Machine Learning-based Clinical Decision Support System for Early Diagnosis from Real-time Physiological Data

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***Abstract*— This research aims to design a self-organizing decision support system for early diagnosis of key physiological events. The proposed system consists of pre-processing, clustering and diagnostic system, based on self-organizing fuzzy logic modeling. The clustering technique was employed with empirical pattern analysis, particularly when the information available is incomplete or the data model is affected by vagueness, which is mostly the case with medical/clinical data. Clustering module can be viewed as unsupervised learning from a given dataset. This module partitions the patient vital signs to identify the key relationships, patterns and clusters among the medical data. Secondly, it uses self-organizing fuzzy logic modeling for early symptom and event detection. Based on the clustering outcome, when detecting abnormal signs, a high level of agreement was observed between system interpretation and human expert diagnosis of the physiological events and signs.**

Keywords*— Clinical decision support system; Patient monitoring; Machine learning; Early diagnosis of clinical events; Self-organising fuzzy system; Clustering analysis

I. Introduction

In the last two decades, the development of patient monitoring system has been significantly increased especially in the area of general medicine, vital sign monitoring, clinical decision support systems, smart alarm monitoring and other computer aided diagnotic systems [1]. Currently, clinical decision support systems and expert systems are considered as the most common areas used by clinicians to make better decisions [1]. Meanwhile, the number of people who require continuous health monitoring has risen with the increase in population and multiple chronic disease, which may lead to the rise in global healthcare cost [1-3]. Patient monitoring systems can play a major role in improving healthcare, particularly in the older community including disabled and chronically ill patients [1, 2]. These systems bring potential benefits to both patients and physicians in terms of providing remote monitoring, decision support and reducing the work load of medical staff [2].

Clinical decision support systems (CDSS) and expert systems have been employed in the design of patient monitoring systems to reduce errors, increase accuracy and deliver precise care with quality outcome [3]. Fuzzy logic was introduced as a way of capturing key rules associated with clinical decision making in a machine readable format so that advanced learning algorithms could be employed for better and accurate CDSS Machine learning (Fuzzy logic) systems are true advancement towards supporting the management of complex treatments in the intensive care unit [4], reducing instability between physicians' diagnosis and helping to achieve better clinical endpoints [5]. Fuzzy logic theory delivers an efficient approach for designing a system that is too complex or vague to admit precise mathematical analysis. It builds a flexible information processing platform for the purpose of soft decision approach through approximating human decision making [6, 7]. This research aims to support clinical diagnosis using machine learning for early detection of several physiological events, such as, Bradycardia, Tachycardia, Hypotension, Hypertension and Hypovolaemia.

II. Role of CDSS in Patient Monitoring

The CDSS are useful in early detection of various case-specific health deteriorations and assist physicians with prescribed medical treatment to conduct detailed investigations [8]. However, a recent study found that despite society support for information technology, only limited evidence agree that CDSS improve patient reported outcomes and quality of life and therefore, more research on CDSS and patient reported outcomes are needed [9]. A recent review recommended that every healthcare organization should have a CDSS in place with workflow for automated monitoring of patient's vital signs [9]. The role of CDSS is considered as one of the most critical aspects of patient monitoring and decision support when using alerts and reminders. It is established that early detection of critical illness frequently demonstrates the benefit of an early intervention, which may reduce fatal encounters. [9, 10].

A common example of a CDSS system implemented in a clinical settings for monitoring inpatient's vital signs for early identification is called the Early Warning Score (EWS) [11]. The EWS score can be calculated from common physiological parameters described in this paper. Derangement in any of the parameters is assigned a number and the sum of these is used

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to calculate an overall EWS. There has been rapid growth in machine learning-based CDSS and other disease-specific decision support tools to help clinicians make better and informed decision [11, 12].

III. The Proposed Monitoring and Diagnosis System

Main components of the proposed system include; input data collection, pre-processing, clustering, fuzzy modeling and diagnosis output are shown in Figure 1. Moreover, Table I, shows the relationship between the possible symptoms and physiological parameters.

TABLE I. RELATIONSHIP BETWEEN DIAGNOSED SYMPTOMS AND PHYSIOLOGICAL DATA

Events/Parameters	Heart Rate	Blood Pressure	Pulse Volume
Bradycardia	L	H, N, L	H, N, L
Tachycardia	H	H, L	L, N
Hypotension	H, N	L	L
Hypertension	H, N, L	H	H, N
Hypovolaemia	H	L	L

Where H is high, N is normal, L is low and a combination of H, N, L shows that depending on the age and patient's condition, either one is possible.

A. Pre-processing

To remove the noise and artifacts we implemented; low pass filtering, removing missing values (zeros or negative), sampling the data, checking and removing outliers from the data set, and calculating statistical/descriptive values such as; maximum, minimum, mean, median, mode, standard deviation and range, in order to have a normalized data set throughout the diagnosis [13, 14].

B. Clustering

The proposed CDSS adopted two most common clustering mechanisms, in order to classify data with high accuracy and reliability. Due to the nature of the clinical data, which is complex and often incomplete, the proposed system employed patterns of clinical data in order to established decision support model by using training and learning dataset in an unsupervised learning approach [15]. For evaluating and system validation, two fuzzy clustering techniques including fuzzy c-means clustering (FCM) and fuzzy k-means clustering (FKM) were adopted. Data clustering/ classification was performed after applying most common pre-processing methods used in big data applications and healthcare system analysis.[15].

C. Diagnosis Output

The proposed diagnostic system, based on self-organizing fuzzy logic modeling, has been proposed using vital signals. The system detects abnormal signs which are directly related to five key symptoms; Bradycardia, Tachycardia, Hypotension, Hypertension and Hypovolaemia. During the training phase, we set the output based on the following training rules/conditions:

1. *If (HR is L) and (BP is L) and (PV is H) then (Bradycardia)*
2. *If (HR is H) and (BP is H) and (PV is N) then (Tachycardia)*
3. *If (HR is H) and (BP is L) and (PV is L) then (Tachycardia)*
4. *If (HR is N) and (BP is L) and (PV is L) then (Hypotension)*
5. *If (HR is N) and (BP is H) and (PV is H) then (Hypertension)*
6. *If (HR is H) and (BP is L) and (PV is L) then (Hypovolaemia)*
7. *If (HR is L) and (BP is L) and (PV is L) then (Low-vital-signs)*
8. *If (HR is H) and (BP is H) and (PV is H) then (High-*

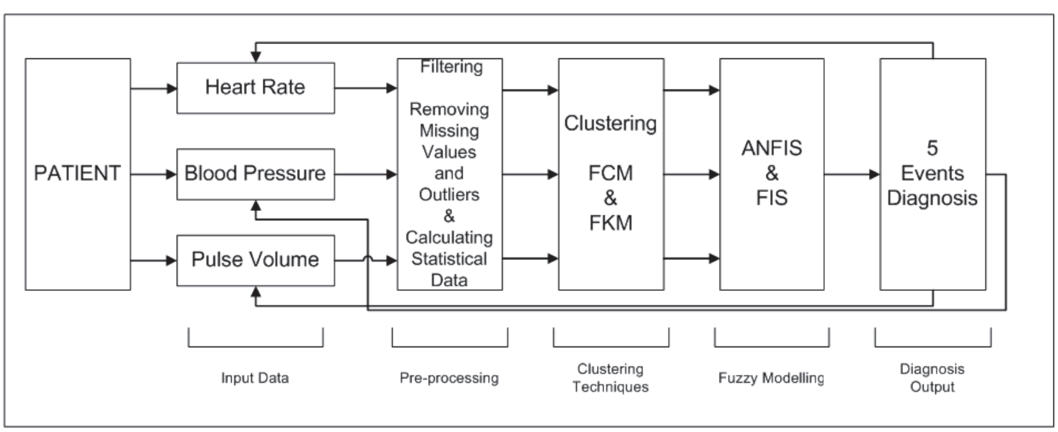

Figure 1: Block diagram of the proposed monitoring and diagnosis system.

vital-signs)

9. *If (HR is L) and (BP is L) and (PV is N) then (Low-vital-signs)*
10. *If (HR is H) and (BP is H) and (PV is N) then (High-vital-signs)*

Although more rules could be added but we limited them to 10 rules to reduce false alarms rate (false positive and false negative). In the last case (rule 10), the diagnosis result will show "High-vital-signs". This is because when two or more out of the three vital signs go higher than the normal range then system check against the expert given rules, if no exact rule is found then the system will warn as 'High vital signs'.

After setting the output, we feed related data to the same symptom (Hypotension) as the input. Then the system can be trained with multiple data sets of each symptom. The initial training data set for the self-organizing fuzzy model was selected from the authentic diagnosis database called MIMIC II waveform [16]. We selected approximately 446 records from the MIMIC II database [16] for classifying symptoms. The system was trained in such a way that whenever the new patient's data enters with similar symptom it generates an output based on the trained input datasets with early alerts/warnings.

Table II shows comparison of the proposed CDSS with different clustering methods. It is also apparent that, the system can achieve better accuracy with the trained 446 records from MIMIC II database. The system was then tested with 30 hospitalized patient datasets (Table III).

TABLE II. COMPARISON OF RESULTS FOR CLUSTERING AND CLASSIFICATION

Study	***Data***	***# Patients***	***Method***	***Accuracy (%)***	***Sensitivity (%)***
Amin et al. [16]	ECG signal	30	DTW & Fuzzy Rules	93	93
Zheng et al. [17]	ECG waveform	6[a]	SNN and SAA	94.40	NA
Faezeh et al. [18]	Medical data	768 patterns#	FACT#	71.31	NA
Yu & Wu [19]	Psychological Measurement	321 students	FIRM	80.3	NA
Proposed CDSS	Medical Data (HR, BP, PV)	446 Records	FCM	92.51	94.53
			FKM	89.62	93.08

a. Where DTW is dynamic time warping, 'a' each of the six samples contained approximately 2000 waveforms, SNN is Sanger neural network, SAA is simulated annealing algorithm, FACT is fuzzy adaptive clustering technique, # values of Pima Indians Diabetes, FIRM is fuzzy item response model, BP is blood pressure, PV is pulse volume and NA is not available.

IV. SYSTEM RESULTS

To measure the level of acceptance between the system generated outcome and the human expert's diagnosis, we used Kappa analysi (i.e. as the measure of how accurately the system can mimic human performance). The proposed system raised a total of 52 alarms and out of these, 47 alarms matched with the expert's diagnosis. Table III shows the system generated alarms related to vital signs data collated from 30 hospitalized older adults and medical expert's diagnosis for the same patients' dataset.

TABLE III. SYSTEM GENERATED ALARMS

Physical Signs	***Proposed System***	***Medical Expert***
Hypotension	8	8
Hypertension	11	9
Tachycardia	12	12
Hypoxaemia	15	15
Hypothermia	6	3
Total	52	47

The proposed system achieved an overall positive agreement (Po) with the accuracy of 95% and Kappa value of 91%. As a result, there were a total of five false positives generated, three of them were related to 'possible hypothermia'. This diagnostic was due to recording the ear temperature of the patient at below threshold value. While for this case,, the expert considered that the ear temperature value as boarder line of the threshold and would have delayed to see some more readings before considering this as an alert to a 'possible hypothermia'. We adjusted the proposed system to the assessment method undertook by the expert by taking the average of at least three values before generating an alert.

Similarly, the two false positives were related to 'possible tachycardia and hypertension'. The reason for alert generation in this case was due to the value of recorded BP which was slightly above the threshold and the value of recorded HR was very high. The system detects this event as a significant change in the patient's BP and HR when compared to the previous two readings. The medical expert agreed with the alert for 'tachycardia' but disagreed with the 'hypertension' explaining that the blood pressure values were borderline. It was not justifiable to say 'possible hypertension',but the expert agrees with the alert for 'tachycardia'.

V. CONCLUSION

The clinical decision support system was trained offline for performance evaluation purpose using clinical normal threshold-based values and approximately abnormal value-datasets. Two methods have been implemented and tested against MIMIC II dataset for medical diagnosis using HR, BP and PV. It is also proven that FCM can be used in this type of medical data where following the relationship between data and a particular physiological event is essential. The FCM algorithm will be modified using new fuzzy rules and membership functions to cluster more classes. The clustered data will be fed to the fuzzy neural module for self-organizing the limits, rules and memberships to detect several events.

The number of training epochs chosen for the proposed system in each scenario is determined based on the desired accuracy. In each data set, we first trained and compared the network(s) extensively to achieve the best outcome, i.e., smallest convergence error. The training of the proposed system is stopped once the minimum desirable error is achieved.

The proposed clinical decision support system was tested with 30 patient datasets and established a robust mechanism of data classification using neural fuzzy methodology. The proposed CDSS is capable of optimising and adjusting the mapping according to the patterns from training and learning data.

The fuzzy rules and mapping mechanism proposed here can be optimized in order to reduce the number of rules, balance the membership functions and manage the complexity according to the input and output parameters. Moreover, the proposed clinical decision support system required further real-time testing in a wider (acute or surgical) hospital setting with a larger sample size to enhance the system accuracy and stability.

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