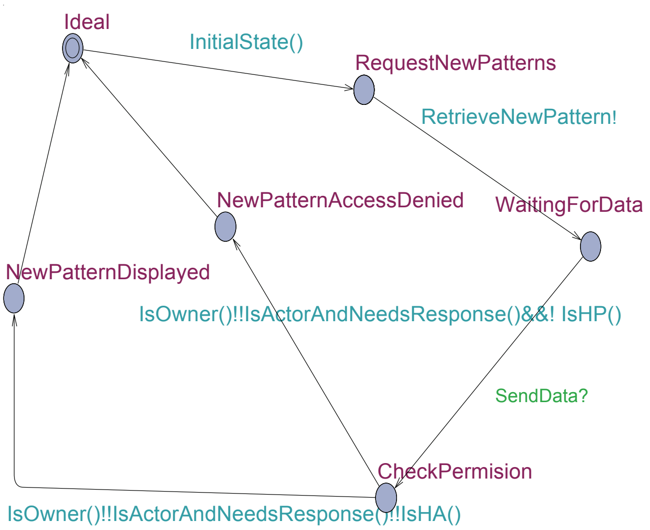

Fig. 7. Model of view New Treatments Patterns

To test the requirement that only the user, HA, or the HP who performed action can view the new treatment patterns, we first verify that there is a path in the model where a user who is not related to the cases can receive an access denied result using the following query:
E<> (!userIsOwner && !userIsHP && !userIsActor && userIsHACaseAccessControl.CaseAccessDenied)

This results in "Property is not satisfied", which was the desired outcome.

Using this method, we were able to verify that the model met the requirements for the view, edit and modify cases with all relevant access categories.

The role of the HA is predominately of case ownership and authentication to edit, delete and amend the cases to the case library. The role of the HP is predominantly of visualisation and information sharing. These requirements are satisfied with the condition provided.

V. Conclusion and Future Work

Clinical Decision support is "any electronic system designed to aid directly in clinical decision making, in which characteristics of individual patients are used to generate patient specific assessments or recommendations to be presented to clinicians for consideration".

Theoretical frameworks under this implementation of the process of expert clinical decision making are a research challenge. It is understood that the implementation of such an expert system with clinical decision making capabilities has the potential to enhance the quality of clinical decisions and improve the efficiency of the flow of information between hierarchical structures of the processes of clinical decision making at NICU. Therefore, it is believed that the Model which has been introduced here is of flexible architectures that are in support of the larger domain and more useful than domain specific models.

The study design establishes a model to manage the problems in NICU for the reduction of the mortality rate and the improvement of the use of the descriptive, predictive and prescriptive analysis to identify new patterns of treatments to assist nurses/physicians to enhance the quality and the efficiency of treatment in NICU with the effective use of data in data mining algorithms. A prototype for a clinical decision theoretical expert system has been developed using case based reasoning and rule based reasoning. This model offers significant benefits to the patients, physicians and other staff at NICU and makes the process of decision-making efficient and accurate. The NICU has the capacity to introduce this protocol to the decision-making processes at ICUS in a Sri Lankan context which, at present is manually carried out. Hence, this research brings benefits to the whole society of Sri Lanka and is essentially an avenue to reduce the rate of mortality at NICU including near misses by using clinical decision theoretical expert systems established as a long-term goal.

We wish to implement this model in areal time scenario to make use of this advantage.

VI. LIMINATION OF THE STUDY

This paper formulates a real world scenario in an ICU setting based on the situation, scenario and dataflow when making clinical decision making. The experiment is confined to the conceptual framework actual clinical experimentation is expected to take place as part of ongoing research. The data flow model and processes simulations are based on the clinical expertise and technological requirements identified in the NICU. This paper offers a conceptual perspective by presenting our conceptual framework in a practical scenario however actual data and patient scenarios are not available.

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