Diagnosing People at Risk of Heart Diseases Using the Arduino Platform Under the IoT Platform

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Abstract*—Using the Arduino platform under the Internet of Things (IoT) platform to diagnose individuals at risk of heart diseases. An enormous volume of data focus has been placed on delivering high-quality healthcare in response to the increasing prevalence of life-threatening health conditions among patients. Several factors contribute to the health conditions of individuals, and certain diseases can be severe and even fatal. Both in industrialised and developing nations, cardiovascular illnesses have surpassed all others as the leading causes in the last few decades. Significant decreases in mortality may be achieved by detecting cardiac problems early and keeping medical experts closely monitored. Unfortunately, it is not currently possible to accurately detect heart diseases in all cases and provide round-the-clock consultation with medical experts. This is due to the need for additional knowledge, time, and expertise. Aiming to identify possible heart illness using Deep Learning (DL) methods, this research proposes a concept for an IoT-based system that could foresee the occurrence of heart disease. This paper introduces a pre-processing technique, Transfer by Subspace Similarity (TBSS), aimed at enhancing the accuracy of electrocardiogram (ECG) signal classification. This proposed IoT implementation includes using the Arduino IoT operating system to store and evaluate data gathered by the Pulse Sensor. The raw data collected includes interference that decreases the precision of the classification. A novel pre-processing technique is used to remove distorted ECG signals. To find out how well the classifier worked, this study used the Hybrid Model (CNN-LSTM) classifier algorithms. These algorithms detect normal and abnormal heartbeat rates based on temporal and spatial features. A Deep Learning (DL) model that uses Talos for hyper-parameter optimisation has been recommended. This approach dramatically improves the accuracy of heart disease predictions. The experimental findings clearly show that Machine Learning (ML) methods for classification perform much better after pre-processing. Using the widely recognised MIT-BIH-AR database, we assess the planned outline in comparison to MCH ResNet. This system leverages a CNN-LSTM model, which was optimized using hyper-parameter tuning with Talos, achieving outstanding metrics. Specifically, it recorded an accuracy of 99.1%, a precision of 98.8%, a recall of 99.5%, an F1-score of 99.1%, and an AUC-ROC of 0.99.

Keywords*—Arduino platform; internet of things; heart disease diagnosis; high-quality healthcare; cardiovascular diseases; deep learning

I. Introduction

The healthcare industry has seen significant changes worldwide in the last decade due to digitization and digital transformation [1-2]. The progress of human evolution has been closely intertwined as a result of technological and scientific progress. The Internet of Things (IoT) is a significant driver of Information and Communications Technology (ICT) technological advancement, propelling numerous sectors towards automation and decentralised intelligence [3]. The IoT is constantly evolving and profoundly impacts every aspect of our lives, almost like a living being. Scientific and technical advancements have been driven by healthcare-related activities since the emergence of technology services that enabled the remote collection, analysis, and control of patients' conditions. IoT is playing a significant role in driving innovations in healthcare and ultimately transforming the industry. It does this by collecting the physiological data of patients using wireless sensor networks and wearable devices [4].

Although Machine Learning (ML) algorithms have been used in stratified healthcare research, there is an increasing recognition of the importance of incorporating ML algorithms into healthcare diagnosis systems [5–7]. There is a plethora of medical data available for analysis using ML methods since the health sector has collected it over the last decade. This analysis can help identify patterns, create Smart Diagnosis Systems (SDS), and uncover valuable insights to address numerous challenges [8]. Amongst the numerous illnesses, cardiovascular diseases (CVD) stand out as the primary cause of death globally. However, in today's fast-paced society, many individuals tend to neglect regular medical check-ups unless they experience significant health problems. Similarly, many individuals neglect routine heart check-ups due to the time-consuming and inconvenient nature of traditional methods for obtaining these checkups. Not being aware of their current heart condition can lead to serious health issues and, in the most extreme cases, unexpected fatalities.

An SDS is essential to conveniently and efficiently monitor one's heart condition. In today's world, the IoT has become an essential asset to the healthcare sector. Its key features, including connectivity, sensing, reliability, linearity, and intelligence, have proven invaluable [9]. It is a method of revolutionising modern healthcare by offering personalised and proactive care, using devices that can sense and monitor important health indicators like pulse rate, blood pressure, and electrocardiogram (ECG) [10–12]. A collection of wearable sensor devices can collect physiological evidence as it happens. Once this data is processed, it can be transformed into health records that are valuable for diagnosing, treating, and recovering from CVD. Once more, ML is an application of Artificial Intelligence (AI) that can use past knowledge to make predictions about future events using labelled examples [13-16].

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This study adds a cardiac patient monitoring device that uses the IoT idea with many physiological data sensors and an Arduino microcontroller. Sensor networks employ the IoT to collect, process, and communicate data from one node to another. The IoT is a young and quickly evolving technology that enables many sensors and data collectors to sense, exchange, and interact over Internet Protocol (IP) networks, whether public, private, or otherwise. The sensors collect data at regular intervals, analyse it, and then use it to initiate the necessary action. An intelligent cloud-based network for investigation, arranging, and decision-making is also available to them.

The first step in developing a CVD model integrated with IoT sensors is to obtain data from patients who are wearing the IoT sensor. The data has to be collected for extended periods for better comprehension and recognition of respiration rate, heart rate, and other critical indicators. Thus, the data can reveal all the irregularities that are noticed in a patient's heartbeat, which can be the reason for some diseases. Now, the Deep Learning (DL) algorithm can be applied to simulate the model that will identify the difference between normal and abnormal rhythms in both waves and correctly detect disorders from the data. Again, the developed model can be applied in real situations, and in this case, it can be updated in case errors appear. When the model is refined to a satisfactory level of accuracy, it may be sent out to the IoT sensors to monitor the heart rate of the individual and notify the healthcare team in the event that any heart condition is identified.

The primary objectives of this work:

1) This study aims to create a wearable hardware device that can effectively extract vital heart condition measurement signs from the user's body in real time, including ECG data.

2) Data pre-processing methods apply to the data collected from IoT sensors related to heart disease risk prediction—transfer by Subspace Similarity (TBSS) aimed to improve the categorization accuracy of ECG signals.

3) The strategy that has been recommended is that it is possible to estimate the probability that a patient has CVD using a Hybrid Model (CNN-LSTM) classifier, which incorporates an attention mechanism.

4) A DL model has been proposed that utilises Talos for hyperparameter optimisation. This approach dramatically improves the accuracy of Heart Disease Predictions (HDP).

The rest of the article is structured into four major sections. Section I is an introduction, Section II is a literature review, Section III is a technique section, Section IV is an analysis of the findings, and Section V is a conclusion with future scope.

II. Literature Survey

Several studies have been tested on HDP using IoT and ML techniques. As an illustration, research by [17-20] examined four heart disease datasets from UCI to predict CVD using ML algorithms. Their findings indicated that Logistic Regression had the highest accuracy rate at 86.5%.

In a study by [21-23], they implemented hybrid ML techniques to HDP. A different study presented a UCI dataset and found that Random Forest (RF) had the most accuracy, 89%, for HDP. Meanwhile, [24-26] demonstrated that a Multilayer Perceptron Neural Network (MPNN) with backpropagation achieved an accuracy of approximately 100% in HDP using 40% of the UCI Cleaveland dataset as training data. [27-29] conducted a meta-analysis to assess and explain the overall predictive ability of ML algorithms in CVD.

Further, [30-35] proposed ontology-based recommendations to provide patients with personalized suggestions containing their past clinical records and real-time data. Once again, remarkable research has portrayed the potential HDP from ECG-based data only.

For example, [36-40] presented an HDP system that capitalizes on big data and the AD8232 ECG sensor for collecting the data. This system effectively eliminates noise from raw ECG signals and crucial Feature Extraction (FE) to aid in diagnosis, providing valuable support to patients and medical experts.

In a similar study, [41-45] demonstrated the detection of CVD using a Support Vector Machine (SVM) and Neural Network. They analysed FE from processed ECG signals. In addition, [46-49] proposed DL methods in conjunction with the Internet of Medical Things (IoMT) to create a screening system for CVD. Human skin temperature and blood circulation are the two variables that this method uses. Nonetheless, a licenced examiner or competent doctor had to review the results of the medical tests as part of the process.

In their study, [50-55] discussed various ML techniques that focused on real-time and remote health monitoring on IoT setup, specifically concerning cloud computing. Input was obtained from the public data set HC, which was stored on the cloud. The system provided recommendations based on the available data stored in the cloud, including historical and empirical data. In their study, [56-60] introduced a multi-sensory system that used an intelligent IoT to collect data from Wireless Body Area Sensors (WBAS). This method was designed to alert users to the possibility of cardiac arrest in its early stages. Prior research attempted to develop an undetectable, intelligent IoT system that could take readings of vital signs from a user's phone without drawing attention to itself.

In their study, [61-65] proposed a method that used ML techniques to identify essential features. This meant that there was better precision in the HDP. The RF and Linear methods have been combined [66-70] to form a hybrid RF with a linear model. In the research work of [71-73], the authors proposed a multi-sensory system based on IoT technology that collects readings of heart rates and body temperatures. Data from ECG and the body temperature were acquired on a smartphone in real-life conditions with an intelligent skin attached using a Bluetooth chip for low-power connectivity. Sophisticated signal processing and a collection of sensor data have been processed using ML methods to make an accurate HDP of the probability of an imminent heart attack.

In the paper, [74-78] developed a brilliant Health Care Kit based on IoT technology. They proposed collecting multiple data parameters from the patient and forwarding timely notifications regarding patient health to the doctor for their knowledge and awareness. However, their system is not capable of determining any diabetic condition of the patients; thus, it cannot detect any heart attack problem of the patient caused by diabetes or obesity.

In this paper, [79-80] proposed a system where Arduino Uno and an Infrared (IR)-based sensor have been used to monitor the heart rate. The device shall track all the physical parameters, such as heartbeats, and provide a physician with the collected data through the Short Message Service (SMS). However, IR sensors are not capable of providing precise heart rate measurements. In their study, [81-85] introduced a heart rate counter based on a Microcontroller that was designed to be affordable. Microcontrollers have been used for heart rate measurement with the help of an IR sensor. However, it should be noted that IR sensors may not provide precise heart rate values and lack versatility [86-90].

III. Methods and Materials

As CVDs account for a significant percentage of deaths across the globe, it is essential that they should be detected and monitored at an early stage. Most of the existing HDP systems lack accuracy, and they require continuous medical regulation. This project devised the solution for the above-stated problems by developing an IoT-based HDP system on a platform called Arduino. In the proposed system [91-95], a novel preprocessing method called TBSS-Transfer by Subspace Similarity is used to classify the ECG signal accurately [96-100].

A. Problem Definition

With a collection of raw ECG signals $X = \{x_1, x_2, \dots, x_n\}$ obtained using a Pulse Sensor on the Arduino platform, the objective is to precisely categorise these signals as either normal or abnormal heartbeat rhythms. There is the noise and interference problem, to start with, with the raw ECG signals. To a great extent, it may badly affect the accuracy of the classification performed. This is the problem formulation as follows:

Each instance is represented by an ECG signal, (x_i) , which consists of a series of time points, $x_i = \{x_{i1}, x_{i2}, \dots, x_{iT}\}$. Utilise the TBSS technique to effectively eliminate any noise and interference present in the raw ECG signals, resulting in a set of cleaned signals denoted as $X_{clean} = \{x'_1, x'_2, \dots, x'_n\}$. Mathematically, this preprocessing step can be represented as a function f_{TBSS}, EQU (1).

$$X_{clean} = f_{TBSS}(X) \tag{1}$$

Identify essential characteristics by extracting features $F_i = \{f_{i1}, f_{i2}, \dots, f_{im}\}$ from each processed ECG signal x'_i, where m is the total number of features. Then, utilize a hybrid CNN-LSTM classifier C to classify the FE into normal or abnormal heartbeat rhythms.

The function C assigns labels y_i to the feature set F_i, EQU (2).

$$y_i = C(F_i) \tag{2}$$

The labels for y_i are binary.

B. Proposed Methodology

The proposed methodology in this section for constructing IoT-based CVD prediction using the Arduino platform involves data collection, preprocessing done through Transfer by Subspace Similarity (TBSS), feature extraction, classification using the hybrid CNN-LSTM model with hyper-parameter optimization using Talos, and performance evaluation.

1) IoT model design: The IoT device for cardiac illness forecasting is built to function using a microcontroller and several sensors. The primary components used in this setup include the LM35 Temperature Sensor, AD8232 ECG Sensor, and Pulse Sensor, Arduino Uno. The multi-sensor, along with the portable IoT-based microcontroller suggested system of CVD prediction, gathers and processes the physiological data in this paper. The body temperature reading is given using the LM35 Temperature Sensor. It gives an analogue output proportional to temperature that ranges with ±0.5 $°C$ accuracy. The Pulse Sensor measures the user's heart rate by blood flow through the finger in order to deliver analogue signals through its output, which represents the heartbeat. AD8232 ECG Sensor ensures that the electrical activity of the heartbeat is taken so that an output ECG signal can be delivered. Since it provides high-quality signals, the operational amplifiers and filters are built for signal conditioning. With a USB connection, six analogue inputs, fourteen digital input/output pins, and an ATmega328P core, this microcontroller board is known as Arduino Uno. It communicates with sensors to collect data and then uploads it to the cloud. Such meticulous planning allows for comprehensive and precise surveillance of the HDP of cardiac illness. Fig. 1 shows the IoT Model design for HDP.

2) AD8232 ECG sensor: This sensor acquires the heart's electrical activities. With an output connection to an analogue input pin, which is A2 in Arduino Uno, this sensor gives the ECG signal, which forms the basis for diagnosing heart conditions. This sensor is critical since it provides details of the electrical activities that are going on in the heart and can, therefore, detect any abnormal heart activities. The processing unit of this system is the Arduino Uno microcontroller. Here, programming does all the data readings from all connected sensors; some initial preprocessing is done for noisy data. These processed bits of data are sent into a cloud-based IoT Platform. All the sensors inter-interface with the Arduino Uno through the analogue input pins of the board. For wireless communication, a Wi-Fi (or) Bluetooth module is used. The system uses a Wi-Fi module like ESP8266, for instance, or Bluetooth, like the HC-05. Using the Wi-Fi module, Arduino could send the data directly to a cloud server using the Message Queuing Telemetry Transport (MQTT) protocol. The protocol is. Light messaging protocol is super ideal for IoT applications. On the other hand, the Bluetooth module sends it to nearby devices, such as a Smartphone, that would forward this data to the cloud server.

The transmitted data is stored in a cloud-hosted database, commonly of the NoSQL type, such as MongoDB, in order to handle the unstructured nature of the sensor data. The cloud storage solution provides scalability and security to store large volumes of data that can be accessed anytime. The raw ECG data is cloud-prepped and cleaned for noise by using the technique of Transfer by Subspace Similarity or, basically, TBSS. From the cleaned-up data, FE accommodates the temporal and spatial features of the ECG signals.

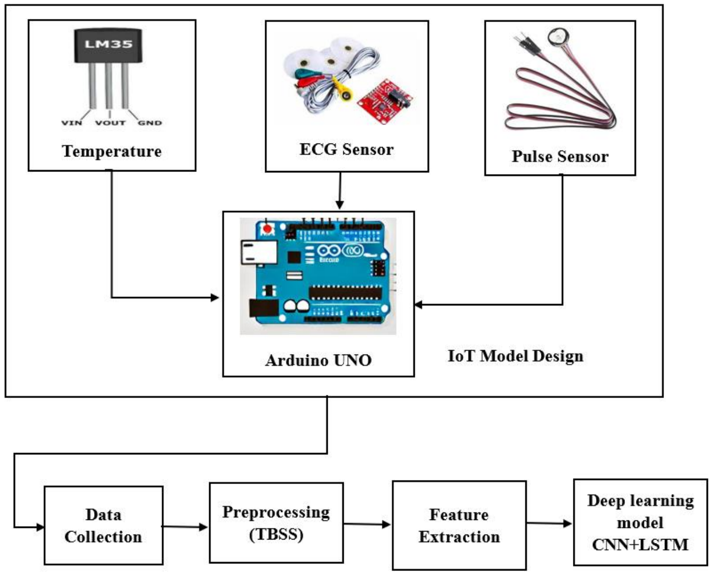


Fig. 1. The IoT model for CVD prediction.

C. Data Collection

The dataset of heart disease was developed from the UCI Machine Learning Repository. Out of the 75 sets of attributes in this data set, only 14 have been considered for prediction purposes. The dataset includes the records of 303 patients, encompassing various factors. There are different types of chest pain, including typical angina, non-anginal pain, atypical angina, or asymptomatic. Resting ECG results may include regular patterns, ST-T wave abnormalities, and indications of left ventricular hypertrophy according to Estes' criteria. Meanwhile, thalassemia is categorised into three types: usual, fixed defect, and reversible defect. This extensive dataset allows for a thorough analysis, enabling the system to accurately predict heart disease using a wide range of patient profiles.

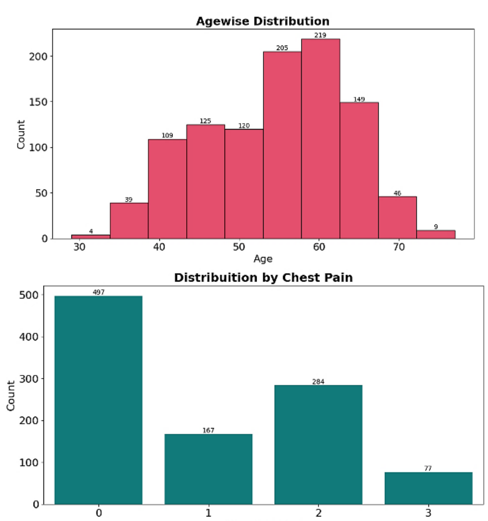


Fig. 2. (a) Data distribution per age (b) data distribution per chest pain type.

Fig. 2(b) illustrates the distribution of chest pain types among patients in the dataset. A total of 497 patients experience typical angina, which is characterised by its predictability and association with physical exertion or stress. There are an additional 284 patients who are experiencing non-anginal pain, which is not related to any heart problems. There are 167 patients who have been diagnosed with atypical angina, a condition that is characterised by its unpredictable nature and lack of association with physical exertion. Finally, there are 77 patients who do not experience chest pain despite potentially having underlying heart issues. This distribution is beneficial for accurately diagnosing heart conditions, training ML models, and efficiently planning healthcare resources.

1) Preprocessing of TBSS: For the HDP technology to be reliable and accurate, the data must be adequately extracted. In order to ensure that the ECG signals collected by the sensors we use are noise-free, researchers use an advanced technique called TBSS in the present study. This approach is essential for filtering unprocessed sensor data, which is overflowing with noise and distortion and may significantly affect our prediction algorithms' accuracy. By transforming the uncompressed signals into a refined subspace and minimising errors, the TBSS approach improves the level of accuracy of ECG signal classification.

The initial stage of the recommended method is collecting unprocessed ECG signals employing the AD8232 ECG Sensor that is connected to the Arduino Uno programming board. Interference from electricity and patient motion are two of the numerous forms of noise that can be detected in these signals. The application of digital filters makes it possible to deal with the starting point noise. The vital elements of the ECG signals can be separated from noise in the background and baseline variation through the use of these filters. Principal Component

Analysis (PCA) is an approach that represents the filtered signals in a lower-dimensional subspace. By filtering to eliminate extra noise, these methods reliably capture the vital features of the ECG signals. Researchers test the predicted signals to a set of ideal ECG signals within the domain in order to analyse data. Here, we compare the corrupted signals to the clean signals of reference in the simulated space to determine how comparable they are. Using this comparable metric system, researchers can determine precisely how comparable the good-quality signals are to the noisy ones. This can be represented formally as EQU (3).

$$S\left(X_{clean}, X_{noisy}\right) = \sum_{i=1}^{n}\left(\frac{X_{clean,i} \cdot X_{noisy,i}}{\|X_{clean,i}\|\|X_{noisy,i}\|}\right) \quad (3)$$

where X_{clean} are the reference clean signals, X_{noisy} are the noisy signals, and S is the similarity measure. In order to create unreliable signals that appear increasingly similar to the free signals from the signal's source, researchers use the calculated similarity to modify signals. This method improves the ECG signals by eliminating unwanted FP and noise in the background.

The result of the TBSS process is a set of cleaned ECG signals $X_{clean} == \{x'_1, x'_2, \dots, x'_n\}$ which are then ready for further FE and classification. The TBSS technique gives us the ability to enhance the ECG quality of the signal significantly. A precise human HDP algorithm requires precise FE and classification, which have been significantly improved by higher quality. By ensuring more clean data, the TBSS preliminary processing phase is essential to enhancing the overall accuracy and reliability of the HDP system.

Algorithm 1. Algorithm for TBSS

Input: Raw ECG signals X, Reference clean signals X_{clean}
Output: Cleaned ECG signals X'_{clean}
Step 1. 1: $X_{filtered} \leftarrow$ *ApplyNoiseFiltering(X)*
Step 2. 2: $X_{projected} \leftarrow$ *ApplySubspaceProjection*($X_{filtered}$)
Step 3. 3: $X_{reconstructed} \leftarrow$ []
Step 4. 4: *for each* x_{pi} *in* $X_{projected}$ *do*
Step 5. 5: $S \leftarrow$ *CalculateSimilarity*(X_{clean}, x_{pi})
Step 6. 6: $x_{ri} \leftarrow$ *AdjustSignal*(x_{pi}, S, X_{clean})
Step 7. 7: *Append* x_{ri} *to* $X_{reconstructed}$
Step 8. 8: *end for*
Step 9. 9: $X'_{clean} \leftarrow X_{reconstructed}$
Step 10. 10: *return* X'_{clean}
Function ApplyNoiseFiltering(X)
$X_{filtered} \leftarrow$ []
For Each x_i *in X, Do*
$x_{pi} \leftarrow$ *LowPassFilter*(x_i)
$x_{pi} \leftarrow$ *HighPassFilter*(x_{pi})
$x_{pi} \leftarrow$ *BandPassFilter*(x_{pi})
Append x_{pi} *to* $X_{filtered}$
End For
Return $X_{filtered}$
Function ApplySubspaceProjection($X_{filtered}$)
$X_{projected} \leftarrow$ *PCA*($X_{filtered}$)
Return $X_{projected}$
Function CalculateSimilarity(X_{clean}, x_{pi})
For Each X_{clean_j} *in* X_{clean}*Do*
S += (*DotProduct*(X_{clean_j}, x_{pi}) / (*Norm*(X_{clean_j}) * *Norm*(x_{pi})))
End For
Return S
Function AdjustSignal(x_{pi}, S, X_{clean})
$x_{ri} \leftarrow x_{pi}$ * S
For Each X_{clean_j} *in* X_{clean} *do*
x_{ri} += X_{clean_j} * (S / *length*(X_{clean}))
End For
Return x_{ri}

D. FE Using Convolutional Neural Network (CNN)

The key component of the preliminary processing queue, FE transforms filtered ECG signals into beneficial attributes for an algorithm that HDP`. To perform automated FE from the initially processed ECG signals, researchers use CNNs in the present investigation. CNNs are particularly effective in capturing local patterns in data, making them ideal for processing time-series signals like ECGs.

The cleaned ECG signals $X_{clean} == \{x'_1, x'_2, \dots, x'_n\}$ are segmented into fixed-length windows to standardize the input size for the CNN. A CNN model is constructed with multiple layers, each designed to extract different levels of features from the ECG signals. Fig. 3 shows the Planned CNN for FE.

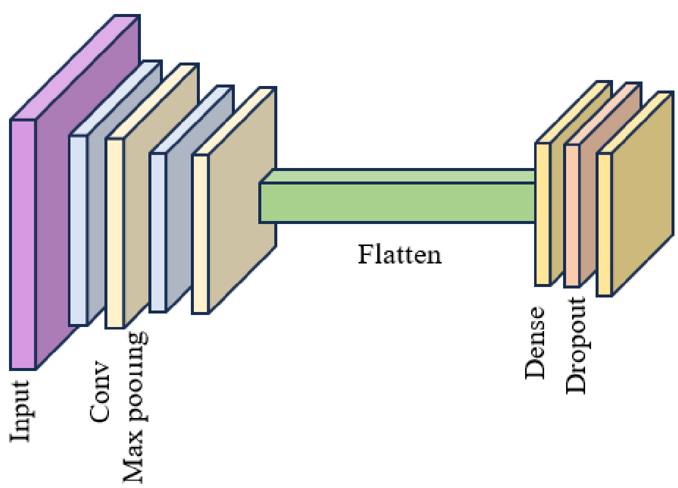


Fig. 3. The proposed CNN model for FE.

The input layer receives the segmented ECG signals. Each segment is represented as a matrix $S \in \mathbb{R}^{T \times C}$, where T is the length of the segment, and C is the number of channels or features.

The convolutional layers utilise multiple filters to analyse the input data and identify local patterns, such as peaks and valleys in the ECG signals. Filters $'w'$ slide over the input data and perform a convolution operation to generate a feature map. The first convolutional layer applies $'F_1'$ filters of size $k_1 \times C$ to the input segments. It produces feature maps M_1 by convolving the filters with the input EQU (4).

$$M_{\{1,j\}} = \sigma(W_{\{1,j\}} * S + b_{\{1,j\}}) \tag{4}$$

where $W_{\{1,j\}}$ and $b_{\{1,j\}}$ are the weights and biases of the j-th filter, $' * '$ denotes the convolution operation, and $'\sigma'$ is the activation function (ReLU). Subsequent convolutional layers apply $'F_l'$ filters of size $k_l \times 1$ to the feature maps from the previous layer, EQU (5).

$$M_{\{l,j\}} = \sigma(W_{\{l,j\}} * M_{\{l-1\}} + b_{\{l,j\}}) \tag{5}$$

In order to make the feature maps more concise while keeping all the relevant data, pooling layers are implemented, typically using max pooling or average pooling. Max pooling reduces each feature map by taking the maximum value within non-overlapping regions of size -*np*, represented as EQU (6)

$$P_{\{l,j\}} = Maxpool(M_{\{l,j\}}, p) \tag{6}$$

The resulting feature maps are flattened into a single vector. This vector represents the extracted features from the input ECG segment. Let $'f'$ denote the flattened feature vector. The flattened vector is fed into fully connected layers to combine the extracted features and enable further learning, EQU (7).

$$h_i = \sigma(W_i f + b_i) \tag{7}$$

where W_i and b_i are the weights and biases of the i-th fully connected layer. When it comes to classification, the output layer usually employs a sigmoid or SoftMax activation process. In this test case, the features are classified into normal or abnormal heartbeat rates. This is represented as EQU (8).

$$y = SoftMax\left(W_{\{out\}} h + b_{\{out\}}\right) \tag{8}$$

where $'y'$ is the output probability distribution over classes. The first Conv1D layer applies 32 filters of size 5 to the input data using a one-dimensional convolution operation with a Rectified Linear Unit (ReLU) activation function. To further reduce the data's density while keeping the most relevant features, the MaxPooling1D layer uses max pooling with a pool size of 2. A second Conv1D layer then applies 64 filters of size 3 and ReLU activation to the output of the previous layer. Following this, another MaxPooling1D layer with a pool size of 2 further down-samples the data. In order to make it suitable for entry to the thick layers, the Flatten layer converts the output through a one-dimensional array, a fully connected Dense layer with 128 units and a ReLU activation function is then applied to the flattened data.

To prevent overfitting, a dropout layer is used, applying dropout regularization with a rate of 0.5 and randomly setting 50% of the input units to zero during training. Lastly, the two classes' categorization probabilities are produced by the 2-unit Dense output layer using a SoftMax activation function.

E. *Proposed Model of Hybrid CNN-LSTM with Talos Hyper-Parameter Optimization*

The CNN+LSTM hybrid model brings together the rewards of CNN+LSTM. While LSTMs are suitable for learning dependencies over time, CNNs, on the other hand, tend to be utilized more effectively in spatial FE from the ECG signals. Additional improvement in performance is achieved by using Talos for hyper-parameter optimization. Fig. 4 shows the Architecture of the Hybrid CNN+LSTM with Talos Hyper-Parameter Optimization.

Spatial FE from the pre-processed ECG signals by passing them through convolutional layers. These patterns in the ECG data include QRS complexes, P and T-waves. The sequence of spatial features that are assumed by CNN is then fed into LSTM layers to capture temporal dependencies. By doing so, the temporal patterns and trends in the ECG signals are learnt by the model for accurate HDP, which is very important. The output from the LSTM layers is fed into fully connected layers to combine the features and produce the final heart rate prediction.

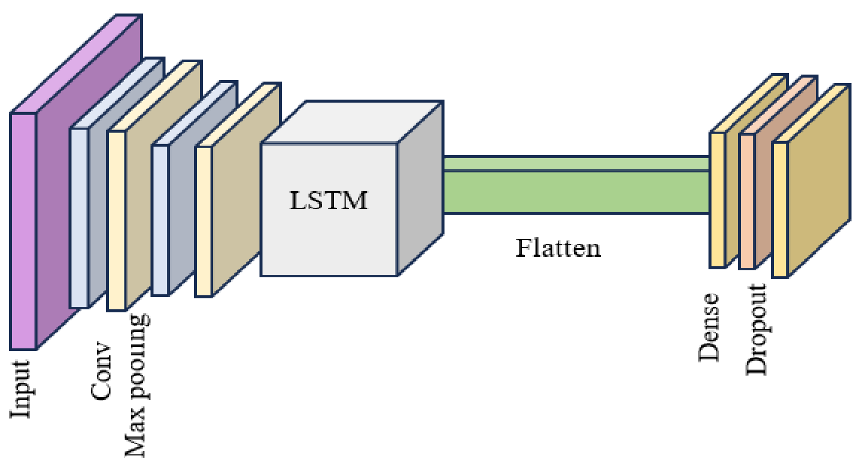


Fig. 4. Architecture of hybrid CNN+LSTM model with talos hyper-parameter optimization.

For a sequence of CNN feature vectors $\{x_t\}$ where t is the time step, EQU (9) to EQI (14).

LSTM Cell Computations,

$$fg_t = \sigma(W_{fg} \cdot [h_{t-1}, x_t] + b_{fg}) \quad (9)$$

$$it_t = \sigma(W_{it} \cdot [h_{t-1}, x_t] + b_{it}) \quad (10)$$

$$\widetilde{Cg}_t = \sigma(W_{cg} \cdot [h_{t-1}, x_t] + b_{cg}) \quad (11)$$

$$Cg_t = fg_t \odot Cg_{t-1} + \widetilde{Cg}_t \quad (12)$$

$$ot_t = \sigma(W_{ot} \cdot [h_{t-1}, x_t] + b_{ot}) \quad (13)$$

$$h_t = ot_t \odot tanh(Cg_t) \quad (14)$$

where 'σ' is the sigmoid function, $tanh$ is the hyperbolic tangent function, W and b are weights and biases, and $\odot$ denotes element-wise multiplication.

For the LSTM output h_t at the final time step T, EQU (15).

$$y = W_y \cdot h_T + b_y \quad (15)$$

where W_y and b_y are the weights and biases of the fully connected layer. The hybrid CNN+LSTM starts with an input layer that determines the form of the information. To start with, there is the first Conv1D layer, which uses 1-D convolution operation with ReLU activation function by applying 32 filters of size 5 to the input data then followed by a MaxPooling1D layer having pool size two, thus reducing data dimensionality and maintaining significant features. The next step is another Conv1D layer holding 64 filters of size 3 together with the activation function of ReLu for extracting more spatial features. Additionally, this includes another MaxPooling1D layer using pool size 2 to down-sample further the data. Secondly, the model also comes with a 100-unit-layered LSTM, which then processes the sequence of features derived from CNN layers by capturing the temporal dependencies in the data.

The resulting output from this layer is then 1-D-arrayed into a flattened array using a flattened layer before being fed to dense layers. After that, there is a dense layer with 128 neurons and a ReLU activation function, which continues processing the extracted features. A dropout rate of 0.5 has been used in this model in order to avoid overfitting; it means that during training, half of all input units will be randomly set to '0' every time. Finally, the model finishes with a SoftMax activation function in its output Dense Layer, which contains two units representing classification probabilities for normal or abnormal class options. Through the Talos software package, various hyperparameters such as filter number, learning rates, kernel sizes, and number of LSTM units, dropouts' rates, batch_size are optimized, increasing the performance and robustness of this model.

Algorithm 2. Algorithm for Hyper Parameter Optimization using Talos

Input: Pre-processed ECG data X, labels y, parameter grid P
Output: Optimized CNN-LSTM with best hyper-parameter configuration
Step 1: Data Preparation
1.1 Split data into training and testing sets
$(X_{train}, X_{test}, y_{train}, y_{test})$ = *train_test_split (X, y, $test_{size}$ =0.2, $random_{state}$=42)*
1.2 Standardize the data using StandardScaler
X_{train} = *scaler.fit_transform (X_{train}.reshape(-1, X_{train}.shape[-1])). reshape(X_{train}.shape)*
X_{test} = *scaler. Transform (X_{test} .reshape(-1, X_{test} .shape[-1])). reshape(X_{test}.shape)*
1.3 Convert labels to categorical format
y_{train} = *to_categorical (y_{train}, num_classes=2)*
y_{test} = *to_categorical (y_{test}, num_classes=2)*
Step 2: Model Creation Function
2.1 Define create_model function to build and compile the CNN-LSTM using hyper-parameters from P
Step 3: Define Parameter Grid
3.1 Specify the range of hyper-parameters in P
Step 4: Perform Hyper-Parameter Optimization
4.1 Use the Talos Scan function to train models with different hyper-parameter combinations
t=talos.Scan(x=X_{train},y=y_{train}, params=P, model=create_model, experiment_name='hybrid_cnn_lstm', x_{val} =X_{test}, y_{val}=y_{test})
Step 5: Analyze Results
5.1 Analyze results using the Talos Analyze function to identify the best hyper-parameter
Configuration
a = Talos.Analyze(t)
5.2 Print or store analyzed data print(a.data)
Step 6: Deploy Best Model
6.1 Retrieve and save the best model configuration using the Talos Deploy function
$best_{model}$ = *Talos.Deploy(t, 'best_model')*
End Algorithm

IV. Result Analysis

A. About Simulation Data and Tool

This section analyses the performance of the optimized CNN+LSTM after hyper-parameter optimization using Talos. This study evaluates the model using numerous metrics, compares its performance with baseline models, and gains insights from the hyperparameter tuning process. These measures are used to measure how well the model works. The term "accuracy" refers to the number of correctly anticipated events in a fraction of all cases, EQU (16).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (16)$$

where TP is true positive, TN is true negative, FP is false positive, and FN is false negative. Precision, EQU (17), is the proportion of accurate analyses to the total number of accurate predictions.

$$\text{Precision (Pre)} = \frac{TrPt}{TrPt + FaPt} \quad (17)$$

The sensitivity or recall of a model of prediction is expressed as the percentage of accurate predictions compared with the overall number of positive cases, represented as EQU (18).

$$\text{Recall(Rec)} = \frac{TrPt}{TrPt + FaNt} \quad (18)$$

EQU (19) demonstrates that the F1-score, an unbiased measurement, provides the harmonic mean of recall and accuracy.

$$\mathrm{F1-score} = 2 \times \frac{\mathrm{Pre \cdot Rec}}{\mathrm{Pre + Rec}} \tag{19}$$

Considering the test set, the improved CNN+LSTM's metrics for performance are displayed in Table I. These parameters entirely assess the ability of the model to differentiate between normal and abnormal ECG signals.

TABLE I. PERFORMANCE ASSESSMENT OF THE CNN+LSTM HDP

Metric	Value
Accuracy	99.1%
Precision	98.8%
Recall	99.5%
F1-Score	99.1%
AUC-ROC	0.99

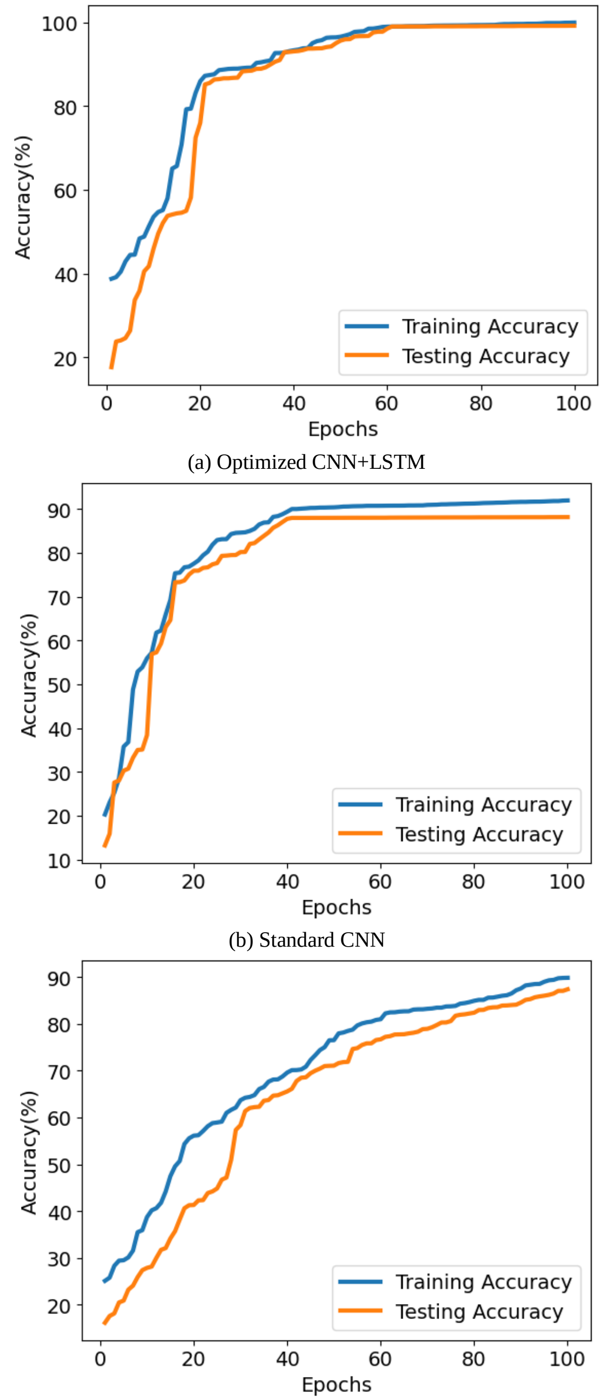
The optimised CNN+LSTM improves the standard model in ECG signal classification based on its success measures. The algorithm is highly successful, with statistics like an F1-score of 99.1%, a recall of 99.5%, a precision of 98.8%, and an area under the curve (AUC-ROC) of 0.99. The accuracy of the method for HDP is demonstrated by the above findings. In Table II, the developers observe how the improved CNN+LSTM fares in comparison to two baseline models, one of which uses CNN and the other LSTM. The comparison below indicates that the CNN+LSTM's hybrid model and hyper-parameter optimisation significantly boosted performance.

TABLE II. PERFORMANCE COMPARISON OF THE PROPOSED OPTIMISED CNN+LSTM WITH THE BASELINE MODEL

Metric	Optimized CNN+LSTM	Baseline CNN	Baseline LSTM
Accuracy	99.1%	88.1%	87.4%
Precision	98.8%	86.5%	85.8%
Recall	99.5%	89.0%	88.5%
F1-Score	99.1%	87.7%	87.1%
AUC-ROC	0.99	0.91	0.90

Metrics for accuracy indicate that the CNN+LSTM with optimisations functions exceptionally well regarding ECG signal detection. The model exhibits high performance with 99.1% accuracy, 98.8% precision, 99.5% recall, 99.1% F1-score, and 0.99 AUC-ROC. The validity of the method for HDP has been demonstrated by the above findings. Incorporating CNN and LSTM layers and fine-tuning hyper-parameters provides significant improvements throughout all metrics when compared to the standard CNN and LSTM. With this fine-tuned approach, researchers have a robust and accurate method for HDD.

Fig. 5 provides outcomes demonstrating how the improved CNN+LSTM is superior to the standard models. Throughout the duration of the epochs, the improved CNN+LSTM exhibits significant enhancements to reliability rates. Beginning at approximately 17.64%, the model achieves a maximum accuracy of 99.19%, showcasing a strong learning process and impressive final performance. On the other hand, the Standard CNN exhibits a consistent rise before reaching a plateau of approximately 88%. It starts at 13.19% but falls short of the impressive accuracy levels achieved by the optimised model.



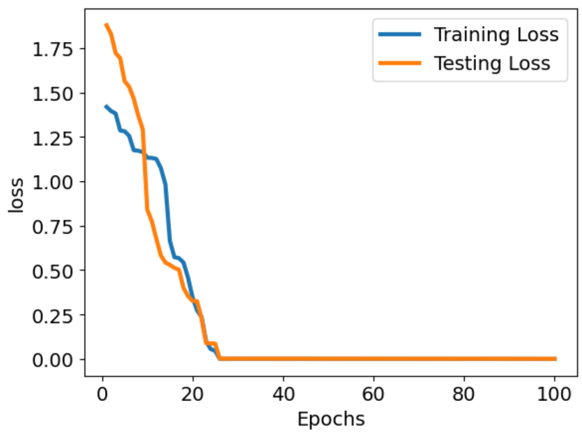
(a) Optimized CNN+LSTM

(b) Standard CNN

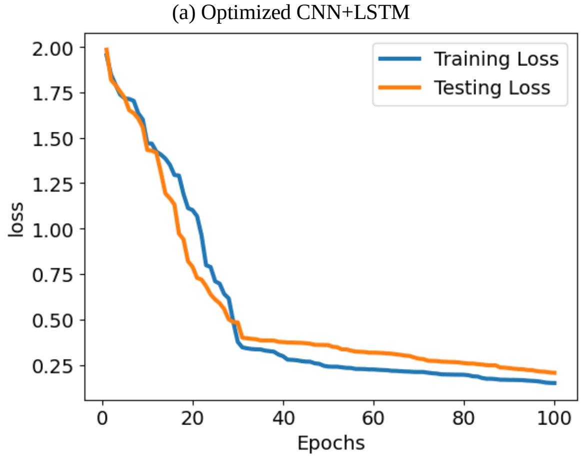
(c) Standard LSTM

Fig. 5. Accuracy of the proposed vs standard model (a) Optimized CNN+LSTM (b) Standard CNN (c) Standard LSTM.

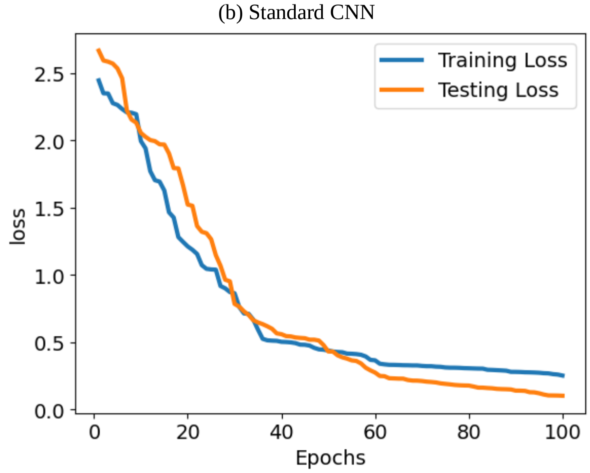
In comparison, the initial LSTM begins at 16.18% and gradually improves over time, reaching a peak of 87.39%. However, it does not match the performance achieved by the optimised CNN+LSTM. The optimised CNN+LSTM demonstrates excellent accuracy, suggesting its ability to capture spatial and temporal features of ECG signals effectively. Hyper-parameter optimisation is vital for achieving high performance, as demonstrated by the significant improvements over the baseline models. This comparison clearly highlights the superiority of the optimised CNN+LSTM for ECG signal classification, confirming the gain of integrating CNN and LSTM layers and fine-tuning their hyper-parameters to improve model performance.



(a) Optimized CNN+LSTM



(b) Standard CNN



(c) Standard LSTM

Fig. 6. Loss of the proposed vs Standard model (a) Optimized CNN+LSTM (b) Standard CNN (c) Standard LSTM.

The performance metrics shown in Fig. 6 determine the higher effectiveness of the optimised CNN+LSTM in minimising loss. The CNN+LSTM shows a remarkable and consistent reduction in loss in the training process. It starts at around 1.88 and reaches an impressively low value of 0.001 at the end of training. The significant decrease in performance suggests that the model is effectively acquiring knowledge and progressing towards convergence. By contrast, the baseline CNN exhibits a steady decline in loss, starting at 1.98 and reaching approximately 0.206 after the training phase. Although the CNN demonstrates improvement, it falls short of achieving the same low-loss values as the optimised CNN+LSTM.

The standard LSTM continues a similar pattern, with a comparatively sizeable first loss of 2.67 that reduces to about 0.102 as training progresses. The LSTM model's efficiency is poor despite this significant loss reduction. With its exceptional performance, the improved CNN-LSTM reduces loss dramatically while maintaining the temporal and spatial features of ECG signals. The value of optimising hyperparameter settings is demonstrated by a significant decrease in loss when compared to the standard model. Its accuracy has been significantly boosted owing to this refining analysis, and it is currently highly successful for ECG signal classification.

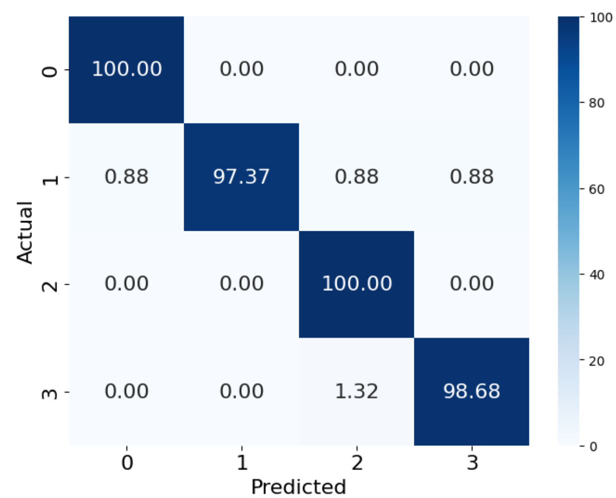


Fig. 7. Confusion Matrix (CM) of the proposed model on the optimized CNN+LSTM.

Fig. 7 indicates the CM for the recommended model, using the optimized CNN-LSTM, and highlights its classification performance across four classes: "Typical Angina" (0), "Atypical Angina" (1), "Non-Anginal Pain" (2), and "Asymptomatic" (3). The model achieved perfect classification for "Typical Angina" (0) and "Non-Anginal Pain" (2), accurately identifying 100% of examples in these classes. For "Atypical Angina" (1), the model adequately classified 97.37% of examples, with minor misclassifications: 0.88% into "Typical Angina" (0), "Non-Anginal Pain" (2), and "Asymptomatic" (3). The "Asymptomatic" (3) class had a precise classification rate of 98.68%, with 1.32% of examples misclassified as "Non-Anginal Pain" (2). Overall, the optimized CNN+LSTM model proves high accuracy, mainly excelling in the "Typical Angina" (0) and "Non-Anginal Pain" (2) categories. The trivial misclassifications in the "Atypical Angina" (1) and "Asymptomatic" (3) classes are nominal, signifying that the model effectively distinguishes between different types of chest pain. This analysis highlights the reliability and precision of the projected model, highlighting its potential for accurate HDP with only slight areas requiring further improvement.

V. Conclusion and Future Work

The adoption of an Internet of Things (IoT)-based Heart Disease Prediction (HDP) system that uses Deep Learning (DL) methods and the platform developed by Arduino to sort electrocardiogram (ECG) signals into four classes—"Typical Angina" "Atypical Angina," "Non-Anginal Pain," and "Asymptomatic"—has been demonstrated. Applying hyper-parameter optimisation with Talos, also known as this framework, improved a CNN-LSTM, which generated excellent metrics. It obtained preciseness of 98.8%, recall of 99.5%, F1-score of 99.1%, and AUC-ROC of 0.99, in specific. Accuracy was 99.1%. The results show the accuracy with which the system can distinguish between numerous sorts of coronary artery disease. The study introduced an innovative preliminary processing approach termed Transfer by Subspace Similarity (TBSS). TBSS effectively eliminated errors from ECG signals, which significantly improved the accuracy of classification. The higher accuracy of the Machine Learning (ML) algorithms was backed by thorough evaluation with the renowned MIT-BIH-AR database, which emphasised the success of the hybrid CNN-LSTM. The proposed approach possesses the capacity to predict the risk of heart disease accurately, and this research emphasises the model's potential, which renders it a valuable tool for medical investigations.

Implementing real-time deployments, researching more complex layouts, integrating new feature engineering methods, and enhancing data heterogeneity through augmentation will be the key objectives of future work. Enhancing the model's accessibility and performing significant research investigations to verify its effectiveness in real-life scenarios are also important. Further modifications to the described model, enhancing its accuracy, reliability, and application across different types of healthcare, may be feasible following more research into these domains. In the future, this will lead to better patient health and enable the earlier HDP problems.

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