Modeling of a Health Care Monitoring System using Wireless Sensor Network Integrated with Internet of Things
Methodology

1. Introduction

Global ageing is widespread, deep, persistent, and the demand for chronic and geriatric care is rising at home. Chronic illnesses are the primary cause of mortality and incapacity in the globe. It is estimated that there are 16.7 million and 7.1 million fatalities from cardiovascular illnesses and hypertension per year. Diabetic adult populations should reach 300 million by 2025. Wearable health equipment innovations using sophisticated and compact sensors in or around the human body, the wearable and sensing technologies combining electronics to wireless communication have changed health care. Integration of these sensors with emerging healthcare technologies is the paradigm change towards energy efficient, battery-conscious, dependable, intelligent and overwhelming health centers to serve the elderly patients at remote area. Body Sensor Networks (BSN) is an essential and viable contender to further enhance the healthcare industry by promoting research and development [1].

2. Wearable Sensors

The quantity of wearable sensors in the market has grown significantly in the previous ten years. The major cause for this expansion is the growth in average people's age and the requirement for continual health surveillance owing to lifestyle and health issues associated by ageing. With the help of wearable sensors, patients can be provided medical aid on time as the doctor, or the medical staff can get a real time feedback about the health of the patient wearing these devices.

Vital signs of patients are of great importance since they assist people to access their health at any moment, they are crucial in the recovery process and in the monitoring of patient rehabilitation. Efficient recording of vital signs of patients might potentially play a crucial role in life-saving emergencies. The initial responsibility is to capture essential signals in the event of an emergency. The constant monitoring of risk threats to patient’s lives is enabled by garments coupled with wearable solutions as commercial mobile sensors or emergency medical equipment (EMS), emergency rooms (ER) or ICU settings.

Various types of wearable sensing devices are utilized for observing vital signs:

2.1. Cuff-less blood pressure monitoring system

Conventional methods utilize a cuff for blood pressure measurement and cannot be measured continuously [2]. This system consists of prototype of wristband type cuff-less BP monitor and the Heart Rate (HR) prototype for the BP estimate and smartphone apps. The gadget is exclusively used for signal gathering using Bluetooth Low Energy (BLE) connection and linked through smart phone. Figure 1 shows the Cuff-less blood pressure monitoring system [3].

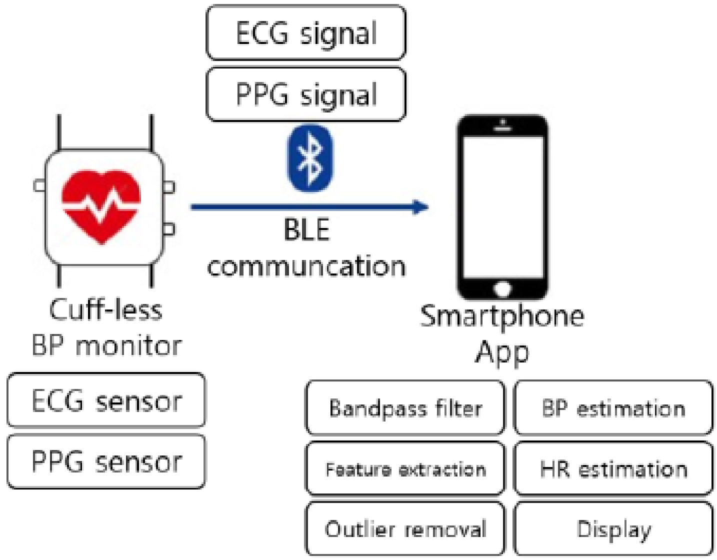

Figure 1. Cuff-less blood pressure monitoring system

The gadget is intended for mobile and user convenience as a wristband kind. The system circuit includes ECG (ADS293, Texas Instruments) and PPG (AFE4403, Texas instruments) analogue front end (AFE) and MCU (MCU) (CC2640R2F, Texas Instruments). Photo sensor with green LED (NJL5310R, NJR) as reflecting PPG sensor has been utilized to obtain more data from pulsative media than from non-pulsative medium [4]. Three dry electrodes are utilized to prevent skin issue and half-permanent usage as the ECG sensor made of stainless steel (STS-303).

2.2. Pulse Rate Sensor

The average pulse is between 60-100 beats/min for healthy persons. The pulse rate with disease, activity, injury and emotion can change and increase. Figure 2 shows the Pulse Rate Sensor.

Figure 2. Pulse Rate Sensor [5]

Pulse Sensor is a plug and play device compatible with Arduino utilized for pulse rate measurement.

2.3. Sensors for Body Temperature

Body temperature is one of the factors which continues to change, depending on our health and activities. In many respects but under the armpit, in the ear, in the mouth and in the rectum, it may be measured. Normal body temperature measured in Celsius by 35-37. It is called fever if it is higher than 37.8°C. If the temperature is not controlled and it continues to rise, this may lead to a heart stroke mainly for elderly [6]. Figure 3 shows the body temperature measurement sensor.

Figure 3. Body temperature Measurement Sensor

The voltage measurement throughout the diode may be read. The sensor is precise, and the voltage drop is recorded b/w the base transistor and the emitter as shown in Figure 3, which occurs with an increased voltage and a rise in temperature.

2.4. Respiration Rate measurement

The respiration rate is defined as the no. of breaths/min. When a person is at rest, the rate is usually calculated by counting how many breaths they take in 1 minute and estimating how many times their chest upsurges. Fever, sickness and other medical conditions may cause a rise in respiration rates. An adult’s breathing rate should be between 12 and amp; 16 breaths/ min while they are at rest. The measurement of breathing rate sensors sensitive thermal mass flow sensors may be utilized. It has been employed on numerous medical equipment such fans, spirometers and nebulizers in the LME/LDE digital low-differential pressure sensors.

2.5. Pulse Rate Oximeter

Equally the level of oxygen saturation (SpO2) and the heart rate is measured using a finger pulse oximeter. It is made up of red or infrared LEDs and a photodetector which collects light from the measurement source. Its principle operates by measuring the light absorption properties of hemoglobin in the blood using red or infrared light. Reliant on if the hemoglobin is oxygenated or deoxygenated (fascinates less infrared light), the hemoglobin groups may fascinate energy of different wavelengths of light, as seen in Figure 4.

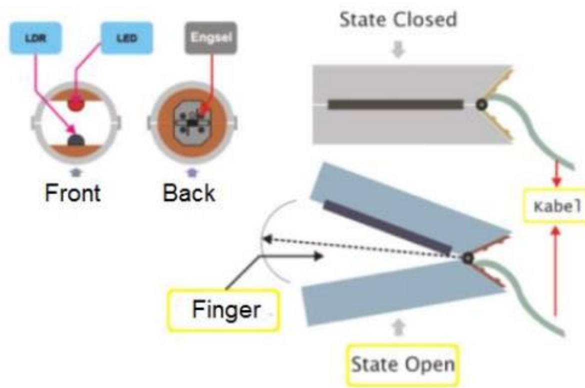

Figure 4. Design of pulse oximetry sensor [7]

2.6. ECG Sensing

The heart rate electrical movement is measured by this small chip called AD8232 [8]. It measures the heart rate and provides the signal which can be precisely connected to any controller like MSP430, Arduino, Raspberry-pi. The ECG signal is obtained by placing electrodes on the body part these signals are amplified by using AD8232 sensor which utilize low power and reduce the noise [9]. Figure 5 shows the AD8232 Sensor for ECG Sensing.

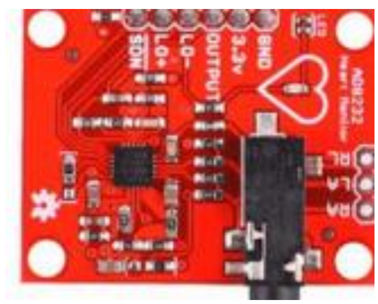

Figure 5. AD8232 Sensor

The Location of BCG, ECG, PPG and Reference Bp cuffs are shown in figure 6.

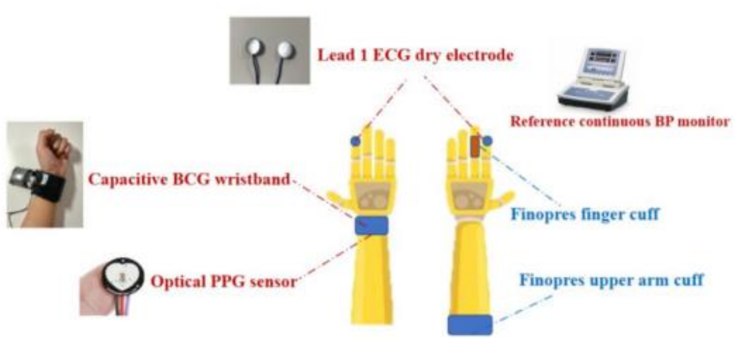

Figure 6. Locations of BCG, ECG, PPG and reference BP cuffs [10]

2.7. Activity Recognition.

It forecast a person's movement based on sensor data and it traditionally needs extensive domain signal processing and knowledge methods to accurately design functionality from raw data to meet a Machine Learning model.

3. Problem Formulation

Wireless sensor networks and WBANs are finding great acceptance in many fields including health care. The literature review has helped in understanding that security challenges, power management and data/bandwidth optimization issues exist in Wireless Networks, that need to be addressed. The review has also helped in establishing the fact that no focus has till date been made to update patient queue based on criticality of patient as identified by parameter recordings of wearable sensors.

Research Problem

An analysis of recent literature is used to identify the different issues that persist in current studies. The following are some of the issues that remain in the study field: There are questions over the use of lightweight Wearable sensors, as well as the accuracy of the data collected by these sensors.

- Wireless sensor networks and wireless body area networks (WBANs) have never been used to upgrade patient queues for emergency relief before.
- There are concerns around data transfer speeds and wireless sensor network optimization.
- Determining the volume of data from WSN nodes that can be safely forwarded to IoT devices is a critical concern.

This methodology uses different types of sensors for tracking Patient's health. All the sensors relate to the IoT devices. This methodology overcomes the cost of health care and support the hospital to improve and enhance the treatment process. To remove all the research problems this methodology uses Fuzzy neural Network and IndRNN. A fuzzy neural network is generally a neural network where the I/p as well as the connection weights are fuzzy members. FNN are an example of a hybrid approach. Making a Longer and deeper RNN is known as IndRNN. The rectified linear unit can be utilized to train an IndRNN.

4. Research Methodology

Important techniques used in this Research Methodology are as follows:

4.1 Fuzzy Neural Network Model

A single model is insufficient to solve the problem. So, two or more models are included to resolve the problem. A hybrid system is created when multiple models are merged to provide an appropriate approach to the problem. The neural networks and fuzzy logic system described as the fuzzy neural network, are used in a hybrid system to determine the priority of the task. In this Methodology, FNN is used for identifying the priority of the patient in a queue based on decision generated. Neural networks are more concerned with perceiving trends than with the reasoning of how decisions are taken [11]. While these fuzzy logic systems are good at demonstrating how decisions are taken, inference rules are problematic to implement because previous information is needed [12]. The fuzzy neural network is the product of these limitations. Fuzzy machine rules are derived from neural network patterns. This mechanism starts with a "fuzzy neuron," which is separated into 2 stages as follows [13].

i. The creation of a fuzzy neuron model

ii. Expansion of a model and algorithm for incorporating fuzziness into the neural system.

This is a neural network which generates neural outputs. The fuzzy interface's inference rules are stored in the machine as a library and applied for decision-making, as well as providing learning algorithms for the neural network like previous information. The propagation algorithm gathers data from neural networks, so the process is slow.

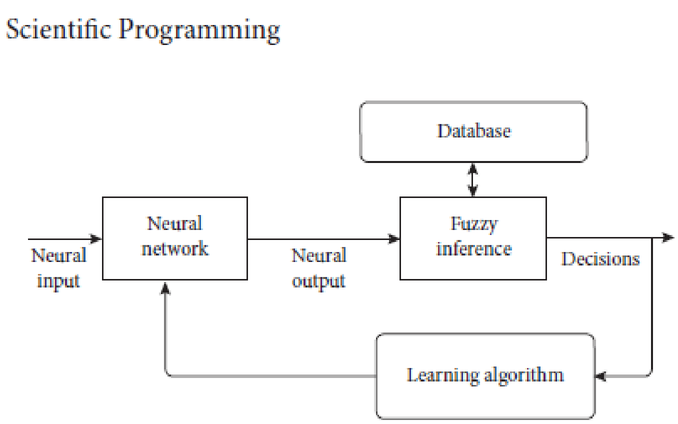

Figure 7. FNN Model

It is difficult to incorporate concrete data into a neural network to explain learning strategies. Since fuzzy rules are clarified which have improved results, they are utilized in limited systems where information learning is difficult. To monitor the knowledge base, it uses a fine-tuning refreshing data process. Figure 7 shows the FNN Model.

4.2 Independently Recurrent Neural Network (IndRNN)

An IndRNN can be effectively supervised to stop gradient explosion and disappearing glitches although permitting the network to understand long-term dependencies.

Furthermore, non-saturated activation functions like the rectified linear unit can be used to train an IndRNN. Several IndRNN can be loaded to create a network that is larger than the current RNNs.

IndRNN have exposed to do well on a variety of tasks as compared to traditional RNNs and LSTMs. It is used for accessing the sequential data. Good performances have been achieved on various tasks by using IndRNN. Figure 8 shows diagrammatical representation of IndRNN where two layers are used one is layer 1 and other is layer 2.

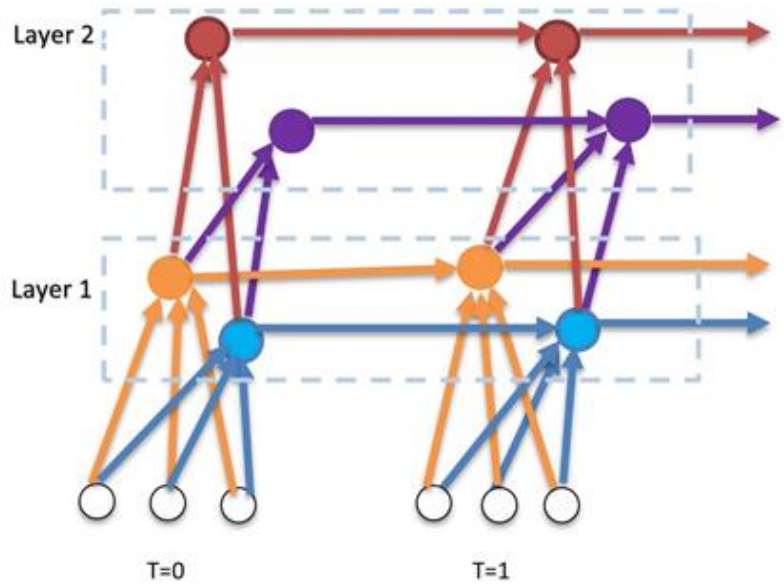

Figure 8. IndRNN [14]

Advantage of IndRNN

This has a lot of benefits to the conventional method.

- The gradient backpropagation over time can be managed to solve the gradient disappearing and explosion issues.
- It can maintain long-term memory to execute lengthy sequences. Practicals have shown that an IndRNN can access series of over five thousand steps well, whereas a Long short-term memory can only process sequences of less than one thousand steps.
- To increase the depth of the network, several layers of IndRNN can be proficiently stacked, particularly with residual connections over layers.
- It decreases computation time at each time level and is up to 10 times faster than the widely utilized Long short-term memory (LSTM).
- It can process extremely long sequences and build extremely deep networks.

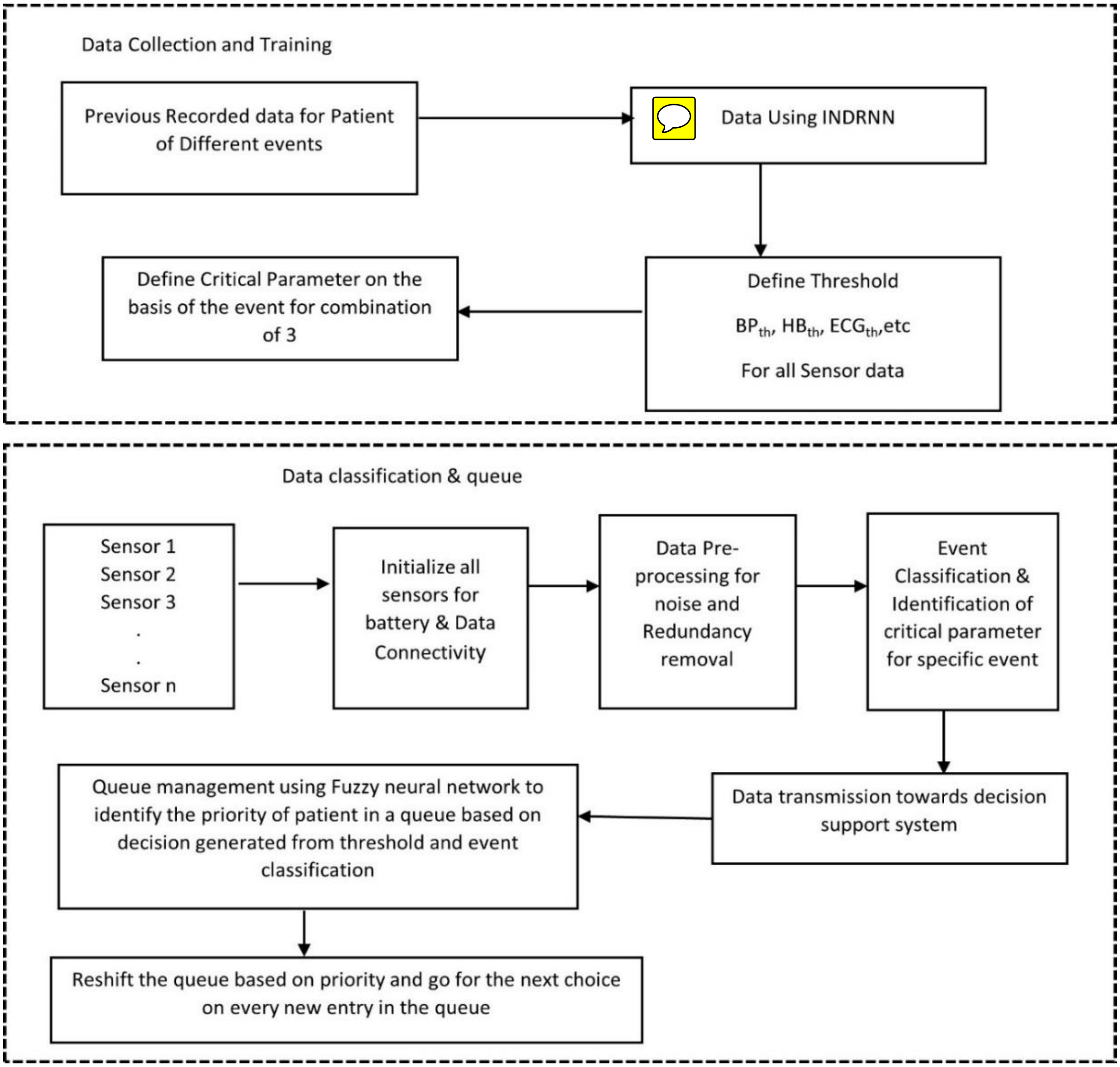

Figure 9. Proposed methodology in pictorial representation.

Step 1: Data Collection and Training

As demonstrated in Figure 9, previous recorded data for patient of different event is used to identify the Patient's problem or condition. After Identify the data or event it has passed to the IndRNN. It is used for accessing the sequential data. After this the event or the data is compared with threshold value such as BP_{th}, HB_{th}, ECG_{th} etc. If the incoming data value is mismatch to the threshold data, then the situation of the patient is critical. Critical Parameter are decided based on the event for combination of 3 parameter is used.

Step 2: Data Collection and Queue

Different types of sensors are used to identify or measuring the Patient's condition and they communicate the data through the processing unit. The sensors are initialized now for battery and data connectivity. The Data is passed to the Data Preprocessing or redundancy for removing all the unwanted noise and disturbances. The time is to classify and identify to the specific event. After this data is transferred to the decision support system. To know whom patient's condition is on priority for this a queue management is used. This process is repeat like this when the new event or new entry is generated in the queue.

In simple words, the patient who have injure may be the issue is high Blood pressure or any other issue. To know the patient's condition in this methodology, define 3 types of parameters set. According to these 3 different Parameter now set the 3 different threshold values. The parameter value is mismatch if compared to the threshold value it means the situation is critical. This process is under data collection and training.

All sensors are the IoT devices. First, initialize all the sensors by checking their battery and data connectivity. After this, sensors attach with the patients. Pre-processing method and redundancy have use for removing all the unwanted noise. Now the receive input is identified to know the which event is providing the data, this is known as classification of the data. Now according to this manage the queue. This process is repeat when new data is coming. This process works even when there is more than one patient for example a regular patient and an event-based patient. This concept will assist doctors and provide help to track the health of the patient worldwide. IoT acquired data can assist patients easily recover and patients may be provided with improved medical care at a reasonable price.

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