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Simulation Based Economical Approach for Detecting Heart Disease Earlier from ECG Data

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Abstract
Cardiovascular diseases present significant challenges to public health in developing countries. The high costs of traditional treatments and the limited availability of specialized medical equipment contribute to these challenges. Current diagnostic methods often rely on specific electrocardiogram (ECG) parameters, which may not capture the nuanced complexities necessary for accurate diagnosis. To address these issues, our study proposes an innovative solution: an accessible and cost-effective ECG monitoring system. This system not only captures electrical signals from the heart but also translates them into numerical values using advanced modulation techniques. A trained deep learning model then analyzes this data to accurately identify any potential complications or confirm a healthy cardiac state. Our approach also allows for remote diagnosis and treatment. By utilizing an MQTT server, ECG data can be efficiently transmitted to experts for evaluation and intervention when necessary. Our meticulously fine-tuned Artificial Neural Network (ANN) architecture has achieved an impressive accuracy of 95.64%, surpassing existing methodologies in this field. Designed with resource-strapped regions in mind, our system offers a lifeline to rural areas lacking access to medical professionals and advanced equipment. Its affordability ensures that even individuals with limited financial means can benefit from timely and accurate cardiac monitoring, potentially saving lives and reducing the burden of cardiovascular diseases in underprivileged communities.

Keywords: Artificial Neural Network (ANN); Cardiovascular D isease; Electrocardiogram; Heart Disease; Modulation Techniques; MQTT Server.

1- Introduction

Cardiovascular diseases (CVDs) are a global health concern that poses a persistent threat to millions of people [1]. The heart and blood vessels are particularly vulnerable to CVDs, with coronary artery disease being a major contributing factor to the high death rates associated with these diseases [2]. In fact, it is estimated that CVDs account for 36% of deaths worldwide in the European Union alone [3]. Early detection of heart ailments is crucial for effectively addressing cardiovascular diseases. Continuous monitoring and measurement of heartbeats play a key role in this process. Electrocardiogram (ECG) signals, which provide comprehensive insights into heart-related issues through the analysis of physiological data, are a crucial tool [4,5]. Thanks to technological advancements, ECG monitoring devices now offer reliable measurement and observation of these signals [6,7]. However, there are ongoing concerns among researchers regarding the analysis of the data gathered from ECG monitoring devices. Critics argue that previously suggested devices are inadequate in keeping up with emerging technologies and lack comprehensiveness [8–10]. While some ECG monitoring devices boast specialized technology, others rely on context and server-based functionality [11,13]. Itt has been obesity has a major role in cardiovascular diseases that denotes heavily in the increment of heart rate. This highlights the pressing need for universal ECG monitoring equipment that can better assess and understand cardiac issues. By facilitating early detection and prevention of CVDs, these tools have the potential to save numerous lives [14]. The primary objective of this ANN architecture is to uncover patterns in ECG data that may be difficult to detect by the human eye, thereby enhancing diagnostic capabilities. This advancement enables the early identification of cardiac issues, which is crucial for prompt treatment. In Bangladesh, a developing nation where 73% of individuals are reported to suffer from one or more cardiovascular diseases (CVDs), rural communities face significant healthcare challenges, including a lack of medical professionals and inadequate supplies. The motivation of this research is to address the health care challenges, especially in the domain of cardiovascular where most developing countries are suffering. Furthermore, an IoT-based device for detecting cardiovascular disease is proposed with less cost as economically these types of devices are not easy to buy. A proper communication medium between the device and doctors over the channel. Furthermore, the credibility of the data is being examined using multiple Machine Learning and Deep Learning architectures. Furthermore, the question arises what the proper model to will be to work with IoT devices. In [12], it has been discussed that DL architectures might not work properly with spatila and sequential data but can be effective if modified properly. Taking this into account authors have explored the opportunity to apply ANN in the gathered dataset. Finally, the primary focus is to proposing a IoT device that will be affordable for the people from underdeveloped countries.

This research paper addresses the following questions:

RQ1: How can cheaper IoT devices be bought for people from underdeveloped or developing countries?

RQ2: Can ANN be modified enough to communicate with IoT based devices properly?

The major contributions of this paper can be summarized as:

I) Implementing and validating real time gathered dataset that will be sent through IoT servers so that diseases can be detected earlier.
II) Proposing a shallow neural network that will instantly detect heart diseases from real-time data. Necessary suggestions will be provided instantly.
III) Building a low-cost device that will assist people from underdeveloped countries in order to detect heart diseases. The device is lightweight and portable.

The recent research from the literature has been discussed in section 2. The methodology and methods have been proposed in the section 3. Experimental results are shown in section 4 and finally, the future work and conclusion have been discussed in section 5.

2- Literature Review

The Internet of Things (IoT) is a fast-moving field in computer science that focuses on effectively sharing data between devices via cloud servers. The effectiveness of the cloud server being used determines how smoothly data is transferred. The authors of [14] offer a unique approach to signal capture in addition to signal preprocessing; nevertheless, an adequate encryption model is not implemented in this study. In [15], a crucial suggestion for Internet of Things (IoT)-based monitoring systems with sophisticated data visualization is made. But there is a significant difference in how deep learning (DL) structures and machine learning (ML) algorithms are integrated in this idea [16], which calls for more investigation. The state of IoT-based ECG monitoring systems [17–20] has given important new information on this field.

Predominantly, research has focused on signal collection, with a pivotal concern being data preparation. [21] addresses this by employing time-based feature integration for data purification. The microcontroller board utilized, namely the Arduino Uno, centers around the ATmega328T. Earlier studies have extensively utilized the Arduino Uno for cardiac signal acquisition [22–24], emphasizing its cost-effectiveness and ease of integration in such contexts.

The literature review explores various developments in the realm of Electrocardiogram (ECG) monitoring systems and associated technologies. In reference, an Internet of Things (IoT)-based ECG and vitals monitoring system is detailed, incorporating parameters such as QRS complex, heart rate, blood oxygen levels, and body temperature [25]. The iterative design approach is emphasized to reduce the device's overall cost. However, the three-lead end-to-end ECG acquisition system constructed proves inadequate for capturing all regular and augmented parameters of ECG signals. Moving on to fetal Electrocardiogram (FECG) monitoring, a system has been developed [26], concentrating on FECG and fetal heart rate (FHR) with an emphasis on an Android application. Nevertheless, improvement is deemed necessary, urging the incorporation of more miniaturized patches and real-time analytics via cloud computing. Addressing concerns about cardiovascular disease (CVDs) severity and the lack of precautionary monitoring systems, a low-cost solution is presented [27], aiming to reduce harmonic distortions and input inferred noise in ECG signal frequencies. This system highlights the need for an efficient cloud server for instantaneous data transfer. In another study [28], authors introduce a wearable Tele-ECG and heart rate monitoring system, integrating a Singlet and Holter-based ECG system with a mobile application. Despite focusing on parameters such as P, Q, R, S, T peaks, the system requires additional sensors for a more comprehensive measurement of heart disease-related parameters. The proposed IoT-assisted ECG monitoring framework in [29] emphasizes secure data transmission for continuous cardiovascular health monitoring through automatic classification and real-time implementation. However, there's a call for advanced machine learning algorithms to enhance prediction accuracy. A smartphone-based ECG monitoring device is proposed in to evaluate post-ablation patients with atrial fibrillation. The focus lies on the ECG check monitoring protocol, considering sinus rhythm and sinus tachycardia. However, concerns are raised about the lack of a proper detection mechanism for ECG parameters, and the reported accuracy stands at around 93%. Some of the major research gaps are stated in Table 1.

Table 1: Identified Research Gap from the Literature

Reference	***Contributions***	***Research Gap***
Serhani ***et al.***	Precise collection of data sending through the IoT network.	No applications of DL methods to capture the proper semantics.
Ghosh ***et al.***	Integration of ML methods for detection purposes. Many algorithms are explored.	Device is costly and difficult to afford for under developed people.
Faruk ***et al***.	Enhanced accuracy than the state-of-the-art architectures.	The model is not lightweight and takes time to propagate real time data.
Rahman **et al.**	Methodology is described properly.	No proper system is available.

Based on the research gap available in the literature, it is important to identify a novel approach that will be available for the underdeveloped countries. This research focuses on proposing an approach that will integrate the DL approach detect cardiovascular diseases precisely along with the cost of the device is lower that can be affordable for rural people. The lightweight nature allows to detect cardiovascular diseases easily. The spatial information is also captured properly by the proposed model.

The below section comprehensively addresses the architectures, method of converting ECG signal, overall methodologies, and procedures employed in conducting the research. Initially, data collection was facilitated through the utilization of an ECG monitoring system, which is interconnected with 12 leads and necessary Internet of Things (IoT) devices. The proposed method of converting ECG signal is illustrated in section 3.

3- Materials and Methodology

Algorithm 1: *ECG Data Classification using ANN*

1. **Input:** ECG dataset with multiple columns
2. **Output:** Model performance evaluated using Precision, Recall, F1-score,
   and trainable parameters
3. **Step 1: Load the Dataset**
4. Load the ECG dataset.
5. Split the dataset into features (X) and labels (Y).
6. **Step 2: Parameter Tuning**
7. Identify hyperparameters to tune, such as learning rate, batch size,
   number of layers, and neurons.
8. Use grid search or random search to find the optimal hyperparameters.
9. **Step 3: Data Preprocessing**
10. Handle missing values using imputation techniques.
11. Normalize or standardize the data.
12. Apply noise reduction techniques if required (e.g., bandpass filtering).
13. Split the dataset into training, validation, and test sets.
14. **Step 4: Model Design**
15. Design an Artificial Neural Network (ANN) with an appropriate
    architecture.
16. Define the input layer based on the number of features.
17. Add hidden layers with appropriate activation functions (e.g., ReLU).
18. Define the output layer with a softmax activation function.
19. **Step 5: Model Training**
20. Compile the model with an appropriate optimizer (e.g., Adam) and loss
    function (e.g., categorical crossentropy).
21. Train the model on the training set.
22. Validate the model on the validation set during training.
23. **Step 6: Model Evaluation**
24. Evaluate the model's performance on the test set.

25. Calculate Precision, Recall, and F1-score for each class.
26. Analyze the trainable parameters in the model.
27. **Step 7: Performance Analysis**
28. Compare the model's performance based on the metrics.
29. Adjust hyperparameters or model architecture if necessary to improve performance.
30. Fine-tune the model using additional rounds of training and validation if required.
31. **Step 8: Final Model**
32. Save the final model and its parameters.
33. Document the model's performance metrics.
34. **Step 9: Reporting**
35. Prepare a report summarizing the methodology, results, and performance of the model.
36. Include plots of loss, accuracy, and confusion matrix if applicable.

Algorithm 1: Proposed Workflow

Algorithm 1 discusses the potential workflow of this research. Here, it is seen that, the dataset is loaded at first, then necessary parameter tuning has been performed in Table 2. For the preprocessing purpose, normalization, handling missing data and noise reduction is performed. Furthermore, authors are focused on designing the model with ANN that has been trained with the added hidden layers of ReLU. The performance of the model is analyzed and fine-tuned that has been reported with multiple performance metrics.

A threshold (τ) value condition on the amplitude of the signal will be calculated by the following proposed formula 1.

$$\tau = (0.6) \times m \tag{1}$$

Where m is the ISO electric line value. According to the characteristics of the ECG signal, it is possible to find out the different range of the amplitude for P, Q, R, S, and T parameters by applying the threshold value. An analog-to-digital converter needs to be configured to get the numerical value. This numerical value can be divided by the total number of parameters in a window of ECG signal to get the base numerical values as row data. This row data can be multiplied by different ratios of each parameter of the ECG signal to get the individual numerical value of P, Q, R, S, and T parameters. The formulation of converted numerical values is shown in Table 2. The parameters P, Q, R, S, T, U are tuned by the authors based on mathematical statistics [24].

In the second stage, augmented parameters (RR, PR, QT, QTc interval, and QRS complex) of the ECG signal can be considered to make better decisions about heart conditions provided in consultation with experts in cardiovascular diseases.

The proposed algorithm for formulation of RR interval can be established from the following steps

Table 2. The formulation of the parameters

ECG Basic Parameter	*Formulation of the parameter*	*Remarks*
P	$P = row\ data \times 1.1$	Always less than R peak
Q	$Q = row\ data \times 0.8$	Always less than P,T peak
R	$R = row\ data \times 2.0$	Maximum peak of ECG signal
S	$S = row\ data \times 0.7$	Always less than P,T peak
T	$T = row\ data \times 1.0$	Always less than R peak
U	$U = row\ data \times 0.4$	Always less than P,T peak

Step 1: Determine the overall sampling frequency (f_s) by giving a sample rate from the total ECG signal which is generated from the proposed device.

Step 2: Determine the sampling frequency (f_x) by partitioning the overall sampling frequency (f_s) according to the number of R peaks from each f_s.

Step 3: Individual window base average RR interval can be derived from the formula 2, which is denoted as $IWt_{rr}avg$.

$$IWt_{rr}avg = \frac{Trr_i}{number\ of\ R\ peak} = Trr_i = \frac{R_{loc(i+1)} - R_{loc(i)}}{(f_x)} \tag{2}$$

The other parameters PR, QT, QTc interval, and QRS complex can be calculated from the conventional methods [4], which is shown as following:

$$OWt_{rr(i)} = \frac{IWt_{rr}avg(i+1) - IWt_{rr}avg(i)}{f_s} \tag{3}$$

$$t_{pr}(i) = \frac{(R_{loc(i)} - P_{loc(i)})}{f_s} \tag{4}$$

$$t_{qt}(i) = \frac{t_{loc(i)} + (t_{rr(i)} \times 0.13) - (Q_{loc(i)} - x)}{f_s} \tag{5}$$

$$t_{qt(corr)}(i) = \frac{t_{qt(i)}}{f_s \times \sqrt{t_{rr(i)}}}\ t_{qrs}(i) = \frac{(S_{loc(i)} + x) - (P_{loc(i)} - x)}{f_s} \tag{6}$$

The proposed algorithm for the formulation of ST-Segment can be established from the following:

$$t_{st}(i) = \frac{(T_{loc(i)} - S_{loc(i)})}{f_s} \tag{7}$$

Where $S_{loc(i)}$ is called $J - point$ or S Depolarization, and $T_{loc(i)}$ is called $K - point$ or Beginning of the T wave.

The numerical values of these augmented parameters can be found by a computational programming application and the generated numerical values will be stored in cloud using MQTT technology.

Subsequently, meticulous preparation was undertaken to ensure a thorough understanding of the acquired data. Following this, an Artificial Neural Network (ANN) was employed to process the refined data. Fine-tuning of the model's hyperparameters ensued to attain the most optimal outcomes. Lastly, a diverse range of evaluation metrics were employed to gauge the performance of the model. Figure 1 illustrates the chronological sequence of actions undertaken throughout the entirety of the research work.

The process encompasses six primary phases prior to evaluating the outcomes. Initially, the designated equipment is employed to sense the data as suggested. Subsequently, the time intervals are converted into floating-point values upon retrieval. The initial presentation of the readings is in a waveform format, from which numerical values are derived based on the waveform intervals. Subsequent to this, the data undergoes preprocessing, entailing dimensionality reduction and null value elimination. Following preprocessing, the input is channeled into the proposed architecture of the artificial neural network. Various metrics are then employed to gauge the performance. Figure 1 elucidates the sequential execution of the entire investigative procedure.

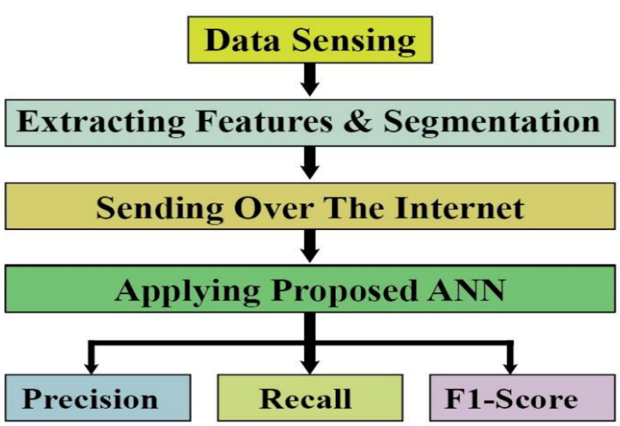

Fig 1: Methodology of the research

3-1- Requirements for setting up the device

The authors have focused primarily on establishing optimal conditions for successful implementation. The primary mechanism employed for collecting physiological data from patients' bodies is the ECG sensor network. To facilitate seamless data transmission, wireless channels are maintained using cloud-based IoT platforms. Within this framework, the AD8232 chip, utilized for electrical activity calculation, is integrated to record data from the device. Embedded within the chip is an integrated circuit (IC) responsible for signal amplification and extraction of requisite qualities. Electrocardiography serves as a pivotal diagnostic tool for numerous heart conditions, with several procedural steps involved in the data collection process. The initial step involves the implantation of multiple electrode pads—preferably three—into the patient's body for data collection. These pads play a crucial role in capturing data from the patient's body, which is subsequently transmitted to the AD8232 chip for analysis. Subsequently, the procedure entails the setup of a screen, commonly referred to as the Arduino COM port screen, through which medical specialists receive the data. Additionally, a Wi-Fi module is configured to facilitate data transmission from the device to experts. The detailed ECG curve displayed on the screen aids medical professionals in interpreting the data more effectively. The final stage entails deploying an Android app equipped with features that provide relevant suggestions. This app displays the ECG curve, aiding patients in comprehending the condition of their hearts better. Data transmission to the app is facilitated by the ECG sensors' ability to connect to integrated Wi-Fi. Moreover, ensuring the correct operation of the device, the Arduino Mega 2560 and earlier processors are configured to function between -3.3 and 3.3 volts, with pins appropriately connected from ground to ground.

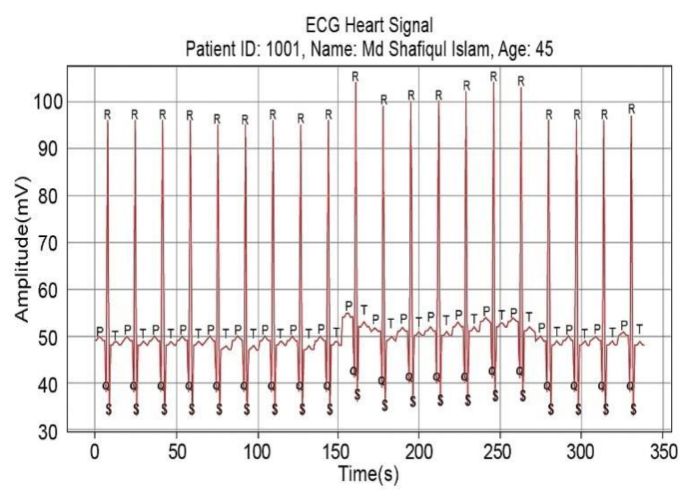

Fig 2: Visual Representation for Acquired ECG Data

3-2- Equipment Cost

The device's detailed cost is given in Table 3. It is clear that the gadget can be constructed for as little as 4231 BDT, or, at the present exchange rate, 38.41 USD. This is the primary system's cost. There will be additional expenses, which cover cloud support and the monitor.

Table 3. Cost calculation of constructing the device

Name of the Components	***Cost in Bangladeshi Taka (BDT)***
Sensors	1142
Cables	174
Wi-Fi module	375
Serial converter	194
Breadboard	175
Arduino mega	934
Pins and others	294
Total	**4231 BDT**

Most of the devices that were proposed for detecting cardiovascular disease, most device cost around 1200 USD to 1800 USD [13,16,17]. On the other hand, the cost of the proposed device is only 39.5 USD. That is why this device is more affordable for people with low income.

3-3- Details of the Platform

The integration of technology within the medical industry has revolutionized the diagnosis and treatment of a myriad of medical conditions. Among the most profound technological advancements lies the development of ECG devices, designed to monitor the heart's electrical activity. These devices play a crucial role in identifying and treating various cardiac issues such as arrhythmias, ischemia, and heart attacks.

The MQTT [30] server is an ideal choice for transmitting ECG data due to its seamless handling of both analog and digital data. However, before data transmission can begin, certain prerequisites must be met. A minimum of 50 data points is required, and an ERROR alert is triggered if the ECG displays fewer than 70 data points. Furthermore, data transmission will not initiate if there are fewer than 50 data points available. This ensures that doctors receive only accurate and reliable data, which is crucial for precise diagnosis and treatment. To enable data transmission, the analog signal undergoes conversion into a digital format using a digital data converter inconsistency.

3-4- Dataset Building

To procure the necessary data, the authors conducted information gathering from a pool of 8,000 volunteers, spanning ages 18 to 75. Specifically, they recorded the durations between ECG waves, focusing on the P, Q, R, S, and T waves, along with the PR, RR, QRS complex, QT, and QTC intervals. Additionally, essential personal information was incorporated into the dataset.

Comprising 14 columns, each housing distinct data based on various criteria, the dataset primarily draws from ECG data to populate 10 of the 13 columns. Furthermore, it includes details such as an individual's ID, age, and BMI. The inclusion of age and BMI attributes enhances comprehension of an individual's health and well-being. The final column of the dataset provides information on the patient's heart condition, annotated by five Bangladeshi cardiac doctors. After thorough examination of each observation, they determined whether it suggests a healthy or at-risk heart. Table 4 displays attributes and their corresponding data types, offering healthcare professionals a comprehensive overview of the dataset contents. By examining the table, they can gain a better understanding of the dataset, facilitating more informed primary care decisions based on the patient’s health status provided within. Data was gathered from volunteers where both patients with cardiovascular disease and healthy persons were available. During data collection, the protocols that were prescribed by a renowned hospital in Bangladesh is followed. All kinds of data biases are removed using statistical measures. Furthermore, wrongly collected data were eradicated during the preprocessing phase. The dataset does not poses that bias except demographic bias where the age difference is not properly balanced. The reason is that cardiovascular disease is mainly common in elderly people.

Preprocessing plays a pivotal role in enhancing the outcomes of Machine Learning (ML) and Deep Learning (DL) architectures. Fundamentally, the ECG signal furnishes all requisite information. Therefore, preprocessing steps are executed as necessary prior to feeding the data into the suggested optimized architecture.

Table 4. Attributes and their corresponding data types

Attribute Name	***Data Type***
P Wave	float32
Q Wave	float32
R Wave	float32
S Wave	float32
T Wave	float32
PR interval	float32
RR interval	float32
QRS complex	float32
QT-interval	float32
QTC-interval	float32
Age	Int64
BMI	float32
ID	Int64
Risk	Int64

Any empty rows or columns are meticulously addressed by the authors. Moreover, all data types are standardized to Int64 and Float32 formats. Subsequently, the dataset undergoes partitioning into training and testing subsets.

3-5- Data Cleaning and Preparation

During the preparation stages, categorical data is also encoded appropriately. Specifically, labels indicating healthy hearts are assigned values of 0, while those representing hearts at risk are assigned a value of 1. For clarity, a partial view of the dataset is presented in Table 5, providing insight into the encoded categories and their corresponding values.

The authors assess the data quality through the application of diverse statistical methods. Within this research, the evaluation entails measuring both covariance and correlation between the data. Covariance serves as a metric to gauge the relationship between variables, while correlation further elucidates the nature of this relationship, indicating whether the data exhibit linear separability or not. One sample of real-life data for 3 cycles has been given below. For each patient 3 cycles have been considered.

Table 5. Data annotation concerning the heart condition

Cycle	*P*	*Q*	*R*	*S*	*T*	*RR*	*PR*	*QRS*	*QT*	*QTc*
1	49	38	96	33	48	.64	.16	..05	.3	.75
2	49	38	96	33	48	.64	.16	..05	.3	.75
3	54	41	104	36	52	.43	.1	.05	.7	.78

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3-6- Artificial Neural Network

Artificial Neural Networks (ANNs) are sophisticated machine learning models designed to emulate the structure and functionality of the human brain. These networks consist of layers of interconnected neurons that process and transmit data. Among the most commonly utilized types of ANNs is the feedforward neural network, which channels data from the input layer to the output layer in a unidirectional manner, devoid of looping back. To optimize performance for specific tasks, various training techniques are employed, allowing for the adjustment of connection strengths between neurons. ANNs excel in tasks necessitating pattern recognition, such as speech recognition, natural language processing, and image classification. Figure 3 illustrates the architecture of the ANN employed in the study. The authors conducted this study utilizing an 11th generation Core i7 PC equipped with a 1 TB HDD and 32 GB of RAM. The study leveraged the Python programming language, with Tensorflow and Keras serving as integrated libraries for constructing the architecture.

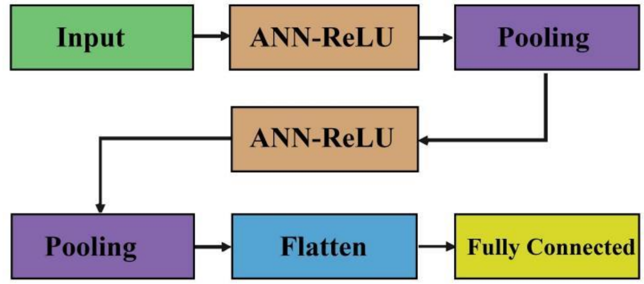

Fig 3. Architectural details of the ANN model

Additionally, Pandas facilitated the conversion of data into a dataframe, while numpy was instrumental in translating all calculations into vector space. Matplotlib.pyplot was utilized for plotting various graphs to aid in data visualization. Furthermore, Sklearn.train_test was employed to partition the data into separate test and train sets.

Table 6. Hyperparametric details of the architecture

Hyperparameters	*Details*
Learning rate	0.001
Loss function	Categorical cross-entropy
Epoch	40
Dropout	0.21
Number of dense layers	3
Trainable parameters	1,24,868
Activation functions	ReLU, softmax

4- Simulation of the Research

The authors aimed to integrate wireless technology and the Internet of Things (IoT) for efficient remote patient monitoring. The main technical objective is to develop an ECG sensor module that can accurately capture the heart's electrical signals, including the P, Q, R, S, and T waves [31], in real-time with high precision. These signals are thoroughly analyzed and extracted from the continuous ECG data stream.

ECG signals are wirelessly transmitted using robust communication protocols such as Bluetooth Low Energy (BLE) or Wi-Fi Direct, ensuring secure and rapid data transfer to a central server.

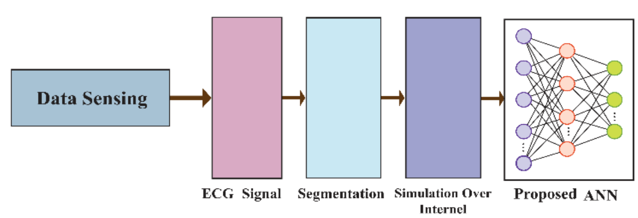

Fig. 4. Some significant stages of data processing

The system's architecture is carefully designed to accurately capture and transmit subtle variations in the amplitude and morphology of the PQRST complex. Figure 4 illustrates key stages from data sensing to processing through an artificial neural network.

Additionally, considerable emphasis is placed on optimizing power efficiency and scalability to support an expanding nework of interconnected devices. This focus aims to ensure prolonged battery life and seamless integration into healthcare infrastructure. Figure **5** provides a functional overview of the entire system.

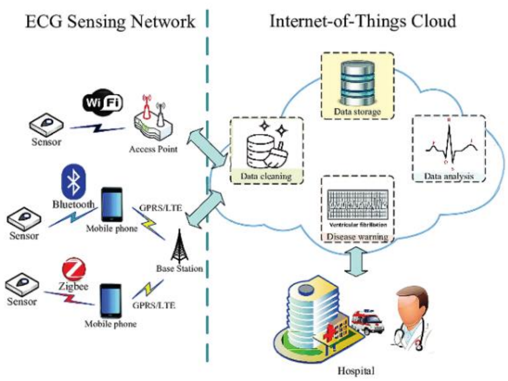

Fig. 5. Working of the whole system

5- Experimental Result Analysis

Initially, the dataset is employed to train the model, imparting knowledge on how attribute values differ between a healthy heart and one experiencing issues. Once trained and tested, the model can effectively evaluate readings obtained from the device, distinguishing between normal readings and those requiring further attention. The authors have meticulously tracked several performance measures to evaluate the model's efficacy. Key metrics assessed include accuracy, precision, recall, and F1-score, as detailed in equations (11) through (14). From the literature it has found that, in [32] the proposed AlexNet method performs much better than traditional machine learning models and other deep learning techniques. It achieved very high results in all major evaluation areas: 98.96% accuracy, 98.53% precision, 95.26% recall, 94.56% F1-score, and a correlation score of 0.988. These results are clearly better than other models, like the Support Vector Machine, which only reached 89% accuracy, and many others that stayed below 90%. This shows that the method is very good at correctly identifying different types of heart signals in electrocardiogram data. One of the key reasons behind this strong performance is the use of deep learning for feature extraction and a fuzzy bi-clustering approach, which together help the model pick up even small differences in heart patterns. However, one weakness is that the model still sometimes makes mistakes by wrongly classifying healthy or unrelated signals as heart conditions. For example, it wrongly identifies some signals as Atrial Fibrillation, Congestive Heart Failure, or Normal Sinus Rhythm, leading to small false positive rates of 2.5%, 3.0%, and 2.0% respectively. The study notes that while the model is highly effective, there is still room to reduce these incorrect predictions.

The outcome that the suggested ANN model produced is depicted in Table 7. Four measures are included in the performance analysis: F1-score, accuracy, recall, and precision. Overall, the Model's performance is extraordinary [32].

Table 7. Performance analysis of the system

Metrics	***Performance***
Accuracy	95.44%
Precision	94.35%
Recall	95.47%
F1-Score	95.64%

After completing the analysis, the authors focused on comparing the outcomes with state-of-the-art ML and DL architectures.

Initially, they compared the proposed model against the most advanced machine learning models, followed by comparisons with deep learning architectures.

According to their assessment, the suggested ANN model outperforms all existing highly effective ML and DL models, boasting an average F1 score of 98.87%. The comparison analysis is depicted in Figure 6.

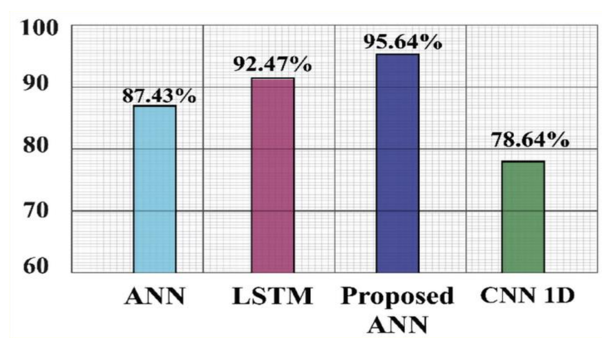

Fig. 6. Performance comparison of the proposed model with other state-of-the-art models

The results illustrated in Figure 6 highlight a notable enhancement in performance when compared to other models, with the deep neural network (DNN) emerging as the closest competitor. Furthermore, the authors juxtaposed the suggested model with the best deep learning architectures, considering the quantity of trainable parameters in each model. Notably, the suggested model surpassed others by a considerable margin.

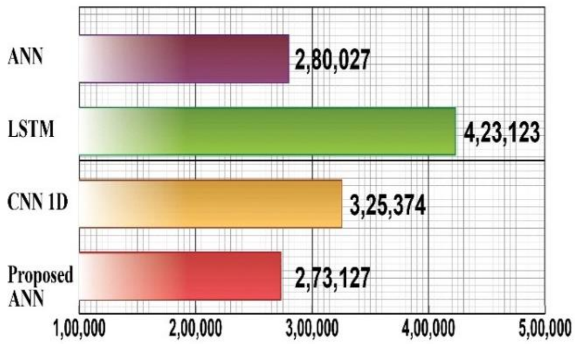

Fig. 7. Performance comparison given the number of trainable parameters

Figure 7 illustrates the count of trainable parameters for each of the DL architectures with which our model competed. Comparative analysis between the suggested ANN architecture and other DL architectures reveals that fewer trainable parameters are required, as evidenced by experimental results. From this result, it is evident, that the proposed model and device integrate properly to detect cardiovascular disease in a proper and economically friendly way. Furthermore, the device has a quick response time that will help doctors and patients to get benefits. Moreover, as the research is focused for the under developing countries that is why this device will help the whole medical sector of the world. The primary problem with LSTM is that it requires extensive data for understanding the sequencing. LSTM is very good in text data but not always in numerical values. Furthermore, CNN 1D can not perform proper with sequential data. That is why ANN is performing better and less trainable parameters because of optimization.

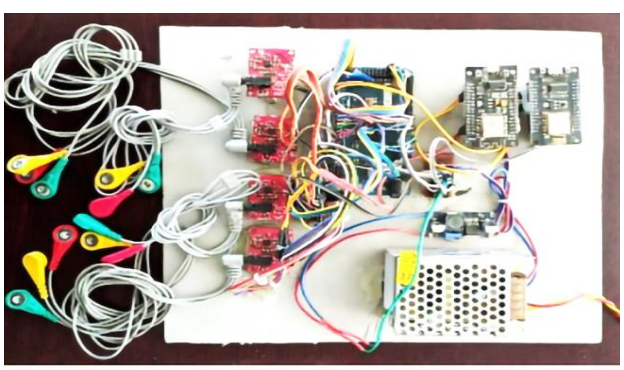

Fig. 8. The physical system corroborating this study

Figure 8 depicts the physical system supporting this study. This device is responsible for collecting personal data from users, which is then analyzed to provide them with the emergency medical attention they may require.

6- Conclusion

Leading the way in modern wellness, this study presents an IoT-based healthcare network that seamlessly integrates advanced sensors attached to the human body. A key innovation is the provision of continuous patient monitoring through multiple channels, including phone messaging services, live monitoring, websites, and apps. By blending state-of-the-art medical devices and applications with traditional medical practices, this approach aims to maximize effectiveness and make high-quality healthcare more accessible and affordable. Taking this into consideration, authors has focused on developing a IoT based device where it can used for medical purposes easily. The methodology suggest that with proper tuning and integration of ANN results in good result in classifying cardiovascular diseases. This work will aid the underprivileged countries to improve their medical sector. With the knowledge transferring from ANN, it is easier to determine the role of DL is immense. Furthermore, the proposed model is lightweight in nature. This research has resulted in the development of a cost-effective IoT-based ECG monitoring device, priced at only 38.41 USD. Experimental results show that using Artificial Neural Network (ANN) procedures, the system achieves 95.64 percent accuracy, outperforming alternative methods. The integration of IoT technologies with smartphones offers significant development. The broader implication is to integrate with real-life hospitals where this device and proposed model can be utilized to detect cardio-vascular disease at an earlier stage. The mortality rate can be reduced significantly in such cases. The research shows, this device has the ability to provide future direction in the health informatics field.

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