International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7890
***Article Received**: 30 May 2023 **Revised:** 25 July 2023 **Accepted:** 14 August 2023*

Revolutionizing Healthcare through Health Monitoring Applications with Wearable Biomedical Devices

Sujata S. Alegavi[1], Bhushankumar Nemade[2*], Vinayak Bharadi[3], Shiwani Gupta[4], Vidyadhari Singh[5], Archana Belge[6]
[1]Thakur College of Engineering and Technology, Mumbai University, India,
[2*]Mukesh Patel School of Technology Management & Engineering, NMIMS University, India,
[3]Finolex Academy of Management and Technology, Mumbai University, India,
[4]Thakur College of Engineering and Technology, Mumbai University, India,
[5]Thakur College of Engineering and Technology, Mumbai University, India,
[6]Thakur College of Engineering and Technology, Mumbai University, India.
[1]sujata.alegavi@gmail.com, [2]bnemade@gmail.com, [3]vinayak.bharadi@outlook.com, [4]shiwanigupta_om@live.com,
[5]vidyadhari.singh@thakureducation.org, [6]archana.belge@thakureducation.org

Abstract: The Internet of Things (IoT) has revolutionized the connectivity and communication of tangible objects, and it serves as a versatile and cost-effective solution in the healthcare sector, particularly in regions with limited healthcare infrastructure. This research explores the application of sensors such as LM35, AD8232, and MAX30100 for the detection of vital health indicators, including body temperature, pulse rate, electrocardiogram (ECG), and oxygen saturation levels, with data transmission through IoT cloud, offering real-time parameter access via an Android application for non-invasive remote patient monitoring. The study aims to expand healthcare services to various settings, such as hospitals, commercial areas, educational institutions, workplaces, and residential neighborhoods. After the COVID-19 pandemic, IoT-enabled continuous monitoring of critical health metrics such as temperature and pulse rate has become increasingly crucial for early illness detection and efficient communication with healthcare providers. Our low-cost wearable device, which includes ECG monitoring, aims to bridge the accessibility gap for people with limited financial resources, with the primary goal of providing efficient healthcare solutions to underserved rural areas while also contributing valuable data to future medical research. Our proposed system is a low-cost, high-efficiency solution that outperforms existing systems in healthcare data collection and patient monitoring. It improves access to vital health data and shows economic benefits, indicating a significant advancement in healthcare technology.

Keywords: Wearable Devices, Internet of Things (IoT), ECG, Temperature, Covid-19, Cloud Services.

I. Introduction

The term "Things begin to exhibit cognitive abilities" accurately captures the revolutionary potential of the Internet of Things (IoT). In the domain of the Internet of Things (IoT), any tangible object or entity can be transformed into a "thing" by being endowed with a distinct and exclusive identity, commonly referred to as a Unique Identity (UID). The network of networked items linked to unique identifiers (UIDs) demonstrates a notable capacity to independently sense, gather, and send data, frequently with limited human involvement. The Internet of Things (IoT) fundamentally offers a framework in which items surpass their conventional responsibilities, facilitating the exchange and sharing of data from remote locations. The Internet of Things (IoT) has demonstrated reliability, versatility, and cost-effectiveness, particularly in the healthcare industry. It provides unique technological opportunities to improve high-quality healthcare services and enhance current medical procedures.

Vital signs, such as body temperature, are significant indications of an individual's overall health condition. The assessment of body temperature has a dual purpose: it facilitates the identification of fever and offers valuable insights into broader health issues. Acknowledging the impact of environmental influences on body temperature necessitates an expectation of fluctuations throughout the day, with generally lower temperatures observed in the morning and higher temperatures observed in the afternoon. A commonly accepted average body temperature is 37 °C or 98.6 °F, highlighting the importance of considering physiological and environmental factors when assessing temperature changes.

Likewise, measuring an individual's pulse rate, expressed as the number of heartbeats per minute (BPM), is crucial in evaluating cardiovascular health. There is a commonly accepted range of 72 to 100 beats per minute (BPM) that is considered normal. However, any departures from this range may require observation and even intervention. The pulse rate is directly influenced by physical activity, as exercise leads to an elevation in pulse rate. At the same time, the fitness level is associated with the rate at which the pulse rate returns to its initial baseline.

In the context of India, a nation that ranks as the world's second-most populous, the rural population has significant challenges regarding insufficient access to healthcare specialists. The existing contrast between public and private healthcare establishments and the inequalities in healthcare resources between rural and urban areas further intensifies the difficulty. The healthcare system in India is confronted with the formidable challenge of catering to the demands of its swiftly expanding populace, especially in geographically isolated and underprivileged areas. Telemedicine has emerged as a viable approach to alleviate the gap in medical services by enabling healthcare delivery without the need for physical presence. This practice assumes particular relevance in light of the uneven distribution of healthcare professionals. The cost-effectiveness and accessibility of telemedicine play a crucial role in delivering diagnosis and care to persons residing in remote regions, hence mitigating the healthcare disparity. Integrating wearable biomedical equipment, Internet of Things (IoT) infrastructure, and remote healthcare delivery offers a novel method for ongoing health monitoring. This technology enables the capture and transmission of data, including body temperature and heart rate, providing patients with real-time insights and medical professionals with archived and essential information on the cloud. The progress described has noteworthy implications for rural areas with limited resources and technologically advanced campuses, demonstrating the possibility of wearable gadgets promoting equal healthcare access.

II. Literature Survey

The global outbreak of COVID-19 has spurred extensive research efforts towards efficient detection and prediction strategies. Several technical papers have been published, each contributing to our understanding of the virus and proposing innovative solutions. In a study, the use of deep learning techniques for COVID-19 detection through medical imaging analysis is done. They demonstrated the potential of deep neural networks in accurately distinguishing COVID-19 cases from other respiratory illnesses using chest X-ray images, showcasing the significance of AI-driven diagnostic tools.

A wearable IoT-based system for continuous health monitoring was introduced to address the need for real-time monitoring and prediction. The device integrated sensors to measure temperature, heart rate, and oxygen levels, transmitting data to the cloud for remote monitoring. By enabling early detection of anomalies, such devices hold promise in tracking potential COVID-19 symptoms and providing timely medical interventions, especially in resource-limited settings.

Predictive modeling has also gained traction as an essential tool for anticipating disease spread, which employed a data-driven approach to develop a predictive model that accounted for multiple factors influencing COVID-19 transmission. This model considered demographics, mobility patterns, and preventive measures to forecast the virus's spread accurately. This highlights the significance of accurate data collection and analysis in designing effective containment strategies.

Several wireless body sensor networks have been developed in the current environment to monitor a person's health continuously. The initial WBSN that the researchers created makes use of an atmega-8 microcontroller that has several sensors built into it. An integrated sensor-based IOT device called a Galileo board offers a medical platform for reviewing electrocardiogram (ECG) information and basing monitoring heart function on that algorithm. The crucial problem of fault-tolerant health data services is the main topic of Woo et al. In order to do this, the authors present a fault-tolerant algorithm, and the suggested design offers a gateway that may be joined to create a fault-tolerant connected network. Additionally, the gateway keeps a backup copy of the prior gateway. A small wearable gadget with a non-intrusive sensor will make it possible to capture vast amounts of data automatically. This will assist in lowering costs and fewer frequent doctor or medical facility trips. Swaroop et al. concentrated on developing a real-time health monitoring system that can support the patient's health record and also on various methods of data transmission via the internet, messaging services, and mobile applications. Implementing a medical care system for a remote population should allow for ongoing data analysis and be simple enough for anyone with minimal medical experience to use.

Instead of a wearable gadget, a diagnosis system is required for remote health monitoring because people in rural areas cannot afford wearable technology.

In order to gather real-time health data from patients, the m-health system developed by Almotiri et al. (2016) makes use of the capabilities of mobile devices. Only specific clients can access the network servers where the data will be stored by the system connected to the internet. The system uses body sensor networks and wearable technology to collect data that can be utilized to diagnose individuals medically. The system's emphasis on real-time data collecting offers insightful information about patient health and empowers medical professionals to choose appropriate treatments. Patients can now be monitored remotely thanks to wearable technology and sensor networks, giving patients and medical personnel more freedom and convenience. By enabling proactive patient health management, this approach has considerable potential to improve patient outcomes and save healthcare costs [1].

An IoT-based framework was created by the study's authors (Lopes et al., [2014]) to enhance the quality of life for those who have disabilities. To help the disabled community, the framework recognized IoT technologies and their applications in the healthcare industry. The most recent IoT innovations and their effects on the health and well-being of people with impairments were examined using two use scenarios. The findings showed that IoT technologies have enormous potential for enhancing the quality of life for people with disabilities in the healthcare industry. The study also showed that the disabled community might significantly profit from a comprehensive framework encompassing numerous IoT technologies [4].

The researchers developed a system (Thakre et al., [2022]) that uses intelligent sensors and communication technology to remotely monitor the health of soldiers while they are engaged in combat. This technology would allow for real-time study of the health status of soldiers by transmitting the processed data from the smart sensors to a personal server. Wireless notifications would be sent to the base station to ensure quick notice and action if any irregularities were found. Soldiers would be provided with ESP32 modules to enable smooth and dependable connectivity in difficult military circumstances, facilitating effective communication. A specific mobile app would also be created to track soldiers' whereabouts and enable real-time monitoring of their health indicators [13].

The researchers suggested A healthcare monitoring system (Khin Thet et al., [2019]) to ensure ongoing observation of a patient's physiological parameters. The key benefit of this approach is that users can obtain the results at any time and from any location. Additionally, in aberrant health circumstances, doctors can be alerted via text messages, enabling prompt intervention. The system uses various sensors, including blood pressure, temperature, and heartbeat sensors, to evaluate signals and quickly identify normal or abnormal situations. This makes it possible for medical experts to closely monitor a patient's health and make prompt treatment decisions [15].

The researchers suggested a Zigbee and GSM-based patient health monitoring system (Sorte et al., [2016]). The system was designed to continually and in real-time monitor patient health indicators such as body temperature, heart rate, and ECG. The system wirelessly transmitted the patient's parameters to a centralized ARDUINO platform for analysis using Zigbee wireless technology. This strategy prevented patients' everyday routines from interfered with while ensuring dependable and energy-efficient patient monitoring. The system allowed clinicians to precisely monitor the patient's health status and make informed judgments by continuously analyzing and monitoring the patient's parameters. Zigbee technology's real-time data transfer allows for immediate surveillance, enhancing communication between the patient and the doctor [11].

The researchers (Krishnan et al., [2018]) created a creative concept that would use a Patient Health Monitoring system to lower the rate of unexpected mortality. In the event of a medical emergency, this device uses sensor technology and internet access to enable prompt communication with loved ones. The study aims to continuously monitor the patient's health status using temperature and cardiac sensors. The primary processing unit, an Arduino Uno microcontroller, is coupled to these sensors. As a wireless sensing node, the microcontroller is further integrated with an LCD and a Wi-Fi module to enable data transmission to a selected web server [2].

To store and process massive data—remarkably scalable sensor data—the work by Manogaran et al. (2023) presents a new architecture for IoT implementation in healthcare applications. Meta Fog-Redirection (MF-R) and Grouping and Choosing (GC) architecture are the two fundamental sub-architectures that comprise the suggested architecture. The proposed framework provides a reliable and scalable solution for processing and managing sensor data in healthcare applications by fusing the MF-R and GC architectures. Advanced analytics and real-time decision-making in the healthcare industry are made possible by using big data technologies and incorporating fog computing and cloud computing [5].

Researchers (Saha et al., 2018) presented a system where sensors collect data on a range of patient health-related factors, the Internet of Things archives that data, and a website displays it to allow for remote monitoring. The system's small size and sensors' usage limit human mistakes and the amount of space in the room. The researchers also emphasized a distinctive feature of their suggested remedy, which entails setting alarms to ensure that the patient receives the prescribed medication on time. Additionally, if any health parameter exceeds the threshold value, the system incorporates a notification strategy through email and SMS notifications.[7]

Monitoring athletes' internal and external efforts within sports teams has undergone a revolutionary change thanks to wearable technologies (Seshadri et al., 2019). To personalize recovery procedures for each athlete, there is still a medical need within the sports community to obtain more information about the internal workload of the athlete. The technical gap that sports medicine professionals need to fill to tailor hydration and recovery plans for each athlete is the capacity to continuously and non-invasively monitor biomarkers from saliva or sweat.[9]

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7890
***Article Received**: 30 May 2023 **Revised:** 25 July 2023 **Accepted:** 14 August 2023*

According to the research, a real-time health monitoring system should retain a patient's primary health parameters and make the information accessible to a doctor for monitoring via various communication channels. By enabling multiplexed data transfer across three modes—Bluetooth Low Energy (BLE), GSM (messaging services), and Wi-Fi (Internet), the suggested health monitoring system seeks to enhance healthcare delivery. [12]

In this study, the authors suggest a system that uses a pulse sensor to determine BPM and an AD8232 single lead heartbeat sensor to extract the ECG signal (Rahman et al., 2021). An ESP32 microcontroller with Wi-Fi capabilities is used to transfer the sensor data collected by these sensors to a cloud server over the internet for remote monitoring by a health professional. The suggested system uses the Ubidots and Thingspeak platforms as cloud servers [6]. Since it is difficult to monitor patients constantly for 24 hours, the authors (Kumar et al., 2017) devised a system that uses IoT to monitor the health status of patients and give screening to doctors or paramedical staff. The system uses non-invasive sensors to monitor several health indicators, including blood sugar, ECG, respiration rate, body temperature, posture, and pulse rate. The identified biomedical data is uploaded to a brand-new cloud server called "Thingspeak" in the suggested system [3].

III. Methodology

The primary objective of this study is to design and implement an integrated framework encompassing many modalities, such as electrocardiogram (ECG), temperature, and pulse rate data, to detect and forecast cases of COVID-19 effectively. The present study will acquire real-time physiological data from participants, encompassing electrocardiogram (ECG) signals, body temperature measurements, and pulse rates. Sophisticated signal processing methodologies will be utilized to extract pertinent characteristics from the obtained data, particularly discerning patterns that suggest COVID-19 infection. Subsequently, machine learning techniques will be utilized to construct prediction models that can detect initial indications of the disease by leveraging the collective data obtained from electrocardiogram (ECG), temperature, and pulse rate. The objective is to develop a precise and dependable method that can aid healthcare practitioners in detecting prospective COVID-19 cases and forecasting the disease's evolution. This would contribute to prompt treatments and enhanced patient care. Block diagram of the designed model is shown Figure 1.

A). Hardware Implementation of the wearable device:

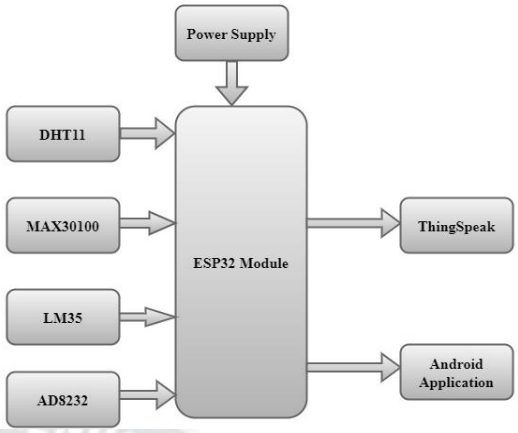

Fig 1. Block Diagram of the Module

The microcontroller utilized in the developed model is an ESP32. The use of an LM35 sensor determines the temperature of the user. The MAX30100 is utilized for the measurement of both the user's heart rate and oxygen saturation. The AD8232 is utilized for electrocardiogram (ECG) monitoring. The monitoring of temperature and humidity is conducted through the utilization of a DHT11 device. The ESP32, functioning as a microcontroller with internet capabilities, establishes a connection to a Wi-Fi access point to gain internet access. The collected data is afterward documented on a remote server. The utilization of ThingSpeak Cloud serves as the server. Furthermore, an Android application that has been specifically developed displays this data. Modular is a software development platform utilized for the creation of Android applications. Furthermore, the Kodular App provides users with pedometer functionality and the ability to get GPS location data.

The present study entails the creation of an all-encompassing framework for identifying and forecasting COVID-19, utilizing the collective capabilities of electrocardiogram (ECG), temperature, and pulse rate data. As depicted in Figure 1, the comprehensive operational framework and related block diagram delineate the system's complexities. The Wi-Fi capabilities of the ESP32 module play a crucial role as a communication channel. The acquisition of critical input data is facilitated by various sensors, such as the DHT11 sensor for measuring temperature and humidity, the MAX30100 sensor for monitoring pulse rate, the LM35 sensor for measuring temperature, and the AD8232 sensor for capturing ECG signals. The sensor inputs undergo thorough processing utilizing sophisticated signal processing techniques to identify significant features indicative of patterns associated with COVID-19 infection. Predictive models are developed by integrating machine learning algorithms, combining data obtained from input such as ECG, temperature, and pulse rate.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7890
***Article Received**: 30 May 2023 **Revised:** 25 July 2023 **Accepted:** 14 August 2023*

The confluence of these variables results in an accurate and resilient system with the ability to rapidly detect prospective instances of COVID-19 and anticipate the trajectory of the illness. The dissemination and display of output is facilitated by utilizing both an Android application and the ThingSpeak platform. These technological components bridge the gap between the underlying technology and the end user, providing user-friendly interfaces and real-time insights. The primary objective of this comprehensive approach is to provide healthcare practitioners with precise resources that facilitate early identification and well-informed decision-making in the fight against COVID-19.

B). Flowchart of the wearable device:

Within COVID-19 detection and prediction, the operational flow is precisely constructed by integrating several technological components, validation processes, and predictive modeling techniques and is shown in figure 2. The fundamental basis of the system entails supplying power to the ESP32 module, which serves as the central hub for data collection and communication. The initial verification procedure rigorously examines the integrity of each connection, promptly generating an error message or refraining from capturing data if any erroneous connections are detected. This stage is of utmost importance as it guarantees the dependability of data collecting. After undergoing validation, the system initiates the sensors' activation.

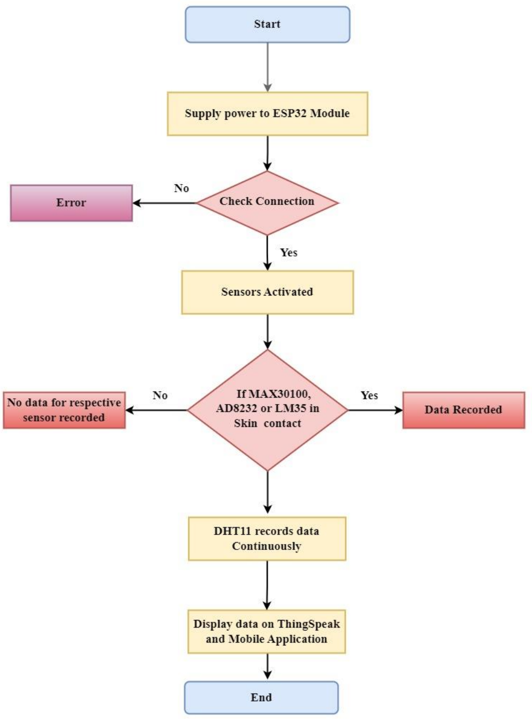

Fig 2. Flow chart of the model

A full array of physiological data acquisition is achieved by utilizing multiple sensors, namely the DHT11, MAX30100, LM35, and AD8232. The MAX30100 and AD8232 sensors are designed to collect data only when directly touching the body. In contrast, the LM35 and DHT11 sensors continuously gather information regardless of body contact. Implementing this coordinated data collection technique signifies the initiation of the system's extensive health monitoring functionalities.

In order to utilize the accumulated data for prediction objectives, a comprehensive Machine Learning (ML) model was carefully constructed. This model exemplifies the integration of data improvement approaches with the augmentation of predictive skills. The architectural design illustrated in the following diagram has been carefully devised to accommodate the complexities of the training process, ensuring that the machine learning model effectively learns and captures the underlying patterns. As the machine learning model progresses through multiple iterations of training cycles, it improves the data quality and develops its ability to make accurate predictions. The primary goal is to develop a predictive model capable of effectively establishing a connection between physiological characteristics and potential signs of COVID-19. This model would facilitate early identification and prediction, hence facilitating informed decision-making. The comprehensive methodology, encompassing the entire process from data gathering to predictive modeling, establishes a robust instrument for healthcare professionals. This culminates in the capacity to effectively utilize the abundance of information to identify and address cases of COVID-19 promptly.

C). Flowchart for the Prediction model:

In order to provide prediction utilizing collected features, we designed an ML model that improves the quality of data and the predictive power of a Machine Learning model. The architecture shown in the Figure below has been used for training purposes.

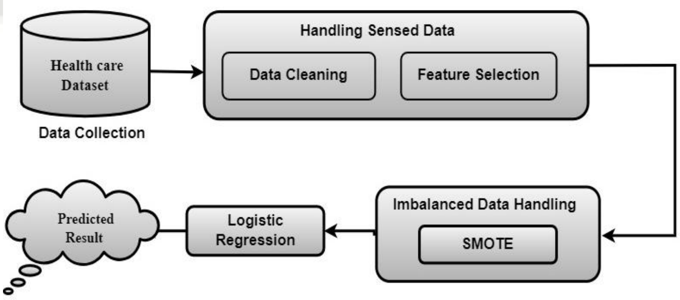

Fig 3. The proposed system architecture

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7890
***Article Received**: 30 May 2023 **Revised:** 25 July 2023 **Accepted:** 14 August 2023*

The architecture of the proposed system is shown in Figure 3 and is described using the following steps.

i. Healthcare Data Collection:

This step systematically gathers healthcare-related data from various sources, such as electronic health records, patient surveys, medical devices, or clinical trials. The collected data typically includes information about patients or subjects and their health-related attributes. It is described mathematically as using equation 1.

$$D = \{(X_1, Y_1), (X_2, Y_2), \ldots, (X_n, Y_n)\} \qquad (1)$$

Where D represents the dataset and (X_i, Y_i) represents an individual data point, X_i is a vector of features describing a patient, and Y_i is the corresponding target variable, often indicating a health outcome or condition for that patient.

ii. Data Cleaning:

Data cleaning is the process of preparing the collected data for analysis. It involves handling missing values, detecting and addressing outliers, and standardizing data to ensure it is in a suitable format for analysis. For handling missing values, we replace missing values in feature j with a calculated statistic (e.g., mean μ or median M) based on the available data using equation 2.

$$Xij = Xij' \text{ if } Xij' \text{ is not missing, else } Xij = \mu \text{ (or M)} \qquad (2)$$

For outlier detection and removal, the method uses measures like the Z-score or Interquartile Range (IQR) and either removes or adjusts them using Equation 3.

$$\text{Z-score} = (Xij - \mu) / \sigma \text{ and } IQR = Q3 - Q1 \qquad (3)$$

Data Standardization uses a mean of 0 and a standard deviation of 1 for each feature using equation 4.

$$Xij = (Xij - \mu) / \sigma \qquad (4)$$

iii. Feature Selection:

Feature selection is choosing the dataset's most relevant features (attributes) to improve model performance and reduce dimensionality. The information gained from each feature Xi concerning the target variable Y using entropy measures to assess their importance is evaluated using equation (5).

$$I(Xi, Y) = H(Y) - H(Y|Xi) \qquad (5)$$

The recursive Feature Elimination (RFE) method is utilized by optimizing a feature subset by considering an objective function J(X) that combines model performance C(X) with a penalty for the number of selected features ($\alpha * |X|$) using equation 6.

$$J(X) = C(X) - \alpha * |X| \qquad (6)$$

iv. SMOTE for Classification:

SMOTE (Synthetic Minority Over-sampling Technique) is employed when dealing with imbalanced classification problems, particularly in healthcare data. It generates synthetic samples for the minority class to balance the dataset. For each minority class sample (Xi, Yi), identify its k nearest neighbors within the minority class based on a distance metric. Generating Synthetic Samples (Xs, Ys) by interpolating between the selected minority sample (Xi, Yi) and one of its nearest neighbors (Xj, Yj) using equation 7.

$$Xs = Xi + \lambda * (Xj - Xi) \qquad (7)$$

Where λ is a random value between 0 and 1, we added synthetic samples to the dataset using equation 8.

$$Dataset=ADD(Xs = Xi + \lambda * (Xj - Xi)\ ) \qquad (8)$$

Incorporate the newly generated synthetic samples (Xs, Ys) into the dataset to balance the class distribution. Then, add (Xs and Ys) to the dataset. Next, we split data and trained utilizing the designed mathematical for the classifier that showed maximum improvement in performance. In the second stage of the Multistage model, we plotted the Learning curve for all selected probabilistic heterogenous and tree-based homogenous models to check for generalization gap. This gap was reduced using hyperparameter tuning. An optimal train set size with a minimum generalization gap was found for each model. Models were trained using this optimal sample size. The designed mathematical model suits sparse data. Adam optimized Logistic Regression model is demonstrated in the algorithm below where random weights weigh features, and bias is added; we compute sigmoid, gradient, moment, and root mean square. We further update weight and bias and iterate till convergence. We choose Adam over other optimizers such as momentum, nestorov, degrade, adadelta, and RMSprop as it has faster computation time because fewer parameters are there for tuning. The default optimizer for LoR is LBFGS (limited memory quasi-newton method), which does not converge for medium and large-sized datasets. The pseudocode where initialization is performed till line no. 8 and regression equation is framed in line no. 10. Sigmoid is computed followed by gradient.

Algorithm for the prediction model:

	Algorithm
1	**Inputs:**
2	Features and Label
3	**Output:**
4	Class prediction
5	**Begin**

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7890
***Article Received**: 30 May 2023 **Revised:** 25 July 2023 **Accepted:** 14 August 2023*

6	Initialize learning_rate, n_iter, beta_1, beta_2, ep silon, moment for weights, rms prop for wei ghts, moment for bias, rms prop for bias
7	Derive rows and columns from the dataset.
8	Initialize weights and bias.
9	For n_iter
10	Take the dot product of the X matrix with weights and add bias.
11	Compute sigmoid
12	Compute gradient for weights and biase s.
13	Compute moments and RMS for weight s.
14	Compute moments and RMS for bias.
15	Update weight and bias.
16	**End For**
17	Return prediction
18	**End**

The temperature sensor is a semiconductor device with a linear voltage-temperature relationship specified as ten mV °C using equation 9.

$$V_0 [T] = 0.01 (3.5) \quad (9)$$

Where V_0 is the sensor output voltage in volts, and T is the temperature in °C

The pulse oximeter determines the absorption ratio by analyzing the light absorption of two wavelengths from the pulsatile-added volume of oxygenated arterial blood (AC/DC). SpO2 is extracted from a memory table that was generated using empirical formulae. A SpO2 of 85% is represented by a ratio of 1, a SpO2 of 100% by a ratio of 4, and a SpO2 of 0% by a ratio of 3. The table must be based on experimental measurements taken from healthy patients to increase its trustworthiness. Another method of estimating SpO2 involves applying the following equation with the AC component of the signal and the determined ratio. The value of RX100 is SpO2.
In humidity sensor DHT11, the relative Humidity is determined using equation 10.

$$R_H - \left(\frac{PW}{Ps}\right)\times 100\% \quad (10)$$

where RH: Relative Humidity: Density of water vapor: Density of water vapor saturation

A). Temperature:

i. **Mean and Standard Deviation:** The Mean (μ) of temperature values $T[n]$ are calculated using equation 11.

$$\mu = \frac{1}{N}\sum_{n=0}^{N-1} T[n] \quad (11)$$

Standard Deviation (σ) of temperature values $T[n]$ are calculated using the equation 12 and 13, respectively.

$$SD = \sqrt{\frac{1}{N}\sum_{n-o}^{N-1}(T[n]-\mu)^2} \quad (12)$$

$$\sigma = \sqrt{(\frac{1}{N}\sum_{n=0}^{N-1}(T[N]-\mu)^\wedge 2} \quad (13)$$

ii. **Temperature Fluctuations:** Compute the range of temperature fluctuations using equation 14.
Temperature Range=max(T)−min(T) (14)

iii. **Temperature Gradient:**
Estimate the temperature gradient over a specific time interval using equation 15.

$$\text{Temperature Gradient} = \frac{T[N-1]-T[0]}{N-1} \quad (15)$$

B). Pulse Rate:

i. **Pulse Rate Estimation:** Calculate the average number of pulses per minute from the pulse intervals using equation 16.

$$\text{Pulse Rate(bpm)} = \frac{60}{Mean\ (PI)} \quad (16)$$

ii. **Heart Rate Variability (HRV) from Pulse Intervals:** Compute various HRV features from pulse intervals. SDNN (Standard Deviation of NN Intervals) is computed using equation (17).

$$\text{SDNN} = \sqrt{\frac{1}{N-1}\sum_{i-1}^{N-1}(PI[i]-\mu PI)^2)} \quad (17)$$

RMSSD (Root Mean Square of Successive Differences) is computed using 18.

$$\text{RMSSD} = \sqrt{\frac{1}{N-1}\sum_{i-1}^{N-1}(PI[i]-(PI[i]-1)2)} \quad (18)$$

C). ECG (Electrocardiogram)

Heart Rate Calculation from RR Intervals: Calculate the average heart rate (beats per minute) from RR intervals using equation 19.

$$\text{Heart Rate(bpm)} = \frac{60}{Mean\ (RR)} \quad (19)$$

Frequency-Domain Analysis: Calculate the RR intervals' power spectral density (PSD) using the Fast Fourier Transform (FFT). Extract frequency-domain features such as LF (Low Frequency) and HF (High Frequency) power.

i. **QRS Complex Detection:** Detect QRS complexes in the ECG signal using peak detection methods. Calculate the RR intervals (time between successive R-peaks).
ii. **Heart Rate Variability (HRV) from RR Intervals:** Compute various HRV features from RR intervals (similar to the pulse rate HRV features).
iii. **ST Segment Analysis:** Detect and analyze ST segment deviations to assess potential cardiac ischemia or other anomalies.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7890
***Article Received**: 30 May 2023 **Revised:** 25 July 2023 **Accepted:** 14 August 2023*

IV. Circuit Diagram and Hardware Development

The pursuit of efficient solutions for detecting and predicting COVID-19 culminates in the intricate integration of advanced technology. An exemplary demonstration of this collaborative effect may be observed in the harmonious incorporation of the ESP32 microcontroller, intricately combined with a Wi-Fi module and augmented by a selection of vital sensors such as the DHT11, MAX30100, AD8232, and LM35. The integration of several components forms the coherent amalgamation that underpins the system's ability to acquire, process, and transmit dynamic data. This integration is considered a fundamental aspect of contemporary health monitoring technologies. Figures 4 and 5 are the proposed system's circuit diagram and hardware module.

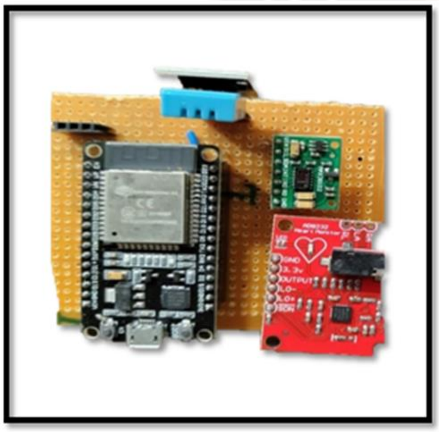

Fig 4. Circuit Diagram of the model

As illustrated, the skillful coordination of these elements highlights the significant consequences of integrating hardware and software domains in addressing the complex issues presented by COVID-19 detection and prediction.

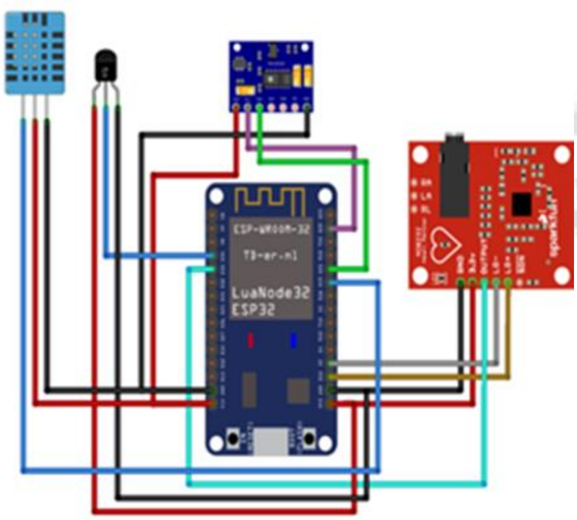

Fig 5. Circuit Diagram of the model

This study presents the validation and testing of the linked system utilizing the online simulation platform TinkerCad, which replicates real-world situations. By conducting rigorous experiments within the simulated environment, we successfully integrated the ESP32 microcontroller, Wi-Fi module, and a set of sensors. The efficacy and feasibility of the proposed integration are demonstrated by the proficient development and assessment of connections inside the TinkerCad framework.

V. Software Simulations

The integration of the ESP32 microcontroller, intricately combined with a Wi-Fi module and augmented by a selection of vital sensors such as the DHT11, MAX30100, AD8232, and LM35, is shown in Figure 6. The integration of several components forms the coherent amalgamation that underpins the system's ability to acquire, process, and transmit dynamic data. This integration is considered a fundamental aspect of contemporary health monitoring technologies. As illustrated, the skillful coordination of these elements highlights the significant consequences of integrating hardware and software domains in addressing the complex issues presented by COVID-19 detection and prediction. This study presents the validation and testing of the linked system utilizing the online simulation platform TinkerCad, which replicates real-world situations.

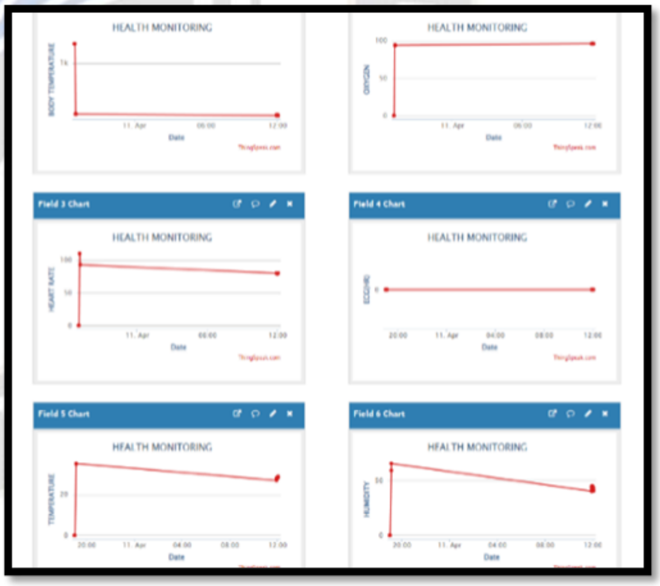

Fig 6. Cloud Data

By conducting rigorous experiments within the simulated environment, we successfully integrated the ESP32 microcontroller, Wi-Fi module, and a set of sensors. The efficacy and feasibility of the proposed integration are demonstrated by the proficient development and assessment of connections inside the TinkerCad framework.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7890
***Article Received:** 30 May 2023 **Revised:** 25 July 2023 **Accepted:** 14 August 2023*

b. App Development (KODULAR Implementation)

The Android application developed to detect and predict COVID-19, utilizing Kodular, demonstrates a novel method for administering and sharing health data and interface is represented in figure 7. The application effectively incorporates various health measurements, encompassing temperature, oxygen levels, heart rate, and electrocardiogram (ECG) data. This comprehensive platform offers individuals the ability to monitor their vital indicators diligently. Significantly, the application goes beyond mere data gathering and facilitates the secure communication of users' health indicators to medical professionals, enabling timely intervention.

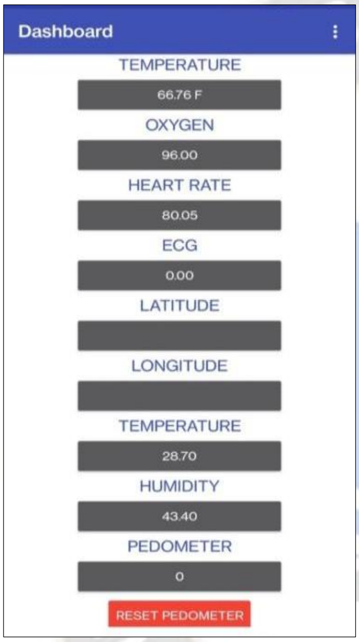

Fig 7. Android Application

The strategic implementation of Kodular showcases the capacity of technology to bridge the divide between personal health awareness and professional medical knowledge, as shown in Fig 7. This positioning of the platform establishes it as a fundamental tool in promoting proactive health monitoring and facilitating remote medical support.

VI. Results and Validation

An innovative technology that permits continuous monitoring of numerous health markers and relieves patients of the stress of frequent hospital visits has a prototype made for it. With practically real-time updates on important health indicators, this automated system enables patients to check their health condition from the comfort of their homes. Our methodology can prevent hospitalization by identifying changes in a patient's condition early on and can enhance patient health-related outcomes.

The paper "Design and Development of smart wearable for Continuous Health Monitoring" is about a wearable device that continuously uses various sensors and microcontrollers to monitor various health parameters. The device is designed to be worn on the wrist and can provide real-time feedback to the user. The core of the system is the ESP32 microcontroller, a low-power, high-performance chip ideal for IoT applications. The microcontroller interfaces with various sensors, including the LM35 temperature sensor, MAX30100 pulse oximeter, AD8232 ECG sensor, and DHT11 humidity and temperature sensor. The LM35 temperature sensor measures the wearer's body temperature, while the MAX30100 sensor measures the oxygen saturation level and pulse rate. The AD8232 ECG sensor measures the heart rate and rhythm of the wearer, and the DHT11 sensor measures the humidity and temperature of the environment. All these sensors are connected to the ESP32 microcontroller, which processes the data and sends it to the Android app for visualization. The Android app displays the real-time readings of all the sensors, and the user can also see the historical data in the app.

To make the device more user-friendly, a 3D-printed casing is made, making it wearable and easy to use. The casing houses all the sensors and the ESP32 microcontroller. The wearable is powered by a rechargeable battery, making it portable and convenient. A zero PCB simplifies the circuitry and makes the device more compact. The zero PCB is a printed circuit board that eliminates the need for wires and connectors, making the device more reliable and robust. Our solution also enables doctors to access a comprehensive log of patient data, facilitating a more thorough analysis of the efficacy of treatments and other interventions. This real-time data allows for more accurate assessments of a patient's progress and enables timely interventions when necessary. Table 1 describes is the comparative study of various human vitals, tested with our model and Industrial grade equipment. A certified doctor takes all the readings in Yashashavi Hospital, Malad Mumbai.

Table 1: Comparison of Oxygen reading with Industrial grade equipment

OXYGEN (%)	
Proposed Work	**Industrial grade equipment**
93.86	94.01
94.85	95.72
94.14	95.89
95.47	96.85
94.68	95.75
96.09	97.06
97.02	95.28
93.72	92.82
92.39	92.95
93.5	94.16

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7890
***Article Received**: 30 May 2023 **Revised:** 25 July 2023 **Accepted:** 14 August 2023*

The results reported in this study provide a comparison analysis of oxygen saturation levels, represented as a percentage, between the suggested methodology and commercially available industrial-grade equipment. The data exhibits a discernible pattern in the measurements of oxygen saturation observed in various cases. In the present study, the observed oxygen saturation values range from 92.39% to 97.02%, demonstrating a certain level of variability in the recorded measurements. In contrast, using industrial-grade equipment consistently results in slightly elevated levels of oxygen saturation, ranging from 92.82% to 97.06%. The results suggest a significant convergence in the oxygen saturation ranges observed by both the proposed system and the industrial-grade equipment. The presented study demonstrates high accuracy in measuring oxygen saturation, as evidenced by the near resemblance of the recorded values to those obtained using professional-grade equipment. Nevertheless, several occurrences demonstrate minor discrepancies between the two. For example, the proposed study demonstrates an oxygen saturation level of 96.09%, which is somewhat lower than the industrial-grade equipment's value of 97.06%. Similarly, a further data point reveals a marginally elevated oxygen saturation level, precisely 95.47%, in the proposed study, in contrast to the 94.68% observed in the industrial-grade counterpart. In general, the oxygen saturation findings demonstrate the proposed research's capacity to get oxygen saturation measures comparable to those obtained from proven industrial-grade equipment. This substantiates the viability of the suggested tool as a dependable means of health monitoring.

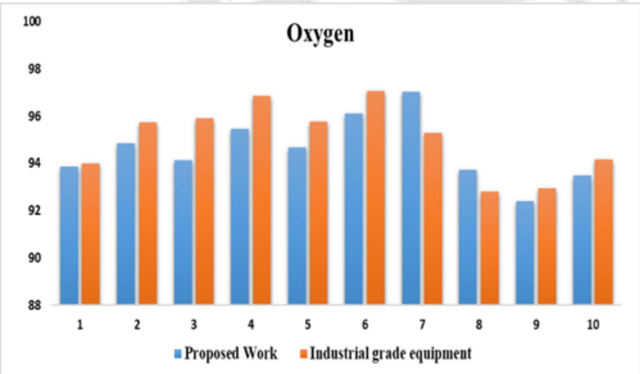

Fig 8. Graph of Oxygen readings

Fig.8 compares the oxygen levels of the proposed model and the industrial-grade equipment measured. The data suggests that the proposed model has a high degree of accuracy in measuring oxygen levels, with a maximum difference of 1.63% compared to industrial-grade equipment. Based on the results of Figure 8, it can be concluded that the proposed model is highly effective and accurate in measuring oxygen levels. Therefore, this model could be highly beneficial for patients who require constant monitoring of their oxygen levels, as it provides a reliable, accurate, and cost-effective alternative to industrial-grade equipment. The data in Table No. 2 compares heart rate readings, expressed in beats per minute (bpm), between the proposed work and equipment of industrial-grade quality. The observations presented in this study depict the patterns of heart rate fluctuations seen in several cases. The heart rate data of the proposed experiment demonstrates a range of variability, spanning from 78.03 beats per minute (bpm) to 99.54 bpm. Simultaneously, the industrial-grade apparatus documents heart rates ranging from 78.69 beats per minute (bpm) to 98.37 bpm. The presented data provides a comparative assessment of heart rate measurements conducted using two different technologies.

Table 2: Comparison of Heart Rate reading with Industrial grade equipment

Heart Rate (in bpm)	
Proposed Work	**Industrial grade equipment**
79.02	80.67
80.52	79.94
88.83	87.94
93.27	93.33
90.78	90.19
78.03	78.69
87.31	88.17
99.54	98.37
80.16	81.69
88.95	88.4

Upon analyzing the heart rate measurements, it becomes evident that solid correlations and minor deviations exist between the proposed work and the industrial-grade equipment. For example, at a particular occurrence, the proposed work documents a heart rate of 78.03 beats per minute (bpm), whereas the industrial-grade equipment registers a heart rate of 78.69 bpm, suggesting a slight discrepancy. Similarly, an additional data point indicates a suggested work heart rate of 99.54 bpm compared to an industrial-grade heart rate of 98.37 bpm, illustrating a slight differentiation. The data demonstrates a constant correlation between the two systems, as evidenced by the tight alignment of heart rate readings with each other's patterns. The findings underscore the potential of the suggested work in effectively assessing heart rates, hence establishing its feasibility as a dependable instrument for heart rate monitoring.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7890
***Article Received:** 30 May 2023 **Revised:** 25 July 2023 **Accepted:** 14 August 2023*

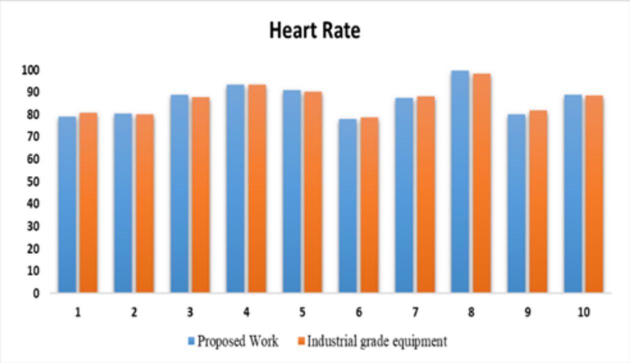

Fig 9. Graph of Heart Rate readings

Fig.9 compares heart rate levels measured by the proposed model and industrial-grade equipment. The range of heart rate measurements is from 78.03 bpm to 99.54 bpm, which suggests that the heart rates being measured are within a normal range for most healthy adults. Most measurements obtained from the two devices are very close in value, with only minor differences. The overall difference between the two sets of measurements across all ten pairs is 0.53 bpm, which suggests that the two devices are generally accurate and produce similar results.

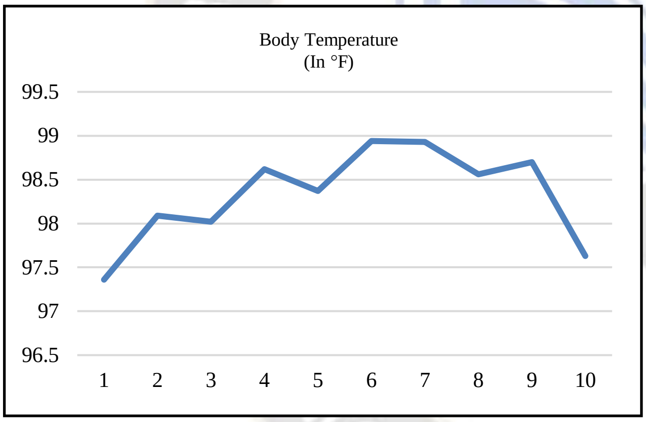

Fig 10. Change in Body Temperature

Figure 10 shows the change in body temperature measured by the proposed model. The data shows the variation in body temperature of a patient over a period of time. Based on the results of figure 10, it can be concluded that the body temperature is in the normal range of 97 ºF to 99 ºF. The model could be highly beneficial for patients who require constant body temperature monitoring, as it provides a reliable, accurate, and cost-effective alternative to industrial-grade equipment.

Table 3: Mean Comparison (%)

Parameter	Proposed Model	Industry Grade Equipment
Oxygen	97.8	97.98
Heart Rate	93.95	94.24
Body Temperature	99°F	98.8°F

The data shown in Table 3 compares the suggested model and commercially available equipment regarding three essential health parameters: oxygen saturation, heart rate, and body temperature. Upon analysis of the oxygen saturation measurements, it is observed that the proposed model exhibits an average value of 95.0625%, whereas the industry-grade equipment demonstrates an average value of 94.8054%. The slight discrepancy highlights a strong correlation between the two measurement systems, as evidenced by the suggested model's ability to evaluate oxygen levels comparable to the established industry norm. Regarding heart rate measurements, the proposed model demonstrates an average of 94.184 beats per minute (bpm), while the industry-standard equipment displays a slightly higher average heart rate of 94.9182 bpm. Notwithstanding this slight deviation, the data underscores a constant trend in heart rate readings, suggesting that the suggested model successfully captures the dynamics of heart rate that correspond to the recognized industry standard. The Table 4 shows the reading of oxygen, heart rate and body temperature for proposed model and industrial grade equipment.

i. **Oxygen:** The proposed model has a slightly higher mean oxygen value (95.0625) than the industry-grade equipment (94.8054). This suggests that the proposed model may provide more accurate or higher oxygen readings on average. This advantage can be beneficial in scenarios where accurate oxygen level monitoring is crucial, such as in medical or high-altitude environments.

ii. **Heart Rate:** Although the industry-grade equipment has a higher mean heart rate value (94.9182) compared to the proposed model (94.184), the difference is relatively small and can be considered for readings that can be taken with a tolerance value as small as 0.0001.

3. **Body Temperature:** The proposed model reports a lower mean body temperature value (98.054 ºF) than the industry-grade equipment (98.849 ºF). This suggests that the proposed model may provide more accurate or lower body temperature readings on average. This advantage can benefit medical applications where precise body temperature monitoring is essential, such as detecting fever or monitoring patients' health conditions. Finally, regarding the evaluation of body temperature, the suggested model registers an average body temperature of 98.054°F. However, the equipment commonly used in the industry indicates a marginally higher average of 98.849°F. This observation highlights a certain level of disparity between the two methods regarding measuring body temperature.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7890
***Article Received**: 30 May 2023 **Revised:** 25 July 2023 **Accepted:** 14 August 2023*

Table 4: Model Comparison (%)

Parameter	The proposed Model	Industry Grade Equipment
Oxygen	95.0625	94.8054
Heart Rate	94.184	94.9182
Body Temperature	98.054°F	98.849°F

Evaluating the suggested model and industry-grade equipment regarding essential health metrics yields significant insights on their respective performance. Regarding the measurement of oxygen, the model under consideration exhibits an oxygen level of 97.8%, while the equipment commonly used in the industry registers a slightly higher level of 97.98%. The slight discrepancy implies a strong correlation between the two systems' precision of oxygen saturation measurements.

Shifting the focus to heart rate measurements, the proposed model records a heart rate of 93.95 beats per minute (bpm), whereas the industry-grade equipment captures a slightly higher heart rate of 94.24 bpm. The minor discrepancy observed can be attributed to the comparability of the two devices' heart rate monitoring capabilities, as both yield comparable results consistent with recognized standards. Finally, the analysis of body temperature readings demonstrates that the suggested model registers a body temperature of 99°F, while the industry-standard equipment records a somewhat lower body temperature of 98.8°F. This differentiation reflects a slight deviation in the temperature measurement capability of the two systems.

1. **Oxygen:** The proposed model has a mode value of 97.8 for oxygen levels, while the industry-grade equipment has a slightly higher mode value of 97.98. This suggests that the proposed model may provide more consistent or more frequently observed oxygen readings at 97.8, which can be advantageous in scenarios where precise and reliable oxygen level monitoring is crucial.

2. Heart Rate: The proposed model has a mode value of 93.95 for heart rate, while the industry-grade equipment has a slightly higher mode value of 94.24. Similar to the oxygen parameter, the proposed model may provide more consistent or more frequently observed heart rate readings at 93.95. This can be advantageous in applications where accurate and reliable heart rate monitoring is essentia.

3. Body Temperature: The proposed model reports a mode value of 99ºF for body temperature, whereas the industry-grade equipment has a mode value of 98.8 ºF. This indicates that the proposed model may provide more consistent or frequently observed body temperature readings at 99ºF. This advantage can be valuable in medical settings where precise and reliable body temperature monitoring is critical for diagnosis and patient care.

Table 5: Mean-square error deviation

MSE	
Oxygen	1.2397
Heart Rate	0.9091

The mean square error (MSE) as shown in table 5 gives the comparison quantitatively that assesses measurement accuracy by evaluating the average squared discrepancies between observed values and their corresponding actual values. The mean squared error (MSE) in measuring oxygen saturation is 1.2397. The value above denotes the mean of the squared disparities between the anticipated and observed oxygen levels, hence signifying the extent of variability between the two datasets. Likewise, within the domain of heart rate measurements, the calculated mean squared error (MSE) equates to 0.9091. The figure above represents the mean of the squared differences between the anticipated and observed heart rates, providing insight into the overall precision of the measurements in relation to their actual values.

The comparison of mean squared errors (MSE) is a significant metric for assessing the effectiveness of the measuring system. It allows for identifying the degree to which the recorded measurements differ from their actual values. More minor mean squared error (MSE) readings indicate greater accuracy and a more robust correspondence between the expected and actual data. Therefore, the computed mean squared error (MSE) values provide significant insights into the accuracy and dependability of the oxygen saturation and heart rate data. For the variable "Oxygen": The MSE is 1.2397. This suggests that, on average, the squared difference between predicted and actual oxygen values is 1.2397. For the variable "Heart Rate": The MSE is 0.9091. This indicates that, on average, the squared difference between predicted and actual heart rate values is 0.9091. These MSE values quantify the overall prediction accuracy for each variable, with lower values indicating better predictive performance

Table 6: Root square mean error deviation

RSMD	
Oxygen	1.1619
Heart Rate	1.1108

Table 6 shows the RSMD of the values of heart rate and oxygen. The root-mean-square deviation (RSMD) measures the average deviation between two sets of values. Calculating the RSMD allows us to quantify the differences between the proposed work's oxygen and heart rate values and the industrial-grade equipment. In table 7, one can see the comparison of different products currently available in the market. It shows the comparison of different parameters, available features, and costs compared with our model.

Table 7: Comparison of Current Products

Features/ brand	Sony Smartwat	BoAT Xtend	Samsung Gear	Moto 380	LGG WatchR	Fitbit	Proposed Model
Body Temperature	×	✓	×	×	×	✓	✓
Oxygen Level	✓	✓	×	×	×	✓	✓
Heart Rate Monitor	×	✓	✓	✓	✓	✓	✓
ECG	×	×	×	×	×	×	✓
Humidity Sensing	×	✓	×	×	×	✓	✓
Cloud data storage	×	×	×	×	×	×	✓
Location A Pedometer	×	×	✓	×	×	✓	✓

The comparison elucidates the existence or nonexistence of diverse attributes among numerous wristwatch companies, including Apple, Sony wristwatch, boAT Xtend, Samsung Gear, Moto 380, LG G WatchR, Fitbit, and the hypothetical model. Each brand undergoes evaluation based on many aspects, like body temperature monitoring, oxygen level tracking, heart rate monitoring, ECG capabilities, humidity sensing, cloud data storage, and position tracking with a pedometer. Regarding monitoring body temperature, it is worth noting that the Apple Watch, Sony Smartwatch, boAT Xtend, Samsung Gear, and Moto 380 lack this functionality. Conversely, the proposed model incorporates this essential element for measuring one's health. The differentiation above establishes a clear separation, potentially introducing a significant aspect to the health monitoring field. The Sony Smartwatch, boAT Xtend, Samsung Gear, and Moto 380 are the devices supporting monitoring oxygen levels. The proposed model also has this functionality. The alignment of the suggested model highlights its conformity to contemporary health monitoring requirements. The Sony Smartwatch and the suggested device incorporate a heart rate monitor feature, indicating a mutual emphasis on cardiovascular health. Significantly, the proposed model incorporates an electrocardiogram (ECG) feature, setting it apart from competing brands and augmenting its capacity for comprehensive health evaluation. Additional comparisons indicate that the LG G WatchR and the suggested device support humidity sensing, suggesting a specific emphasis on environmental considerations. Cloud data storage is a crucial component of maintaining health records and is widely utilized across the assessed brands, including the suggested model.

Moreover, including location tracking functionality through a pedometer is a prevalent characteristic observed in several brands, such as the Sony Smartwatch, boAT Xtend, Samsung Gear, Moto 380, and the aforementioned proposed model. This characteristic highlights the incorporating of fitness monitoring and portability features in these intelligent timepieces. The suggested model exhibits a distinctive combination of characteristics that establishes it as a comprehensive solution for monitoring health. The suggested model showcases a comprehensive health assessment and management approach, incorporating unique features such as body temperature monitoring and ECG capability.

VII. Conclusion and Future Work Directions

The successful experimentation has resulted in the developing of an innovative prototype—an automated health monitoring system that can potentially transform the healthcare industry significantly. This innovative system can free individuals from the limitations of frequent hospital visits, providing a revolutionary solution that enables patients to diligently monitor their health status from the comfort of their own homes. This system facilitates the dissemination of timely information regarding essential health parameters, empowering patients to engage in informed health management. Significantly, the proficiency of this technology in identifying initial aberrations in a patient's health trajectory has the potential to prevent hospitalization and enhance patient welfare.

Furthermore, this technology presents itself as a valuable asset for healthcare providers, granting them unrestricted access to a comprehensive repository of patient information. The reservoir facilitates not just the examination of treatment success at a detailed level but also provides opportunities for complex interventions that contribute to enhanced health outcomes. The system's proficiency in enabling real-time data evaluation provides medical professionals with the necessary knowledge to make prompt and well-informed judgments customized to meet each patient's specific needs. The proposed technology can be installed in hospitals, allowing for the collection and online database storage of vast data. Through an application, even the findings can be made accessible from a mobile device. The system can be further enhanced by incorporating artificial intelligence system components to benefit patients and medical professionals. Data mining can be used to investigate the parameters and results of numerous patients' medical histories to look for recurring patterns and orderly relationships in COVID-19. For example, the effects can also be approximated if a patient's health metrics are changing like another patient in the database. It would be simpler for doctors and medical researchers to identify a solution if the same patterns were discovered frequently.

VIII. Feasible Applications

There is no denying the presence of wearable technology in our lives, particularly among early adopters. In order to successfully enter the consumer market, numerous technological companies and industries have invested in developing cutting-edge wearable solutions. Hospitals, shopping centers, schools, offices, and commercial and residential areas are just a few. The following are some of the many advantages of our model:

7.1 Implementation in Hospitals: Health monitoring is crucial for prevention, especially if early disease identification might lessen suffering and medical expenses. Maintaining your body's health is a challenge. No one can maintain good health for long if the essential vital indications of excellent health are not monitored. Keeping track of blood pressure, body temperature, pulse, heart rate, and breathing rate allows patients and medical staff in a hospital to respond correctly.

7.2 Gyms/Fitness Centers: Athletes frequently employ a variety of functions during their training and workout sessions, including heart rate monitoring, sleep tracking, and calorie tracking. Smartwatches give customers access to all these capabilities and enable them to understand their physiological data better while exercising.

7.3 Fitness Enthusiasts: People who track their daily activity and are concerned about their health require a daily health parameter monitoring device. They would benefit from this equipment because it will display their daily vitals and assist them in maintaining their health and physical fitness.

References

[1] D. S. R. Krishnan, S. C. Gupta, and T. Choudhury, "An IoT-based Patient Health Monitoring System," in 2018 International Conference on Advances in Computing and Communication Engineering (ICACCE), August 2018, pp. 1–7.

[2] D. Azariadi, V. Tsoutsouras, S. Xydis, and D. Soudris, "ECG signal analysis and arrhythmia detection on IoT wearable medical devices," in 2016 5th International Conference on Modern Circuits. And Systems Technologies (MOCAST), June 2016, pp. 1–4.

[3] K. N. Swaroop, K. Chandu, R. Gorrepotu, and S. Deb, "A health monitoring system for vital signs using IoT," Internet of Things, vol. 5, pp. 116–129, March 2019.

[4] G. Manogaran, R. Varatharajan, D. Lopez, P. M. Kumar, R. Sundarasekar, and C. Thota, "A new architecture of Internet of Things and big data ecosystem for secured smart healthcare monitoring and alerting system," Futur. Gener. Comput. Syst., vol. 82, pp. 375–387, May 2018.

[5] S. V Zanjal and G. R. Talmale, "Medicine Reminder and Monitoring System for Secure Health Using IOT," Procedia Comput. Sci., vol. 78, pp. 471–476, 2016.

[6] F. Firouzi et al., "Internet-of-Things and big data for smarter healthcare: From device to architecture, applications, and analytics," Futur. Gener. Comput. Syst., vol. 78, pp. 583–586, January 2018.

[7] B. Farahani, F. Firouzi, V. Chang, M. Badaroglu, N. Constant, and K. Mankodiya, "Towards fog-driven IoT eHealth: Promises and challenges of IoT in medicine and healthcare," Futur. Gener. Comput. Syst., vol. 78, pp. 659–676, January 2018.

[8] M. Hassanalieragh et al., "Health Monitoring and Management Using Internet-of-Things (IoT) Sensing with Cloud-Based Processing: Opportunities and Challenges," in 2015 IEEE International Conference on Services Computing, August 2015, pp. 285–292.

[9] J. Saha et al., "Advanced IOT based combined remote health monitoring, home automation, and alarm system," in 2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC), February 2018, pp. 602–606.

[10] Sultan H Almotiri, Murtaza A Khan, and Mohammed A Alghamdi. Mobile health (m- m-health) system in the context of IoT. In 2016 IEEE 4th international conference on the future Internet of things and cloud workshops (FiCloudW), pages 39–42. IEEE, 2016.

[11] D Shiva Rama Krishnan, Subhash Chand Gupta, and Tanupriya Choudhury. An IoT based patient health monitoring system. In the 2018 international conference on advances in computing and communication engineering (ICACCE), pages 01–07. IEEE, 2018.

[12] S Pradeep Kumar, Vemuri Richard Ranjan Samson, PLSD Malleswara Rao, and K Kedar Eswar. Intelligent health monitoring system of patients through IoT. In the 2017 international conference on I-SMAC (IoT in social, mobile, analytics and cloud, pages 551–556. IEEE, 2017.

[13] Nuno Vasco Lopes, Filipe Pinto, Pedro Furtado, and Jorge Silva. Iot architecture proposal for disabled people. In 2014 IEEE 10th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob), pages 152–158. IEEE, 2014.

[14] Gunasekaran Manogaran, Ramachandran Varatharajan, Daphne Lopez, Priyan Malarvizhi Kumar, Revathi Sundarasekar, and Chandu Thota. A new architecture of **the** internet of Things and extensive data ecosystem for secured intelligent healthcare monitoring and alerting system. Fu- ture Generation Computer Systems, 82:375–387, 2018.

[15] Md Abdur Rahman, Yue Li, Tanzim Nabeed, and Md Toufiqur Rahman. Remote monitoring of heart rate and ECG signal using esp32. In 2021 4th International Conference on Advanced Electronic Materials, Computers and Software Engineering (AEMCSE), 604–610. IEEE, 2021.

[16] Jayeeta Saha, Arnab Kumar Saha, Aiswarya Chatterjee, Suyash Agrawal, Ankita Saha, Avirup Kar, and Himadri Nath Saha. Advanced IoT-based combined remote health monitoring, home automation, and alarm system. In 2018 IEEE 8th annual

Computing and communication workshop and Conference (CCWC), pages 602–606. IEEE, 2018.
[17] Sharanbasappa Sali and C Parvathi. Health monitoring system using wireless sensor network. International Journal of Engineering Research and Applications, 8, 2018.
[18] Dhruv R Seshadri, Ryan T Li, James E Voos, James R Rowbottom, Celeste M Alfes, Christian A Zorman, and Colin K Drummond. Wearable sensors for monitoring the athlete's physiological and biochemical profile. NPJ digital medicine, 2(1):72, 2019.
[19] Andrej Škraba, Andrej Koložvari, Davorin Kofjacˇ, Radovan Stojanovic´, Eugene Se- menkin, and Vladimir Stanovov. Prototype of group heart rate monitoring with esp32. In 2019 8th Mediterranean Conference on Embedded Computing (MECO), pages 1–4. IEEE, 2019.
[20] Swayanjeet Sorte. Zigbee and gsm based patient health monitoring system. IEEE Int. J. Eng. Sci. Res. Technol, 3:445–451, 2016.
[21] K Narendra Swaroop, Kavitha Chandu, Ramesh Gorrepotu, and Subimal Deb. A health monitoring system for vital signs using iot. Internet of Things, 5:116–129, 2019.
[22] Laxman Thakre, Nayan Patil, Prashant Kapse, and Piyush Potbhare. Implementation of soldier tracking and health monitoring system. In 2022 10th International Conference on Emerging Trends in Engineering and Technology-Signal and Information Processing (ICETET-SIP-22), pages 01–05. IEEE, 2022.
[23] Nishita M Topale, Sarvesh S Desai, and Rohit R Bhagat. Remote health monitoring during covid-19 pandemic: A case for home-based care. Indian Journal of Community Medicine, 46(3):401–404, 2021.
[24] Khin Thet Wai, Nyan Phyo Aung, and Lwin Lwin Htay. Internet of things (iot) based healthcare monitoring system using nodemcu and arduino uno. Published in International Journal of Trend in Scientific Research and Development (ijtsrd), 3(5):755–759, 2019.