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IoT Empowerment in Healthcare: Detailed ECG Analysis and Prediction by using 2D Gaussian Filter

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ABSTRACT Currently, healthcare sector is the most dynamic sector in terms of introducing new technologies and services. An innovative advancement in this sector is the remote or portable monitoring of patients, which is proving to be very beneficial in a world with a rapidly expanding population, rising health issues, and limited access to medical facilities. A patient monitoring equipment is often used to quantitatively measure a patient's vital signs, including blood pressure, temperature, ECG, heart rate, and SpO2. This study attempts to enhance the future of healthcare by developing such a patient monitoring system. The ECG dataset was downloaded from CPEIC. The device created for this study can measure four parameters, namely ECG, SpO2, heart rate, and body temperature. The values are displayed on an LCD screen and the device is IoT-based, allowing data transmission to a web application for easy and universal access. To address the issues encountered, the device is designed to be cost-effective, dependable, and portable. The ECG output of this IoT-based model was thoroughly examined and tested using a deep learning model known as Inception V3 to determine the accuracy and dependability of the network. The model obtained phenomenal training loss of 0.1315 and a training accuracy of 96.66%. On the validation set, it achieved a validation loss of 0.1146 and a validation accuracy of 96.90%. Two-dimensional Gaussian elimination was used to remove noise from ECG images.

INDEX TERMS computer vision, Gaussian filter, healthcare, health management systems, IOT, machine learning, patients, vital signs

I. INTRODUCTION

Deep learning (DL) models rely on Artificial Neural Networks (ANNs), modeled after the structure of the human brain. Each layer in these networks consists of interconnected nodes (neurons) that process input data. As the data moves through these layers, the network gradually learns to recognize increasingly complex patterns. For example, in image recognition, the first layers may detect edges, while deeper layers identify shapes or specific objects [1].

The widespread use of E-health or mobile health has significantly impacted the global healthcare business. Doctors and healthcare professionals are opting for these solutions to address issues such as the scarcity of equipment, hospital resources, and patient overload. This research was undertaken to provide an effective solution to the above challenges by focusing on the Patient Monitoring System (PMS) or multiparameter monitor, which is the most often used piece of equipment.

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SpO2 recording, also known as pulse oximeter, is a technique used to measure blood gases and detect medical problems, including hypoxemia. Oxygen is the primary gas tested in the blood non-invasively by pulse oximetry. This approach is often used in occupational therapy, Intensive Care Units (ICUs), clinics, and is also advised for incorporation into the everyday routines of some individuals with coronary heart problems [2]. Blood oxygen saturation is quantified as a percentage. The typical blood oxygen saturation level is between 95% and 100%. Some sources indicate that levels beyond 92% may potentially be acceptable in certain situations, but anything below this threshold is considered to be life-threatening [3]. Optical sensors, including an LED and a phototransistor, are used to measure blood oxygen saturation via the process of light absorption [4], [5].

Heart rate is the measurement of the number of heart beats per minute. Heart rate is a crucial factor in assessing heart health, cardiovascular conditions, cardiovascular risk, and atherosclerosis [6]. Heart rate may be measured in several ways. One approach involves measuring the heart rate physically.

A method used for the said purpose is counting pulse on the patient's wrist for one minute. Another modality uses a pulse sensor that can tell the frequency of heartbeats by measuring the amount of light absorbed by the circulating blood. In the third method, ECG is used for measuring the heart rate based on counts per minutes. Usually, the heart rate for an individual at rest ranges from 60 to 100 beats per minute, however, it may slightly differ in males and females. When a person exercises, their heart rate goes up and down [7]. ECG is one of the most important part of the examination of a patient. Compared to the past, it has significantly improved the early detection and prognosis of cardiovascular diseases and general health. ECG has played a vital role in pushing cardiology forward [8], [9].

This study contributes Remote Patient Monitoring (RPM) technologies, enabling healthcare providers to track patients' health remotely through wearable devices and sensors. This is especially useful for patients with chronic conditions such as diabetes and hypertension, since it supports continuous health management and helps prevent hospital readmissions. By offering real-time monitoring, RPM can catch early warning signs and allow for timely interventions, ultimately improving patient outcomes and reducing the need for frequent in-person visits. In this study, a prototype is created with integrated sensors to collect crucial data. It was connected to the Internet of Things (IoT) which expanded its capabilities and sent real-time data to healthcare professionals.

This article is organized into five key sections. Section I 'Introduction' provides a general overview of the topic, highlighting its importance and outlining the primary objectives of the research. Section II 'Related Work' reviews previous studies and existing research in the field. Section III 'Methodology' explains the methods, tools, and procedures used in this research, detailing how data was collected and analyzed. Section IV presents the findings, using tables, charts, and other visual aids to interpret the data and discuss the outcomes. Finally, Section V 'Conclusion' summarizes the key insights, reflecting on the results and their implications, and suggests potential directions for future research.

II. RELATED WORK

An ECG illustrates the heart's electrical activity via a wave pattern that details each stage of a single beating. ECG aids in diagnosing various cardiac diseases including arrhythmia and ischemia [10]. Body temperature is a critical sign that should be regularly monitored to assess the illness's severity, since a higher temperature indicates a more significant impact of the disease on the body [11].

The healthcare sector is making technological advancements rapidly, leading to the development of various patient monitoring systems. These systems involve constant checking of physical parameters by a handheld method and notifying healthcare specialists of any serious conditions [12]. Emphasizing the significance of remote health and its practical applications in meeting consumer demand and cost efficiency is beneficial for the design and development process [13]. Applications include heart rate monitors, employing smartphones, and hemoglobin meters. Literature has examined the current apps for monitoring infants [14]. Health monitoring systems are categorized into two classes, namely advanced systems and traditional systems. Comparing various health monitoring systems revealed flaws and shortcomings in the current systems. Smart systems use wireless and remote health monitoring technology, while conventional systems rely on wired health monitoring equipment [15].

Advanced systems have discovered particular qualities via their development tools, such as the prototype medical equipment known as electrocardiography. This device was coupled with a mobile phone to provide a quicker and more efficient analysis of findings [16]. Kim. C. and Soong. A. performed research on healthcare apps using IoT. The poll intended to offer in-depth insights on how RFID, multi-agent, and IoT technologies may enhance people's technological access, improve health facilities, and streamline the healthcare procedures [17]. These technologies are also used to improve the process of transferring data from a device to a web application and provide several options for data storage [18]. Certain IoT solutions are more beneficial and useful for assessing, using, and applying data in the healthcare sector, for instance, telemedicine and mobile medical treatment [19]. Moreover, some systems might be beneficial by offering enhanced consultation and clinical monitoring via telemedicine, various media, and modern technology [20]. Health department may oversee patient activities, collect patients' data, and transmit it remotely over the IoT. Securing data transfer is crucial to maintain this relationship. IoT in healthcare is implemented by designing the technology using robust and diverse communication protocols. An information-rich health application is managed by using a resource-based data recovery technique. This technology is integrated with a smart box to track patient actions, functioning as a medical system. Soni said that the IoT deployment involves maintaining four protocol layers. Systems at the physical layer are linked to sensors and transmitters. The sensors relay signals to the web portal via a network layer. The middle layer has the capability to store data in the web portal and provides access to the data. Diagnostic and analytic procedures occur at the application layer. The substantial employment rate of IoT indicates the significant role of the medical technology sector in the European economy. By contrast, the European pharmaceutical sector has a workforce of 740,000 individuals [21].

RPM systems offer significant opportunities to improve patient care. However, they also present several research gaps, limitations, and challenges that must be addressed to ensure effective implementation and scalability.

A. RESEARCH GAPS AND LIMITATIONS

1)INTEGRATION AND INTEROPERABILITY

A key gap in RPM research is the need for better integration between various devices and systems. The lack of interoperability among devices from different manufacturers makes data sharing difficult, which can hinder comprehensive patient monitoring [22].

2)DATA SECURITY AND PRIVACY

3)Since RPM systems handle sensitive patient data, research is needed to strengthen cyber security. This includes developing secure protocols to prevent data breaches and ensuring adherence to regulations such as HIPAA and GDPR [23].

3) USER-CENTRIC DESIGN

Many RPM systems are not designed with the end user in mind, leading to low adoption rates by patients and healthcare providers. Research should focus on creating user-centered designs that cater to the unique needs of diverse patient populations [24].

To conclude, while RPM systems hold the promise of transforming patient care, addressing these research gaps, limitations, and challenges is essential for their successful implementation and broader adoption in healthcare.

III. METHODOLOGY

The materials utilized to create a functional prototype included sensors and components. The study utilized a microcontroller as the central component, a DS18B20 temperature sensor for temperature monitoring, a custom heart rate sensor for heart rate recording, a custom SpO2 sensor for blood oxygen saturation sensing, an LCD for displaying results, and a Node ESP32**.**

A. DEVICE FUNCTIONALITY

Custom sensors are used to record the biological signals emitted by the human body. Flowcharts depict the sequential process of the machine, starting with detecting the bio signals of the patient's body, passing through signal filtering, and transforming them into microcontroller-readable signals before displaying them on the screen and web application. Figure 1 illustrates the device's operation, detailing the processing of bio signals from the body and the presentation of findings on screen using a block diagram, as well as the streaming of data to web.

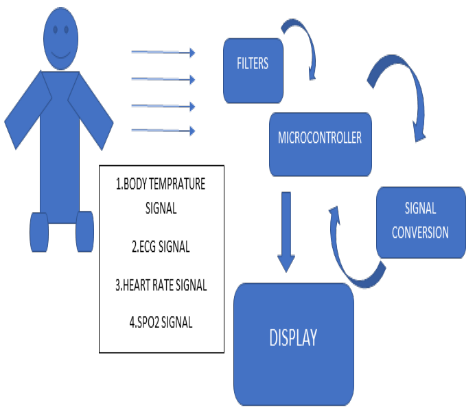

FIGURE 1. Device Functionality

B. SPO2 MEASUREMENT

Flow chart illustrates the comprehensive operation of the SpO2 sensor and microcontroller collaborating to produce the intended result. Figure 2 illustrates the process of measuring SpO2 from the finger. The SpO2 measurement is carried out using a specialized module built with the IC Max30100, which is capable of measuring both pulse rate and SpO2 levels. However, in this study, it is exclusively utilized for SpO2 measurement. IC integrates both LED and infrared (IR) light as the source and detector, simplifying the circuit design. To function properly, it requires a set of minimal supporting components mounted on a board. It also demands a pull-up resistor and capacitor connected to data communication pin, with power supplied as specified in the datasheet.

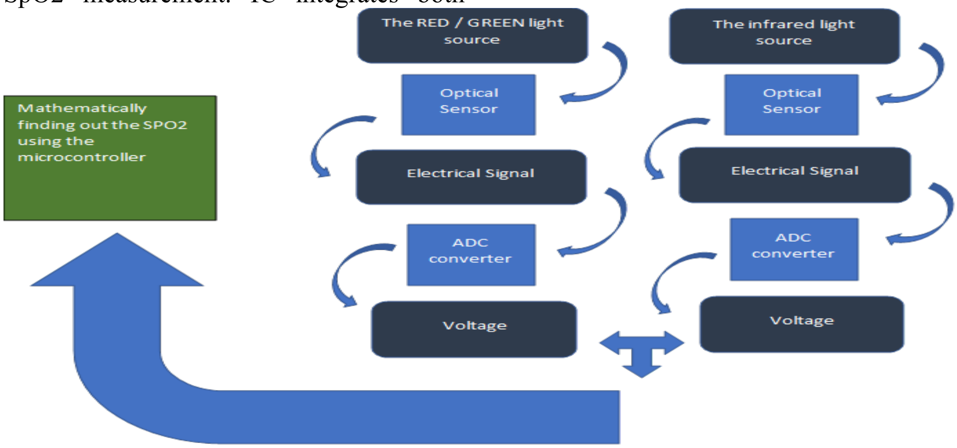

FIGURE 2. Structure of SpO2 data recording

C. TEMPERATURE RECORDING

The flowchart shows how body temperature and microprocessor work synchronously in order to reach the particular goal. Figure 3 illustrates the temperature sensor in operation and starts from sensing voltage fluctuations caused by ambient heat and terminates by providing the final temperature.

D. RECORDING OF ECG SIGNALS AND HEART RATE VALUES

The diagram (Figure 4) illustrates how ECG, microcontroller, and heart rate sensor collaborate to produce the required

ECG and heart rate output. Figure 4 illustrates the operation of the ECG and heart rate sensor, starting with recording the voltage change following the cardiac cycle to capturing the heart rate and generating the result.

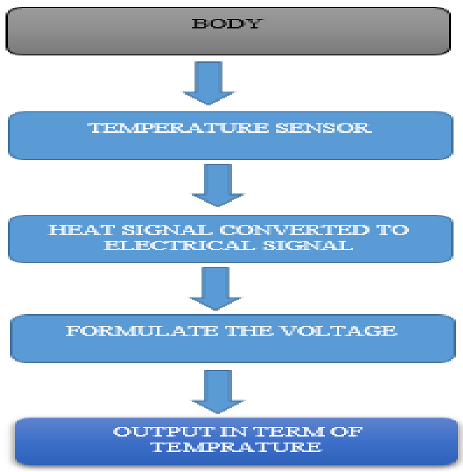

FIGURE 3. Body Temperature Recording Structure

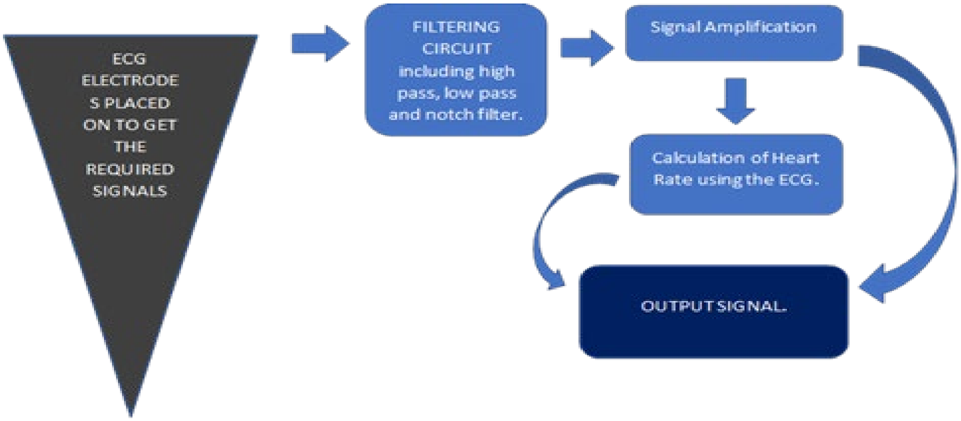

FIGURE 4. ECG and Heart Rate Recording Structure

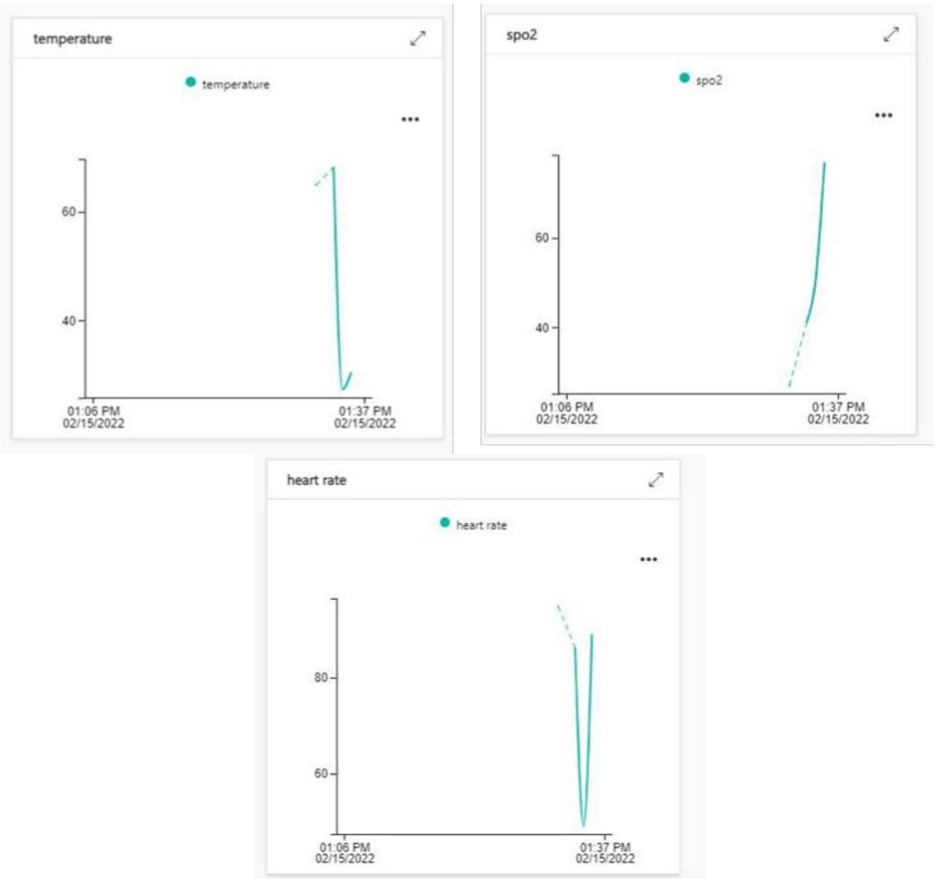

FIGURE 5. *(a, b, c)*

E. WEB PORTAL

A web portal is created to display real-time data and save it in a SQL database, as seen in Figures 5 (a), (b), (C)

IV. RESULTS

A. CARDIAC RHYTHM FINDINGS

Each one of the three volunteers underwent three heart rate tests using the planned prototype and a CE registered pulse oximeter. The tests included obtaining a continuous heart rate reading for about 2 minutes from the prototype. Table 1 and Table 2 compare the heart rate data, whereas Figure 6 displays the results from the prototype and Figure 7 shows the reading from the pulse oximeter.

TABLE I
PULSE READINGS OF PATIENTS

ID.	1st Reading	2nd Reading	3rd Reading	Difference
Patient 1	76	77	76	76.3
Patient 2	79	80	80	79.6
Patient 3	65	66	66	65.6

TABLE II
OXIMETER PULSE RATES

ID.	1st Reading	2nd Reading	3rd Reading	Difference
Patient 1	78	78	78	78
Patient 2	82	82	82	82
Patient 3	68	67	67	67

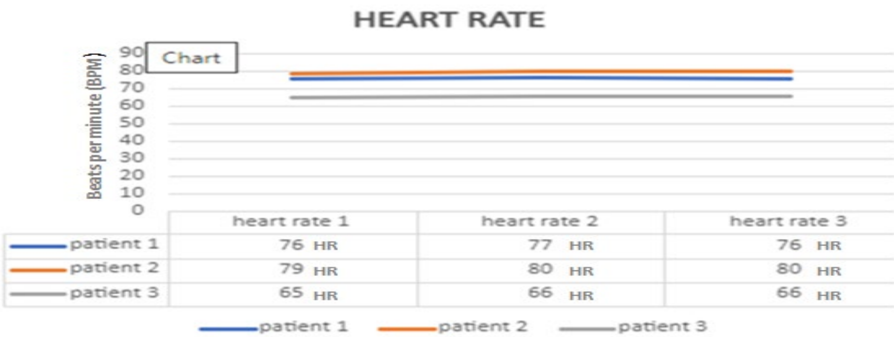

FIGURE 6. Results

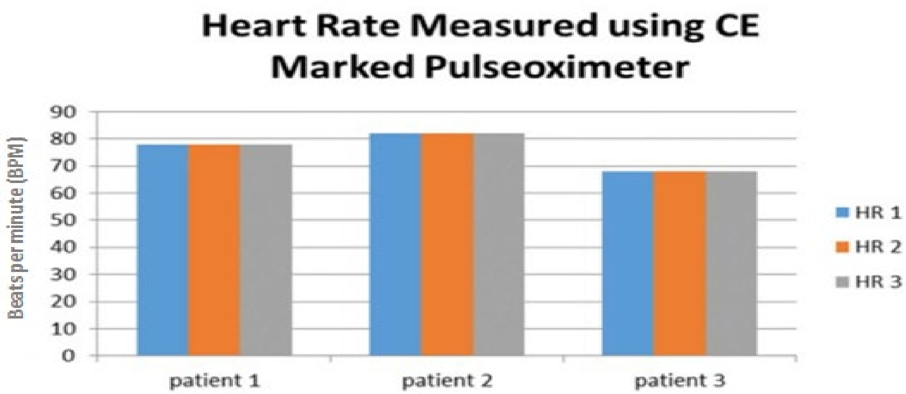

FIGURE 7. Pulse Oximeter with CE Marking

B. BODY TEMPERATURE RESULTS

All three individuals had their body temperature measured three times using both the created prototype and a mercury thermometer for a continuous measurement duration of 120 seconds using the prototype. Table III and Table IV provide a thorough comparison of body temperature readings. Figure 8 shows the body temperature readings from the device, while Figure 9 displays the results from the mercury thermometer.

TABLE III
TEMPERATURE

ID	1st Reading (°c)	2nd Reading (°c)	3rd Reading (°c)	Absolute Difference (°c)
Patient 1	34.6	35.8	36.8	35.77
Patient 2	36.9	36.4	35.1	36.13
Patient 3	38.5	37.3	37.3	37.7

TABLE IV
MERCURY THERMOMETER RESULTS

Subject No.	1st (°c)	2nd (°c)	3rd (°c)	Absolute Mean (°c)
Sub 1	35.5	35.3	35.8	35.53
Sub 2	37.3	37.5	37.9	37.56
Sub 3	38.7	38.4	38.2	38.43

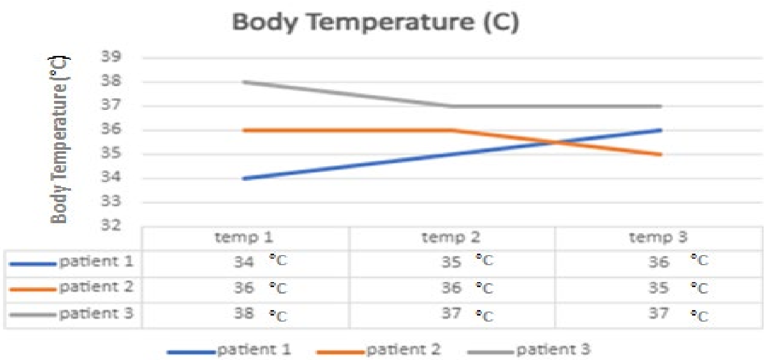

FIGURE 8. Results for Body Temperature

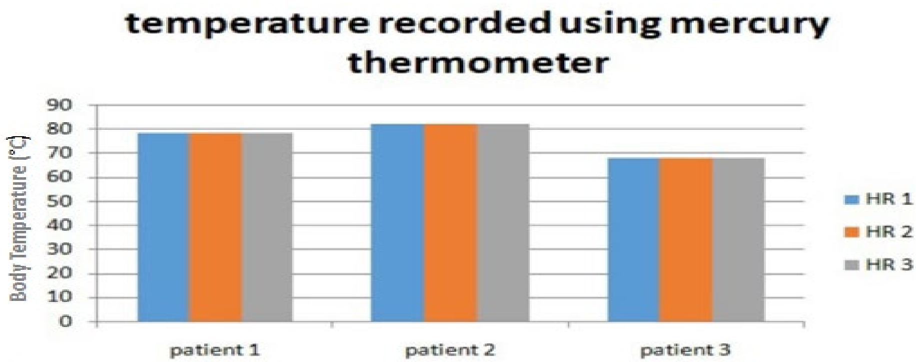

FIGURE 9. Mercury Thermometer Body Temperature

C. PRECISION

Tables V, VI, and VII show the accuracy and precision of many parameters measured by the prototype in comparison to the CE approved devices. Table VIII displays the percentage of errors for each parameter.

TABLE V
BODY TEMPERATURE ACCURACY

Patient No.	Mean Device (°c)	Mean mercury thermometer (°c)	Accuracy %	Mean accuracy % temperature
Patient 1	35.5	35.7	100	98.11 %
Patient 2	35.68	37.5	96.2	
Patient 3	37.34	38.4	98.15	

Table V presents temperature readings from both a mean device and a mercury thermometer for three patients. For Patient 1, the mean device and the mercury thermometer recorded the same temperature of 35°C, resulting in 100% accuracy. Across all patients, the mean accuracy for body temperature was calculated to be 98.11%. However, for Patient 2, there is a slight discrepancy between the mean device's recording of 35.6°C and the mercury thermometer's reading of 37°C, resulting in an accuracy of 96.2%. Patient 3 shows a similar pattern, where the average device measurement is 37.3°C, while the mercury thermometer reads 38°C, resulting in an accuracy of 98.15%. The little variations in individual results do not significantly impact the overall dependability of the equipment for measuring body temperature, although some inconsistency persists across different patients.

TABLE VI
ACCURACY FOR HEART RATE

ID.	Mean device (bpm)	Mean CE marked (bpm)	Accuracy %	Precision %
1	76.25	78	97.8	97.11 %
2	79.55	82	97.07	
3	65.71	68	96.4	

Table VII displays the heart rate readings from a mean device and a CE approved device for three distinct individuals. The average heart rate of Patient 1 measured by the device is 76.3 bpm, whereas the CE device recorded 78 bpm, resulting in an accuracy of 97.8%. The average accuracy rate for heart rate among all patients is 97.11%. For Patient 2, there is a little difference between the average heart rate recorded by the device at 79.6 bpm and the reading of 82 bpm by the CE device, resulting in an accuracy of 97.07%. Patient 3 has an average device heart rate of 65.6 bpm, whereas the CE device shows a value of 68 bpm, resulting in an accuracy of 96.4%. Although some differences in individual readings persist, the average accuracy indicates an overall dependability of the device for heart rate measurements, with variances seen across individuals.

TABLE VII
ACCURACY FOR SPO2

Person /Patients	Mean	Mean marked CE %	Accuracy %	Mean accuracy % for spo_2
1st	97.9	98	99.8	99.73 %
2nd	97.7	97	100	
3rd	98.4	99	99.3	

Table VII displays oxygen saturation (SpO2) levels for three individuals obtained from both an average device and a CE approved equipment. The mean SpO2 value of Patient 1 is 97.9%, which closely aligns with the CE recognized device's reading of 98%, resulting in an accuracy of 99.8%. The average accuracy rate for SpO2 across all patients is 99.73%. The average device SpO2 value of Patient 2 is 97.7%, which aligns with the CE recognized device's reading of 97%, achieving an accuracy of 100%. Similarly, the mean device SpO2 reading of Patient 3 is 98.4%, which is very close to the CE marked device's reading of 99%, yielding an accuracy of 99.3%. These results indicate a high level of accuracy for the mean device in measuring SpO2, with consistent performance across the patients sampled.

D. DEEP LEARNING IN HEALTHCARE

Deep learning has demonstrated significant potential in revolutionizing healthcare by facilitating more precise disease diagnosis, tailored treatments, and better patient outcomes. Key applications of deep learning in healthcare includes the following.

1) MEDICAL IMAGING ANALYSIS

Deep learning models are highly effective at analyzing medical images, such as X-rays, CT scans, MRIs, and pathology slides to detect diseases, assess their severity, and predict patient outcomes. For instance, these models can accurately identify early signs of breast cancer, lung cancer, heart disease, and neurological disorders in medical images [25].

2) ELECTRONIC HEALTH RECORD (EHR) ANALYSIS

By analyzing Electronic Health Record (EHR) data, deep learning can detect patterns to predict disease risks, identify adverse events, and recommend personalized treatments. These models can process both structured data, such as lab results and diagnoses, and unstructured data, such as clinical notes, to support more informed clinical decisions [26].

3) WEARABLES AND REMOTE MONITORING

Deep learning algorithms can analyze data from wearable devices and home sensors to track patient health, detect irregularities, and anticipate adverse events. This enables early interventions and remote patient monitoring, improving care accessibility [27]. Despite the promise deep learning holds in healthcare, challenges related to data quality, model transparency, and regulatory approval persist. Ongoing research continues to address these challenges, working to integrate deep learning into clinical workflows to enhance patient outcomes and reduce healthcare costs.

E. DEEP NEURAL NETWORK INCEPTION V3

Inception-V3, developed by Google, is a convolutional neural network designed for image identification. It improves on previous inception models with better depth, speed, and parameter efficiency. By using convolution decomposition, it reduces processing costs by breaking down large convolutions into smaller, more manageable ones, allowing for faster inference without sacrificing performance [28].

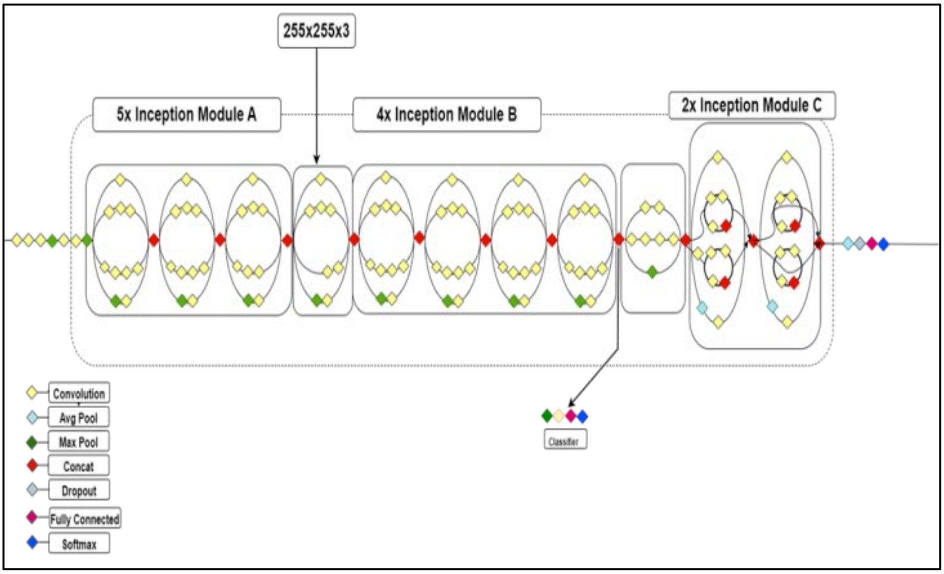

FIGURE 10. Architecture of Inception-V3

Model robustness is considered as the most vital part of the network. ECG pattern and images taken from CPIEC [28] were classified into four (04) different classes for testing and validation. Feature extraction was performed through a deep leaning model called Inception V3. Gaussian elimination filter was applied to remove image noise.

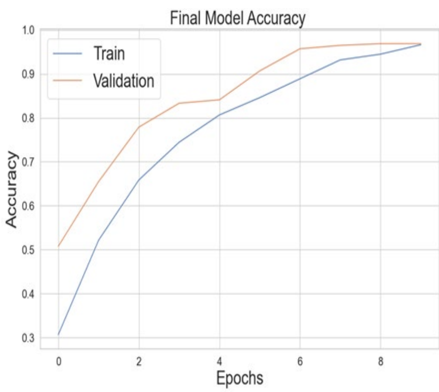

FIGURE 11. Accuracy

Figure 11 represents performance validation and training accuracy of a machine learning model, likely Inception V3, during training and validation phases. The training loss of 0.1315" indicates the average loss or error of the model's predictions on the training dataset, where a lower loss value suggests better alignment between predicted and actual values. The accuracy of “0.9666" signifies the proportion of correct predictions made by the model on the training data, as shown in Figure 11.

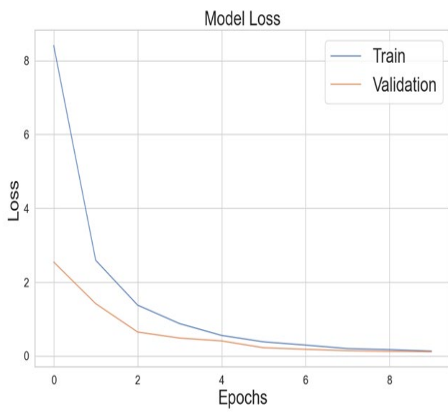

FIGURE 12. Model Loss

On the other hand, validation loss of 0.1146 represents the average loss of the model's predictions on a separate validation dataset, indicating its ability to generalize the unseen data in Figure 12. The validation accuracy is 0.9690", which denotes the accuracy of the model on the validation data, revealing its performance on new, unseen samples. These metrics collectively demonstrate that the model exhibits high accuracy and relatively low loss values, both during training and on unseen validation data, suggesting effective learning and generalization capabilities.

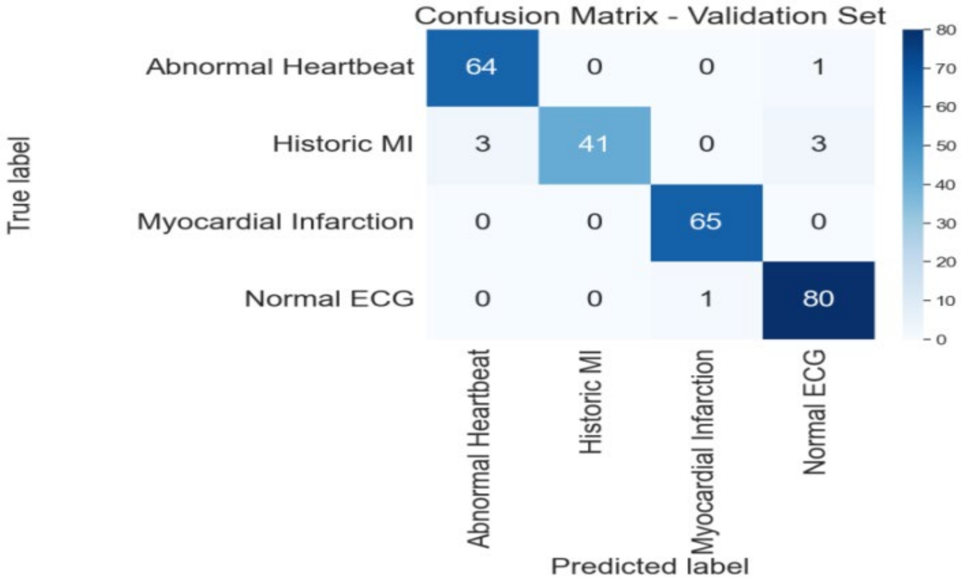

FIGURE 13. Validation

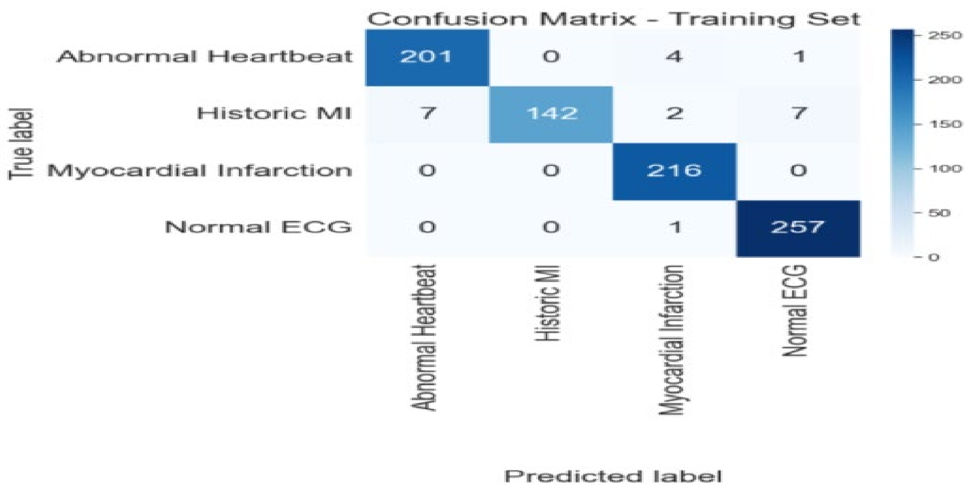

FIGURE 14. Training

A total of 64 instances of 'Abnormal Heartbeat' were accurately diagnosed using 01 Myocardial Infarction (MI) classification. MI had 41 accurately classified cases and 06 misclassified instances. There were 65 cases of accurately classified MI with no errors in classification, indicating a good level of accuracy in detecting this heart condition. Normal ECG properly recognized 80 occurrences with just one misclassification. The analysis shows that the model is very accurate in detecting MI but needs refinement in classifying other conditions such as abnormal heart beat and historic MI, where errors were made**.**

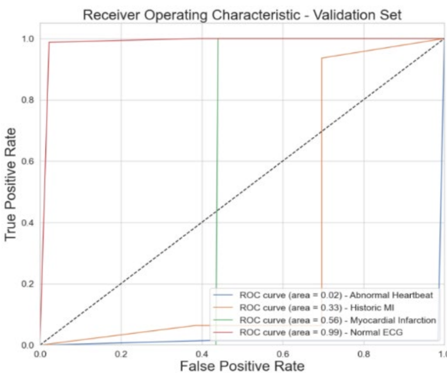

FIGURE 15. ROC / AUC

The table presents the ROC curve values for various classes. For "Abnormal Heartbeat" and "MI (Historical)", the values of ROC curve are 0.02 and 0.33, respectively. For "MI (Current)", the value of ROC curve is 0.56, while it is 0.99 for "Normal ECG". The value selected for each class gives a measure of differential performance for the particular class. A larger value indicates better differentiation between classes.

F. ACCURACY METRIC

The statistics for 'Abnormal Heartbeat' denote a true positive, false positive, true negative, and false negative of 0.919. The respective values of true positives = 57, false positives = 5, true negatives = 190, and false negatives = 5. For MI, accuracy is 1.0, the recall value is 0.84, and the F1-score is 0.913. This estimated output would have 42 true positives, zero false positives, 207 true negatives, and 8 missed diagnoses. The metrics determine the model's performance at differentiating classes, highlighting the strong points and those which carry lower classification accuracy. The model developed for MI has an accuracy of 0.945, a recall value of 1.0, and an F1-score of 0.972, respectively. The class contained 69 correct positives, 4 mistakes, 184 correct negatives, and 0 missed negatives. With a precision score of 0.938 and a recall value of 0.987, Normal ECG achieved an F1-score of 0.962. The data consisted of 75 true positives, as well as 5 false positives. It also contained 176 true negatives, along with 1 false negative. Using these metrics, the model evaluation process is completed with the measuring of the model's ability to precisely identify the cases of MI and Normal ECG and determine what still needs to be improved. Accuracy levels and ECG classification are shown in Figure 17.

TABLE VIII
PERCENTAGE OF ERRORS FOR EACH PARAMETER

Metrics for Abnormal Heartbeat:	Metrics for Historic MI
Precision: 0.91	Precision: 1.0
Recall: 0.91	Recall: 0.84
F1-Score : 0.91	F1-Score: 0.91
TP: 57	TP: 42
FP: 5	FP: 0
TN: 190	TN: 207
FN:5	FN: 8

Metrics for Myocardial Infarction	Metrics for Normal ECG
Precision: 0.945	Precision: 0.9375
Recall: 1.0	Recall: 0.986
F1-Score: 0.971	F1-Score: 0.961
TP: 69	TP: 75
FP: 4	FP: 5
TN:184	TN: 176
FN: 0	FN: 1

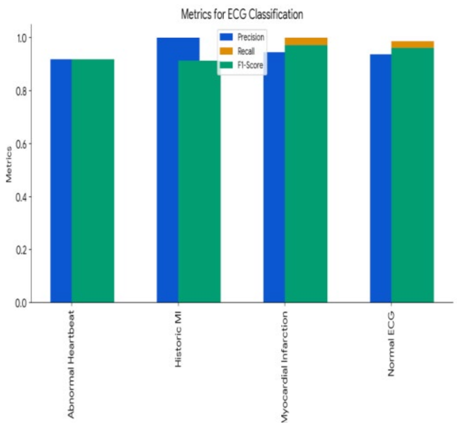

FIGURE 16. Metrices

G. GAUSSIAN ELIMINATION FUNCTION

A Gaussian low-pass filter, which is a common technique in image processing to lower noise and mimic the Gaussian blur effect for photo smoothening, was used for the said purpose. This filter takes off high-frequency elements from the image and thus decreases the amount of noise. This technique is more likely to be used when the portraits of human faces need to be improved, such as the reduction of such imperfections as wrinkled or freckled areas to improve the overall look, especially in connection with social networking sites. Gaussian smoothing is the underlying operation in a number of computer vision applications by virtue of segmenting the image data in various scales. The masking process of Gaussian low-pass filtering is achieved by means of a Gaussian function, which is then utilized to compute the transformation applied to every point that comprise the image, leading to a comprehensive and clear technique to refine the image [29].

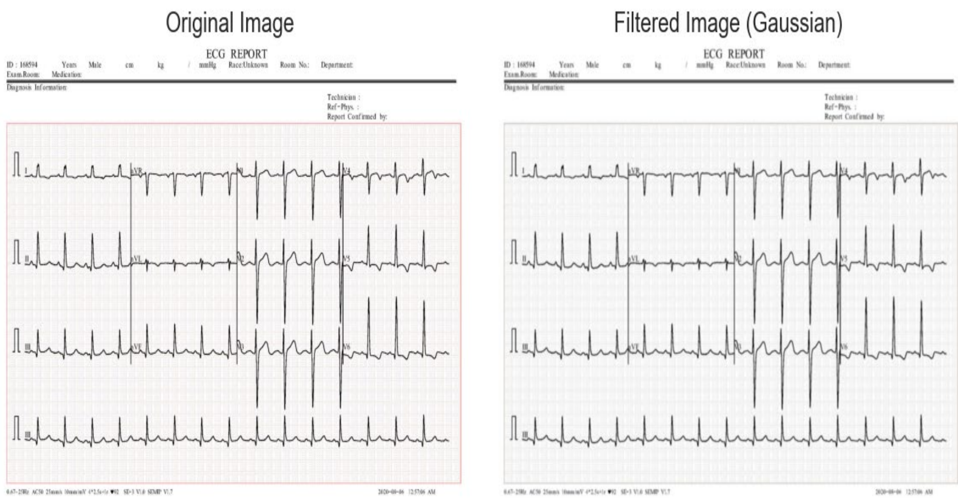

FIGURE 17. ECG Classification

H. DATASET COLLECTION

This study was conducted on two different datasets; one gathered during the prototype's implementation on 13 patients. Due to the unavailability of visual ECG images, public ECG images dataset [30] was incorporated. ECG data contained 04 classes, namely Abnormal Heartbeat (233 patients), Historic MI (172), Myocardial Infarction (239), and Normal ECG (284). The Inception V3 machine learning model was applied to evaluate accuracy metrics and robustness.

V. CONCLUSION

This study focused on the development and manufacturing of a device that would record the required four key parameters. The investigation unearthed the fact that the design of the device and its development already matched with the objectives of the project as they/the device achieved the targeted four vital signs and ensured IoT integration. This study not only contributes to the advancement of the healthcare industry but also provides an efficient and cost-effective solution. The generated data indicates that the device has a good readability to its target application. Unfortunately, the prototype failed to incorporate advanced level sensors because of their high cost. The image of this operational prototype is shown below. Prototype implementation and designing is also mentioned below.

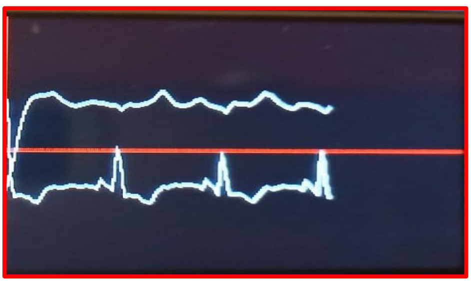

FIGURE 18. ECG for Patient 1

FIGURE 19. ECG for Patient 2

FIGURE 20. ECG for Patient 3

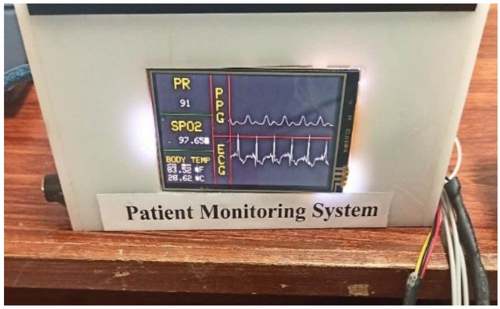

FIGURE 21. Image for the Working Prototype

CONFLICT OF INTEREST

The author of the manuscript has no financial or non-financial conflict of interest in the subject matter or materials discussed in this manuscript.

DATA AVALIABILITY STATEMENT

Data availability is not applicable as no new data was created.

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