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A cost-effective ECG monitoring in rural areas: leveraging artificial neural networks for efficient healthcare solutions

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ABSTRACT

Cardiovascular diseases engender serious public health concerns in developing nations since access to specialized medical equipment is often limited and standard treatment expenses can be prohibitive. This study proposes an efficient and relatively affordable electrocardiogram (ECG) monitoring system that reads and analyzes a person's electrocardiogram data to provide affordable and quality healthcare solutions. The device initially extracts features from electrocardiogram records by reading electrical signals in the heart. Extracted data are then analyzed by a trained deep learning model to determine precisely if the heart is in a healthy state or undergoing complexities. Experimental results showed that the fine-tuned ANN architecture outperformed the state-of-the-art architectures in this field with an accuracy of 98.95%. The data can also be sent to specialists through an MQTT server if necessary, allowing for remote diagnosis and treatment. The system is intended to be deployed in countries where rural regions lack access to specialized healthcare equipment and professionals. Additionally, the device is inexpensive and, hence can be made accessible to people with limited affordability.

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1. INTRODUCTION

Cardiovascular diseases (CVDs) are a growing health concern worldwide, affecting millions of people each year [1]. The impact of CVDs is particularly severe on the heart and blood vessels, with coronary artery disease being a major contributor to the high mortality rate associated with CVDs [2]. It is estimated that CVDs account for approximately 36% of deaths in the European Union [3].

Early detection of heart diseases is crucial in preventing and treating CVDs. One of the primary methods for detecting heart disease is through the measurement and continuous monitoring of heartbeats. Electrocardiogram (ECG) signals provide a detailed understanding of heart conditions by analyzing physiological signals [4], [5]. Thanks to technological advancements, ECG signals can now be accurately measured and observed using ECG monitoring devices [6], [7]. Despite the availability of ECG monitoring devices, analyzing the data obtained from them remains a major concern for researchers. Previously proposed devices have been criticized for their lack of comprehensiveness and inability to keep up with the latest technological trends [8]–[10]. Some ECG monitoring devices operate on a context and server basis [11], [12], while others are equipped with specific technologies. Therefore, there is a need for generalized ECG monitoring devices that can be used globally to better analyze and understand heart conditions. These devices would facilitate the early detection and prevention of CVDs, potentially saving countless lives.

This research aims to propose an ECG monitoring device that integrates the latest technologies to obtain electrocardiogram data precisely. ECG is a non-invasive and widely used method to monitor and diagnose heart-related problems. It records the electrical activity of the heart muscle and provides a graphical representation of the heart's rhythm. In recent years, there has been a significant increase in the use of ECG monitoring devices due to the rise in CVDs where the heart undergoes difficulties functioning properly. However, the efficacy of the devices has always been a major concern. This research proposes a solution to this problem by developing a device that is not only accurate but also affordable and accessible to people living in developing countries like Bangladesh. After data acquisition, proper analysis is necessary to ensure the quality of the data, which would in turn lead us to better results. We have performed statistical analysis on the collected data to ensure that they have the inherent potential to produce the desired outcome.

An artificial neural network (ANN) is a deep learning (DL) architecture that evaluates complex patterns in data. Ozkan *et al.* [13] propose a fine-tuned ANN model to receive instant results in the absence of specialists. The ANN architecture is designed to identify patterns in the ECG signals that are not visible to the naked eye. This enables early detection of heart disease, which is critical for timely treatment. Bangladesh is a developing country where around 73% of the population suffers from different CVDs. Rural areas of Bangladesh lack proper medical services due to the absence of medical specialists and pertinent equipment. This device enables us to understand abnormalities in the ECG signals at any moment, and the sensors along with the fine-tuned ANN architectures provide precise results and early detection of heart diseases. This is a significant breakthrough in healthcare technology as it allows people in rural areas to receive early treatment for heart-related problems.

In addition to proposing the ECG monitoring device, the authors also provide a dataset consisting of different values of ECG signal parameters, which was actually used in this research. This dataset can be used to conduct research in the respective field. The proposed ECG monitoring device has several benefits, including affordability, accuracy, and accessibility. The fine-tuned ANN architecture is also compared with state-of-the-art architectures to verify its effectiveness. This research makes significant contributions to the field of healthcare technology and has the potential to save many lives by providing timely treatment for heart-related problems. In a comparison of the proposed model with the literature, the major drawback of the previous research is the unavailability of a low-cost ECG monitoring device that will allow us to measure ECG data instantly. Apart from that, the interface of the previously suggested devices is not that user-friendly. This research aims to solve those problems. The cost of the ECG system is cheap which can be affordable by people from all sectors. Integration of ANN in the mentioned device allows data to be trained precisely so that a predicted result will be shown on the interface of the device based on the data it will read. The major contributions of this research are:

a. Proposing a 12-lead ECG monitoring device that captures ECG signals instantly. The device is affordable to rural people in developing countries like Bangladesh.
b. Constructing a dataset containing electrocardiogram data of people aged between 18 and 70, along with their ID, age, and BMI. The quality of data is evaluated using different statistical methods.
c. Proposing a fine-tuned ANN architecture for understanding complex patterns in the dataset. This model is compared against other state-of-the-art architectures to determine the one with the optimum outcome.

The organization of the paper includes a literature review in section 2. The necessary methodologies of this research are described in section 3. Section 4 reflects a detailed description of the proposed ANN architecture. Analysis of the obtained experimental results is discussed in section 5. The future aspect of this research is discussed in section 6.

2. LITERATURE REVIEW

Internet of things (IoT) is a trending concern of computer science that deals with transmitting data from one device to another efficiently by means of cloud servers. An efficient cloud server is required for transferring data instantly. Prasad and Kavanashree [14] proposed a novel way of signal acquisition along with signal preprocessing. No proper encryption model has been utilized in this study. IoT based monitoring systems have been primarily proposed in [15] that include proper data visualization. Integration of DL architectures and machine learning (ML) algorithms are mislaid here. IoT-based ECG monitoring systems have added a new dimension to this field [16]–[19]. Most of the studies focused on signal acquisition where data preprocessing is a major concern. Data cleansing has been performed with the integration time-based feature integration has been performed in [20]. Arduino Uno is a microcontroller board based on the ATmega328T. Predominantly previous studies have utilized Arduino Uno for obtaining signals from the heart [21]–[23]. Arduino Uno is easy to integrate along with the cost of devices is also lower in such cases. With the introduction of the latest microcontrollers raspberry pi has also been amalgamated in many studies

[24]–[26]. But affording the costs of such devices is a major concern for a majority percentage of users. ECG monitoring activities are moving towards wireless systems.

Artificial intelligence (AI) has the advantage of being employed in wireless systems. It can be employed to construct effective machines that can be instrumental to novel purposes. The majority of research in this sector does not include the power of AI. ML algorithms can identify complex patterns in data using feature selection procedures. The supremacy of DL architectures over ML algorithms is in terms of identifying complex data patterns with ambiguous data. Taking all the research gaps into account, the authors have focused on proposing a 12-lead ECG monitoring system that can instantly capture data from the electrical pulses of the heart. The further activity includes providing the data to the specialists over a cloud server. Reliability and scalability are the major priority while wielding the message queuing telemetry transport (MQTT) server. The data obtained from patients will be utilized for research purposes. The authors also have integrated a fine-tuned DL architecture to get a primary result from the device in the absence of medical specialists. Based on the result provided by the DL architecture patients can be given primary treatment for avoiding unexpected death. Detailed reports can be provided later by the experts for further advanced treatment. To ensure the availability of this device to the rural people of underdeveloped countries, the authors have ensured the cost of this device is affordable to all. Detailed experimental analysis shows the proposed ANN model has shown effectiveness over all the previously studied research in terms of different evaluation metrics and trainable parameters. The proposed ECG monitoring device is also an optimized solution for patients and medical specialists. A detailed comparison has been depicted in Table 1 to provide a clear view regarding the significance of this research.

Table 1. Performance comparison of the proposed model with other ML and DL ones

Models used in ECG devices	Accuracy (%)
SVM	69.35
Naïve bayes	76.36
1D-CNN	78.23
Proposed architecture	98.87

3. RESEARCH METHODOLOGY

This section addresses the tools, techniques, architectures, and procedures adopted to carry out this research. At first, necessary data has been acquired through the ECG monitoring device. Furthermore, necessary preprocessing has been performed in order to understand the data properly. The cleaned data is provided to an ANN after that. To achieve the best result, the hyperparameters of the trained model are fine-tuned. Finally, the success of the model is evaluated using various evaluation metrics. Figure 1 depicts the steps that have been performed throughout the whole research.

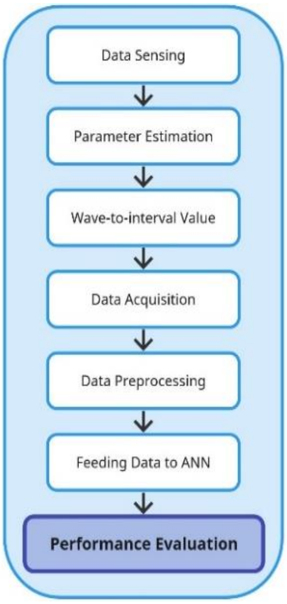

Figure 1. The proposed methodology of this research

3.1. Workflow of this research

The methodology comprises six major steps before finally evaluating the performance. Initially, we need to sense the data by means of the device we proposed. Time intervals were extracted and converted into floating-point values. Initially, the reading is in a wave format, where the wave intervals are converted to numeric values. The data is then preprocessed, which includes deleting null values and reducing columns. Once the preprocessing is done, the data is then fed into the proposed ANN architecture. To evaluate the performance, several metrics are utilized. Figure 1 shows how the whole study was carried out in a sequential manner.

3.2. Network requirements

The authors have focused on setting up the proper environment to ensure effective implementation. The ECG sensing network is the primary environment that gathers physiological data from the patients' bodies. The authors maintain wireless channels to send data over an IoT cloud platform. This platform is used to record data from the device using the AD8232 chip, which is utilized to calculate electrical activity.

The chip is integrated with an IC that amplifies the signals and can extract necessary properties. Electrocardiography is applied to diagnose numerous cardiac problems. The process of gathering data involves multiple steps that are outlined.

a. Implanting a number of electrode pads, preferably three, into the body of the patient to gather data is the first step. These pads play a key role in gathering data from the body of the patient. The data is then sent to the AD8232 chip for analysis.
b. Establishing a screen, which can be referred to as the Arduino com port screen, is the second step in the process. This screen is used to provide data to medical specialists. A Wi-Fi module is also set up to transmit data from the device to specialists. The screen provides a detailed ECG curve that helps medical specialists to understand the data better.
c. Implementing an android app to provide appropriate suggestions is the third step. This app is designed to display the ECG curve, which can help patients understand their cardiac health better. The ECG sensors have the capability to connect with the built-in Wi-Fi, which makes it easier to transmit data to the app. Additionally, the Arduino Mega 2560 and previous chips remain active from -3.3 V to 3.3 V. The pins are also connected from ground to ground, which ensures that the device functions properly.
d. The final step in the process is to achieve better performance. To achieve this, A0 and LO- to 11, and LO+ to 10 are utilized. These components help to ensure that the device functions optimally. The device must be placed on the top of the patient's chest to observe and obtain the data.

The process of implementing this device involves several steps that ensure effective data gathering and transmission. The authors have made use of advanced technologies, including wireless channels and IoT cloud platforms, to ensure that the device functions properly. By following the outlined steps, medical specialists can obtain accurate data that can help diagnose numerous cardiac problems.

3.3. Environment for the cloud platform

The use of technology in the medical field has revolutionized the diagnosis and treatment of various health conditions. One of the most important technological advancements is the development of ECG devices that are used to monitor the electrical activity of the heart. These devices are used to diagnose and manage a wide range of heart conditions, including arrhythmias, ischemia, and heart attacks.

As mentioned above, the authors of this document aim to provide medical specialists with data as early as possible. This data is gathered from ECG device sensors and is transferred through a cloud medium using a Wi-Fi module. To ensure that the data is transmitted reliably and efficiently, the MQTT server is used, which is known for its scalability and reliability. Both analog and digital data can be sent through the MQTT server, which makes it an ideal choice for transmitting ECG data.

However, there are certain conditions that must be met before the data can be transmitted. The primary condition is that the data must be greater than 50. If the data is 70 and the ECG shows fewer than 70, an ERROR message will be provided. On the other hand, if the data count is less than 50, the process will not start. This ensures that only accurate and reliable data is transmitted to the specialists, which is critical for accurate diagnosis and treatment.

After the data has been collected and verified, the next step is to convert the analog signal to digital. A digital data converter is used for this purpose, which ensures that the data is in a format that can be easily processed and analyzed. ESP8266 is integrated with the Arduino board for uploading data to the desired cloud platform. The third pin of this module must be connected to GND. After the program has been completed, the RX, TX, and GPIO should be disconnected. All the necessary programs for this, along with the DL architecture code, have been uploaded to ensure that the process is streamlined and efficient.

To understand the data pattern and outcomes, an Android application has been implemented. The application provides necessary information in a comprehensible manner and ensures that the specialists can easily analyze the data and make accurate diagnoses. Necessary steps have been taken to make the application platform-independent, which ensures that it can be used on a wide range of devices and platforms.

The gathered data is verified by medical representatives, who ensure that there are no mismatches or errors. If no mismatches are found, the data is further provided to the specialists, who use it to generate the final outcome inside the device. From the signals, several parameters are extracted and analyzed to generate the final outcome, which is critical for accurate diagnosis and treatment.

3.4. Acquisition of data

The authors collected data from 7,000 volunteers between the ages of 18 and 70 to gather necessary information. Specifically, the time intervals between the ECG waves were gathered. The study focused on the P wave, Q wave, R wave, S wave, T wave, PR interval, RR interval, QRS complex, QT interval, and QTC interval. Additionally, some necessary information regarding individuals was recorded in the dataset.

3.5. Dataset description

The dataset consists of 14 columns, containing individual information according to different attributes. 10 out of the 13 columns contain values extracted from the ECG data. The dataset also contain data for a person's age, BMI, and ID. The inclusion of additional age and BMI parameters allows for a more comprehensive understanding of the person's health and well-being. The final column provides data on whether the patient is at risk, or has a healthy heart. The annotation of this column is performed by 5 heart specialists of Bangladesh. They examined each observation of the dataset and made a consensus on determining whether it should imply a healthy heart or a heart at risks.

The ID column serves as an identifier so that the person's details can be accessed anytime, without any chance of mixing up. This ensures that each individual’s data remain separate. Table 2 presents attributes along with their data types. The table provides a detailed overview of the dataset, allowing healthcare professionals a overview and a better understanding of what the dataset contains. The dataset provides valuable information on the patient's health status, enabling healthcare professionals to provide better primary care.

Table 2. Attributes along with 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

3.6. Preprocessing of the data

Preprocessing is often necessary in order to obtain better results from ML and DL architectures. Primarily, all necessary data are obtained from the ECG signal. Before feeding the data into the proposed fine-tuned architecture, some necessary preprocessing is performed. The authors check for any empty rows and columns if there are any, and take care of them. All necessary data are converted to float32 and Int64. The dataset is then split for training and testing purposes. All categorical data is also encoded in the preprocessing steps. A healthy heart is labeled as 0, and a heart that is at risks is labeled as 1. Table 3 shows the partial view of the dataset.

Table 3. Partial view of the dataset

P	Q	R	S	T	PR	RR	QRS	QT	QTC	Age	BMI	ID	Risk
0.2	0.5	0.22	0.07	0.5	0.4	0.57	0.34	0.22	0.32	53	24	1001	1
0.19	0.07	0.16	0.03	0.26	0.2	0.36	0.15	0.22	0.33	27	19	1002	0
0.21	0.39	0.18	0.13	0.27	0.11	0.42	0.18	0.34	0.56	29	33	1003	0

3.7. Data quality measurements

The authors evaluate the quality of data by applying various statistical methods. In this research, covariance, and correlation between data are measured. Covariance represents the relationship between variables. The authors measured the covariance and correlation to express whether the data are linearly separable or not.

$$r = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2}} \quad (1)$$

$$cov(x, y) = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{N-1} \quad (2)$$

Table 4 shows the covariance and correlation coefficients of the parameters. It turns out that the dataset is in a healthy state for feeding to the proposed fine-tuned ANN architecture. The average correlation of the coefficients is 14.74.

Table 4. Covariance among the parameters in the dataset

Parameters	P	Q	R	S	T	PR	RR	QRS	QT	QTC	AGE	BMI
P	42.11	26.36	33.63	38.94	34.64	29.12	31,64	16.37	12.43	35.36	26.77	28.35
Q	5.36	8.48	7.53	4.66	6.78	10.48	37.48	2.48	32.74	5.48	2.53	11.63
R	9.25	4.83	6.46	8.37	2.64	6.94	74.74	8.04	8.37	3.83	5.47	5.74
S	19.74	7.48	9.24	6.37	28.64	9.59	5.37	3.19	24.63	7.48	37.64	3.65
T	49.26	8.49	53.75	3.90	16.38	10.50	4.63	9.54	18.85	3.49	2.47	2.64
PR	10.26	3.63	14.82	4.74	32.64	5.74	7.94	5.77	4.63	8.63	4.37	12.47
RR	8.63	47.37	3.20	8.36	9.35	37.48	35.65	7.28	9.84	9.37	6.84	4.64
QRS	37.63	25.74	11.74	3.75	5.38	29.82	4.02	55.43	15.43	18.74	5.38	6.73
QT	2.74	36.14	4.63	2.84	7.38	11.29	1.46	5.53	7.39	4.14	17.53	3.66
QTC	4.71	35.24	4.52	2.92	7.32	11.21	2.41	4.93	10.87	5.14	16.53	4.12
AGE	22.64	35.47	8.39	43,38	3.72	49.64	53.64	16.23	19.84	6.47	3.65	4.39
BMI	4..04	2.58	42.84	4.63	18.53	2.53	73.54	3.63	3.74	8.47	3.67	3.24

3.8. Cost of the device

The authors of this paper were aware of the cost issues in order to keep the device affordable for people of lower economic status. The major hardware components of this device are discussed above. In Table 4, the detailed cost of the device is provided. From Table 5, it is evident that the device can be built within as low as 2651 BDT which is equivalent to 25.02 USD as per the current rate. This is the cost of the main system. There will be some other costs which include the monitor along with cloud support.

Table 5. Detailed cost calculations of the device

Name of the components	Cost in Bangladeshi Taka (BDT)
Sensors	1053
Cables	102
WiFi module	253
Serial converter	170
Breadboard	125
Arduino Mega	748
Pins and others	200
Total	2651 BDT

4. PROPOSED FINE-TUNED ANN ARCHITECTURE

4.1. Artificial neural network

ANNs are ML models that mimic the structure and operation of the human brain. ANNs consist of layers of interconnected neurons that process and transmit information. The most popular type of ANN is a feedforward neural network, in which data flows from the input layer to the output layer in one direction without looping back. Different training methods can be used to modify the strength of the connections between neurons and improve performance on specific tasks. ANNs are particularly effective at tasks that require pattern recognition, such as speech recognition, natural language processing, and image categorization. In this research, the authors fine-tuned an ANN architecture by manually adjusting all the hyperparameters. They used the python programming language for the DL portion of the project, and integrated various python libraries to predict data. Figure 2 shows the architecture of an ANN.

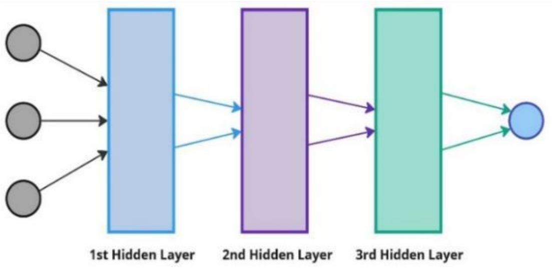

Figure 2. The architecture of an ANN

4.2. Programming environment

For this research, the authors used a Core i7, 11th Gen PC. 32 GB RAM has been used with a 1 TB HDD. Python programming language has been used. Tensorflow and Keras are two libraries that are integrated for building the architecture. To convert the data into a dataframe, pandas has been utilized. To convert all calculations into vector space numpy library is used. For plotting different graphs for data visualization purposes, Matplotlib.pyplot has been imported. Finally, through Sklearn.train_test data has been divided into test and train sets.

4.3. Hyperparameters tuning

The authors have fine-tuned the necessary parameters for obtaining the highest results. Table 6 demonstrates the hyperparameters that have been fine-tuned.

Initially, keras.sequential() was used to initiate the dense layer. Tensorflow is used in the backend. Three fully connected dense layers were created. To understand the loss function, categorical cross-entropy was used. The model was trained for 10 epochs with a learning rate of 0.0001.

Table 6. Hyperparametric details

Name of the hyperparameters	Value
Learning rate	0.0001
Loss function	Categorical cross-entropy
Epoch	10
Dropout	0.04
Number of dense layers	3
Trainable parameters	1,64,868
Activation functions	Relu, relu, softmax

To prevent overfitting, recurrent dropout with a value of 0.04 was applied. The first two hidden layers use ReLu activation function, and the final layer uses softmax. The model converges after 10 epochs.

5. EXPERIMENTAL RESULTS ANALYSIS

Initially, the model is trained with the dataset to make it learn how the attribute values for a healthy heart and a troubled heart vary. Once the model is trained and tested, it can be employed with the device to determine if a reading looks normal or needs special attention. To evaluate the performance of the model, several performance metrics have been observed by the authors. The accuracy, precision, recall, and F1-score are the primary metrics that are evaluated. These metrics are expressed in (3) to (6):

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

$$Recall = \frac{TP}{TP+FN} \tag{4}$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{5}$$

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision+Recall} \tag{6}$$

Figure 3 demonstrates the result shown by the proposed ANN model. The performance analysis covers 4 metrics, namely precision, recall, accuracy, and F1-score. The model performs pretty well in all aspects.

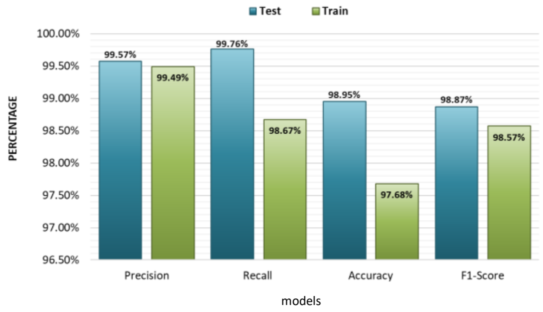

Figure 3. Performance analysis of the proposed model

5.1. Performance comparison

After analyzing the results, the authors focused on comparing them with the most effective architectures in ML and DL. They compared the proposed model with state-of-the-art ML models first, and then with DL architectures as well. The authors compared the proposed model with recent ML architectures and found that the proposed ANN model outperforms all the other most efficient ML and DL models, achieving an average F1 score of 98.87%. The comparison analysis has been demonstrated in Figure 4.

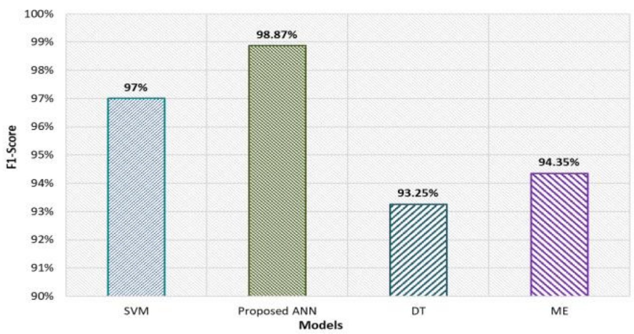

Figure 4. Comparison with the most effective ML models

Figure 5 shows that the proposed ANN model significantly outperforms other models, with the deep neural network (DNN) being the closest contender. The authors also compared the proposed model with the most effective DL architectures taking into account the number of trainable parameters the models have. Fine tuning of the hyperparameters also helped the proposed model perform significantly better than the others.

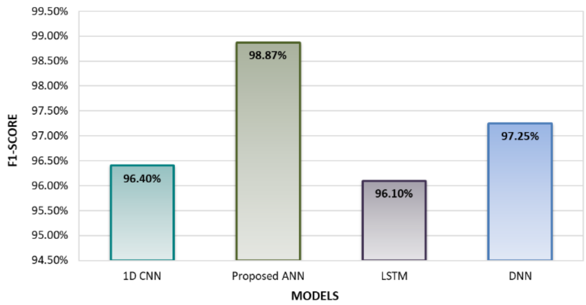

Figure 5. Comparison with the most effective DL architectures

Figure 6 shows the numbers of trainable parameters for the DL architectures that our model contended with. Experimental results show that the proposed ANN architecture requires fewer trainable parameters when compared to other DL architectures. The physical system which corroborates this research is shown in Figure 7. This device is responsible for collecting data from individuals, which are analyzed later on to provide the medical care people need in crisis.

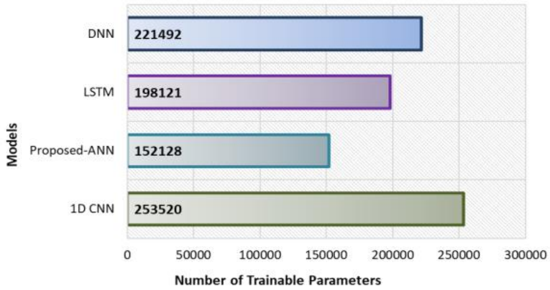

Figure 6. Comparison for the number of trainable parameters

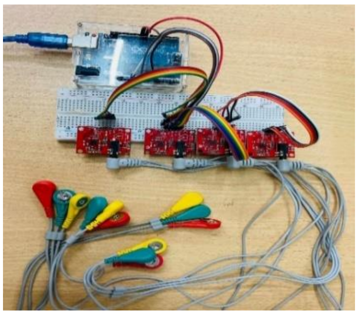

Figure 7. Outlook of the proposed ECG monitoring system

6. CONCLUSION

An IoT-based healthcare network often connects to highly effective sensors connected to the human body in state-of-the-art daily wellness. IoT-based technologies utilized for smartphones or other devices currently have many advantages and prospective results. Continuous remote monitoring of a patient is sometimes a crying need, especially in rural areas where specialists are not easily available and quality medical equipment is inadequate. The provision of continuous patient surveillance via the website and app service, a live monitor, and a phone messaging service is a component of the technological effort in this article. In this study, the standard medical strategy and cutting-edge medical applications are linked together to yield the best outcome. The cost of quality healthcare through this system can be affordable, particularly for people who are not well off and living in underdeveloped localities.

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