Smart wearable Cardio-health monitoring system using Deep Learning Technologies

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Abstract

Every year, the proportion of the population suffering from Cardiovascular Disease (CVD) rises dramatically. According to the World Health Organization (WHO), this disease kills millions of people each year, which is heartbreaking. The remarkable improvement in wearable technology has created opportunities to provide numerous intelligent approaches for tackling this condition efficiently. Furthermore, early detection of CVD improves medication and speeds up the treatment process by clinical professionals. The seriousness of this issue motivated us to propose a wearable smartwatch by integrating Deep Learning (DL) and Internet of Things (IoT) technologies. The DL model is designed using transformer encoders for cardio-health status prediction. To achieve this, Electrocardiogram (ECG) data from the MIT-BIH database is used. The effectiveness of the model is evaluated in terms of accuracy and execution time. Additionally, the model's output is compared with the Convolutional Neural Network (CNN) model. The proposed model achieves the highest accuracy of 98.04% on 2500 test samples. The proposed model is deployed in the cloud. The ECG sensor is fixed to the watch to collect ECG signals from the person and send them to the cloud. The cloud analyzes the data using the deployed DL model and predicts the cardio-health status. If the cardio-health is abnormal, the cloud sends an immediate alert to the registered mobile number. The proposed smart wearable watch can help individuals monitor their health and improve their quality of life.

Keywords—Cardio Vascular Disease, Electrocardiogram, Deep Learning, Signal Processing, Cloud Computing, Notification

Introduction

According to the World Health Organization (WHO), noncommunicable diseases (NCDs) account for 71% of all deaths worldwide, claiming 41 million lives annually [1]. Each year, NCDs cause 15 million deaths among individuals aged 30 to 69, with 85% of these premature deaths occurring in low- or middle-income countries. CVDs are the leading cause of death among NCDs, followed by cancer, respiratory diseases, and diabetes [2]. These statistics underscore the urgent need for preventive and therapeutic interventions to reduce the global burden of CVDs.

CVDs affect the cardiovascular system, leading to conditions such as vascular diseases, rheumatic heart disease, coronary artery disease, and strokes [3]. Heart disease and stroke together contribute to approximately 80% of

all CVD-related deaths, with 33% occurring in adults under the age of 70. Unhealthy behaviors, including imbalanced diets and excessive consumption of sugar, salt, and fats, contribute to obesity and overweight, thereby increasing the risk of CVDs. Identifying individuals at high risk and ensuring they receive appropriate treatment are crucial steps in reducing premature CVD-related deaths [4]. Access to basic health technologies and medications for NCDs is essential to providing effective CVD therapy and counseling in primary healthcare settings.

Low levels of physical activity among CVD patients are associated with higher rates of hospital readmissions, diminished quality of life, and substantial financial burdens on healthcare systems. The syndromic nature, variable presentation, and sudden onset of CVD contribute to low awareness of the disease, which can have poor outcomes without timely diagnosis and treatment. Electrocardiograms (ECGs), a cost-effective diagnostic tool, play a crucial role in routine screening and assessment of CVD [5]. DL technology holds promise for accurate diagnosis of CVDs. Going to the hospital for an ECG could be hard for the patient as well. New generations of wearables are emerging, driven by users' need to monitor their health, and they are making a greater impact in the healthcare sector [6]. The impact of wearable technology on CVD care is increasingly clear, particularly with the inclusion of features that allow these devices to assess data in real-time. The key clinical benefits of wearable technology in the fight against CVD include improved patient-physician communication, personalized treatment, and stroke prevention approaches. Wearables are not only transforming clinical research, but they are also influencing the future of cardiovascular care, both in terms of prevention and therapy.

In this research, we developed a smart watch for cardio-health monitoring. This smart watch is designed by integrating DL and IoT technologies. The smart watch collects the ECG data of the person and sends it to the cloud. The DL model analyzes the data and predicts the cardio-health status. This research helps to avoid the person's regular visits to the hospital while providing 24/7 monitoring.

Literature Survey

Before designing the proposed system, we conducted research on recently available smart wearables for various health parameter analyses, as well as various DL models and IoT platforms used. Some of the important works are shared in this section. An intelligent strategy is used in the study [7] to analyze large physiological data collected by worn smart watches. The initial stage was the constant digital transmission of physiological information from smart watch users. Second, the transmitted information was received by a healthcare management platform via the narrow-band IoT. Doctors evaluated patients' situations by analyzing data using a sophisticated statistical model. Finally, users obtained their medical diagnoses, disease predictions, or warnings via a smartphone app. Paper [8] describes a wearable e-health monitoring framework based on the IoT. It continuously monitors the patient's vital signs. Using the IoT platform, which includes a mobile application and remote Blynk, they developed and deployed an E-Health monitoring framework for cardiac illness monitoring. To verify the system's efficiency, they compared the outcomes with those from the Apple Watch, Samsung Gear S, and the Japan Fukuda ECG Machine. These tools can detect the presence of heart diseases, but they cannot provide a diagnosis. On the other hand, the proposed system can measure ECG signals and other important signal properties, making it helpful for remote patient diagnosis of heart disorders.

The research [9] proposes a wearable health monitoring device that leverages the IoT to follow the whereabouts and vital signs of people in quarantine in real-time from a distance. The system, which includes a watch, a computer, and a monitor, uses ultra-miniaturized optoelectronic and electronic technologies to offer real-time updates on physiological markers. In critical care, the most important variables to monitor are heart rate, peripheral oxygen saturation, and temperature. Healthcare providers can remotely monitor these features, which are automatically uploaded to a cloud database. Multiple patients' vitals can be displayed on the screen in real time, and the terminal can also be used as an early warning system by doctors. Also, it can assist healthcare staff in effectively managing the COVID-19 outbreak by detecting people in need of urgent medical care. The article [10] introduces the 'MedAi' smart watch-based disease prediction system that was developed using machine learning (ML) techniques. A prototype smart watch called 'Sense O'Clock' with multiple sensors that collect vital signs, uses ML to interpret the data and generate predictions, and includes a mobile app to display the results are the three main components. Gathering a dataset of patients' body characteristics from a nearby hospital was conducted by ethical norms, obtaining prior agreement from patients and doctors. Various ML techniques were employed to determine the optimal method. By examining the dataset, it was observed that the Random Forest method achieved a disease prediction accuracy rate of 99.4%, which was significantly higher than previous ML techniques. The device offers 24-hour support by constantly monitoring the user's vital signs and recommending relevant treatments.

The article [11] compares multiple DL techniques for identifying Activities of Daily Living (ADL). Following a mapping of these methodologies, three HAR strategies and a dataset were chosen for evaluation. Experiments were carried out with particular assessment metrics to evaluate the performance of the suggested strategies in ADL recognition. The DeepConvLSTM architecture, which consisted of a single LSTM layer plus recurrent convolutional layers, beat all other approaches studied. These results suggest that software programs developed with this design could assist wristwatch users in gaining greater awareness of their daily activity patterns. The research [12] proposes a health monitoring system based on the IoT framework. The recommended solution utilizes a smartphone app and Global System for Mobile communication (GSM) technology to provide patients with continuous mobile monitoring. The primary objective is to develop an IoT-based reliable patient management platform to monitor patients, whether they are in a healthcare facility or at home, all aimed at delivering excellent treatment. A WiFi module delivers data collected by sensors used to monitor vital parameters to the cloud. Someone created a wireless healthcare monitoring system that can send real-time vital signs to a website. The system's components include sensors, software, a microcontroller (ESP32), and a data collection device. The application on the doctor's mobile device gives him access to the patient's data, which the system monitors, displays, and saves regularly. Also, if any of the metrics exceed a particular threshold, the doctor's phone will receive a notification.

Proposed System
The proposed framework is detailed in this section. To develop a smart wearable for a cardio-health monitoring system, DL and IoT are used. The proposed framework consists of two main parts: one is DL and the other is hardware design and cloud integration. For predicting cardio-health status, the DL model is developed using a publicly available dataset. For continuous monitoring, the hardware is designed in the form of a watch so the person can wear it all the time. The proposed DL model is deployed in the cloud, and the hardware collects

ECG data from the person and sends it to the cloud. In the cloud, the data is analyzed and predictions take place. If any CVD is found from the ECG, the cloud immediately sends a notification to the mobile. The detailed working of the proposed system is shown in Figure 1.
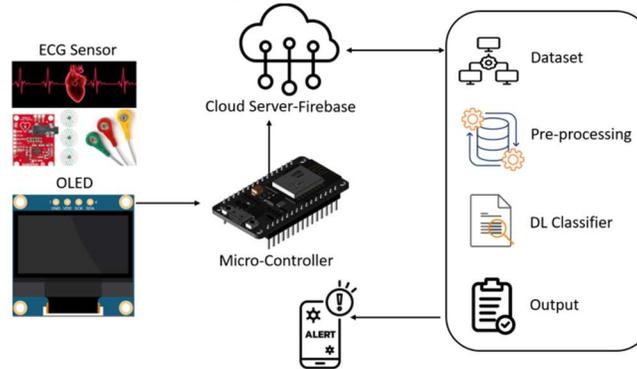

Fig. 1. Workflow of the proposed methodology

DL Model

The DL has three modules: data collection, processing and DL model construction.

Data Acquisition: For this study, the MIT-BIH database [13] was used. Normal signals (NOR), right bundle branch block (RBBB), left bundle branch block (LBBB), atrial premature contraction (APC), and premature ventricular contraction (PVC) were the five types of arrhythmias that were taken into account. Table 1 provides the details of the data used for training and testing purposes. We considered 2,500 samples for each class to ensure a balanced representation. The undersampling techniques were used for balancing. Figure 2 shows the ECG data distribution before and after balancing.

Table 1. Details of ECG data

Heartbeat types	Raw	Balanced	Train	Test
NOR	74,607	2500	2000	500
RBBB	7,250	2500	2000	500
LBBB	8,069	2500	2000	500
APC	2,514	2500	2000	500
PVC	7,127	2500	2000	500
Total	99,567	12,500	10,000	2,500

RAW EEG DATA DISTRIBUTION

APC 3%
PVC 7%
LBBB 8%
RBBB 7%
NOR 75%

a)

BALANCED EEG DATA DISTRIBUTION

PVC 20%
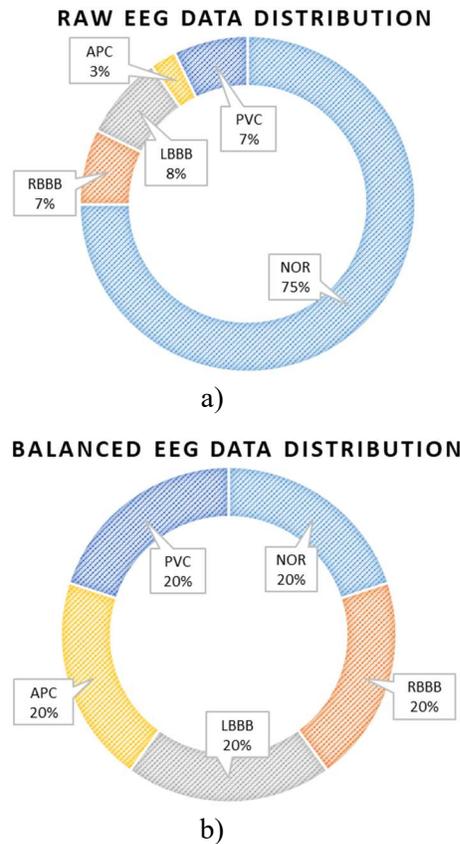NOR 20%
APC 20%
RBBB 20%
LBBB 20%

b)

Fig. 2. ECG data distribution before and after balancing

Data Pre-processing: The ECG pre-processing approach includes the removal of baseline, powerline inference, and normalization.

Baseline Removal: Whenever a cardiac muscle is at rest, its voltage changes, which is known as the baseline voltage. Baseline wanders, a form of low-frequency noise can be caused by the subject's respiration, movement, or electrode displacement [14]. Consequently, it becomes more challenging to locate the R peak. The first step involves obtaining baseline signals from the database. Then we compute and subtract the average signal value from the first step. The formula for removing baselines is given in Equation (1) and (2)

$$mean_{ECG} = \frac{1}{N}\left(\sum_{i=0}^{n} ECG\right) \qquad [1]$$

$$new_{sig} = ECG - mean_{ECG} \qquad [2]$$

Where, ECG represents the starting signal and N represents the total of all signal data points. The $mean_{ECG}$ is determined by dividing the sum of all data points by the total data points. The value of the $mean_{ECG}$ variable is subtracted from the original signal and placed in the new_{sig} variable.

Powerline Interference: A band reject filter can help to reduce or eliminate powerline interference from the ECG data [15]. As a result, we can formulate the equation for an ECG signal band rejection filter as follows:

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$$P(f) = \frac{1}{\left(1 - 2r\cos\left(\frac{2\pi f}{fs}\right) + r^2\right)} \qquad [3]$$

Where, fs represents the sampling frequency, f represents the frequency, r represents the filter pole's radius which decides the notch frequency, and $cos()$ represents the cosine function.

An ECG data has a frequency range of around 0.5 to 85 Hz. The patient's wire was distorted due to alternating current fields. The noise was eliminated using a 1.5 Hz frequency cutoff high-pass filter, as per the Butterworth technique. This filter's frequency response is shown in Equation (4):

$$H(f) = \frac{f}{\sqrt{\left(1 + f^{2/2.5 * 10^{-4}}\right)}} \qquad [4]$$

Where f represents the frequency. The filter's gain increases with frequency, culminating at 0.707 (-3 dB) at the 0.5 Hz cutoff frequency. So the filter reduces frequencies below 0.5 Hz while passing those above that frequency.

Normalization: As a last step in the pre-processing, the signal is scaled from -1 to 1. The min-max scaler function [16] is used and it is given in Equation (5)

$$N_i = \frac{S_i - min(S_i)}{max(S_i) - min(S_i)} \qquad [5]$$

Where, N_i denotes the normalized signal, while S_i represents the clean signal. The difference between the minimum and maximum S_i values is divided using the equation from Reference [1]. After cleaning the signal S_i, we subtract the minimum value from it. We normalize the array's values from -1 to 1.

Proposed DL model Architecture: In this research, we provide a model for predicting cardiovascular health status based on the attention mechanism; Figure 3 depicts the overall framework diagram. We designed the model to capture both spatial and temporal information since the ECG signal is functionally connected across channels and continuous throughout time. The proposed model has two basic components: a spatial transformer encoder (STE) and a temporal transformer encoder (TTE). In TTE, the attention module is employed to identify the relation between sample points; this correlation is subsequently utilized to extract ECG characteristics in the time domain. Because each sample's channel coupling is unique, we designed the STE component to compute the spatial attention for channels to record the coupling correlation between various channel; this allows the network to distinguish the ECG samples more accurately. Finally, global information is gathered and classified using a fully connected layer (FCL).
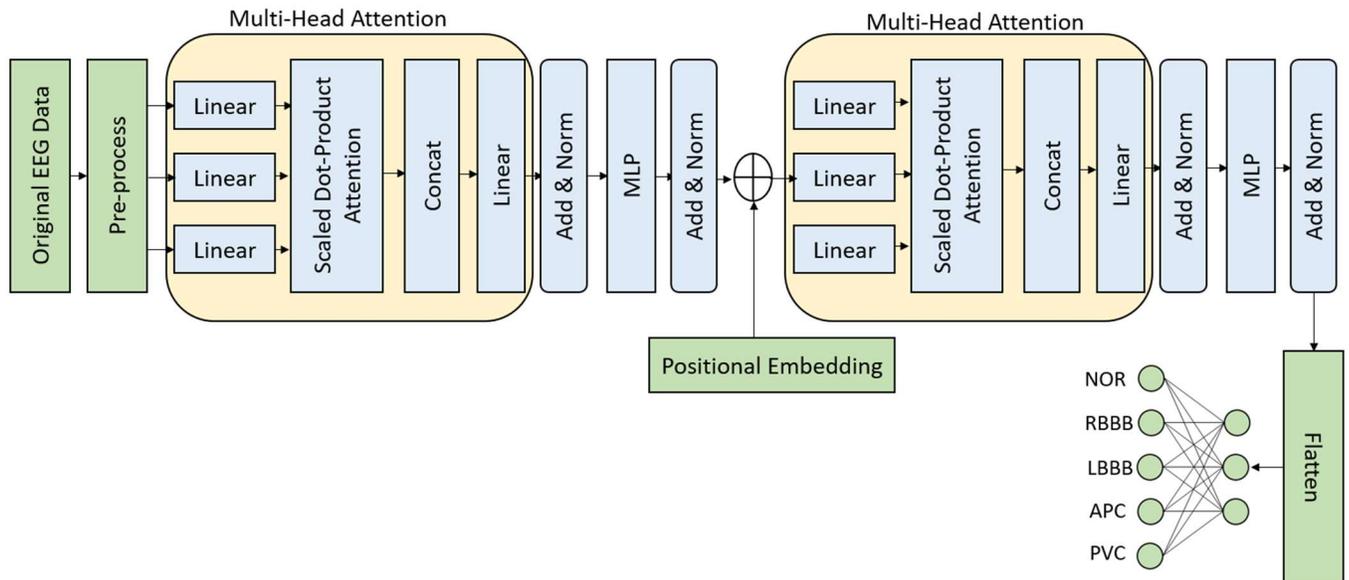
Fig. 3. Proposed DL Model

emporal transformer encoder: To extract time-domain data from ECG signals, we use temporal correlation, which is a relationship between two timestamps [17]. We encode the ECG's temporal information with numerous transformer blocks, borrowing inspiration from the attention mechanism. Unlike convolution, which only evaluates local information, TTE takes into consideration temporal dependencies over long distances. Rather than employing sophisticated transformations, we send pre-processed ECG data directly to the transformer. For predicting the temporal correlations, the network calculates the self-attention in the transformer module for an input $X = [x^1, x^2, …, x^T] \in \mathbb{R}^{T*C}$. We then weigh the total to create the new representation. To calculate self-attention, the Equation is used:

$$Attention(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right) V \qquad [6]$$

Linearly projecting the input yields the scalar component, d_k, as well as the matrices Q, K, and V. With the multi-head attention mechanism applied to the input, we can analyze data from many representation subspaces placed at different points. Each transformer encoder consists of two components: the multi-head attention and the multi-layer perceptron [18]. Residual connections and layer normalization are used in each component for faster and more robust training. Here's an equation for the TTE component:

$$h_l^t = LN(MHA(z_{l-1}^t) + z_{l-1}^t) \quad l = 1, 2, …, L \ [7]$$

$$z_l^t = LN(MLP(h_l^t) + h_l^t) \quad l = 1, 2, …, L \ [8]$$

Spatial transformer encoder: The interdependence of distinct channels in the ECG signal allows for calculating functional connectivity [19]. The signal's channels represent the electrode locations on the scalp. Our goal in developing STE was to mimic TTE's representation of cross-channel spatial information through the attention mechanism. To guarantee the retention of spatial information, we applied the spatial domain's position encoding to the input, and STE to the output:

$$z_0^s = tran(z_L^t) + E_{pos} \qquad [8]$$

Where, the transposition operation is represented by $tran()$ and $E_{pos} \in \mathbb{R}^{C*T}$ indicates the position encoding. The position encoding is achieved using a trigonometric function applied at fixed positions. The symbol z_0^s represents the representation where spatial position information is added. By applying a methodology similar to that of TTE, we can acquire spatial information on the various ECG channels in STE. The process's equation is as follows:

$$h_l^s = LN(MHA(z_{l-1}^s) + z_{l-1}^s) \quad l = 1,2,\dots,L \ [9]$$

$$z_l^s = LN(MLP(h_l^s) + h_l^s) \quad l = 1,2,\dots,L \ [10]$$

Classification layer: The TTE and STE transformer encoder layers improve representation accuracy by integrating time-domain and spatial-domain information. At each TTE sample location, the network learns about the time-domain properties of the ECG data. In the STE, the network learns about the spatial relationships between channels. Finally, a cross-entropy loss function is utilized to optimize a basic FCL, which integrates global information for cardio-health status classification. This layer generates the final categorization output.

$$L = -\frac{1}{N}\sum_{n=1}^{N}\sum_{c=1}^{C} y_n^c \log(\hat{y}_n^c) \qquad [11]$$

Where, N represents the batch size, while C represents the number of categories. The predicted probability of the associated category is given by $\hat{y}_n^c$, where y_n^c represents the actual one-hot label.

Hardware Design

The hardware design includes two main parts: hardware connection and Cloud integration.

Hardware connection: The design smart watch prototype architecture has three key components such as a microcontroller (NodeMCU), a sensor (AD8232) for ECG acquisition, and a display (OLED SSD1306) for displaying the classification result.

The NodeMCU, built on the low-cost ESP8266 System-on-Chip (SoC), offers an open-source environment for developing software and hardware [20]. Espressif Systems' ESP8266 is a product that includes a central processing unit (CPU), random access memory (RAM), wireless networking (WiFi), and a cutting-edge operating system and software development kit, making it ideal for Internet of Things (IoT) applications. The SSD1306 OLED display is a type of dot matrix graphic screen that employs organic light-emitting diode technology. This display is ideal for energy-efficient purposes due to its extremely low power consumption when compared to others. The device supports the I2C serial protocol and has a maximum resolution of 128 × 64 pixels. The AD8232 sensor is an inexpensive board that can measure the electrical activity of the heart [21]. This electrical data can be shown in an analog manner on an electrocardiogram or an equivalent chart. Among its many bio-potential measurement applications, the AD8232 stands out with an integrated signal conditioning circuit for ECG [22]. It is developed to recover, enhance, and filter signals under noisy conditions. The circuit also includes a buffer to set a DC level for the output offset, as well as a Right Leg Drive (RLD). The circuit can be powered by a 2 V battery with a voltage range of 3.5 V.

Cloud Integration: To collect and process the ECG data for predicting cardio-health status, the data and model

should be on the same platform. The Firebase cloud is used to gather the data and deploy the finalized DL model. Firebase is developed by Google for backend cloud computing applications. The Firebase is configured based on our requirements. If the DL model identifies CVD from the ECG data, a message notification is sent to the registered mobile number. The configuration is done on the Firebase for notification messages is shown in Figure 4.
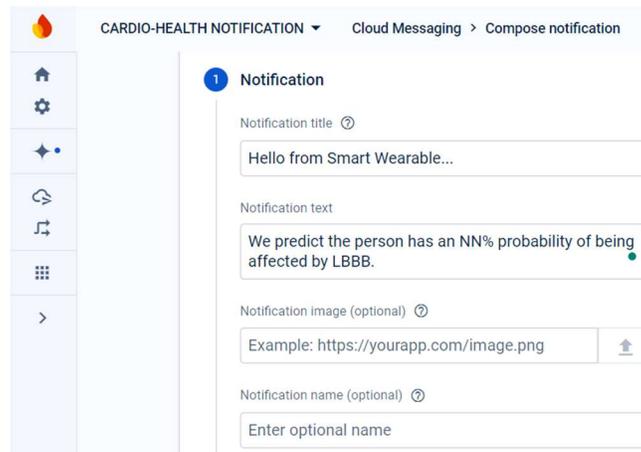

Fig. 4. Firebase configuration for message notification

Proposed System

The research focuses on designing a continuous and accurate cardio-health monitoring system. To achieve this, we integrate two trending technologies: IoT and DL models. ECG physio-parameters and cardio-health status are highly correlated. For continuous monitoring, the wearable watch is designed with IoT facilities, while for health status prediction, the DL model is employed. The outcomes of DL and the designed hardware are discussed in this section.

DL Model for Cardio-health Status Prediction

The cardio-health status is predicted using ECG data. For accurate prediction, the DL model is proposed by integrating spatial and temporal transformer encoders. The outcomes of the proposed model need validation, so we adopt a conventional CNN model with the following architecture [23]: 2 convolutional layers with ReLU activation, followed by 2 pooling layers, and finally a fully connected layer (FCL) with 5 neurons and softmax activation function.

Both models use similar hyperparameters such as sample counts, batches, epochs, and loss functions. The CNN model is evaluated first. The accuracy and loss metrics are calculated to evaluate the model in the training and validation phases. The obtained values for each epoch are plotted, and the performance plots are presented in Figures 5 and 6. The maximum accuracy and minimum loss attained by the CNN are 0.94 and 0.18, respectively.
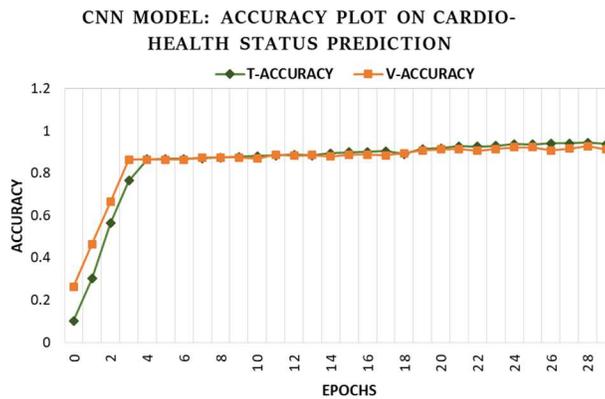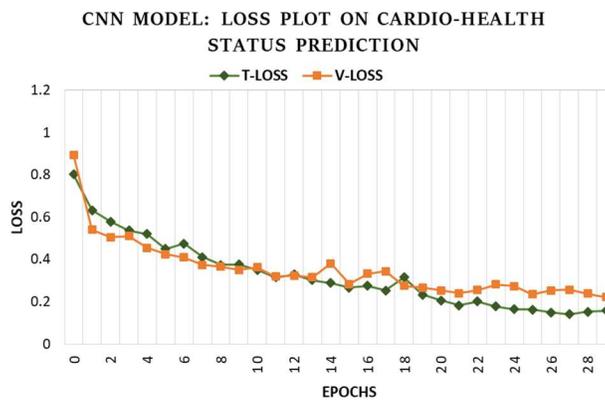
Fig. 5. CNN Model: Accuracy plot

Fig. 6. CNN Model: Loss plot

Next, the proposed model is evaluated. The performance plots of the proposed model using accuracy and loss values are shown in Figures 7 and 8. The maximum accuracy and minimum loss attained by the proposed model are 0.98 and 0.04, respectively. In the training stage, the proposed model performs better.
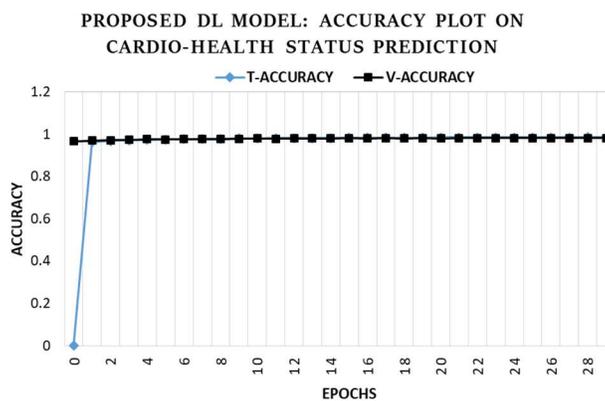

Fig. 7. Proposed DL Model: Accuracy plot

Next, both models are tested using 500 samples under each category. Evaluation factors such as accuracy, specificity, sensitivity, precision, and F1 score are used to analyze the quality of the models [24]. These metrics

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are calculated using true positive, true negative, false positive, and false negative. Table 2 provides the outcomes of the CNN model on cardio-health status prediction, detailing TP, TN, FP, and FN counts for each category, along with metrics [25]. The CNN achieves an accuracy of 92.84%. The average specificity, sensitivity, precision, and F1 values of the CNN model are 92.87%, 92.84%, 92.76%, and 92.79%, respectively.
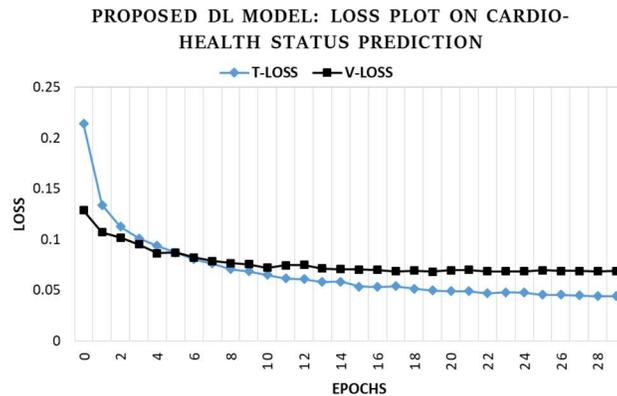

Fig. 8. Proposed DL Model: Loss plot

Table 2. CNN model outcome on cardio-health status prediction

Cardio-Health Status	TP	TN	FP	FN	ACCURACY	SPECIFICITY	SENSITIVITY	PRECISION	F1
NOR	233	238	13	16		94.82%	93.57%	94.72%	94.14%
RBBB	235	228	14	23	92.84%	94.21%	91.09%	94.38%	92.7%
LBBB	231	235	19	15		92.52%	93.9%	92.4%	93.15%
APC	228	231	23	18		90.94%	92.68%	90.84%	91.75%
PVC	225	237	21	17		91.86%	92.98%	91.46%	92.21%
Average						92.87%	92.84%	92.76%	92.79%

The outcomes of the proposed model in the test phase are given in Table 3. The proposed model achieves an accuracy of 98.04%. The metrics such as specificity, sensitivity, precision, and F1 attained by the proposed model are 98.39%, 97.69%, 98.39%, and 98.04%, respectively. Comparing the values in Tables 1 and 2, it is evident that the proposed model performs well in cardio-health status prediction and is eligible for deployment in real-time applications.

Table 3. Proposed DL model outcome on cardio-health status prediction

Cardio-Health Status	TP	TN	FP	FN	ACCURACY	SPECIFICITY	SENSITIVITY	PRECISION	F1
NOR	248	246	2	4		99.19%	98.41%	99.2%	98.8%
RBBB	245	246	4	5	98.04%	98.4%	98%	98.39%	98.2%
LBBB	246	249	2	3		99.2%	98.8%	99.19%	98.99%
APC	244	242	5	9		97.98%	96.44%	97.99%	97.21%
PVC	243	242	7	8		97.19%	96.81%	97.2%	97.01%
Average						98.39%	97.69%	98.39%	98.04%

For continuous monitoring, processing time is also important. Figure 9 presents the accuracy and time plot for various data counts. In the figure, accuracy is presented in % and time in milliseconds. The proposed model takes only 75 milliseconds to process a single sample. Not only does the proposed model meet accuracy requirements, but it also satisfies time constraints.
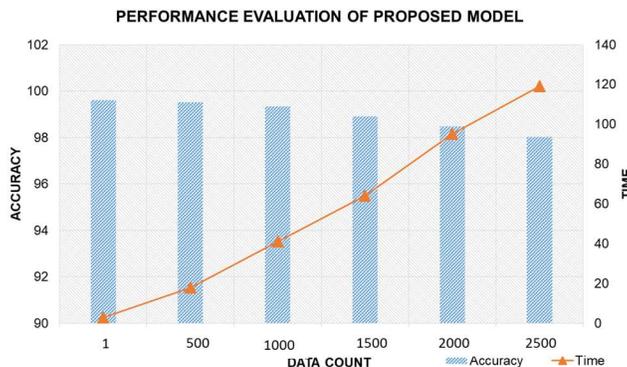

Fig. 9. Proposed DL Model: Evaluation of accuracy and execution time

The proposed model is deployed in the cloud. The designed watch collects ECG data and sends it to the cloud. The DL model in the cloud analyzes the data and predicts the cardio-health status. If the outcome is normal, no action is taken. In cases where the outcome falls under categories like LBBB, RBBB, APC, and PVC, the cloud-based system sends information to the microcontroller fixed in the watch and notifies the registered mobile number. The microcontroller collects the data and displays it on OLED. Figure 10 illustrates the notification sent by the cloud to the registered user.
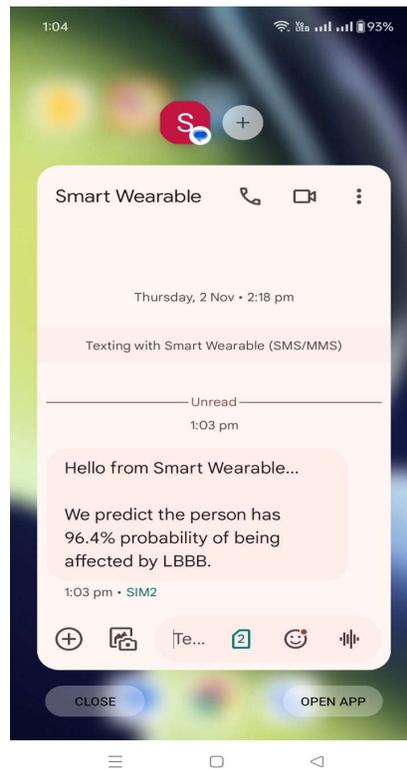
Fig. 10. Alert message on CVD prediction

Conclusion

Recent advancements in cloud computing, wireless communications, and DL technologies, along with widespread access to mobile phones and the proliferation of multimodal data and biosensor devices, have paved a promising path for wearable devices. This research uses advanced technology to design a smart wearable watch for cardio-health monitoring systems. The proposed system sends notifications to registered users for predicting any cardio-disease. The watch is designed with an ECG sensor and OLED display. The sensor collects data and sends it to the cloud. In the cloud, the data are processed by a DL model to identify the cardio-health status. The DL model is based on transformer and encoder architecture for identifying heart diseases from ECG data. The performance of the model is evaluated against a CNN model. The CNN model achieves an accuracy of 92.84%, while our proposed model achieves 98.04%. The designed system accurately detects cardio-health status, and if any abnormalities are found, the cloud sends a notification to the registered mobile device. Additionally, the data is sent to the microcontroller in the watch, which displays the warning on the OLED screen. The proposed system addresses an immediate requirement in this fast-moving world, helping individuals to monitor their health effectively.

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