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RESEARCH ARTICLE

IoT-based Ubiquitous Healthcare System with Intelligent Approach to an Epidemic

Subasis Mohapatra[1], Mannava Yesubabu[2], Amlan Sahoo[1], Subhadarshini Mohanty[1] and Sachi Nandan Mohanty[3,*]

[1]*Department of Computer Science & Engineering, Odisha University of Technology and Research, Bhubaneswar, Odisha, India;* [2]*Department of Computer Sc & Engineering, Vardhaman College of Engineering (Autonomous), Hyderabad, India;* [3]*School of Computer Engineering (SCOPE), VIT-AP University, Andhra Pradesh, India*

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Abstract: The recent pandemic has shown its different shades across various solicitations, especially in the healthcare sector. It has a great impact on transforming the traditional healthcare architecture, which is based on the physical approaching model, into the modern or remote healthcare system. The remote healthcare approach is quite achievable now by utilizing multiple modern technological paradigms like AI, Cloud Computing, Feature Learning, the Internet of Things, *etc*. Accordingly, the pharmaceutical section is the most fascinating province to be inspected by medical experts in restoring the evolutionary healthcare approaches. Covid 19 has created chaos in the society for which many unexpected deaths occur due to delays in medication and the improper prognosis at an irreverent plan. As medical management applications have become ubiquitous in nature and technology-oriented, patient monitoring systems are getting more popular among medical actors. The Internet of Things (IoT) has achieved the solution criteria for providing such a huge service across the globe at any time and in any place. A quite feasible and approachable framework has evolved through this work regarding hardware development and predictive analysis. The desired model illustrates various approaches to the development of a wearable sensor medium that will be directly attached to the body of the patients. These sensor mediums are mostly accountable for observing body parameters like blood pressure, heart rate, temperature, *etc*., and transmit these data to the cloud storage via various intermediate steps. The storage medium in the cloud will be storing the sensor-acquired data in a time-to-time manner for a detailed analysis. Further, the stored data will be normalized and processed across various predictive models. The model with the best accuracy will be treated as the resultant model among the numerous predictive models deployed in the cloud. During the hardware development process, several hardware modules are discussed. After receiving sensor-acquired data, it will be processed by the cloud's multiple machine-learning models. Finally, thorough analytics will be developed based on a meticulous examination of the patients' cardinal, essential, and fundamental data and communicated to the appropriate physicians for action. This model will then be used for the data dissemination procedure, in which an alarm message will be issued to the appropriate authorities.

Keywords: Internet of Things(IoT), predictive analytics, sensor network, healthcare unit, sink node, data analysis, data dissemination; ubiquitous model.

1. INTRODUCTION

In many emerging chunks of the world, where more than three billion people live in rural areas, achieving integral equity in modern healthcare for all individuals is one of the most significant difficulties nowadays. There are numerous hurdles to providing equal medical treatment in these areas. There is a professed dearth of modern healthcare facilities in their immediate surroundings, both in terms of diagnostic equipment and medical actors [1, 2]. As many general practitioners are reluctant to serve in distant areas, most medicare institutions and the availability of modern facilities and scientific equipment are severely hampered [3]. Most sufferers in those concerning areas spend the majority of their day traveling to the nearest healthcare facility, which makes routine screening and examinations difficult. Making arrangements along with facilitating crucial times while in pain and attending the hospital, present an expensive burden for rural inhabitants who are mostly low-income and rely on daily pay. Even if patients eventually arrive at a hospital, physi-

*Address correspondence to this author at the School of Computer Engineering (SCOPE), VIT-AP University, Andhra Pradesh, India;
E-mail: sachinandan09@gmail.com

cians are sometimes too busy to provide any consultation time due to high patient loads and overcrowding [4].

Ubiquitous health monitoring is one of the most potential technical treatments incipient to overcome this universal health parity breach. IoT technologies allow for the detection and continuous remote monitoring of various physiological signals of the human body, such as temperature, blood pressure, heart rate, electrocardiogram (ECG), blood oxygen (SpO2), blood glucose, along with the user actions such as running, standing, walking, sitting, and so on. Various sensors are responsible for tracking these body vitals. These sensors along with the human body, will act as a 'Thing' in an IoT network. These measured metrics can then be sent into automated decision-making systems, which could aid clinicians in making early predictions [5-6]. This will represent the beginning of a significant transition away from the contemporary sensitive disease-diagnosis-treatment paradigm and move towards a pre-emptive predictive-health-management strategy. Incessant monitoring of the human body's vitals, such as blood pressure, temperature, heart rate, blood-oxygen satiety, and so on, is an essential requirement in the modern healthcare system. In this pandemic situation, waiting in line and making arrangements for pathological examinations, as in the standard medical care framework, and constant monitoring of health parameters is not appropriate. As a result, remote health monitoring has been deemed an ideal exploratory tactic for the healthcare industry. It can be expanded to numerous applications by utilizing a promising technical model which is known as the Internet of Things (IoT). The IoT refurbishes physical objects into smart objects by combining communication and sensor technologies with a persistent and omnipresent service system. In this sophisticated technology, patients and sensors will work together as smart things [7]. This makes it possible to provide medical actors and patients with ubiquitous and real-time healthcare services.

Physical, network, and application layers make up the IoT architecture. Sensors are built into smart devices to collect a variety of data. The computational dimensions and life expectancy of these sensors are limiting factors. The primary goal of IoT is to enable communication between numerous objects that are not typical computers. The IoT enables these things to send and receive data across a network. There are numerous protocols in IOT that have been established to provide this communication. BLE, Bluetooth, Wi-Fi, Zigbee, and NFC are some of the most prevalent data link communication protocols used in the Internet of Things. As a result, data processing and distribution must be done in the cloud in addition to data collecting. The network layer is in charge of gathering and processing information. A massive amount of sensor data and a large storage area are required for improved accuracy and precision [8]. Better decisions can be made with the provision of rigorous training on the acquired huge amount of sensor-collected data. Transparency between heterogeneous IoT objects is also facilitated by the network layer. In addition, the Application layer aids in the dissemination of the outcomes via a user interface. As a result, IoT invention vastly extends any real-time framework activity's information system, execution, productivity, speed, and accuracy [9]. Experimentation, information exchange, and real-time visualization, as well as processing, have all empowered the sensor network to be more productive. A real-time, remote, and ubiquitous health observing system can also be defined as continuous observations of the patient's physiological status, as well as the capability of the life support apparatus, without the involvement of any time and accessibility constraints, with health administrators' decisions being intentionally involved. This technology will provide the precise augmentation that medical authorities require, and the equivalent information can be transmitted over the network or the internet. As a result, an alternative methodology that will specifically focus on monitoring a patient's vital circumstances should be developed concerning the traditional architecture.

The proposed framework will be used to demonstrate the following contributions in this article.

- Various parameters of the human body will be collected by a hardware module, and the data will be transmitted further to the cloud for a detailed predictive analysis.
- The design of both hardware and the development of the software architecture for a real-time ubiquitous healthcare platform is emphasized.
- A simulation application is being developed and further analysed by the predictive learners, demonstrating its promising capabilities in substituting the traditional framework.
- The development of such a ubiquitous framework will add a suitable chance to achieve sustainable global healthcare to prevent future pandemics.

The detailed summary of the subsequent chapters of this work is organized as follows. Section II imitates the overview of the recent literature surveys. The proposed framework is demonstrated in Section III in a detailed manner. Section IV depicts the simulation environment of the hardware framework. The result analysis part has been summarized in Section V. Sections VI and VII define the conclusion and future scope of the approached framework, respectively.

2. LITERATURE SURVEY

There have been remarkable works distributed in the related works on the utilization of the Internet of Things (IoT) to circulate savvy medical care administrations. Wu et al. proposed an edge registering-based framework design that incorporated an edge entryway and a mixture switch to give suggestions in different medical care applications [10]. The paper examined a fractional mix and assessment in view of the proposed design with three recreation situations of different IoT applications.

During the Covid-19 quarantine period, Taiwo et al. [11] proposed brilliant medical care support engineering for far-off tolerant observing. Different methodologies have been employed to distinguish possibly infected patients, including patient separation, and consequently, commitments are being made to slow the infection's spread. Singh et al. [12] presented the plan of an IoT-based wearable band (IoT-Q-Band) to identify the scarper in another article. They considered cost-viability, worldwide inventory network interruption, and the WHO's COVID-19 quarantine rules while planning the band (World Health Organization).

Alongside the wearable model, they made a versatile application that reports and tracks criminal quarantine subjects progressively.

Nandyal et al. [13] exhibited a canny framework equipped for observing patients' ongoing well-being status. The mentioned framework could track and screen patients, making it simpler to deal with individuals' parameters. Jerald et al. [14] considered IoT brilliant well-being information confirmation to guarantee the protection and security of medical services data. It portrays different sorts of confirmation designs for expanding the security of sensitive clinical information. Greco et al. [15] coordinated a methodical survey of the utilization of IoT in medical services frameworks. This work likewise incorporated a careful conversion of the significant difficulties while utilizing IoT to convey medical services administrations, as well as an order of the swotted work in the writing.

Experts in [16-22] expect various other IoT-based approaches. Out of which, not a single one of them has made a completely feasible framework system for observing body parameters utilizing IoT. There is a requirement for the turn of events and execution of a useful model that can uphold different body parameters as well as versatile correspondence conventions. In contrast with past examinations, the proposed model addresses a promising answer for different medical service applications, especially for ongoing patients. It can essentially uphold heterogeneous sensor hubs, empowering adaptiveness for further developed IoT interoperability and QoS (Quality of Service).

In earlier research on IoT bases ubiquitous healthcare systems, the sensor nodes were in high demand for capturing various health metrics. Apart from the implementation modules, multiple surveys have been conducted by various professional researchers. Sahu et al. [23] presented a detailed review of an integrated smart healthcare system, which includes various surveys regarding the IoT in healthcare technologies. Singha et al. [24] demonstrated a wearable medium with the help of different communication protocols, which will be helpful in providing remote assistance during the pandemic or in an isolated environment. Jaiswal et al. [25] highlighted the various issues and contests in an IoT-based healthcare system. Lakshmi et al. [26] emphasized a proposed architecture based on the cloud-based IoT healthcare system. Bhatia et al. [27] discussed the basic prevention of encephalitis with the utilization of a fog-based architecture. Anjali et al. [28] proposed a framework to detect and alert the patient about a covid diagnosis based on the acquired symptoms by the sensor network.

In another work, Boddu et al. [29] focused on the survey on accelerating the digital transformation in the medicare system, whereas Gupta et al. [30] described the impact of the digitalized IoT-configured health monitoring system specifically in India. Mohapatra et al. [31] emphasized the usage of smartphones and wearable sensors in remote health monitoring. They suggested a framework to detect any emergency situation according to the sensitivity of the model. Along with the timely broadcast of the sensor data, Kabir et al. [32] described a proposed architecture for isolated patients using machine learning approaches to detect any abnormalities in the detailed diagnosis process. Singla et al. [33] demonstrated the multiple layers involved in an IoT paradigm and analyzed their behavior concerning the improvement of reliability and battery lifetime. Chinchmalatpure et al. [34] addressed the need for a hardware device that will be carried by the patients to make the IoT system applicable and achievable in general.

Various prediction systems in accordance with the detection of the disease and its detailed frameworks have been described in [35-41]. Their discussions analyzed and resulted in minimizing the time factor of the concerned medical authorities and the cost factor of the patient himself. Delegates in [42-51] have anticipated several predictive IoT-based healthcare models. None of them has created a comprehensive, approachable, and feasible framework for monitoring body parameters with the use of IoT, as it requires a huge data collection along with a large storage space. These viable models with many bodily parameters and adaptive communication protocols need to be developed and implemented. In comparison to previous research, the proposed model appears to be a viable answer for a variety of healthcare applications, particularly for chronic patients. It has the potential to greatly handle diverse sensor nodes, enabling adaptiveness for improving the interoperability and QoS (Quality of Service) of the IoT technology.

Achieving global remote healthcare monitoring is one of the challenging issues related to specific problems. Hence, generalized solutions for improving the quality-of-service schemes in terms of time and cost are the need of the hour. Similarly, customized information delivery in real-time is another challenging issue in this computing environment. The development of an efficient algorithm is a requirement for content-based event dissemination in pub/sub-systems. Further integration of sensor networks with cloud computing has been investigated recently. There are many issues associated with the deployment. Keeping the research directions in view, in this article, the proposed frameworks have a solution-centric approach to dissolve traditional healthcare, where an analytical methodology for dedicated monitoring of the health conditions of a patient has been described.

Further, the proposed framework will illustrate the following additional contributions. In particular, the objectives are laid down to the following cores.

- To develop an integrated framework by integrating sensors into the cloud in real time.
- An IoT-based framework is demonstrated for the early prediction and assessment of the disease in the human body.
- The design and development of both hardware and software architecture are integrated and further evaluated for a real-time IoT healthcare application, demonstrating its promising capabilities.

3. PROPOSED METHODOLOGY

Inspired by the motivation of the literature survey, in this work, a detailed proposed framework for the Ubiquitous Healthcare System(UHS) has been drafted. The desired system or model consists of four basic stages, as depicted in Fig. (**1**).

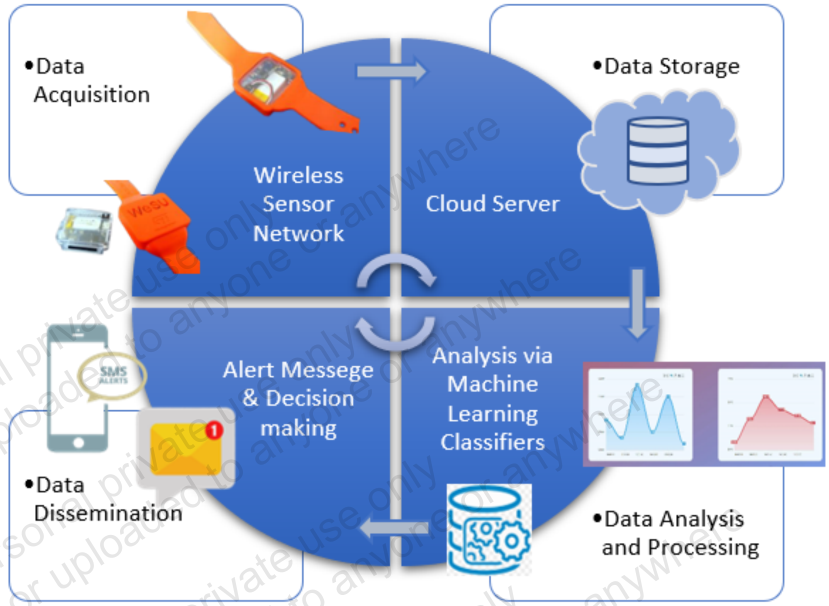


Fig. (1). Proposed framework. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

Table 1. Considered body parameters and their associated sensors in the proposed UHS.

Body Parameters Name	Description	Desirable Range	Corresponding Sensor Unit
Temperature	Temperature	97°-100° F	DS18B20 Temperature Sensor
Heart Rate	Cardiac Cycle Frequency	60 – 100 BPM	SN0203 Heartrate Sensor
ECG	Heart Activity	0.5-100 Hz Frequency	AD8232 ECG Sensor
Respiration Rate	Breathing Rate	18-20 per Minute	MAX30100 Respiration Sensor
Oxygen Saturation	Oxygen Carried in blood	More than 95%	MAX30100 Oximeter Sensor
Blood Pressure	A force of blood Circulation	120/80 mmHg.	Sunrome BP Sensor

Data Acquisition

Data Storage

Data Analysis and Processing

Data Dissemination

The proposed model or framework grips an IoT device along with the predictive analysis of real-time medical data. In the data acquisition unit, the wearable hardware device comprises a few healthcare sensors similar to a blood pressure sensor, pulse sensor, temperature sensor, ECG sensor, sink node, *etc*. The sensor-acquired data will be forwarded to the server setup at the cloud environment via the sink node placed on the base level. Further, the stored data will undergo through the multiple prediction models deployed at the backend architecture of the cloud, which would most likely benefit the medical authorities in the process of diagnosis of a single-band or multi-band disease based on the model output and acquired symptoms. This is the description of the data analysis and processing phase. Finally, in the last data dissemination phase, the decision-making of the concerned medical actors will be conveyed to the caretaker and the patients with an alert or notification message.

The detailed body parameters, their respective threshold values, and the associated sensor module are mentioned in Table **1**.

The respective sensors are responsible for the collection of the concerned patient's vital signs or parameters at a regular intervals of time. These signs can be able to transfer into the cloud database via an intermediate microcontroller and a sink node. The microcontroller can control the flow of the sensor data via an internal program. This program has a certain interval time, which can control the proceeding of the sensor data. Once the data is accumulated at the microcontroller, it is further transferred to a sink node. The responsibility of the sink node is to carry forward the ground-level data to cloud storage. It has direct access to the cloud via the mobile network.

After booting up the module, the hardware device collects different vital signs like blood pressure, temperature, oxygen saturation, *etc*. From time to time manner, the sensor-obtained data is transmitted to the cloud-end, *i.e*., server, via a sink node. In this model, the smartphone is used as a sink node. After the sensor data acquisition, the data are sent in the form of numerical values to a Google sheet via the

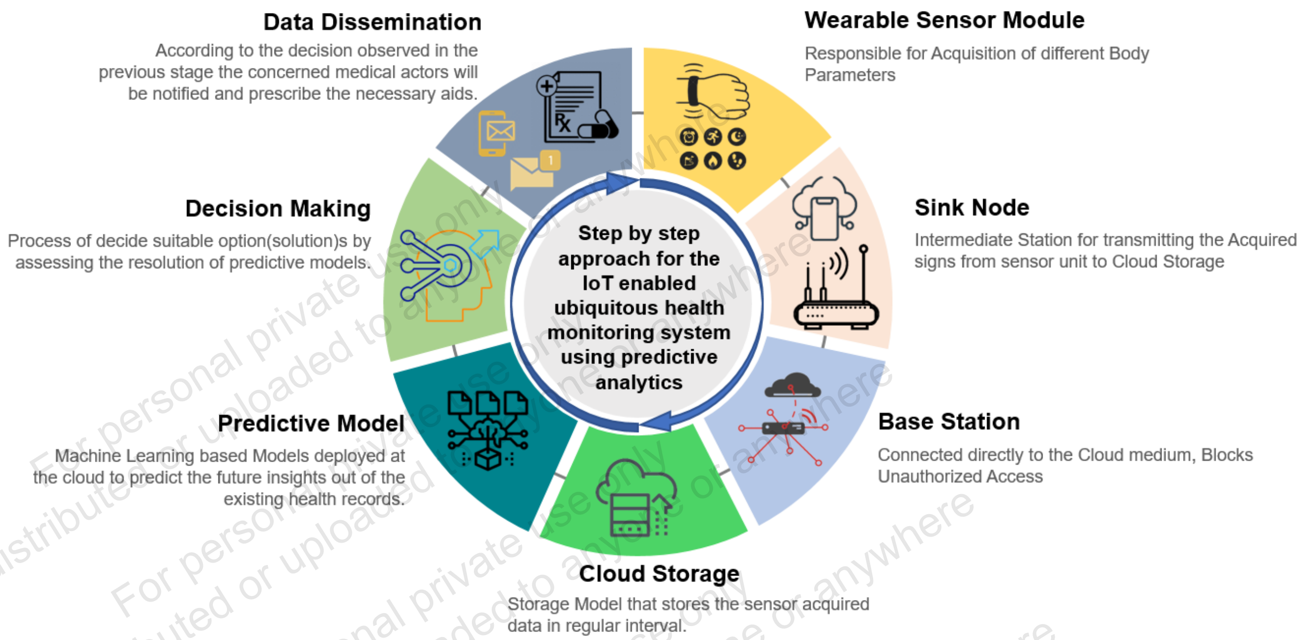


Fig. (2). Detailed workflow of the proposed model. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

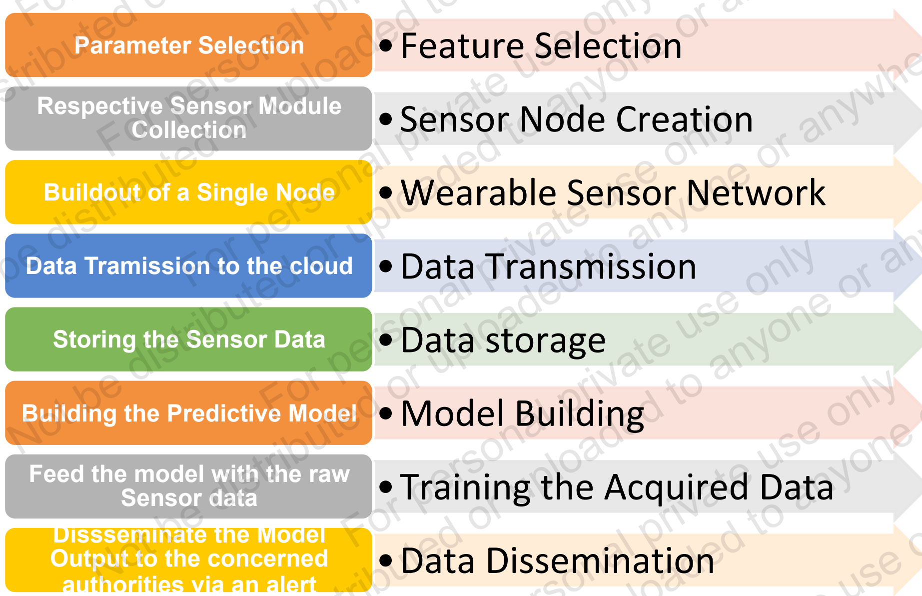


Fig. (3). Detailed flowchart of the proposed model. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

IFTTT platform. IFTTT stands for IF This Then That. It is an interfacing platform that can acquire the sensor data and forward it to Google spreadsheets. The detailed flowchart of the proposed model is represented in Fig. (**2**).

In the data analysis and processing section, various machine learning(ML) models are being deployed in the cloud. After experimenting with some of the existing data sets, the predictive models are trained and positioned in the cloud. After normalizing the acquired data, it will pass through the existing best-suited predictive model for better accuracy. The outcome will be notified via text messages or email to the concerned medical actors in the final data dissemination phase. The comprehensive workflow of the anticipated framework is represented as follows in Fig. (**2**).

The detailed flowchart of the proposed work has been shown in Fig. (**3**). Various stages, including the development of the desired hardware module alongside the building and deployment of the various machine learning prediction models, have been involved in this chart. Further, the data dissemination section is being added to enhance the usability and feasibility of the overall framework. In the initial phase, the major focus would be on the hardware model building after the appropriate feature or parameter selection. Then, a

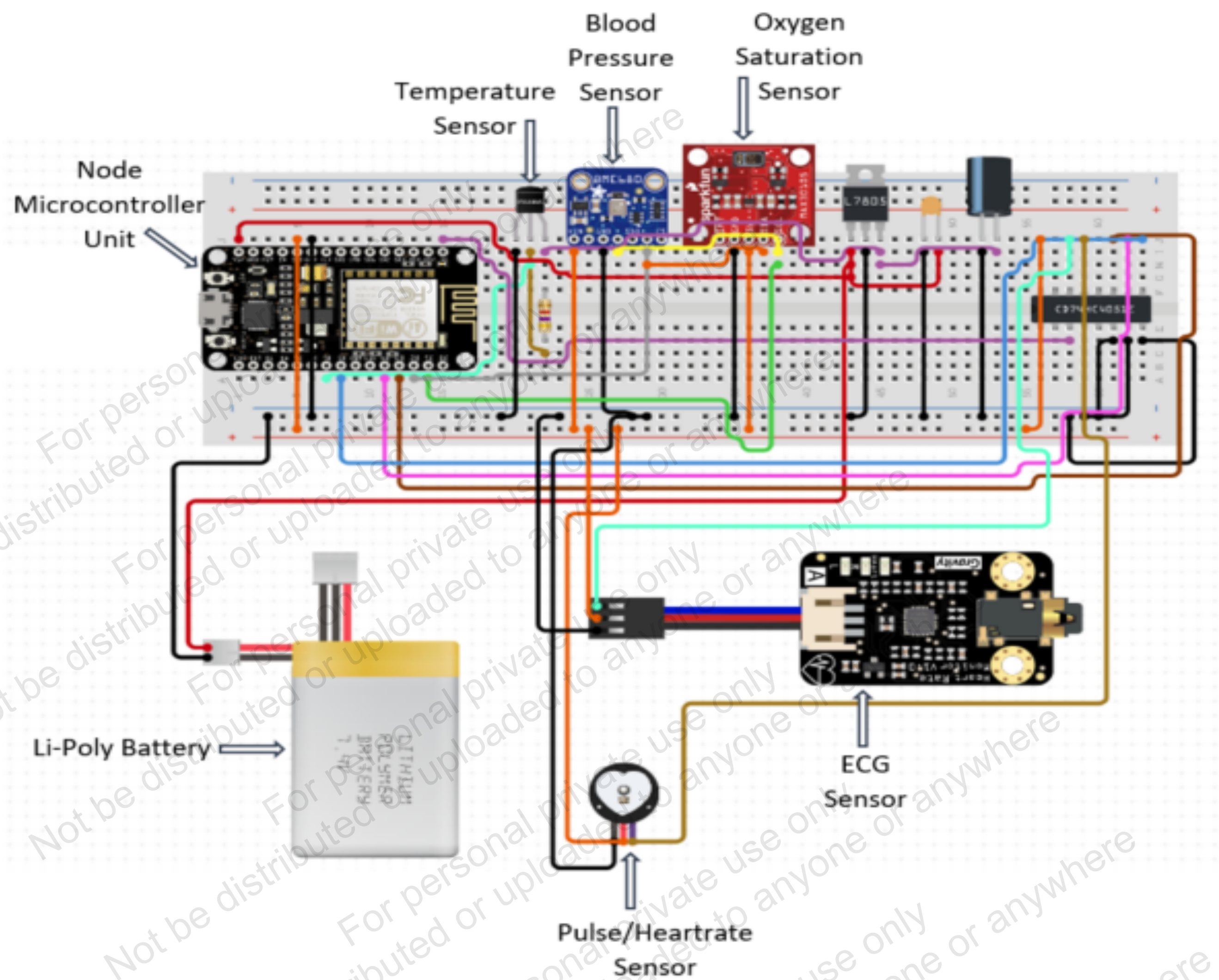


Fig. (4). Circuit diagram of the proposed integrated model. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

single node will be made accessible for this ubiquitous service, which can be further scalable to a broad target area.

4. SIMULATION ENVIRONMENT

In the first step, the data acquisition unit and various individual sensor units are made accessible as feasible wearable nodes. In this phase, for measuring the temperature parameter, the DS18B20 sensor unit is used, the SN0203 unit is used as a pulse sensor, the Sunrome-1437 unit is used as a blood pressure sensor, the MAX30100 unit is used as an oxygen saturation level detection sensor, and the AD8232 unit is used as an ECG sensor. The cumulated sensor data from various sensors are transferred to a microcontroller named Nodemcu. A manufactured Wi-Fi module named ESP8266 has been embedded along with the microcontroller to enable its wireless capability. The major function of this Wi-Fi module is to transmit the sensor-acquired data through a sink medium to the cloud. In this regard smartphone having a mobile network is considered a sink node. The circuit diagram of the proposed integrated framework has been displayed in Fig. (**4**). The developed wearable hardware module was demonstrated earlier in Fig. (**5**). In this work, three desirable hardware modules have been developed concerning the accessibility and feasibility of the motive. A detailed summary of the various hardware modules is discussed in Table **2**.

In the cloud, the raw sensor data will be translated into a normalized form. Here, the preprocessing or the normalization takes place in two ways. The first one is the Standard scalar, which is formulated upon the following formula where x is the sample data point, u is the mean of the training sample, and s is the standard deviation of the same. It is shown in equation (1).

$$z = \frac{(x-u)}{s} \quad (1)$$

The second normalization is named a min-max scalar, where min, max = feature_range. It is shown in equations (2) and (3). Both libraries are provided by the sci-kit-learn library.

$$X_{std} = \frac{(X - Xmin(axis=0))}{(Xmax(axis=0) - Xmin(axis=0))} \quad (2)$$

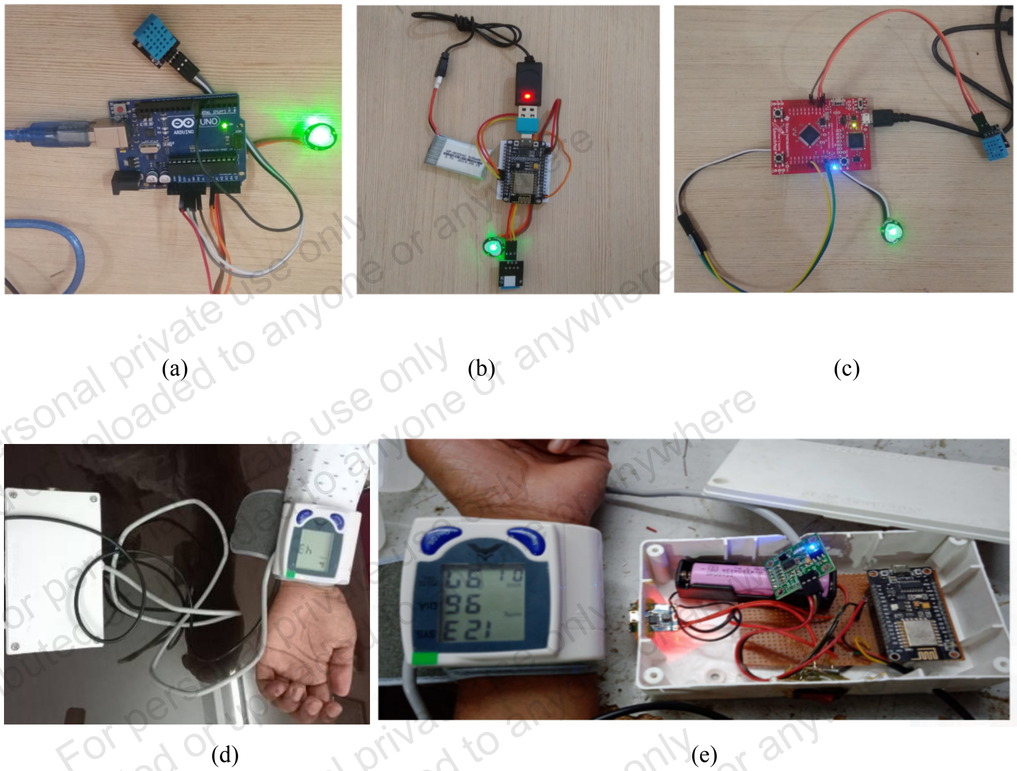


Fig. (5). (**a**) First Model; (**b**) Second Model; (**c**) Third Model; (**d**) Integrated Model; (**e**) Skeleton of the Integrated Model. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

Table 2. Summary of the developed hardware frameworks.

Model Characteristics	First Model	Second Model	Third Model
Supporting Components	• Arduino Uno MCU • Temperature (DHT 11) Sensor • Pulse(SN0203) Sensor • Jumper(Connecting) Wires • USB Power Adapter	• Node Micro-controller (ESP8266 Wi-Fi module embedded) unit • Temperature(LM35) Sensor • Pulse(SN0203) Sensor • Jumper(Connecting) Wires • USB Power Adapter • External Power Source	• TM4C123GXL Launchpad unit • Temperature(DHT11) Sensor • Pulse(SN0203) Sensor • Jumper(Connecting) Wires • USB Power Adapter • External Power Source
Advantages	• Flexibility • Feasibility, • Stand-alone Module • Diligent Module with Individual Sensors	• Compactness • Wireless Connectivity • Flexible with Analog Sensors • Economic with supporting all types of sensors	• Inbuilt processing capacity • Inbuilt Wi-Fi module • Provide scalability in integrating multiple sensors • Flexibility • Adaptive Configuration
Disadvantages	• No Wireless Connectivity • Limited Digital Pins • Requires External Power supply • Multiple sensor integration is a bit complex • Remote access is not possible.	• Less number of digital pins compare to the Arduino module • Requires an External Power supply • Access point configuration should be the same across the simulation environment • Initialization process is a bit complex.	• Requires an external power supply.

Table 3. Parameter setting of various classifiers in the stacking approach.

Classifiers	Classifier Functions	Parameters
Extreme Gradient Boost (XGB)	xgboost.XGBClassifier()	learning_rate=0.01, n_estimators=25, max_depth=15,
Random Forest (RF)	sklearn.ensemble.RandomForestClassifier()	n_estimators=20, criterion='gini', max_depth=5, min_samples_split=2, max_features='sqrt'
K-Nearest Neighbor (KNN)	sklearn.neighbors.KNeighborsClassifier()	n_neighbors=5, weights='uniform', algorithm='auto', metric='minkowski',
Naive Bayes (NB)	sklearn.naive_bayes.GaussianNB()	priors=None, var_smoothing=1e-09
Support Vector Classifier (SVC)	sklearn.svm.SVC()	C=2.0, kernel='rbf', degree=3, gamma='scale'
Stacking	mlextend.classifier.StackingCVClassifier()	classifiers=[xgb,knn,svc,lr,nb],meta_classifier=knn, random_state=0

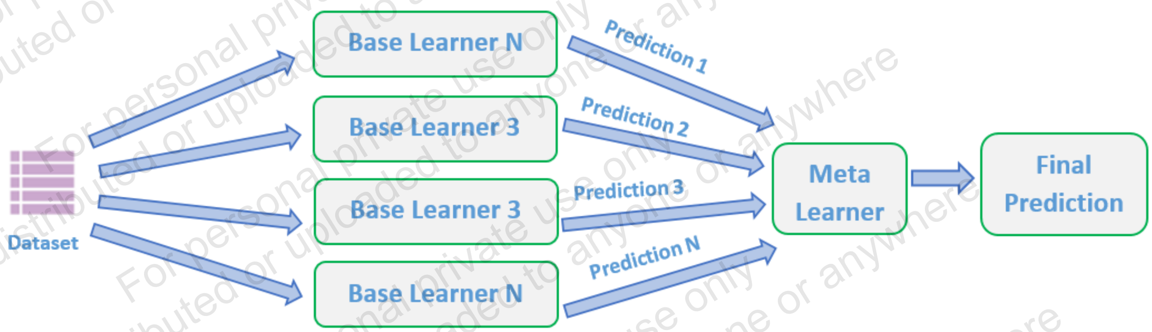


Fig. (6). Flowchart of the ensemble or stacking model. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

$$X_{scaled} = X_{std} * (max - min) + min \quad (3)$$

The simulation results are carried out in the free version of the Google Colab platform. Accordingly, the normalized data are processed through various machine learning classifiers like Logistic Regression(LR) Classifier, Random Forest Classifier(RF), Naive Bayes(NB) Classifier, Extreme Gradient Boost(XGB) Classifier, K-Nearest Neighbor(KNN) Classifier, Decision Tree(DT) Classifier, and Support Vector Classifier(SVC), *etc*. Different hyper parameters' settings have been mentioned in the following Table **3**.

The author approached a stack or ensemble classifier after receiving the individual output across the various classifiers. In the ensemble classifier, the individual classifier will act as the base learner, and further, the output of the base learner will proceed through a meta learner. The meta-learner will be chosen based upon the individual precision of the model. The detailed process of the stacking or ensemble model is depicted below in Fig. (**6**).

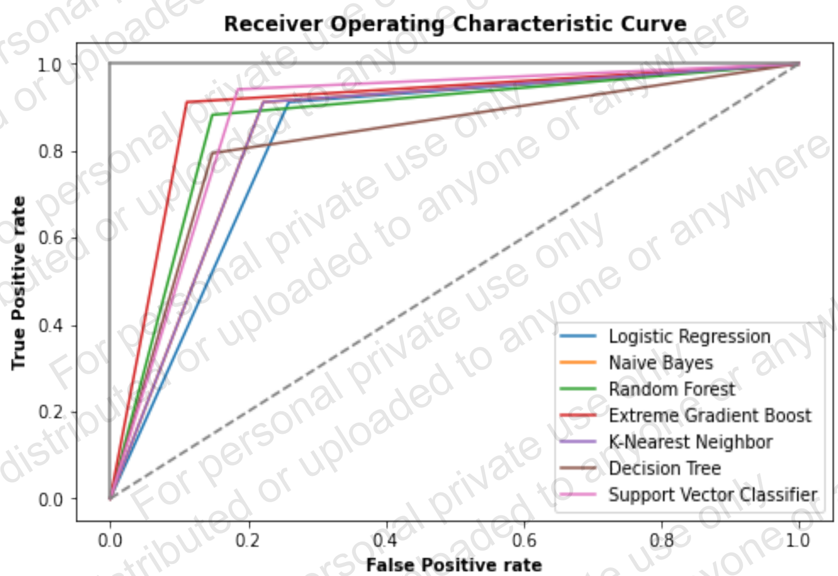
6. RESULT DISCUSSION

During the simulation process, an existing dataset of similar parameters has been analyzed in the cloud. After getting the results of the very first epoch, the real-time data is fed through the model. All the above-mentioned classifiers are observed via the four most common performance benchmarks or criteria, such as accuracy, ROC, precision, F1-score, *etc*. In the simulation process, the performance evaluation has been done in two types of data split ratios, *i.e.*, 70:30 and 80:20. The stacking method is applied to the best 5 and the best 4 classifiers whose accuracy has been significant. Out of all the classifiers, the stacked classifier transcends all the other machine learning classifier models across the metrics (around 93 percent accuracy), precision with 94%, sensitivity with 90%, and specificity with almost 94%. Classifiers, such as SVC-edge, are nearer in terms of accuracy (around 89 percent accuracy), but when compared to other metrics values, the stacked classifier overall gives better precision across all the domains. The detailed observed output of various performance metrics is mentioned in Table **4**. Further, the ROC curve (receiver operating characteristic curve) is plotted in Fig. (**7**) to illustrate the plot for the top two performing classifiers. Various performance matrices, along with the confusion matrix observed during the simulation of the stacking as well as individual models, are depicted in Fig. (**8**). The resultant accuracy of the various classifiers and the stacked classifiers in a bar plot chart is demonstrated in Fig. (**9**).

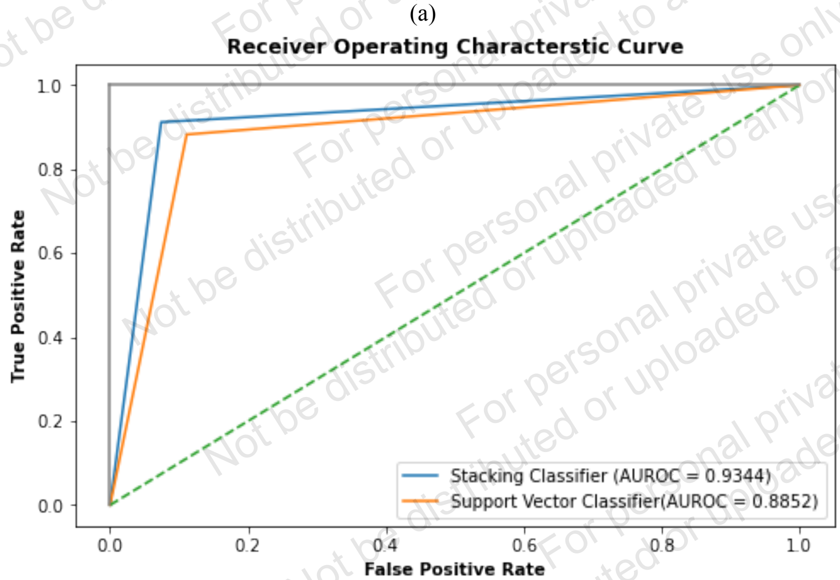
After getting the final output from the models, a notification will be sent to the concerned medical actors concerning the best-performing classifier's outcome. According to the notification, the alert or notification message will be delivered to apprehensive clinicians, such as doctors, caretakers, and the patient, for proper medication assistance. Doctors analyze the model output result and give necessary aid. A sample alert message is depicted in Fig. (**9**). Medical actors will define the diagnosis process concerning the outcome of the model. The resulting output will definitely be helpful in

Table 4. Simulation results obtained during predictive analysis.

Methodology	Preprocessing Technique	Dataset Split Ratio	Accuracy Obtained
Ensemble (Stacking) Model (Best 5)	Standard Scalar	70:30	83.51
Ensemble (Stacking) Model (Best 5)	Min-Max Scalar	70:30	86.81
Ensemble (Stacking) Model (Best 5)	**Standard Scalar**	**80:20**	**93.44**
Ensemble (Stacking) Model (Best 5)	Min-Max Scalar	80.20	91.80
Ensemble (Stacking) Model (Best 4)	Standard Scalar	70:30	82.41
Ensemble (Stacking) Model (Best 4)	Min-Max Scalar	70:30	84.61
Ensemble (Stacking) Model (Best 4)	Standard Scalar	80:20	91.80
Ensemble (Stacking) Model (Best 4)	Min-Max Scalar	80.20	91.80



(a)



(b)

Fig. (7). (**a**) ROC curve of various ML classifiers; (**b**) ROC curve of the Ensemble or Stacking classifier. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

```
confussion matrix
[[23  4]
 [ 7 27]]


Accuracy of DecisionTreeClassifier: 81.9672131147541

              precision    recall  f1-score   support

           0       0.77      0.85      0.81        27
           1       0.87      0.79      0.83        34

    accuracy                           0.82        61
   macro avg       0.82      0.82      0.82        61
weighted avg       0.82      0.82      0.82        61
```

(a)

```
confussion matrix
[[23  4]
 [ 3 31]]


Accuracy of Support Vector Classifier: 88.52459016393442

              precision    recall  f1-score   support

           0       0.88      0.85      0.87        27
           1       0.89      0.91      0.90        34

    accuracy                           0.89        61
   macro avg       0.89      0.88      0.88        61
weighted avg       0.89      0.89      0.88        61
```

(b)

```
confussion matrix
[[21  6]
 [ 3 31]]


Accuracy of Naive Bayes model: 85.24590163934425

              precision    recall  f1-score   support

           0       0.88      0.78      0.82        27
           1       0.84      0.91      0.87        34

    accuracy                           0.85        61
   macro avg       0.86      0.84      0.85        61
weighted avg       0.85      0.85      0.85        61
```

(c)

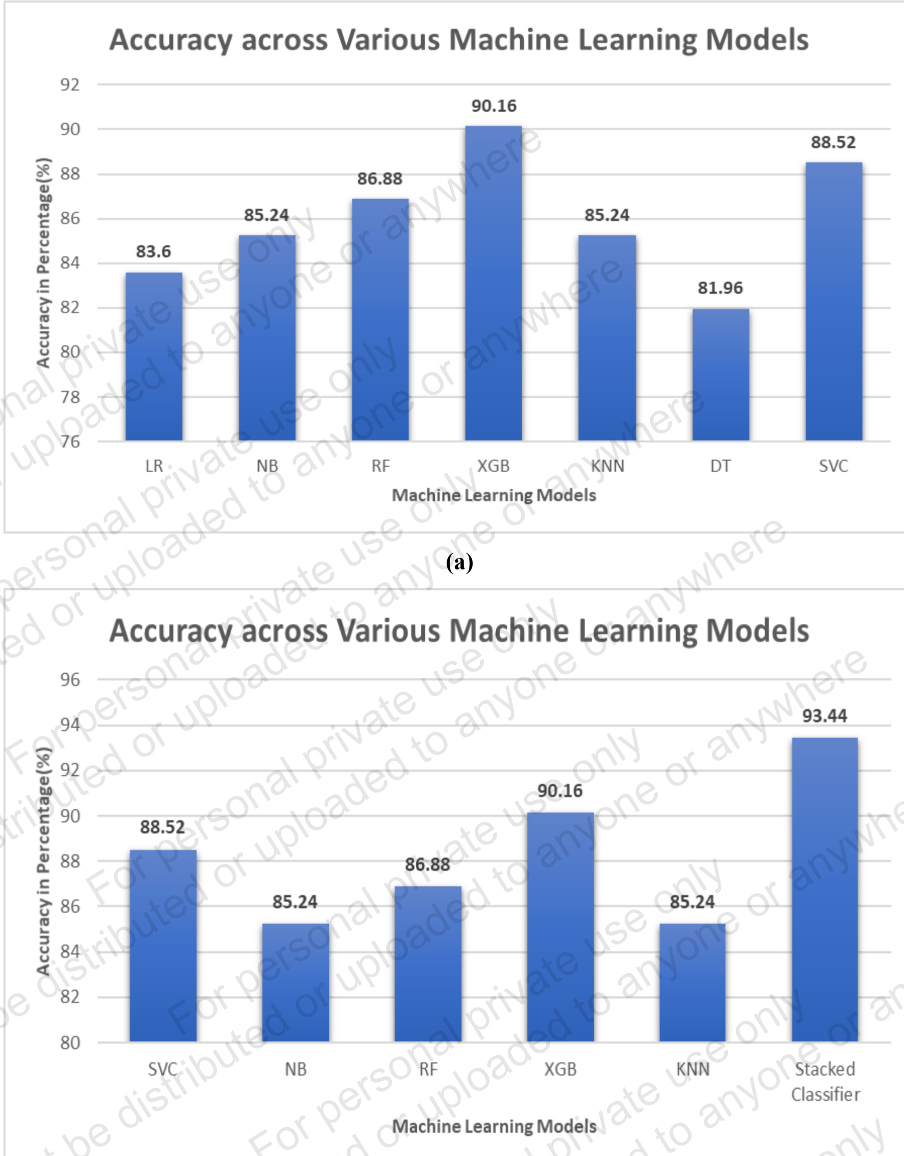
```
confussion matrix
[[24  3]
 [ 3 31]]


Accuracy of Extreme Gradient Boost: 90.1639344262295

              precision    recall  f1-score   support

           0       0.89      0.89      0.89        27
           1       0.91      0.91      0.91        34

    accuracy                           0.90        61
   macro avg       0.90      0.90      0.90        61
weighted avg       0.90      0.90      0.90        61
```

(d)

```
confussion matrix
[[25  2]
 [ 2 32]]


Accuracy of StackingCVClassifier: 93.44262295081968

              precision    recall  f1-score   support

           0       0.93      0.93      0.93        27
           1       0.94      0.94      0.94        34

    accuracy                           0.93        61
   macro avg       0.93      0.93      0.93        61
weighted avg       0.93      0.93      0.93        61
```

(e)

Fig. (8). (**a**) Performance and Confusion Matrix of Decision Tree Classifier; (**b**) Performance and Confusion Matrix of Support Vector Classifier; (**c**) Performance and Confusion Matrix of Naïve Bayes Classifier; (**d**) Performance and Confusion Matrix of Extreme Gradient Boost Classifier; (**e**) Performance and Confusion Matrix of Stacking Classifier. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).



(a)

(b)

Fig. (9). (**a**) Accuracy plot of various ML classifiers; (**b**) Accuracy plot of base and ensemble or stacking classifier. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

the early decision-making of the medical authorities. Further, the caretaker and the patient can take necessary aid according to the suggestion of the medical actors.

CONCLUSION

In the aftermath of the recent epidemic, academics have focused on the situation of healthcare as the most important and fruitful field. Hospitals are finding it increasingly difficult to accommodate and care for all of the patients as the patient population grows. The proposed paradigm uses the Internet of Things to bring together sensor units and predictive analytics as a solution-based approach. The prime motivation for creating such a ubiquitous system is to minimize the cost and time factor of the customary architecture while simultaneously providing a system that can detect anomalies quickly. The primary benefit of this proposed method is that it lowers the expense of traditional healthcare while also saving patients and medical personnel time. Once the health records are available in the storage for analysis then, only the predictive analytics can be done. Though it is not possible to achieve the cent percent accuracy through the predictive models, there is a chance of achieving higher accuracy by rigorous training of the model with the help of a large dataset. In comparison to the existing research models, this proposed work represents an assuring solution to support various healthcare requisitions. It has great support for the compatibility and adaptiveness among the people, which can be used as an asset in achieving a better quality of service in the healthcare ecosystem. Thus, ubiquitous health monitoring derives a slew of benefits and has evolved into a more valuable resource than traditional medicinal care.

The present situation of healthcare has been addressed as

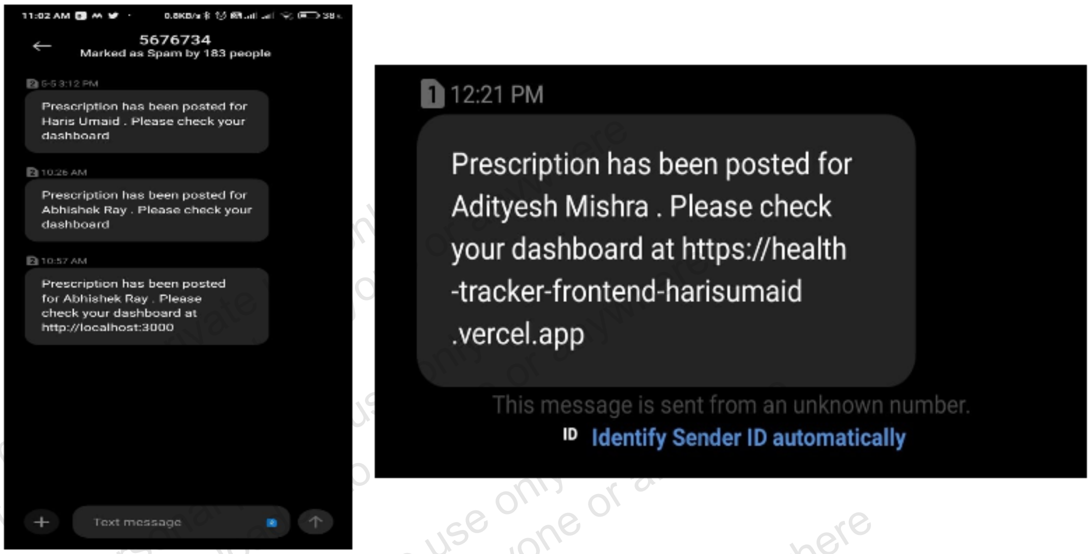


Fig. (9). Alert Message generated at the Medical Actors.

the most crucial and prolific field for research throughout the last pandemic. As there is a clear spike or inflation in the cumulative number of patients, hospitals are finding it increasingly difficult to accommodate and care for all of them. The proposed paradigm uses the Internet of Things to combine heterogeneous sensor platforms and multilevel problem-solving techniques. The fundamental goal of establishing a high-level system is to reduce the diagnosis cost of the evolutionary healthcare model while providing a better, compatible, and adaptive system that can detect anomalies quickly. The primary benefit of this suggested method is that it lowers the expense of conventional healthcare while also saving time for both patients and medical professionals. As a result, it can be used by anyone. It is a simple-to-use and efficient system that offers a lot of versatility and scalability, making it a huge step forward from all other existing customary health monitoring systems. Remote and real-time health monitoring comes with a slew of benefits and has evolved into a more valuable resource in comparison to traditional medical care.

FUTURE SCOPES

Predictive models have a higher accuracy in the existing data sets. To get good accuracy in real-time datasets, we need huge data storage and the concept of big data. Further, getting insightful meaning from the large data set is quite a challenging task to accomplish. Therefore, the following intuitions are derived from this research work as the future scopes.

- Inclusion of more classification models for better accuracy.
- Exploring the big data technology concerning real-time sensor data.
- Need for a supercomputer for quick processing of large datasets.
- Design of adaptive sensor nodes for increasing the usability and compatibility of the module among the people.

CONSENT FOR PUBLICATION

Not applicable

AVAILABILITY OF DATA AND MATERIALS

The data and supportive information are available within the article.

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CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

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