Electrical Engineering Solutions for Personalized Public Health Monitoring Based on Activities and Vital Parameters

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ABSTRACT

The present paper proposes personalised remote healthcare based on soft computing. The primary goal of the thesis is to develop an intelligent, personalised RHM that uses personalised monitoring to create alerts in almost real-time settings and detect abnormalities in the status of human wellness. Since the activities have a significant impact on the vital sign values, the range of linguistic severity class labels in this research work is fixed based on the same, which results in a good level of personalisation of health data. The suggested study project can be very helpful to those under home quarantine or in specially designated quarantine areas, such as hotels, etc. Soft computing techniques offer a chance to create a RHM that can reliably detect changes in the population health state and accurately monitor many or all metrics of interest.

1. Introduction

Emergency scenarios require that the doctor receive information about the patient's condition electronically. The development of wireless technology is exemplified by the wireless portable gadgets, which are essential for patient monitoring in remote locations. Human society expects support services and quick attention in their stead. With the use of readily available smart technological gadgets, current healthcare systems provide senior citizens a range of emergency support options [1]. By pushing a button on a specially made alarm system that should be positioned within easy reach of the patient, the patient can notify the doctor in an emergency [8]. However, the alarm system is rendered useless if the patient is unable to touch the button in life-threatening emergencies where prompt medical treatment is needed [17]. Furthermore, RHM alerts when there is a significant divergence from the standard values and concentrates more on the early detection of life-threatening events based on critical health signals [11]. These crucial health indicators are dynamic, nonlinear, and incredibly erratic. In order to alter the model behaviour in accordance with the streaming essential data, an adaptive learning method is needed [12]. This necessity serves as motivation for the development of a widespread, self-adaptive intelligent remote healthcare system where minimum human interaction is needed for the abnormality identification of health state that quickly results in death [2].

In this instance, section 1 of the paper examines the introduction, and section 2 discusses the review of the Remote health monitoring. Section 3 and 4 presents a discussion of the proposed Remote health monitoring, while Section 5 wraps up the project.

2. Literature Review

Numerous methods, including basic data mining techniques and programmable processors, have been suggested to track and detect abnormalities in an individual's health [3]. However, these present methods do not facilitate the self-adaptivity of data according to the current state of health in real time, which leads to a significant false alarm rate [13]. The advantages and disadvantages of several current health monitoring systems that make decisions about abnormalities using classification algorithms are covered in this article. Because they offer affordable alternatives to widely used and intrusive health monitoring programmes, wearable health sensors have the potential to completely transform the healthcare industry [9]. Utilising wearable sensors has been crucial in tracking an individual's physiological characteristics in order to reduce the amount of time it takes to identify any bodily malfunctions [4]. The term "abnormality detection" refers to the process of identifying deviations, flaws, and errors. There is no efficient method for handling and analysing continuously expanding datasets in real time[16]. The proliferation of digital data, portable health sensors, biomedical devices, self-learning models through artificial intelligence, and other technological advancements has led to the emergence of numerous online healthcare portals and the online presence of the majority of hospitals [14]. Due to the intricacy of healthcare data analysis, researchers have a vast area of work to do. Creating a top-notch, end-to-end solution for remote health care is a significant task for those in the healthcare sector [5]. The amount of information generated, gathered, and stored now is enormous and keeps growing in all directions because of digitization [17]. This compels the researchers to work tirelessly to organise and examine this massive amount of diverse data in order to extract useful information for the creation of automated systems. In a multi-patient setting, scheduling an alert for a critical patient presents a number of real-time issues, including timely alert, safeguarding the critical patient, and making efficient use of the clinicians who are available. [6].

3. Methodology

The fundamental vital signs could be used to detect any changes in health or illness symptoms. The goal of the research is to use a person's unique vital signs, which vary depending on their activity, surroundings, age, and gender, to determine whether they are abnormal [7]. This research work suggests a lightweight method for individualised healthcare that aims to achieve the aforementioned goal by using wearable body sensors to gather vital signs from the subject, analysing the sensed data, and applying soft computing techniques to identify abnormalities in the data. There are four stages to the personalisation process,

i. identifying an individual's activities to determine the linguistic range of vital parameters based on those activities;

ii. clustering incoming data to determine the threshold for each individual's linguistic severity levels;

iii. creating personalised vital health values;

iv. using personalised health values to detect abnormalities; and finally, integrating an appropriate dynamic priority scheduler to shorten the time needed to generate an alert in the event of an abnormality.

The work entails gathering vital signs from the monitored individual using wearable sensors, such as heart rate (HR), blood pressure (BP), both diastolic and systolic, respiration rate (RR), electrocardiogram (ECG), and peripheral oxygen saturation in blood (SpO_2). The monitored person's mobile phone receives the sensed data using Bluetooth. The data is then moved from the mobile device via Wi-Fi or mobile internet to a remote cloud server, where it is first analysed and categorised using statistical techniques. Preprocessing of the gathered data on the server enables additional data analysis leading to high-quality personalisation. The two modules of the proposed work are abnormality detection and activity recognition. Finally, a scheduler is connected with the results to generate alerts [15]. An activity recognition model called Optimised ANFIS using Frequent Pattern Mining (OAFPM) has been proposed to classify the activity of the monitored person, which is used to fix the linguistic range of vital health signs, as the recognition of the monitored person's activities is a crucial component of the health monitoring unit [10].

4. Results and discussion

The abnormality is then confirmed by comparing the trained OAFPM model with an abnormality detection module. As a result, the model continuously learns from observed data. The actions in relation to coordinate values are displayed in Figure 1. Together with other activity, the fall data is dispersed between the lowest and maximum values that could exist. Here, the premise and ensuing parameters are first determined, and the suggested work is then cross-checked to ensure that it accurately recognises the target. The number of people who were taken into consideration for training this OAFPM model determines the cross-validation split.

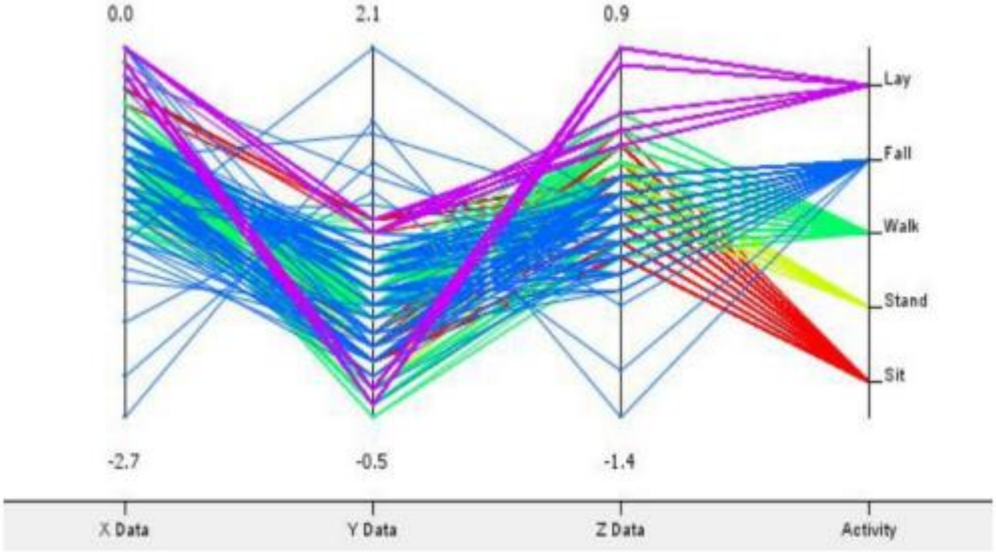

Figure 1: Activities with respect to x, y, z ranges

This research work proposes an optimised ANFIS using frequent pattern mining (OAFPM) mathematical model for activity recognition. It makes use of the Fuzzy Inference System (FIS), Adaptive Neural Network (ANN), and Frequent Pattern Mining (FPM) to accurately identify an individual's activity, thereby fixing the range for linguistic severity class labelling of vital parameters.

Figure 2: Screenshots of the mobile healthcare application

The premise of the suggested OAFPM is based on the real-time input of accelerometer data into the proposed model, while the rules derived from the linear relationship between the input and output define the consequences. The membership functions of each activity are used to identify the first rules, and the FPM technique is used to reduce the number of rules.

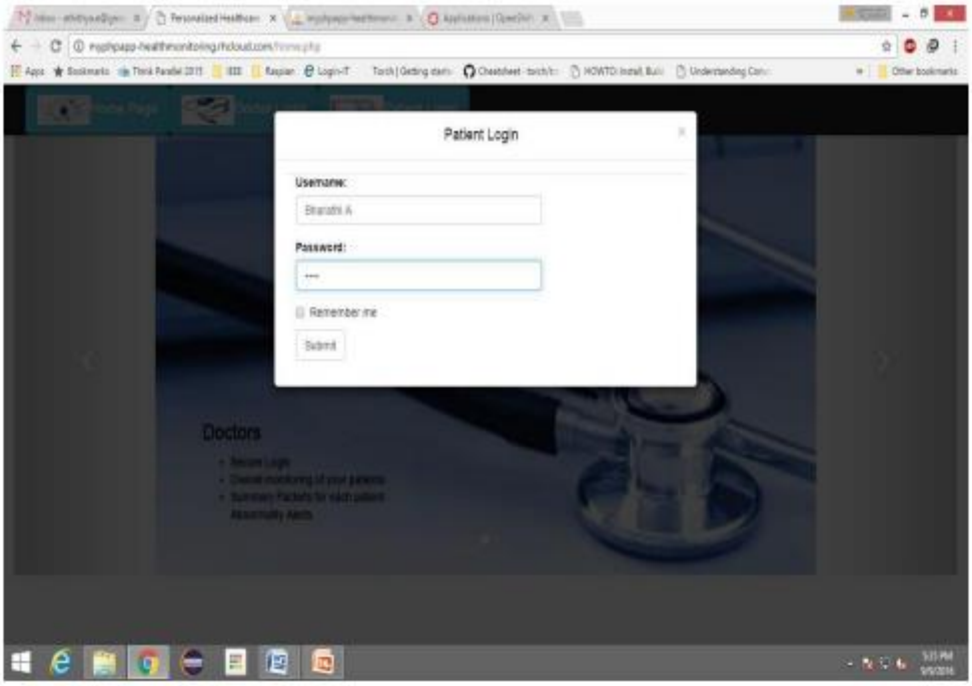

Figure 3: Snapshot of patient login

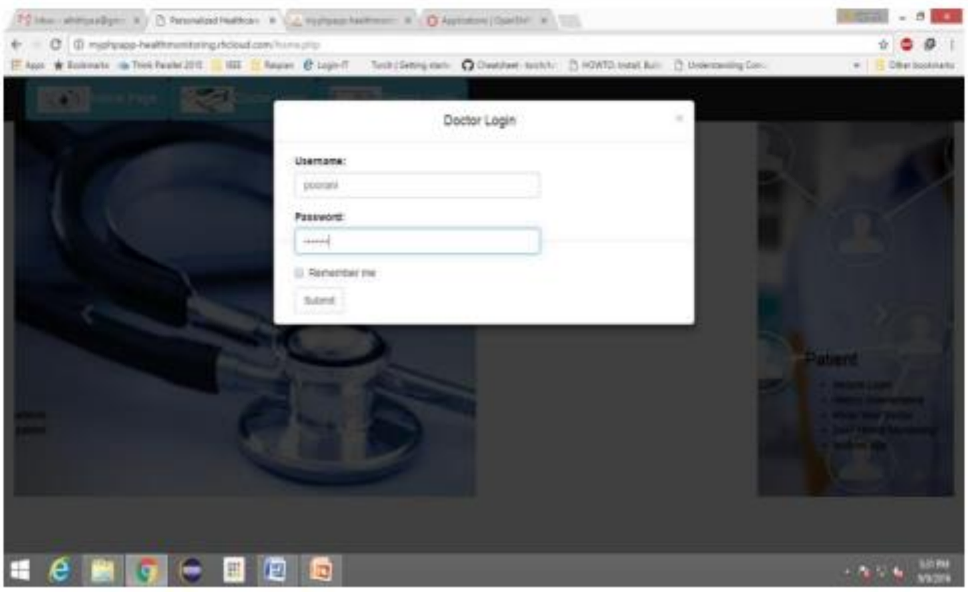

Figure 4: Snapshot of doctor login

In the learning phase, the least-square estimation approach is used to determine the consequent parameters, and the gradient descent method is used to pick the optimal premise parameters. The OAFPM model attained an accuracy rate of 88.9±9.2% due to the reduced rule matrix, ideal values of the premise and consequent parameters, and these factors together. Moreover, by activating fewer nodes for each activity, the computational complexity is also decreased.

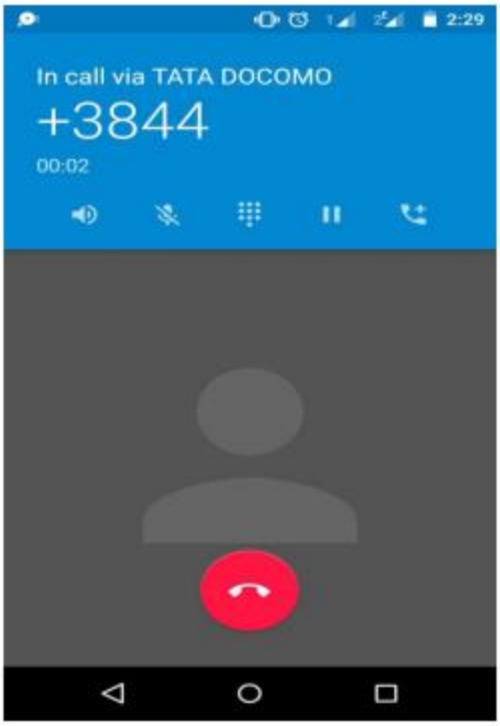

Figure 5: Voice alert to doctor

The RHM's main goal is to send out alerts to those in need with the least amount of latency possible. Here, DPS aims to reach the target with an average MAL of 0.007 milliseconds, and the cloud server that has been implemented offers scalable, reasonably priced, and extremely resilient remote healthcare services. Vital health data collected from individuals who are remote is used to validate the overall model in real time.

5. Conclusion and future scope

In the future, the planned study can be expanded to include high-level efforts for the provision of personalised medication for both communicable and non-communicable diseases. During data analysis, the location and surrounding conditions might be transferred. With the help of mitigation planning and disease outbreak prediction, this offers geospatial health analysis. A potential first response to future epidemics like COVID-19 is the deployment of personalised RHM combining wearable device data, self-reported symptoms, molecular testing, and geolocation data. Furthermore, early detection of diseases such as the corona virus (COVID 19), which causes severe acute respiratory syndrome, can be achieved for patients who are remote by continuous monitoring. Global interest has been piqued in home-based personalised medicine. Future upgrades to the suggested intelligent personalised RHM will include more group and individual activities. Furthermore, the suggested work takes into account a plethora of additional health factors in order to identify early indications of high-risk diseases such as cardiovascular diseases (CVD). It is possible to track changes in critically ill patients, and the research could be improved to forecast severe illness.

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