A cloud-based pervasive application for monitoring oxygen saturation and heart rate using fuzzy-as-a-service

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ABSTRACT

Due to the rapid development of information technology, health monitoring research demands are growing tremendously. People prefer to use wearable devices that consist of sensors, which help in monitoring the health of individuals. This study aims to develop a system that remotely monitors the physiological aspects of individuals, such as blood oxygen saturation and pulse measurement, using wearable sensors and a new cloud-based fuzzy logic system, and generates necessary alarms. Monitoring health remotely based on wearable and non-invasive sensors provides a cost-effective solution, which in turn permits the elderly people to continue to live in his/her home environment as opposed to spending on expensive healthcare facilities. The developed system shall permit smooth physiological monitoring of an individual's health by healthcare personnel in real-time. The developed system will not only assess health conditions but also provide feedback from distant facilities. Moreover, the developed rule-based fuzzy system can infer an individual's health condition. The study uses pulse rate and oxygen saturation data, which are processed by a fuzzy system on the cloud, and the acquired results are displayed on a mobile application.

CCS CONCEPTS

• **Computing methodologies → Vagueness and fuzzy logic**; • **Computer systems organization → Cloud computing**.

KEYWORDS

Pulse oximeter, oxygen saturation, SpO_2, fuzzy logic, activity monitoring.

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1 INTRODUCTION

Owing to the progression in the discipline of medicine, the older adults population rises all over the world together with developed countries thanks to immunisation, superior healthcare conveniences and treatments[12]. This, in turn, results in an increased demand for healthcare facilities in addition to medical staff. Enormous evolution in the electronics industry, for the support of human life, led to the origin of various healthcare devices and sensors [11], namely peacemakers, sphygmomanometers, and electronic stethoscopes. One of the rapidly developing fields is the application of light-weight wearable technologies to monitor human's health conditions on a daily basis [12]. In contrast, for example, electrocardiograms that are present in hospitals need electrodes, which need to be affixed to a human body, and human interference to ensure the functioning of machines. A pulse oximeter is another example of non-invasive devices that are used to uninterruptedly scrutinize oxygen saturation (SpO_2), and heart rate [10].

All over the world, life expectancy has shown tremendous improvements in healthcare caused by rising perception concerning individual and ecological hygiene [19]. According to the World Health Organisation (WHO), the older adults population $\geq$ 65 years are expected to be more than children $<$ 5 years [13]. Note that this massive ageing population would lead to a noteworthy influence on society's social as well as economic structure in terms of healthcare needs. Moreover, healthcare service-associated cost rises because of the rising cost of pharmaceutical drugs and devices [17]. Thus, it is necessary to acquire and realize new tactics and know-how for offering superior quality healthcare services at a cheaper rate to the ageing population, thereby ensuring maximum comfort. Previously, a common method that was used for measuring plasma O_2 diffusion was arterial plasma gas measurement. Arterial plasma gas is a type of plasma test comprising deflating an artery by means of a tinny syringe and removing certain blood from the body. Such a method is insensitive, affluent, not simple and excruciating.

Over time, it has been observed that living standards of people have improved tremendously, specifically when it comes to health-related qualities. As plasma oxygen overload is an essential physiological feature, acquiring real-time monitoring is absolutely essential. Recently, by means of IoT and signal processing techniques, wearable non-invasive plasma O_2 scrutinising has turned out to be possible [6, 8, 22]. People can compute their plasma O_2 saturation, pulse rate, etc. at their residence and acquire data about the changes that take place in their breathing and arterial oxygen saturation. Wearable plasma O_2 diffusion and systems that measure pulse rates have been familiarised via radio-communication networks to team up with distributed IoT resources [7].

To process the collected data from sensors, many Machine Learning tools and techniques are employed. In the research reported here, fuzzy logic systems are employed. They are designed to map an input space into an output space, when the mapping simulates human-like decisions. Fuzzy logic handles uncertain concepts in the form of linguistic variables such as “little”, “decent” and “very”, and associated fuzzy sets to each such variables with membership grades between 0 and 1. When compared with human cognitive traits, fuzzy logic has several advantages, specifically in situations that involve decision support making such as those needed in medical applications [16].

The main contributions of this research are as follows:

- A cloud-based fuzzy system for non-invasive real-time human health monitoring and anomaly detection. To the best of our knowledge, fuzzy systems in the form of cloud-based web services (called Fuzzy-as-a-Service here) has been utilised for the first time for healthcare purposes in our methodology based on IEEE 1855-2016 standard for fuzzy system data exchange;
- The openness of the proposed architecture allows the system's underlying knowledgebase to be easily updatable based on the health experts' recommendations without any hardware/software change on the users side;
- The openness and cloud-based nature of the proposed system can also help efficiently handling a big amount of data for multi-user scenarios. Hence, in this paper, the proposed system is evaluated using data acquired from wearable lightweight oximeter. However, the proposed system can still operate for different sensing sources;

The remainder of this paper is structured as follows: Section 2 focuses on an extensive related work that has been performed in fuzzy logic web services for real-time monitoring of SpO_2 and pulse rate via sensors. Section 3 elaborates on various methodologies that are used in this study, such as data collection, data processing, XML parser, etc., along with the block diagram of the proposed system. Section 4 elucidates on experimental results that are performed in this study. Section 5 concludes the study with scope for future work.

2 RELATED WORK

Tremendous research has been conducted in fuzzy logic web services for real-time monitoring of pulse rate and SpO_2 by means of a sensor-based oximeter. Some of the significant contributions concerning this field has been discussed below.

Authors in [4], implemented a low-cost, non-invasive Arduino UNO-based wearable health monitoring system to continuously measure the blood oxygen level (SpO_2), body temperature and heart rate. A pulse oximetry sensor was used for estimating plasma O_2 level percentage. Also, LEDs and sample and hold circuits were used, thereby giving elevated accurate results on all skin tones and taking into account different finger width wherein the measurement was carried. The measured result was displayed on an LCD and transmitted on an Android mobile via HC-05 Bluetooth module. ESP8266 Wi-Fi shield was used in order to link the sensor system to the Internet and revise vital reading on the server for a particular individual. Compared to commercially available pulse oximeter ChoiceMMed, a 2% deviation was observed in the proposed system, thus proving the high accuracy of the proposed system.

The work reported in [20] proposed an affordable, convenient wrist-based pulse oximeter for tracking cardiac activities like SpO_2 and heart rate. The pulse oximeter was embedded into a wristwatch, which in turn was serially connected to ATmega328p microcontroller for real-time processing. MAXREFDES117 pulse oximeter sensor was used, which provided easy integration with microcontroller and had a built-in level translator and power converter, thereby making the design simple. Also, using HC-05 Bluetooth module, the measured data could be displayed on the nearest smartphone or transferred to a laptop/desktop wherein necessary preprocessing could be performed on MATLAB to obtain a clean PPG signal. Tests were carried out on 200 volunteers where the device gave satisfactory results, thus validating the device.

A non-invasive Arduino-based hypoxic symptoms detection device using fuzzy has been proposed in [10]. The use of the non-invasive technique hampered the result of initial symptoms of hypoxia; therefore, Sugeno Fuzzy method tool was used to detect mild, moderate and severe hypoxia. The device consists of Max30100 sensor integrated with Arduino and a Bluetooth module for transferring data to the smartphone. Twelve trails were carried out, resulting in 2.96% error for O_2 saturation and 2.86% error for heart rate. In addition, 100% accuracy was obtained from the fuzzy method. Furthermore, usage of other method and addition of variation in the input to the fuzzy method would result in more meticulous and accurate results.

The work reported in [23] presented an IoT-based wearable pulse oximeter to measure physiological data such as plasma O_2 saturation (SpO_2), perfusion index (PI) and pulse rate (PR) via signal processing to evaluate data. The accuracy of the entire system was validated by conducting experiments on a simulator and an application to display the result on mobile devices. The output of the device was compared with two commercially available pulse oximeter ChoiceMMed and Innova. For SpO_2 above 90%, the proposed design provided similar results compared to those of ChoiceMMed and Innova with error within the range of 1. For lower values of SpO_2, the higher error rates max deviation of 3 were observed by the other two devices.

An Android-based application on health monitoring using fuzzy logic [19]. The user needed to enter their name and age in the biodata interface of the application and select data to obtain blood saturation level, pulse rate and body temperature via Bluetooth from a nearby wearable device. Fuzzy rules were designed taking into consideration the age, blood saturation level, pulse rate and body temperature, thus displaying the output as unwell, not healthy and healthy based on the fuzzy rules for each parameter. Experimental results showed 79.688%, 71.875% and 50% accuracies for pulse rate, oxygen saturation and body temperature, respectively.

Authors in [3] developed an IoT-based compact, low power, inexpensive and wearable SpO_2 device for health monitoring. A finger sensor and an oximeter were used to measure the oxygen saturation (SpO_2) and heart rate, and the measured data was stored in a database on the server via node MCU. The measured data was available on the website (real-time) wherein a doctor/hospital could monitor a patience's status. For performance analysis of the device, the output was compared to a Mindray patient monitor (standard clinical instrument), wherein the difference was 2.8 bpm for heart rate and ± 1.5% for SpO_2. Transmission delay was calculated by transmitting data 15 times over Wi-Fi with 10 Mbps bandwidth and resulted in an average delay of 3 seconds.

A system to measure oxygen saturation using a pulse oximeter using fuzzy logic is proposed in [5]. In this study, the calibration device was not used, thus making the system inexpensive, but using fuzzy logic, the saturation curve was plotted. For fuzzy model absorption, coefficients of a healthy person and R value obtained from the photodiode were used. Also, a linear relationship was formed between R and SpO_2 with absorption coefficients using linear regression, and the SpO_2 value obtained was compared with that of fuzzy logic. The result showed that the output of fuzzy logic was far more accurate and reliable as compared to the linear regression model.

An IoT-based system for measuring athletes' plasma O_2 saturation and pulse rate during sports training has been developed and reported in [7]. Near IR portable tissue oximeter with STM32 microprocessor for detection was used to measure the two parameters. These parameters were then transmitted to the server via mesh nodes, which used the IEEE 802.15.4 protocol. Also, these two parameters were sent to a doctor or coaches via GPRS/Zigbee/Wi-Fi processed by the detection module, thus indicating the condition of the athlete. Additionally, the data could be ported on smartphones via GPRS/Wi-Fi. The proposed design result was compared and existing device (Philip watch) with standard medical measuring device as a reference. The result obtained was highly accurate and stable over existing devices.

The impact of plasma O_2 saturation and a fuzzy logic system on inspired O_2 prediction for a ventilator system has been analysed in [18]. Statistical pairwise analyses were performed to determine the correlation in a physiological parameter from scientific and medical data for updating fuzzy variables using Mamdani model to predict FiO2, which is fed to the ventilator to preserve SpO_2 within a required level. R programming was used to model the fuzzy system with 75% of clinical data utilized for training and remaining 25% was utilized for testing. The output of the predictive system showed <5% error compared to an acceptable value.

By considering the above-mentioned detailed and illustrative explanations about real-time human health monitoring in addition to its limitations, a fuzzy logic-based web service is proposed that helps in detecting a real-time human health situation via a wearable SpO_2 and heart rate sensors. Unlike current systems, the proposed system makes limited use of both hardware and software. Hence, the proposed system in this paper does not require high computational resources compared to other previous works. This increases the usability and deployability features of the proposed approach in real-life scenarios.

3 METHODOLOGIES

The system flow illustrated in Figure.1, the output acquired from an oximeter sensor will be directly passed to a data processing block. Fuzzy variables and membership functions defined and processed by a rule-based fuzzy logic system and its output are displayed on an Android application. The proposed system which is described in

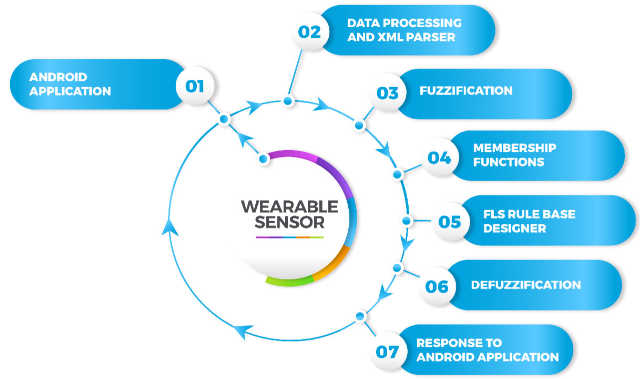

Figure 1: Flowchart of the proposed system.

Figure.2 is developed in such a way that it will monitor an individual's health conditions by means of values that are acquired from heart rate and SpO_2, which acts as the measurement parameters for managing health conditions.

3.1 Data Collection from wearable Sensor

For data collection, BM2000A SmartCare Oximeter wearable wrist pulse oximeter sensor was used[1]. The sensors, namely SpO_2 and heart rate, were used which has shown in Table1. Sensor details with the respective error code are as follows:

- SpO_2 status is 0 if everything is ok.
- **0x01**: SpO_2 sensor not connected
- **0x02**: No finger detected in sensor
- **0x04**: Could not detect pulse
- **0x08**: Indicates the pulse beats

Pleth is the plethysmograph signal shown on the screen of the oximeter and on the app. The RED/IR ADC values are the raw values from the analogue-to-digital converters for the red and infrared sensors in the probe. These are indeed used to calculate the SpO_2 value. Perfusion index is the ratio of the pulsatile blood flow to non-pulsatile.

The sensor receives the input from a human finger that provides information about pulse rate and SpO_2, which shown in Table 1. Once the input is received from the sensor, it is processed by the fuzzy system to determine the status of human health. Once the pulse rate and SpO_2 data are given to the fuzzy logic system, it will process the data in a sequential manner. The rules governing the fuzzy logic processing, that can classify a situation as critical, alert or normal, are shown in Table 2.

[1]More detail about the sensor is available from: http://http://devices.smartcareanalytics.co.uk/

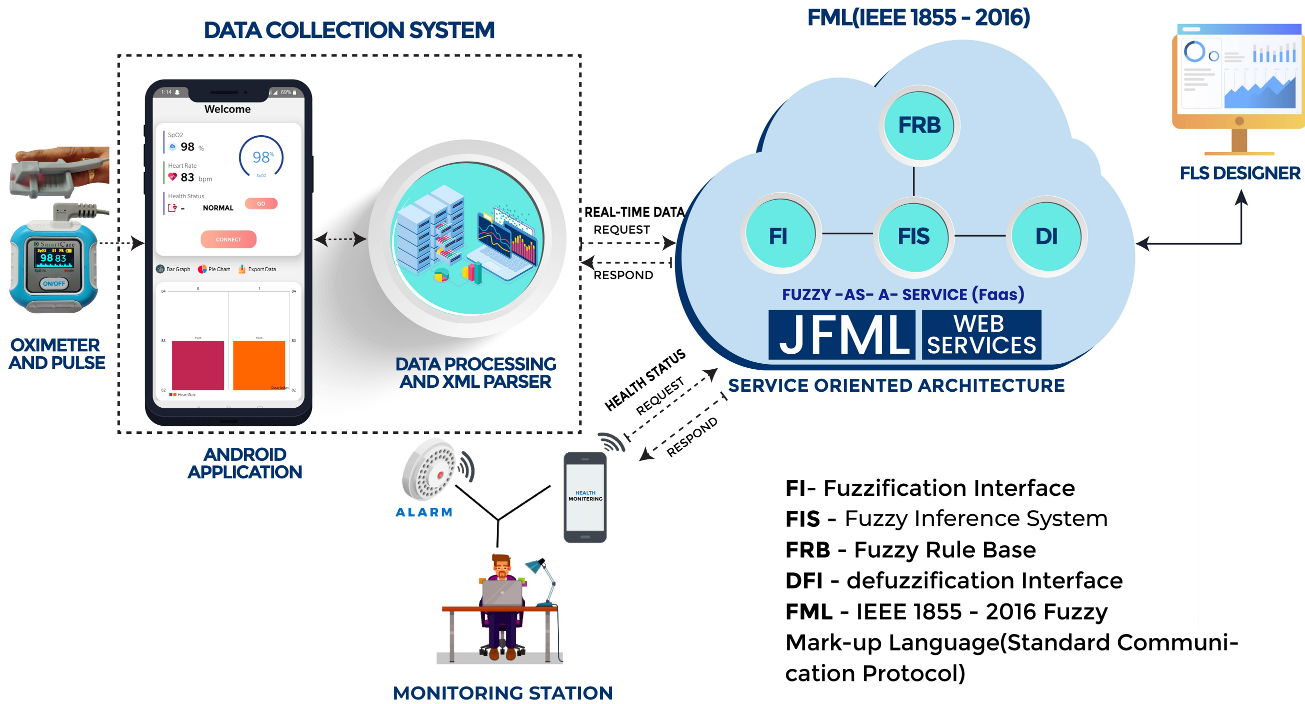

Figure 2: Framework of the proposed architecture including data collection point, data processing, monitoring point, design point and fuzzy logic system

3.2 Data processing

After receiving data from an Android-based wearable device, SpO_2 and heart rate data can be transfer to the cloud server, where Fuzzy Logic System (FLS) file is created. It is required to set the sensor data as input values in the fuzzy system for different variables so that the system can give us the desired output. Two main API function call are designed for data exchange as follows:

setInput(): The API function call “setInput” is used for sending one or more input values to the cloud server. These values are saved at the cloud server so that the fuzzy system can evaluate the end result using the rules stored in its knowledgebase.

getOutput():This API function call is used by the user to receive output values of the FLS by request. The requested output is sent as a fuzzy set or defuzzified values. In getOutput service we intend to find out the result/output of all the data provided in the createFLS and setInput operation. The Fuzzy system evaluates all the input values for the unique URI and based on the rulebase decides the final outcome.

3.3 Fuzzy system implementation

The system architecture is designed to track health conditions using values extracted from heart rate and oxygen saturation which can be used as a health condition measurement system. The wearable device’s output value in the application should be sent and processed using fuzzy logic.

Fuzzification turns input signals into their membership grades to the pre-defined fuzzy sets (critical, alert, low and normal). The system is a dual input system which contains SpO_2 and heart rate, so that the fuzzification is repeated for both inputs. Memberships in a scheme are drawn and every membership is classified as a three turning points with different oximeter values to monitor health condition usually critical in < 30, alert in between > 30 and < 60 and normal in > 60.

- **Fuzzy input set**: SpO_2 is the first input which is fuzzified using four fuzzy sets critical, alert, low and normal. The overall range for SpO_2 is from 0 to 100. Pulse rate is the second input which contains 4 values such as critical, normal, low and alert. The range for pulse rate input is 0 to 180.
- **Compounding**: As shown in Figure.3(a), there are four fuzzy sets associated to oxygen saturation membership, critical which is less than 85%, alert which is between 86% to 90%, low is 91% to 94% and normal is above 95%.
  A membership function of the pulse rate sensor is shown in Figure. 3(b) . There are four fuzzy sets for pulse rate: critical is from 0 to 60 bpm, normal is between 60 bpm to 90 bpm, low is between 90 bpm to 100 bpm and alert is above 100 bpm.

Table 1: Dataset with a few instances of feature-extracted data.

TIMESTAMP (MilliSeconds(MS))	PULSE BPM	SpO_2 PCT	SpO_2 STATUS	PLETH	RED_ADC	IR_ADC	PERFUSION INDEX
0	87	97.7	0	25684	193775	250301	7.8
10	87	97.7	0	27597	193872	249747	7.8
20	87	97.7	0	29524	194064	250321	7.8
30	87	97.7	0	31383	194311	249979	7.8
40	87	97.7	0	33099	194559	251033	7.8
50	87	97.7	0	34598	195154	252450	7.8
60	87	97.7	0	35836	195384	252363	7.8
70	87	97.7	0	36778	195897	253078	7.8
80	87	97.7	0	37403	196275	253831	7.8
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
124490	80	99.4	0	35096	273595	237903	1.4
124500	80	99.4	0	36308	273428	237995	1.4
124510	80	99.4	0	37626	273529	238138	1.4
124520	80	99.4	0	39009	273432	237897	1.4
124530	80	99.4	0	40407	273272	237526	1.4
124540	80	99.4	0	41766	273303	237676	1.4
124550	80	99.4	0	43067	273246	237656	1.4
124560	80	99.4	0	44256	273398	237882	1.4
124570	80	99.4	0	45324	273273	237634	1.4
124580	80	99.4	0	46227	273077	237433	1.4

Table 2: Rules for FLS

No	SPo_2	Pulse	Health Status
1	Critical	Critical	Critical
2	Critical	Normal	Alert
3	Critical	Low	Alert
4	Critical	Alert	Critical
5	Alert	Critical	Critical
6	Alert	Normal	Normal
7	Alert	Low	Normal
8	Alert	Alert	Alert
9	Low	Critical	Alert
10	Low	Normal	Normal
11	Low	Low	Normal
12	Low	Alert	Normal
13	Normal	Critical	Alert
14	Normal	Normal	Normal
15	Normal	Low	Normal
16	Normal	Alert	Normal

A membership function of health status is shown in Figure. 3(c). There are three fuzzy sets for health status, critical is from 0 *bpm* to 30 *bpm*, alert is from 30 *bpm* to 60 *bpm* and normal is from 60 *bpm* to 100 *bpm*.

Rule Base: To perform this experiment, a total of 16 rules are created for identifying health status of human. (table:2).

Defuzzification: Defuzzification is the method that transforms a fuzzy output set into a crisp value. According to the inputs, fuzzy sets and rulebase, the output of the fuzzy system offers three classes, i.e., critical, alert and normal. Figure 3(c) shows the memberships grades for these three output fuzzy sets. The well-known centroid defuzzification method is used to convert the fuzzy output to crisp values. Once this is created, any output below 30 is considered to be critical, between 30 to 60 is considered to be alert and above 60 is treated as normal.

3.4 Software Oriented Architecture

It is a collection of software modules that are autonomously linked, coupled loosely and reusable. Users who have little or no dependency on software and hardware typically use SOA [14]. In our architectural solution, SOA is a web-based service that distributes the main services for fuzzy logic systems on more than one client and servers that can reach multiple users. This is why it is called Fuzzy-as-a-Service (FaaS). FaaS possesses the following built-in flexibility's:

a) Cloud service is created independent of a single fuzzy logic system.
b) Several fuzzy logic systems can be handled concurrently.

Additional details about SOA, how data transmission takes place to the system by the sensors (i.e. IoT), and how this data is stored on the cloud can be found in [9],[15],[16].

IEEE 1855-2016 is an XML-based language that facilitates the modelling of an FLS in a human-understandable, platform-independent

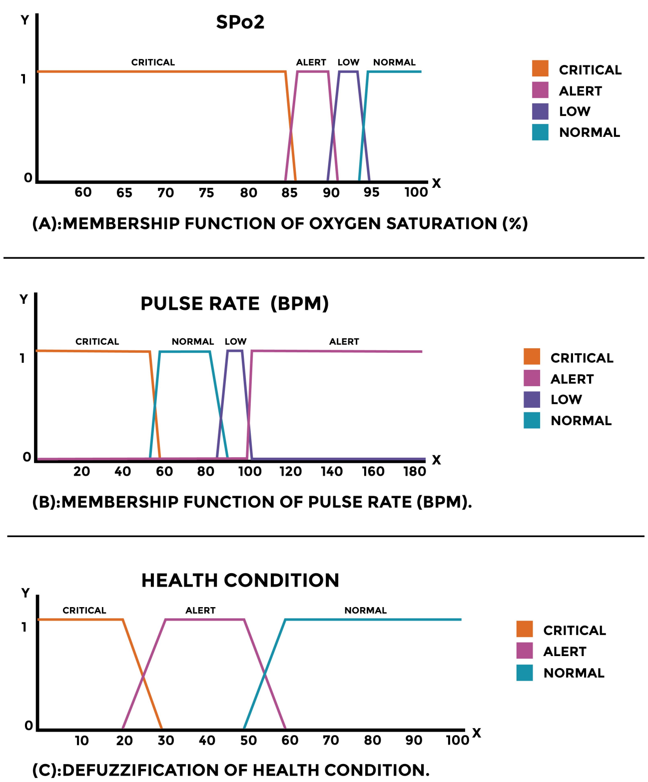

Figure 3: Membership for fuzzy inputs:(a) SpO_2 **(b) Pulse rate and membership for output (c) Health Condition [19]**

and web-compatible format, and it is provided in [2] and standardised in [1]. JFML is a new FML-based open-source library (IEEE 1588-2016) for fuzzy logic computations. A Web application server is built to serve the necessary HTTP messages to/from clients according to the FaaS model. JFML was used by [21] on the built-in application server for fuzzy logic computation. The framework utilises Apache Tomcat as the default Java server application. This configuration is entirely on the AWS server-side, and can be used for various purposes, especially in smart environments where client agents are sensors and/or actuators and monitoring stations.

4 EXPERIMENTAL RESULTS

In this study, the wearable sensor BM2000A wrist pulse oximeter was used to collect real-time data. The data is collected from four participants with the aim to test the architecture. The collected real-time data passed to the server through an android application which evaluates the result based on the fuzzy rules set. Figure. 4(a) shows the health status to be critical when SpO_2 value is 88% and heart rate is 55 bpm (beats per minute), which is very low as per fuzzy calculation. Figure 4(b) shows the health status to be normal when SpO_2 value is 98% and heart rate is 90 bpm as per fuzzy calculation. Figure 4(c) shows how alert is displayed for a health

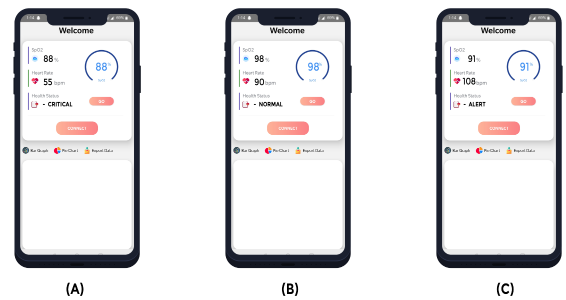

Figure 4: Real-time human health monitoring and processing result a) Critical b) Normal and c) Alert.

status when SpO_2 value is 91% and heart rate is 108 bpm, which is obtained as per fuzzy calculation.

A dataset from Kaggle.com, comprising parameters such as heart rate, temperature and oxygen was taken into account. The dataset generated the result in boolean values where 0 indicated health to be critical and 1 indicated health to be normal.

In our study, two parameters were considered, namely SpO_2 and heart rate, to determine health status. The dataset generated the result in three states, i.e. critical, alert and normal. In addition, the values of illness dataset were used in our study to acquire a real-time health status. The use of the illness dataset's values exhibited similar results to a great extent.

5 CONCLUSION AND FUTURE WORK

This study offered a cloud-based real-time application that monitored oxygen saturation and heart rate using fuzzy-as-a-service. A novel fuzzy logic algorithm was used to detect a human's medical condition with the help of a real-time wearable sensor and cloud-based web services. The sensor tracks a human's day-to-day activities or tasks. SpO_2 and pulse rate were the two major factors that were considered from wearable sensors. The novelty that was followed in this study was that an IEEE1855-2016 algorithm was used in real-time along with fuzzy logic for managing sensor information. Moreover, the study included the use of fuzzy-as-a-service [15], [16] and real-time monitoring of activities, which were previously not conducted in wearable sensors.

As future work directions, the developed system can be extended to detect the symptoms of COVID-19 by utilising temperature, heart rate, and SpO_2 sensors. Also, fuzzy services such as fuzzy querying about fuzzy databases or fuzzy ontologies can be considered for monitoring oxygen saturation and heart rate. Moreover, expanding web services to semantic web services would be beneficial due to the close association between fuzzy markup language and fuzzy ontologies.

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