# Smart Patient Monitoring System

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Patients in ICU are meant to be monitored often and treated accordingly. In the case of diseases like COVID-19, patient health monitoring becomes an essential part. Instant changes in patient vital signs might produce different results in their body conditions. In current systems, nurses are often required to be with the patients to monitor and track their health condition. Due to this, it becomes hectic for the nurses to monitor all the patients at all times. The current system makes the nurses' tasks difficult to manage. But this problem is fixed by the proposed system, thereby reducing the activity. The proposed framework consists of IoT nodes (sensors that collect data), a (mobile) smartphone application, and machine learning tools that estimate patient mortality based on vital signs. The IoT node tracks the patient's vital signs such as temperature, oxygen saturation, and heart rate, updates the mobile application, and displays the user's health with a "normal" or "critical" condition. The application reports the patient's conditions to the nurses immediately with an alarm if the patient reaches a "critical" condition. This automation system takes care of monitoring the patients from anywhere at any time.

**Keywords**: ICU, COVID-19, $SPO_2$.

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## 1 Introduction

With the advancement in the medical field, it is essential to provide health care services online via mobile applications, web applications, etc. Internet of Things (IoT) plays an important role in health care applications. There are various kinds of applications evolving day by day for our health and well–being such as fitness trackers, chatbots, mobile app for video consultation. ICU Patients are meant to be monitored often and treated accordingly. Instant changes in patients' vital signs might produce different results in their body condition so it becomes crucial to monitor the patients often. Vital signs are the indicators of the patient's life-threatening functions in the ICU. The vital signs considered for the ICU patients include Body temperature, Oxygen Saturation SpO2 – peripheral capillary oxygen saturation, Heart rate, Blood Pressure, Glucose level, and Respiratory rate. Through continuous monitoring of the vital signs, clinical deteriorations can be identified well in advance. In general, Blood Pressure is monitored every 1 to 4 hours, Heart rate is monitored for every 1 hour, Temperature is monitored for every 8 hours, respiratory rate is monitored for every 1 to 4 hours andSpO2 is monitored continuously. However, these monitoring strategies vary based on the condition of the patient. Body temperature is that the balance between heat made and heat lost. Infection, Age, Gender, Food, Fluid consumption, Skin exposure, and the stage of the menstrual cycle for women are the factors affecting the body temperature. The normal body temperature of a healthy individual is considered to be 36.8°C ± 0.4°C [98.2°F ± 0.7°F] (measured in the oral cavity) with natural variations of 0.5°C (0.9°F). Usually, we can take 97.7 F to 99.5 F as normal body temperature. Saturation of Peripheral oxygen (SpO2) is a measure of the percentage of oxygen-saturated hemoglobin and is measured by measuring the ratio of oxygenated hemoglobin to the total amount of hemoglobin in the blood by an oximeter or a blood test. This is influenced by the movement of thepatient, incorrect positioning of the probe, Hypothermia, nail polish. Oxygenated hemoglobin absorbs more infrared light and transmits more red lights. Deoxygenated hemoglobin absorbs more red lights and transmits more infrared light. The ratio of absorbed red light to absorbed infrared light(R / IR) varies depending on the amount of oxygenated or deoxygenated hemoglobin. Normally, an R / IR ratio of 0.5 corresponds to about 100% SpO2, a ratio of 1.0 to about 82% SpO2, and a ratio of 2.0 corresponds to 0% SpO2. SpO2 value is between 98% and 100% for healthy people. 95% - 97% is the tolerable value but it is insufficient. Heart Rate is defined as the number of beats per minute and it is calculated through a pulse oximeter sensor module by getting the time between rising and fall of oxygenated blood. When the heart pumps the blood, there flows more blood, thereby the oxygen level is increased. But, when the guts rest, there's a decrease in oxygenated blood. Heart rate varies depending on age. 60 – 100 bpm is the normal heart rate for healthy adults. For infants, it is 120 – 160 bpm and for adolescents, 60 – 90 bpm is considered a normal heart rate level. This paper proposes a system to monitor body temperature, heart rate and SpO2 oxygen saturation through sensors and transmit data via WiFi module which nurse can see from mobile application and is an additional feature; the system predicts the mortality of a patient.

## 2 Related Works

Islam et al. [1] proposed a personalized smart medical system in an IoT environment that could monitor a patient's basic health signs such as heart rate, body temperature as well as room status such as temperature and humidity, CO and CO2 levels where the patient is in real time. They collected the data by using sensors and transferred the data to the ThingSpeak website through the ESP32 WiFi module. The patient's details were displayed on the ThingSpeak website that can be seen by the medical staff after authentication. They tested the system on different subjects under different conditions and compared real and manually observed data on body temperature, heart rate, and room temperature, with a success rate of over 95%.

Vedaei et al. [2] proposed a framework that monitors user health and requires users to maintain physical distance using wearable IoT devices, smartphone applications, and fog-based machine learning tools for data analysis. They used Raspberry PI Zero for collecting health data from sensors and utilized Application Programming Interface (API) to interact with the users on the smartphone application and decision-making system on the fog server for processing the data. They showed a map with different zones along with risks and compared their method with support vector machines, decision trees in terms of accuracy, and F1 score. High accuracy and F1 score were achieved for the proposed method.

Akkas et al. [3] proposed Healthcare and patient monitoring using IoT. They focused on key components of the medical IoT system architecture, from patient monitoring to management and tracking applications. The system consists of five key components: Body sensor network (BSN) nodes, a processor, a central web server, a patient database, and a PC. The Wireless Electrocardiography (ECG) and Pulse Oximeter (SpO2) sensors integrate with other more common sensors and are mounted on a dedicated wireless card to create a BSN loop. The PC is equipped with an interface for recognizing and managing incoming patient sensor data. Finally, they have developed software that allows us to send the information we need to the relevant medical staff, and then the data collected in the central database can be viewed by the medical staff. In this system, which works with triggered queries to the central database, the error rate is less than 5.97%.

Choyon et al. [4] proposed an IOT based health monitoring system using machine learning for the severity prediction facing COVID-19 disease based on the symptoms and real-time natural biological information. They used Arduino, Raspberry PI and Computer vision techniques to train the Raspberry Pi for analyzing the data. Healthcare professionals receive necessary analyzed data from the cloud network and send the necessary instructions for the patient through the network. They established a low-cost system with significant efficiency. They found that logistic regression gave better results than other classifiers which showed 85% accuracy for training data and 85.71% accuracy for validation data.

Ghosh et al. [5] are proposed an IoT Based Real-Time Smart Patient Monitoring Vest. They have developed a system that provides the ability to monitor patients wirelessly using a single jacket. This allows patients to complete their day-to-day tasks without the hassle of bulky surveillance devices. It consists of a Broadcom BCM2837 processor with a built-in WiFi connection to speed up data transfer. Biological signals are sent via the Google Firebase cloud system and fetched into Android apps built with the Google Firebase API. Acquiring patient data with the Android app increases the robustness of the emergency system and gives patients the freedom to participate in their daily lives. It consumes very little power and the cost is very efficient.

Alghatani et al. [6] built two predictions models to predict mortality and ICU length of stay by leveraging six binary classification algorithms such as random forest, support vector machine (SVM), k nearest neighbors (kNN), Linear regression, Linear discriminant analysis and extreme gradient boosting (XGB) algorithms. These models are used for monitoring the health status of patients and generating alerts. The researchers used Medical Information Mart for Intensive Care (MIMIC) database to extract the dataset and prepared the required dataset through Structure Query Language (SQL) queries. By analyzing the results based on sensitivity and considering only vital sign data, not the patient's medical history, they achieved 85% accuracy in mortality prediction and 65%accuracy in ICU length of stay.

# 3 Methods

Continuous monitoring of vital signs is the main idea of the proposed system. The overall architecture of the system is shown in Fig1. From Fig1, it can be seen that the patient’s vital sign data collected from sensors such as Temperature sensor, Max 30100 Pulse oximeter heart rate sensor modules are connected to the Node MCU ESP32 processor. The collected data is stored in the Firebase cloud via the ESP32 WiFi module. After creating an account and logging into the mobile application, the nurses can select the wards and patients for which they want to see the vital sign details. Once after selecting the appropriate patient, their respective vital signs details are fetched from the firebase cloud and rendered in the mobile app. Based on the threshold value of every vital sign, the condition of the patient is displayed as either “normal” or “critical”. If the patient is in a critical condition, an automatic alert will be sent in the form of a notification to the nurse. We can predict the patient’s mortality using the data generated.

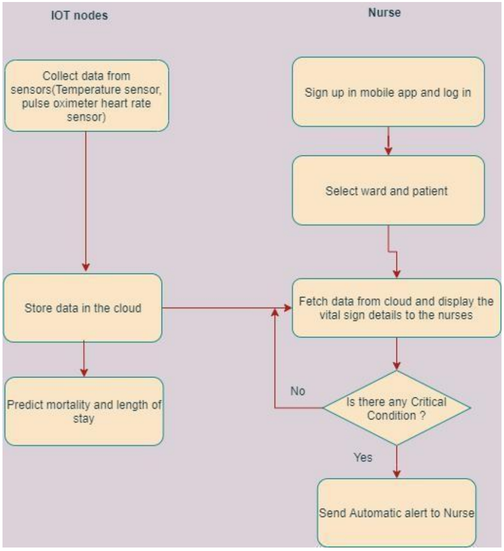


**Fig. 1.1.** The overall system architecture of the smart patient monitoring system

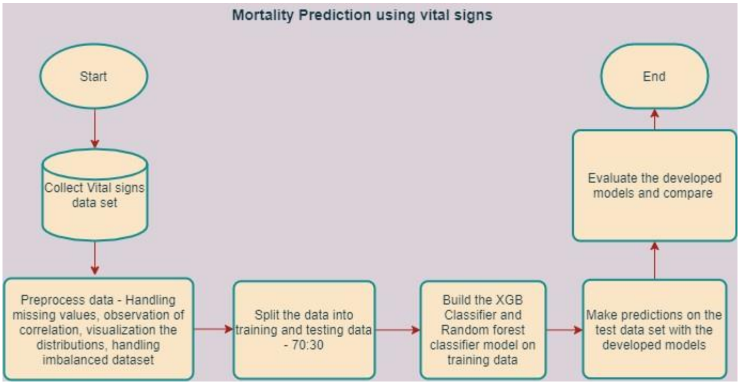


**Fig. 1.2** Mortality Prediction using Vital signs work flow

# 4 Implementation

The system is implemented using various hardware components. All sensors are connected to the node MCU via pins and jumper wires. As the Node MCU ESP 32 has a built-in WiFi module, it is used as a processing device. The circuit diagram of the developed system is shown in Fig2. The Vcc and GND pins of all the sensors are connected with the Vcc and GND pins of Node MCU. The data pin of the LM35, which is a temperature sensor, is connected to the A0 pin of the microcontroller node MCU. The SCL and SDA pins of the Max30100 pulse oximeter heart rate sensor module are connected to pins D1 and D2 of the node MCUE SP32 module, respectively.

The sensor data collection and processing are done with the help of Arduino IDE. The data is stored in Firebase real time data base. Libraries used for sensors are listed below.

- MAX30100_PulseOximeter.h
- MAX30100.h
- ESP8266WiFi.h
- FirebaseESP8266.h
- DateTime.h

The mobile application is developed using android studio platform with Java as the programming language. It consists of the front-end design of the mobile application and integration of the sensor data from the firebase cloud real-time database. The mortality prediction module using XGBoost and Random Forest algorithm is done by using Python in the Jupyter notebook environment. The libraries that are used as part of the implementation are listed below.

**(i) Pandas** – is used for data manipulation and for collecting basic information. It is an open-source, flexible, powerful, and fast library built on top of the Python Programming language.

**(ii) NumPy** – is used for handling missing values and array-based operations as it provides support for multi-dimensional arrays and matrices. It also provides various mathematical functions, random number generators.

**(iii) Matplotlib** – is a cross-platform library used for 2D plotting from the array data. It is a widely-used Python package for data visualization.

**(iv) Seaborn** – is another data visualization library based on Matplotlib and is used for making count plots, heatmap of correlation, and confusion matrix for the developed model.

**(v) Sklearn (Scikit – learn)** –is used for handling missing values splitting training, test data, classification model development, and getting evaluation metrics as it is the most useful library for machine learning in python that provides efficient tools.

**(vi) imblearn (Imbalanced – learn)** – is an open source library relying on scikit–learn which provides techniques to balance the data set in order to make the ratio of the classes equal.

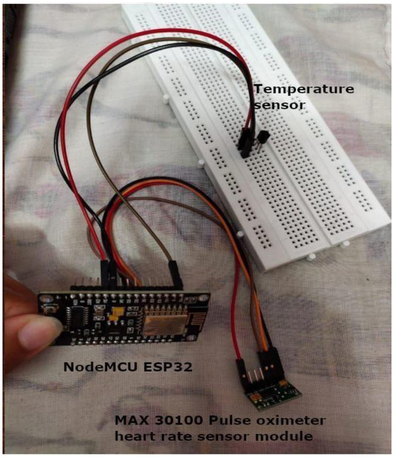


**Fig. 2.** Circuit diagram

# 5 Results

We have taken data set which consists of 51 attributes including class variable and we have chosen 13 attributes namely Group, id, age, gender, BMI, diabetes, heart rate, systolic blood pressure, diastolic blood pressure, respiratory rate, body temperature, SpO2. We handled missing data by replacing the mean value for the independent float variables and the most frequent value for the dependent variable. With the help of visualization, we found that our data set is imbalanced. So, we used the Synthetic Minority Oversampling Technique (SMOTE) to get the balanced data set. Then we split the data into training and testing data at a ratio of 70:30. We built XGBoost classifier model and Random Forest classifier model. We obtained 85% accuracy, 84% for F1 score and 0.92 for AUC in XGBoost classifier model and 81% accuracy, 81% F1 score, and 0.90 for AUC in Random Forest Classifier model. The performance evaluation metrics are presented in the table 1 and also it is illustrated in fig 3. The Extreme Gradient Boosting (XGB) algorithm outperformed well for mortality prediction based on the vital signs.

**Table 1.** Mortality Prediction model performance evaluation

| Algorithm | Accuracy | Recall | AUROC |
|---|---|---|---|
| XGBoost | 0.85 | 0.87 | 0.92 |
| Random Forest | 0.81 | 0.77 | 0.90 |

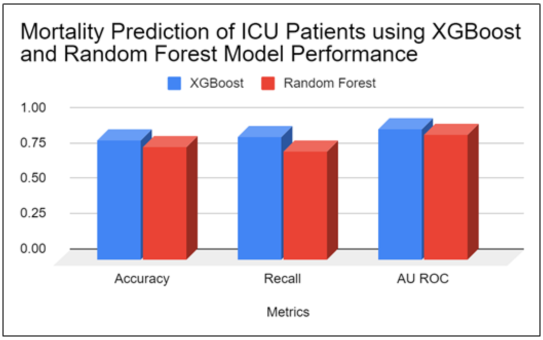


**Fig. 3.** Mortality Prediction model performance evaluation graph

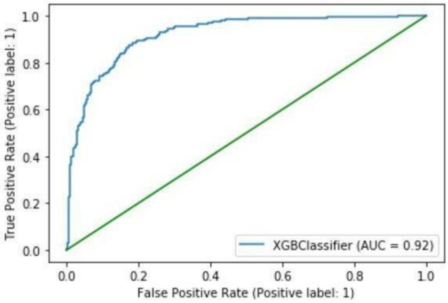


**Fig. 4.1** AUROC curve in mortality prediction using XGBoost classifier

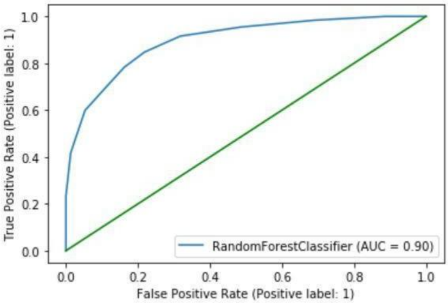


**Fig. 4.2** AUROC curve in mortality prediction using random forest classifier

Comparison of our implementation with the existing system available in the literature based on some factors presented in Table 2 and performance metrics comparison presented in Table 3 and also depicted as a graph in fig 4.3

**Table 2.** Comparison of our system with the existing system available in the literature

| Factors | Our system | Existing system |
|---|---|---|
| **Consideration of vitalsigns for measurement** | Body temperature, Heart Rate, Oxygen Saturation | Body temperature, Heartrate and room humidity |
| **Display** | Custom mobile app with the vital signs details | Thing Speak cloudservice website |
| **Considered Algorithm for mortality prediction** | Extreme Gradient Boosting (XGB), RandomForest | Extreme Gradient Boosting (XGB), LogisticRegression, k Nearest Neighbors, Random Forest, Linear Discriminant Analysis (LDA), Support Vector Machines (SVM) |

**Table 3.** Comparison of mortality prediction using XGBoost model performance metrics for our system and existing model found in literature survey

| Metrics | Our XGBoost model | Existing XGBoostmodel found in literature survey |
|---|---|---|
| **Accuracy** | 0.85 | 0.88 |
| **Sensitivity (Recall)** | 0.87 | 0.14 |
| **AU ROC** | 0.92 | 0.78 |

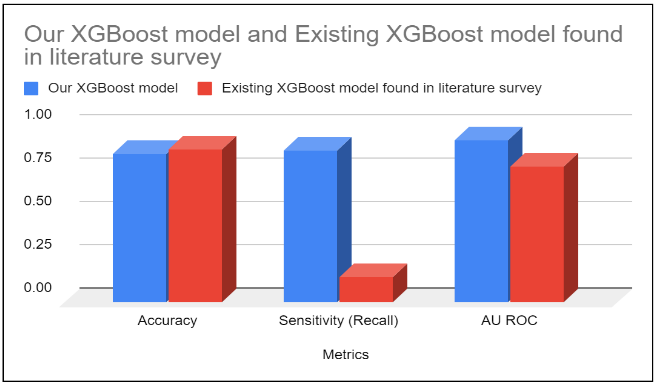


**Fig. 4.3** Performance metrics comparison for the classifier used in our system with the existing system found in literature

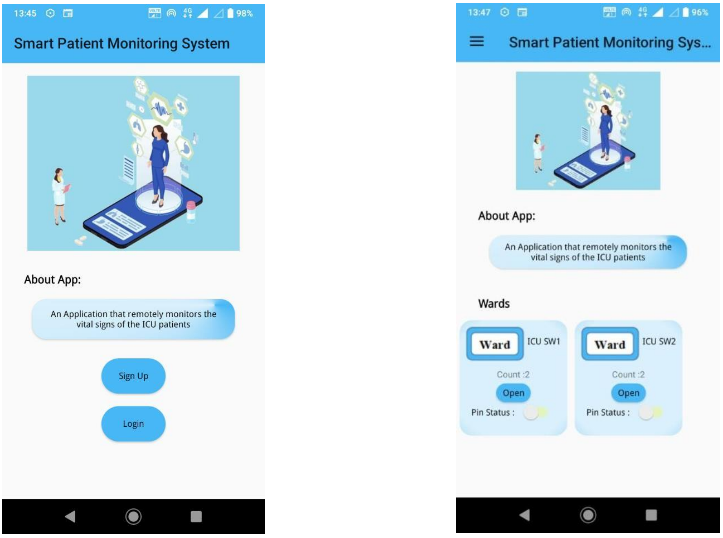


**Fig 5.1** Home page of the application (Left side: Before login, Right side: After login)

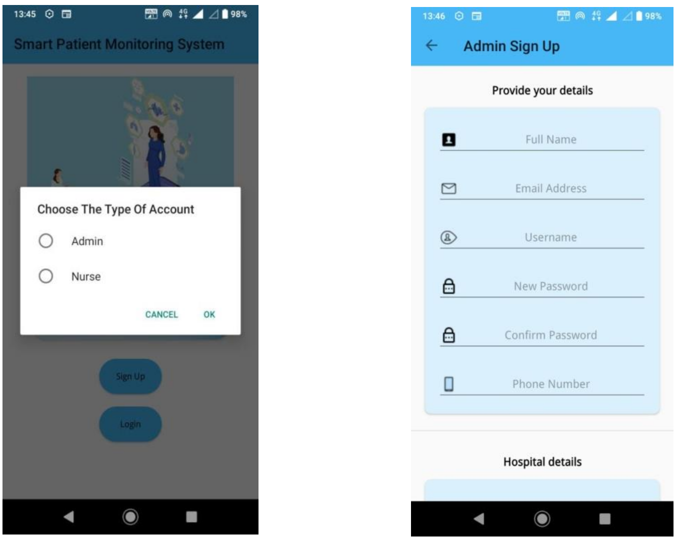


**Fig 5.2** Alert box to select the type of account to sign up and Admin sign up page

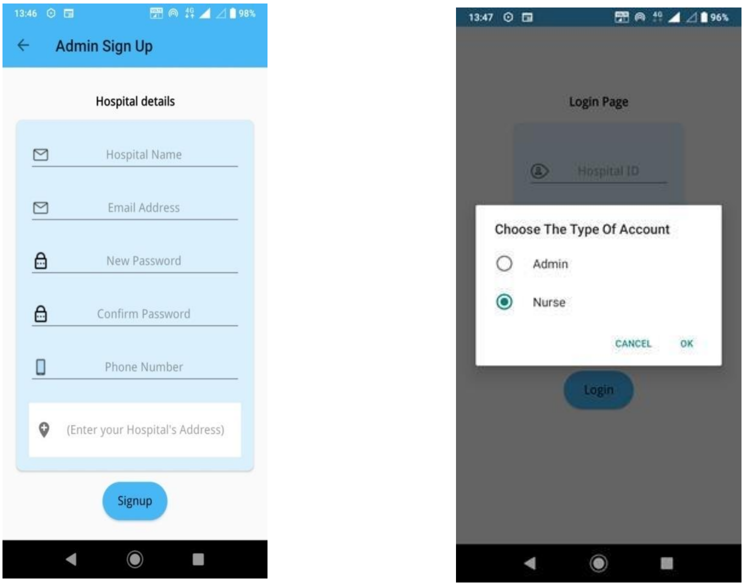


**Fig 5.3** Admin sign up page and Login page with alert dialog to choose the account type to login

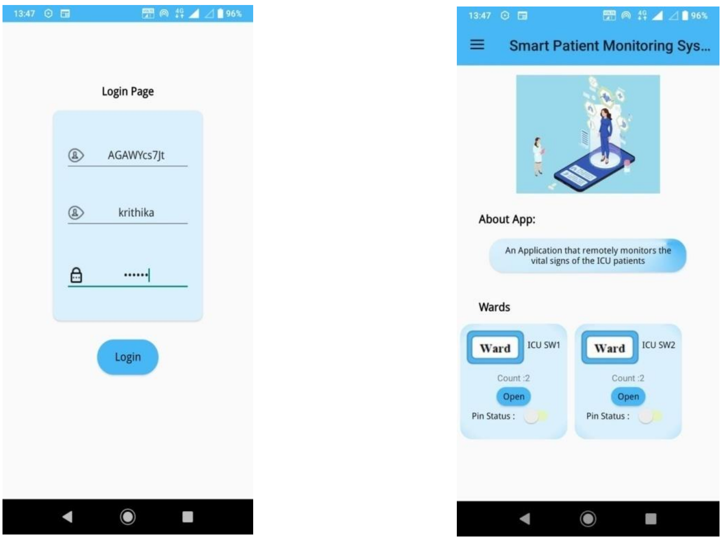


**Fig 5.4** Nurse Login page and Home page after logged in

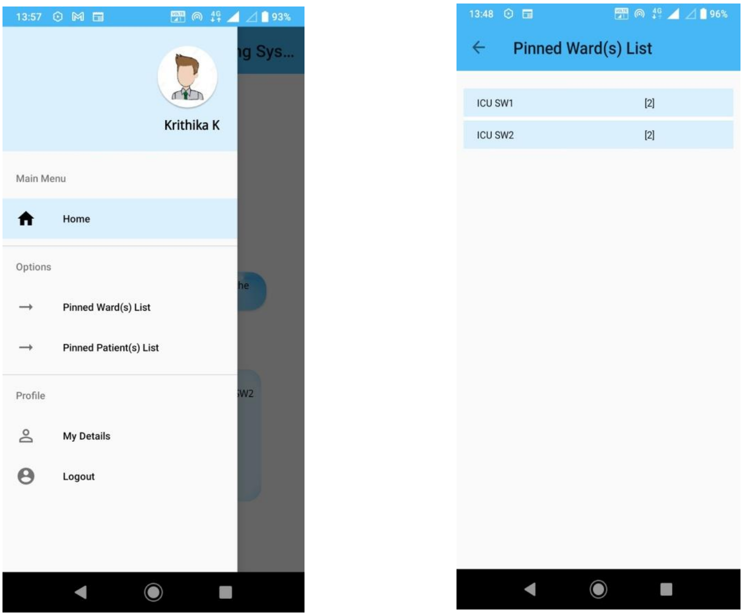


**Fig 5.5** Profile page and Pinned Wards list

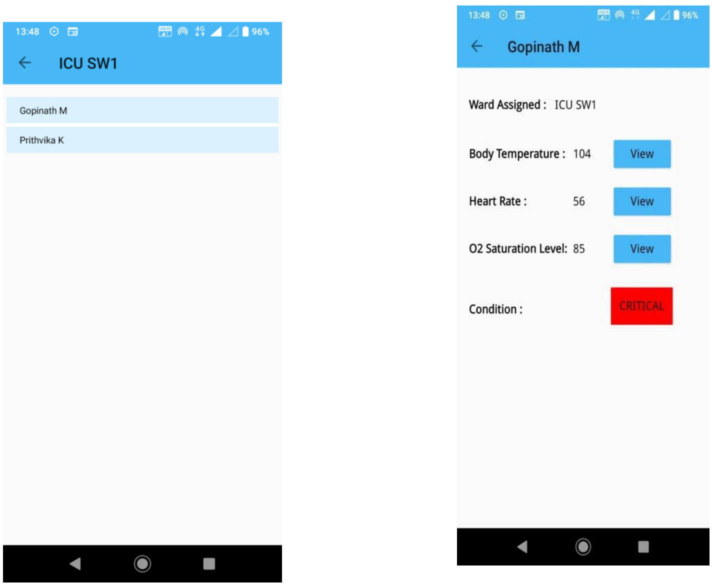


**Fig 5.6** ICU SW1 ward page and Patient Gopinath's page

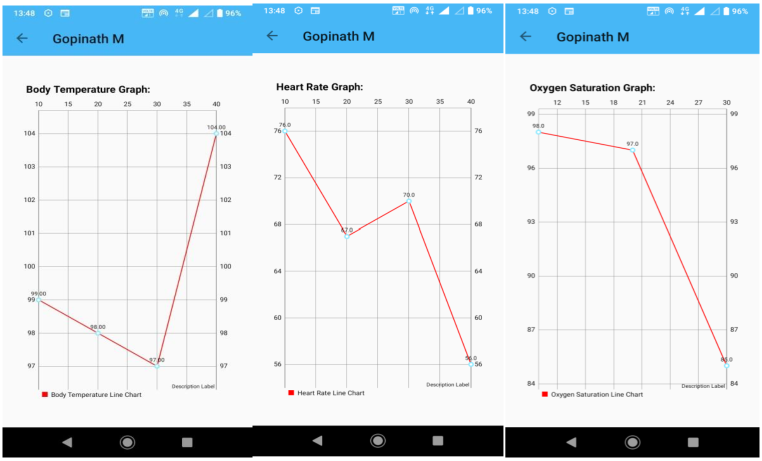


**Fig 5.7** Graphs of Body temperature, Heart rate and Oxygen saturation of the patient

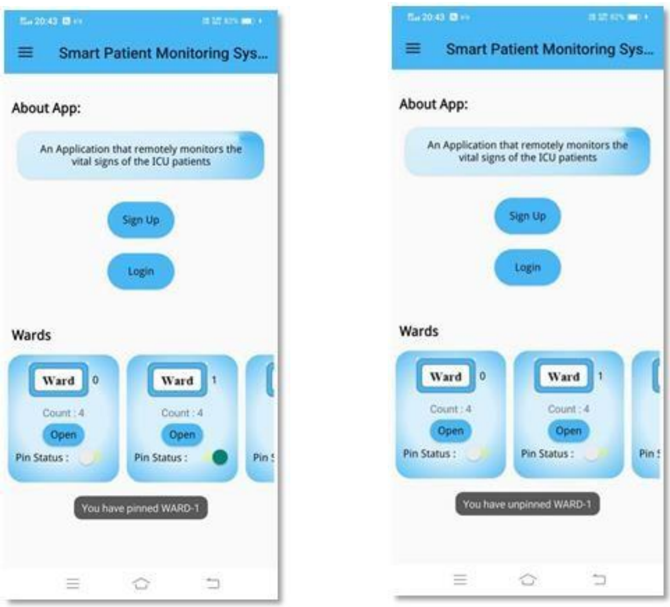


**Fig. 5.8.** Pin and unpin functionalities in the home page of nurse

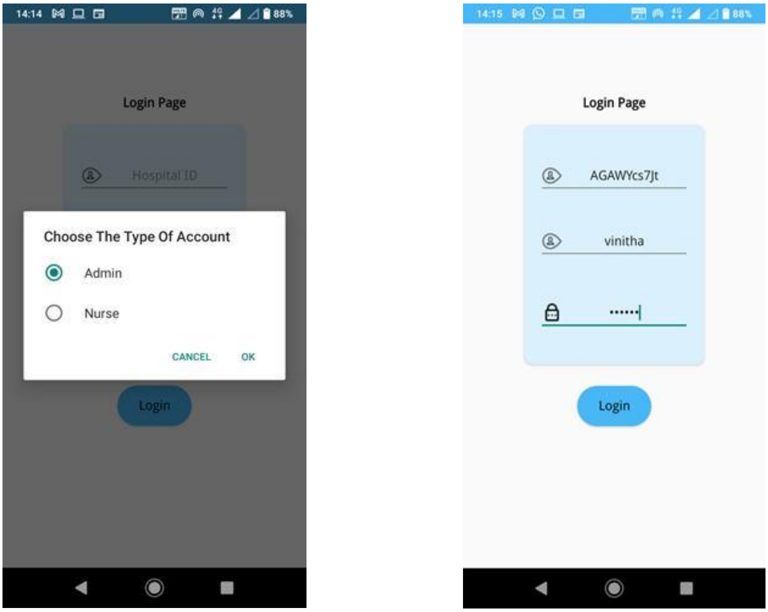


**Fig 5.9** Admin Login page of the application

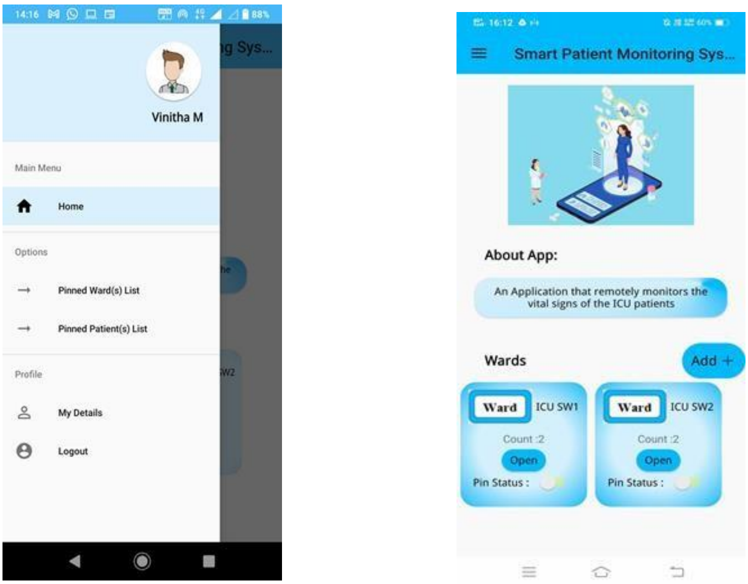


**Fig 5.10** Admin Profile page and home page along with Add+ button

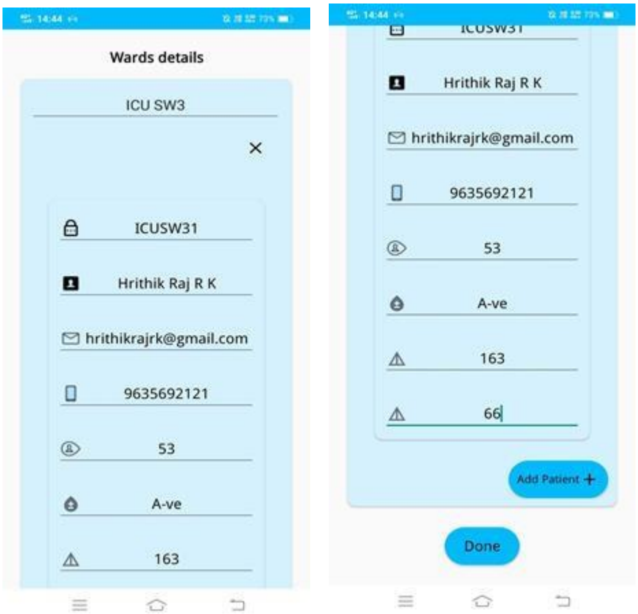


**Fig 5.11** Adding patient in the ward

The vital signs details are displayed correctly from the sensors and the charts are updated accordingly. In mortality prediction we have taken a data set which consists of 51 attributes including class variable and we have chosen 13 attributes namely Group, Id, age, gender, BMI, diabetes, heart rate, Systolic blood pressure, Diastolic blood pressure, Respiratory rate, temperature, SpO2. We handled missing data by replacing mean value for the independent float variables and most frequent value for dependent variable. With the help of visualization, we found that our data set is imbalanced. So, we used the Synthetic Minority Oversampling Technique (SMOTE) to get the balanced data set. Then we splitted the data into training and testing data at a ratio of 70 : 30. We built the XGBoost classifier model and Random Forest classifier model. We obtained 85% accuracy, 84% for F1 score and 0.92 for AUC in XGBoost classifier model and 81% accuracy, 81% F1 score and 0.90 for AUC in Random Forest Classifier model.

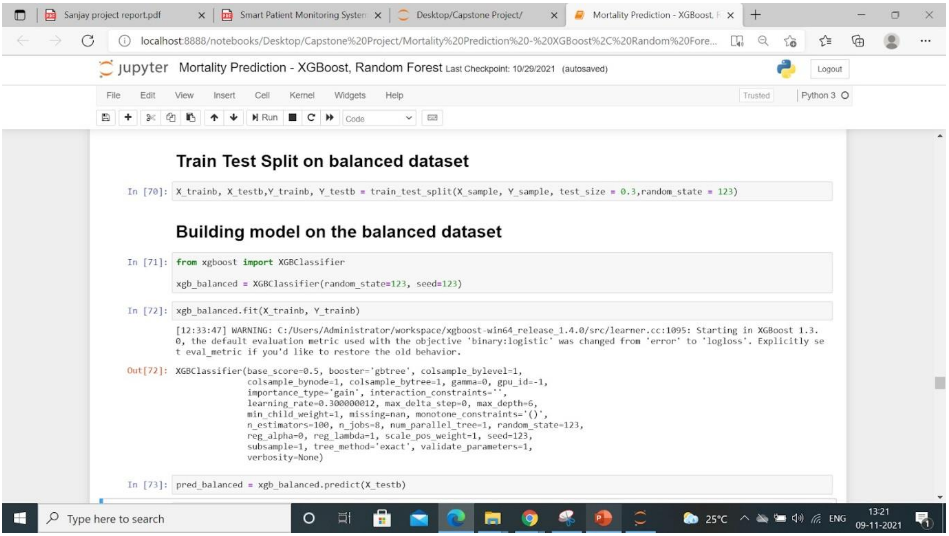

**Fig 5.12** Building model using XGB Classifier

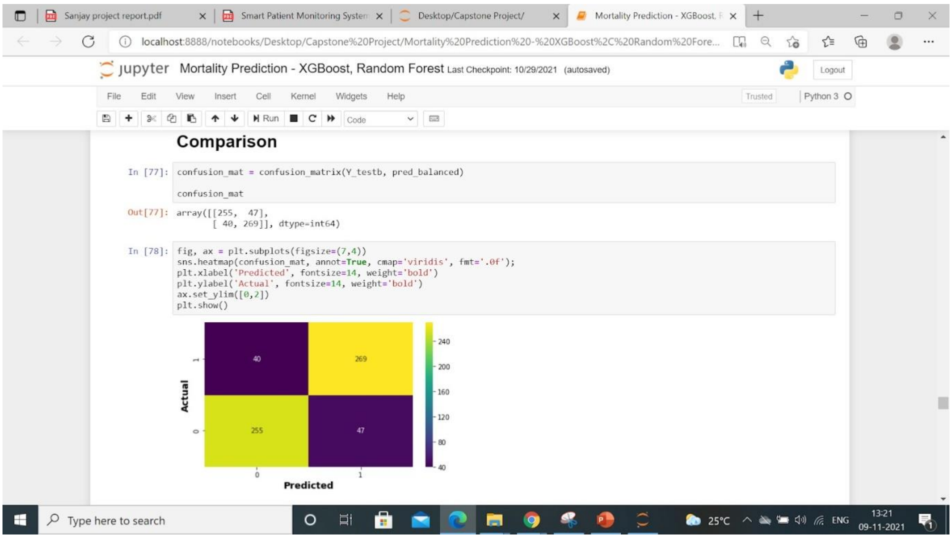

**Fig 5.13** Confusion matrix

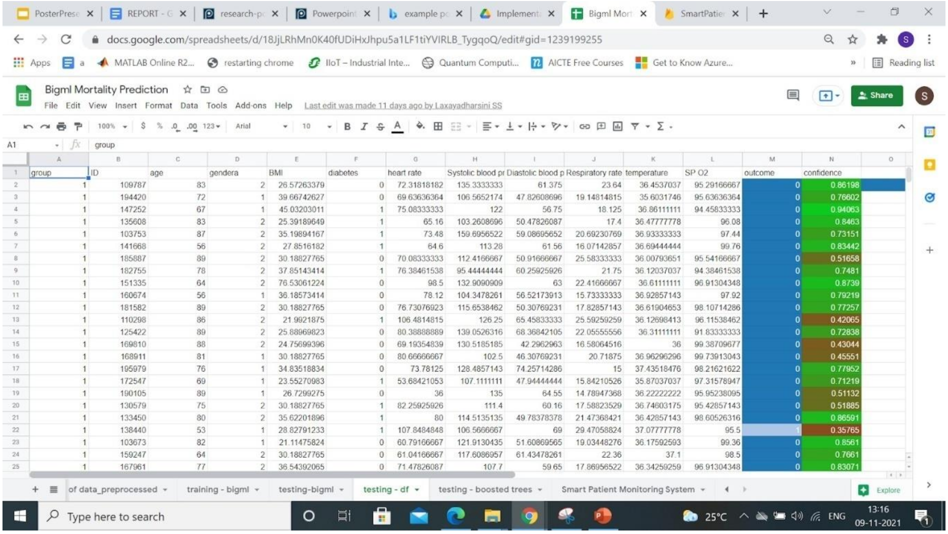


Fig 5.14 Mortality prediction for testing dataset in google sheets using BigMl

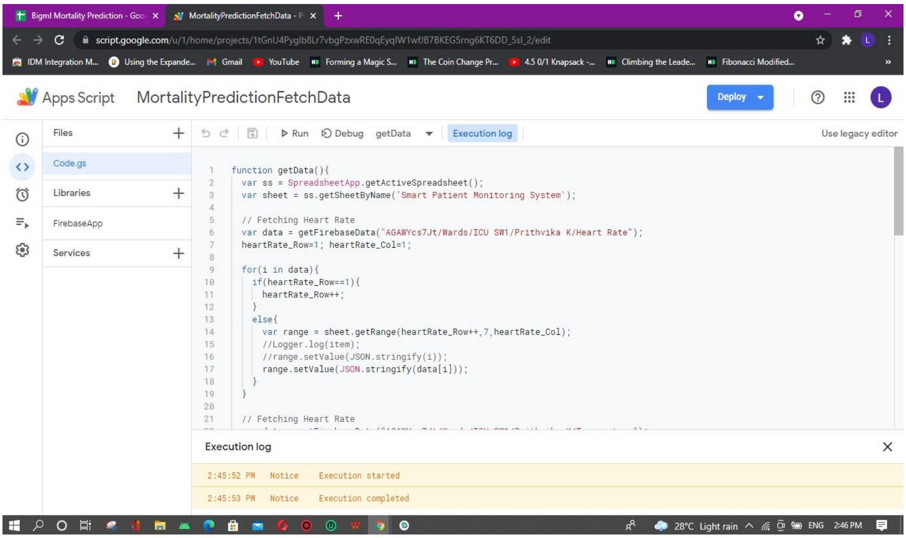


Fig 5.15 Code to fetch data from Google sheet through Apps Script

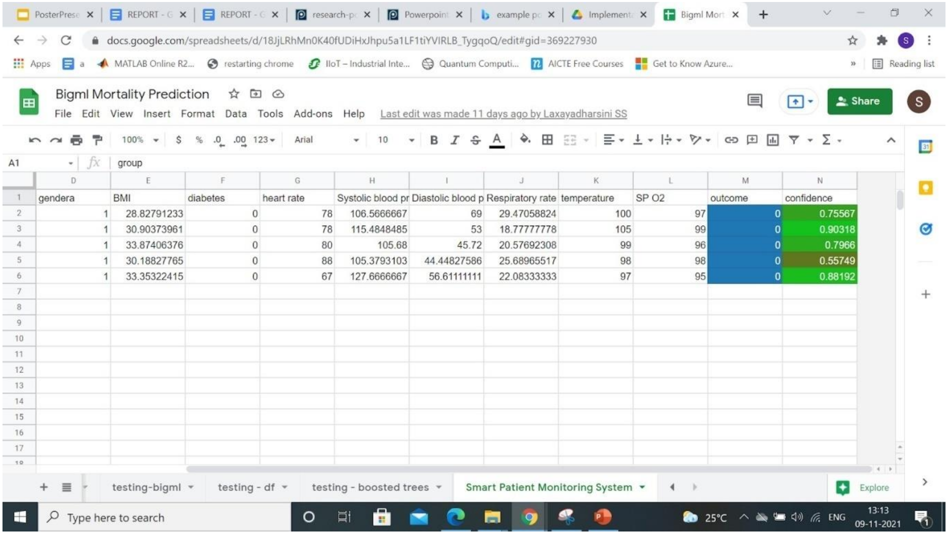

**Fig 5.16** Predicting mortality along with confidence for real time data

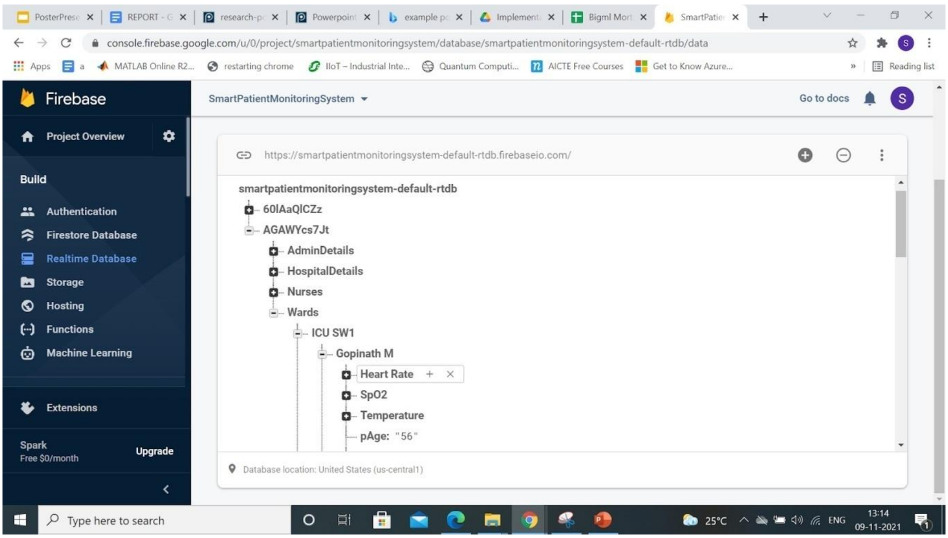

**Fig 5.17** Data in firebase

## 6 Discussion

Thus, the developed smart patient monitoring system enables the nurses to monitor the vital signs of the patients such as body temperature, heart rate, and SpO2 from anywhere and at any time through mobile application after authentication. So that they can easily and quickly communicate with the physicians in case the patient reaches a critical condition. As a result, better treatment can be given to the patients appropriately. The machine learning model helps the hospital management to know about the mortality of the patients which will guide them to allocate Intensive Care Units further. The developed system will be an improvement over the current healthcare system saving huge peoples' lives. Some measurements that are important in determining a patient's condition, such as respiratory rate and blood pressure monitoring, can be addressed for future work.

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