Deep Learning Model for Automated Heart Disease Diagnosis Using ECG Signal

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***Abstract*—The development of technology improves the early detection of disease and diagnosis in the field of medical. Most of the people suffer with heart disease depending on the age factor and is millions of death cases are recorded due to heart attacks. In this paper Heart Rate Variability (HRV) is measured for early detection of Cardio Vascular Disease (CVD). HRV analyse the heartbeats and evaluated the time intervals between the consecutive heart beats. The CPSC 2018 dataset is considered in this paper to evaluate the Electrocardiogram (ECG) signals. Initially the R-R intervals are evaluated. The key features of the HRV like spatial, frequency, Poincare are extracted. Further features are extracted using deep learning model Efficient-Net b0 (ENb0) and classified for identification of heart disease. A Transformer Encoder (TE) layer is added to ENb0 to improve the performance. The Receiver Operating Characteristic (ROC) curve and confusion matrix is achieved using the deep learning classification model. The parameters like accuracy, precision, recall and F1-Score are evaluated using the proposed deep learning model and compared with other techniques. The ENb0 model achieves better efficiency in parameters evaluated and is effective in early detection of CVD and helps to support the research in the field of medical.**

***Keywords*—cardiovascular disease, Electrocardiogram (ECG) signals, R-peak detection, Heart Rate Variability (HRV) analysis, Efficient-Net b0**

I. INTRODUCTION

One of the physiological systems of the human body, the cardiovascular system is distinguished by the intricate interactions between several organs and tissues, such as the heart and blood vessels [1]. A World Health Organisation (WHO) study states that Cardio Vascular Disease (CVD) is the world's biggest cause of mortality [2]. It is estimated that CVDs claim the lives of around 17 million individuals each year. Furthermore, middle-income, and low-income nations account for 75% of all CVD mortality [3]. By 2030, it is anticipated that there would be 23 million fatalities from CVD. In addition, the expense of treating CVD, including the cost of diagnosis and medication, is quite high. An estimated 3.8 trillion dollars will be spent on treatment in low-income and middle-income nations between 2011 and 2025 [4]. One of the leading causes of mortality for people is heart disease. The WHO estimates that heart disease accounts for around 18 million deaths globally, or one-third of all fatalities [5]. The risk of heart disease, which can show up as symptoms like obesity and high blood pressure, is increased by factors including alcohol and tobacco use, poor diets, and insufficient exercise [6]. Getting a proper diagnosis is essential to lowering the risk of death because these symptoms might mimic those of other illnesses. ECG uses non-invasive skin electrodes placed on the chest to record the bioelectric potential produced by the electrical activity of the hearts. As a result, the recorded data regarding cardiac status is represented in terms of amplitude and duration as waves called P-QRS-T (Fig. 1).

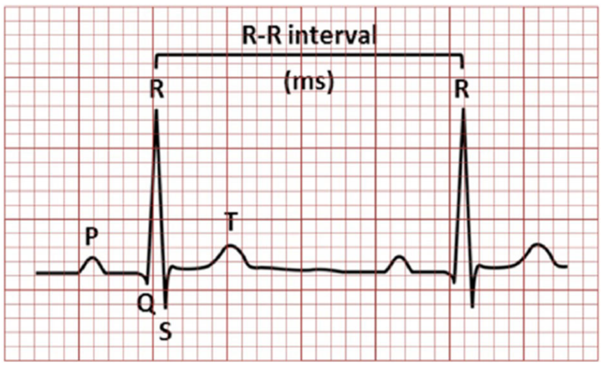

Fig. 1. ECG signal with P-QRS-T points.

Significant information on the state of the heart and the types of illnesses that affect it may be found in this waveform. In a clinical care context, Electrocardiogram (ECG)-based monitoring can be used to identify complicated conditions like arrhythmias or to interpret the heart's fundamental rhythm. Any irregularity in the heart's rhythm or variations in the P-QRS-T wave patterns are signs of cardiac arrhythmia, which may be detected by analysing the signal that was captured.

Cardiovascular illnesses are diagnosed and evaluated by doctors using electrocardiography procedures. Experts use this approach to visually evaluate the ECG signal.

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Because ECG signals are non-stationary, abnormalities might not always show up during recording. Therefore, it takes a lot of time to observe and analyse the recording to correctly diagnose a heart condition from the ECG signal. However, it is exhausting and time-consuming to examine an ECG for an extended period since it requires a lot of data. Furthermore, there is a very significant chance of missing data because of the volume of data employed in the research. Therefore, to help physicians easily and correctly identify cardiac arrhythmias, an automated system that can differentiate between aberrant and normal ECG signals is needed. One potential approach to the diagnosis and prognosis of cardiac disease is machine learning.

Using a variety of techniques, Das *et al*. [7] investigated the identification of cardiac illness. Extreme Gradient Boosting (XGBoost) machine, bagging, random forest, decision tree, K-nearest neighbour, and naive bayes were among the techniques used. The findings were compared using several assessment criteria, including as Area Under the Curve (AUC), F1-Score, accuracy, sensitivity, and precision. Although just 14 characteristics were used in their analysis, the Cleveland dataset, which has 76 features, was used by Gangadhar *et al*. [8]. Age, gender, chest pain, cholesterol, and resting blood pressure were all considered in their study. Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest, decision trees, and K-Nearest Neighbourhood (KNN) were among the techniques used in their investigation. The neural network approach produced the greatest accuracy result, 84.44%.

Sk *et al*. [9] used hybrid machine learning methods, particularly the Adaptive Boosting (AdaBoost) algorithm and Decision Trees. They made use of a subset of the Framingham Heart Study (FHS) dataset called the Framingham Heart Laboratory dataset. Long-term research, the Framingham study examines how environmental factors and genetics affect CVD in both men and women. There are 16 features in the dataset; 70% of the data is used for training, while the remaining percentage is used for testing. Random Forest, K-nearest neighbours, Decision Trees, Logistic Regression, Naïve Bayes, and Ensemble Learning were all used by Chopra *et al*. [10]. Additionally, Principal Component Analysis (PCA) was used to lower the data's dimensionality. The study showed that using PCA improves the detection rate by comparing results obtained with and without its application. Their study made use of the Cleveland dataset, which had 14 characteristics and 303 cases. To assess the accuracy, precision, and recall of each model, Jahed *et al*. [11] investigates several machine learning techniques and data splits. The algorithms forecast heart disease based on individual key markers. Machine learning is used in the identification of heart disease.

In this paper a deep learning concept is proposed for identification of heart disease using 12 lead ECG signal. Though study is still needed to fully utilise Heart Rate Variability (HRV) signals and enhance heart disease diagnosis across a wider range of cardiovascular disorders, the integration of HRV and ECG signals is being examined for heart disease detection. The utilization of deep learning concept on HRV in ECG signals more effectively improve heart disease identification. The model designed summarised as:

i. Developing a deep learning concept for detection of heart disease.
ii. CPSC 2018 dataset model is considered for evaluating the model.
iii. Heart rate variability features are extracted which is a key role for disease detection in early stage.
iv. The features of signals are extracted and classified using ENb0-Transform encoder model.

The paper presents about the introduction of the study and emergence of machine learning algorithms in Section I. Section II gives deep discussion on existing methods in detection of heart disease. Section III discuss about the proposed model in detection of heart disease followed by the experimental results in Section IV. The summary of the paper is given in Section V.

II. Related Work

Several researchers developed diverse, intelligent systems for the analysis of ECG signals for automatic detection of heart disease. The related work on various techniques is discussed in this section. The electrical activity of human hearts is represented by Electrocardiogram (ECG) data, which come in a variety of waveforms with a points P, QPS, and T. The diagnosis of heart is measured by the length, form, and spacing between each waveform's peaks.

The analysis of ECG signal is performed using the algorithms like Two-Event Related Moving-Averages (TERMA) and Fractional-Fourier-Transform (FrFT) [12]. The utilization of these two algorithms together identifies the peaks accurately near different locations. The peak identification is the initial stage in detection of peak. The disease detection needs to be performed. Wasimuddin *et al*. [13] utilized ECG signals and processed with concept of convolutional neural network classification. Myocardial Infraction (MI) is diagnosed in this work by identifying multiple arrhythmias with the help of 2D image of ECG wave.

The diagnosis of CVD is supported by machine learning algorithms. Smigiel *et al*. [14] proposed deep neural network for classification of ECG signals in detection of CVD. The PTB-XL database is used to evaluate the performance of proposed deep learning model. An initial convolutional network-based neural network design, a second SincNet-based neural network architecture, and a third convolutional network-based neural network architecture with extra entropy-based characteristics were all put forth. The heart disease like atrial fibrillation is predicted with the implementation of automated deep learning algorithm [15]. The F1-Score and accuracy achieved are 88.2% and 97.3% respectively. Although it is a serious problem, cardiologists and other medical experts find it to be a challenging and time-consuming task. The following restrictions are all removed by the suggested classifier. Moral violations are decreased by machine learning in medical equipment. The main goal of this work is to determine the R-R interval and analyse the blockage using straightforward methods and algorithms that provide excellent accuracy. The data may be rebuilt using the MIT-BIH dataset [16].

Fall is a major problem since it may have serious bodily and psychological effects. Research on fall detection and prevention is essential because it can help older adults live and move more independently and rely less on carers. In this study, a unique method for fall detection and activity categorisation is the independent use of Electrocardiogram (ECG) data. An approach that classifies ECG data into fall and no fall situations using pre-trained convolutional neural networks AlexNet and GoogLeNet has been suggested [17]. The study used eight volunteers to acquire the ECGs for both falling and no falling situations. An elliptical filter is used to pre-process the data to remove signal disturbances such baseline drift and power-line interface. After the work on fall detection, the diagnosis and detection of heart disease need to be studied and improved. One recent successful development of Deep Learning (DL) methods in the field of artificial intelligence is the adaption of DL architecture. Based on the ANSI-AAMI standard, Bhatia *et al.* [18] created a novel deep Convolutional Neural Network (CNN) and Bidirectional Long-term Short-Term Memory network (BLSTM) model in this study to automatically categorise ECG heartbeats into five classes.

Internet of Things (IoT) based health monitoring systems are becoming more and more well-liked and accepted for ongoing observation and the ability to identify health anomalies based on the data gathered. Signals from Electrocardiograms (ECGs) are frequently utilised to detect cardiac conditions. In this study, a unique approach to ECG monitoring with IoT technology has been suggested. A two-stage method is used by Karthiga *et al.* [19]. For effective data collection, a routing protocol based on Dynamic Source Routing (DSR) and Routing by Energy and Link quality (REL) is proposed in the first stage for the IoT healthcare platform. In the second stage, an ECG classification for arrhythmia is made. Additionally, this study has assessed methods for classifying ECG signals based on Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Convolution Neural Networks (CNNs).

Hybrid model gaining more acute results in the respective fields. CNN- Long Short-Term Memory (LTSM) using is designed for automatic detection and classification of heart disease [20]. The use of 1D ECG signals and are transformed to 2D scalogram images for extraction of features. The results achieved used this model is improved. Later, the combination of deep learning and machine learning is discussed [21]. The detection of heart failure from ECG signals is performed using CNN and SVM. Further the hybrid model trend improves the detection rate. MobileNet V2 and BiLTSM model is developed [22]. The ECG signal is developed over a short period of time and achieved good rate of accuracy in detection of arrhythmia. The accuracy obtained is 91.7%. Arrhythmias diagnosis is performed with the help of ECG signal data as input and processed using 1D-CNN for classification [23].

The Heart Rate Variability (HRV) analysis is gaining more importance which can effectively measure the heartbeats and reflects the functioning of nervous system. Sieciński *et al.* [24] analysed time domain, frequency domain and nonlinear HRV's on ECG. The analysis of HRV is performed on 29 healthy male and 30 unhealthy patients. Further the research of HRV analysis is performed in people with mid age adults [25]. The data collected for analysis is from the people who were kept under different stress levels. The research aim is to assess the ANS dysfunction utilizing the HRV. Li *et al.* [26] evaluated the HRV monitoring capabilities of several wearable devices and talk about how they might be utilised for tracking HRV. Further examined the latest developments in wearable HRV tracking and its applications in illness diagnosis and health monitoring. HRV tracking with wearable technology is a promising technique that may be utilised to enhance personal health, even though there are still numerous obstacles to overcome.

HRV for heart disease is studied. Wang *et al.* [27] utilized HRV analysis for emotion recognition by applying amplitude level quantization technique for extraction of features. The local information in each frequency band of the HRV signal using the ALQ approach to extract rich local information characteristics. A Logistic Regression (LR) classification technique, which may produce reliable and efficient emotion identification, is then used to classify the retrieved features. The HRV assessment is performed for extracting the high contextual information from the ECG sequence [28]. To generate multi-scale ECG representations and model the long-range relationships of ECG time series, the hierarchical transformer framework was created. HRV analysis will improve the detection of heart disease. In this section the focus is to identify the effective models in detection of CVD using HRV and deep learning technique to enhance the proposed work by improving identification accuracy. The understanding of various techniques and analysis help us to improve the working process on the ECG signals. The proposed model concentrates on HRV feature extraction and Efficient-Net b0 deep learning feature extraction and classification technique for identification of heart disease.

III. METHODOLOGY

The main aim of the work is to help patients and medical professionals. This study attempts to forecast the likelihood of heart illness using computerised heart disease prediction. To achieve this objective, we employed various deep learning algorithms on a dataset and present the results in this study report. To elevate the designed model, the ECG signal dataset need to pre-processed for removing the noise, evaluated for detection of R-peak, extraction of features and finally classification is performed using deep learning to identify the heart disease. The entire model is tested using explainable Artificial Intelligence (AI) approach. The methodology designed is improve the detection of CVD and achieved improved results. The designed process flow is shown in Fig. 2.

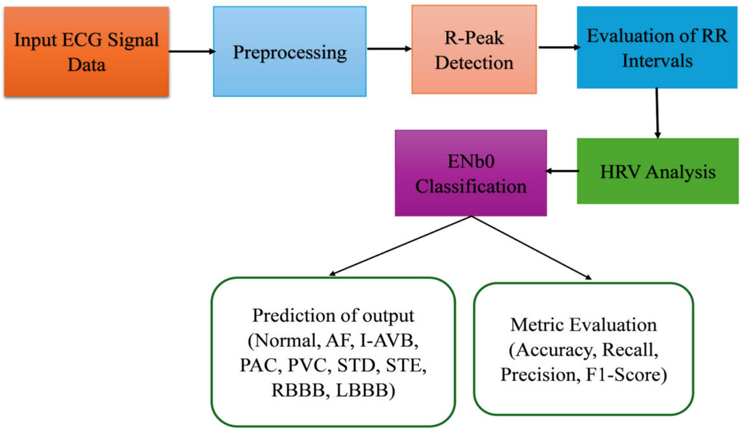

Fig. 2. Framework of proposed model.

A. Preprocessing

The input CPSC 2018 dataset [29] which contains 12 lead ECG signals with 6877 (male: 3699; female: 3178) in size and the signal length varies from 6s to 60 s. The sampling rate at which the signals collected is 500 Hz. The data available in each class are: Normal-2302, AF-526, I-AVB-368, LBBB-236, RBBB-500, PAC-277, PVC-336, STD-332, STE-308 and other recordings of 1692. Nine diagnostic classes are identified on these ECG signals. These signals are pre-processed before performing further state of action.

In accordance with the AHA/ACC/HRS recommendations for ECG acquisition [30] and established signal processing literature [31, 32], a Finite Impulse Response (FIR) bandpass filter with a 0.5–45 Hz cutoff was applied. This range effectively removes baseline wander (<0.5 Hz) and high-frequency noise (>45 Hz) while preserving the essential diagnostic content of the QRS complex and P–T waves [33], making it suitable for HRV feature extraction.

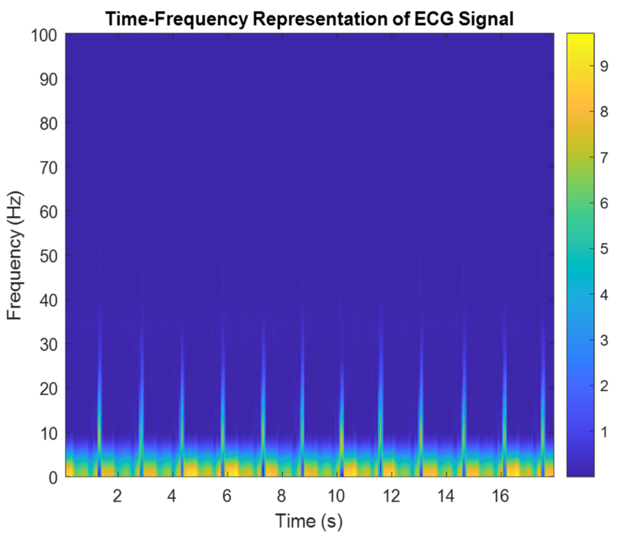

Fig. 3. Time frequency representation of ECG signal.

In this stage the input signal is denoised and removed unwanted artefacts. The signals are passed through a band pass filter for removal of signal noise, and the range is set to 0.5 to 45 Hz. The artefacts like muscle noise and baseline wander are removed to detect the R peaks perfectly.

Further the ECG signal is converted to time frequency representation and is shown in Fig. 3. This is performed to improve the process of feature extraction and HRV analysis can be improved for identification of heart disease. The importance of TFR is to improve the classification process when fetched to the proposed deep learning model.

B. Detection of R Peak

The ECG signal after pre-processing, detection of R peak is performed. The use of R peak detection is to perform HRV analysis. In this paper, a wavelet transform method is used for detection of R peak. The wavelet transform decomposes the ECG signal and finds the detailed coefficients near the QRS wave of the ECG signal. Finally, a threshold is utilized for detection of R peak. The said detection of R peak is shown in Fig. 4.

Using the Wavelet Transform, R-peak detection makes use of the QRS complex's high frequency content and steep slope, particularly the R-peak, the tallest and most noticeable component in an ECG.

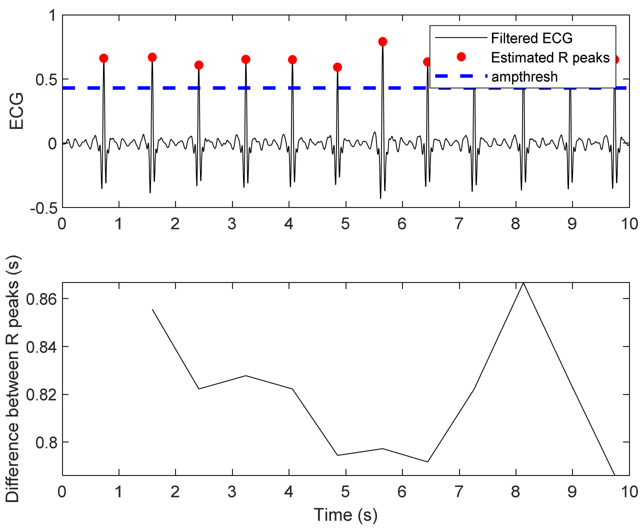

Fig. 4. R peak detection.

C. Evaluation of RR Interval

The *RR* interval evaluation is step for the assessment of heart rate variability. This *RR* interval is evaluated after achieving the array of *R* peaks and calculating the difference between the consecutive *R* peaks. The *RR* interval is measured in milliseconds. The graphical representation of *RR* interval with anomalies is shown in Fig. 5.

The RRI is given as Eq. (1),

$$RR_i = t_{i+1} - t_i \tag{1}$$

where, t_i and t_{i+1} are the time of i^{th} and $(i+1)^{th}$ peak.

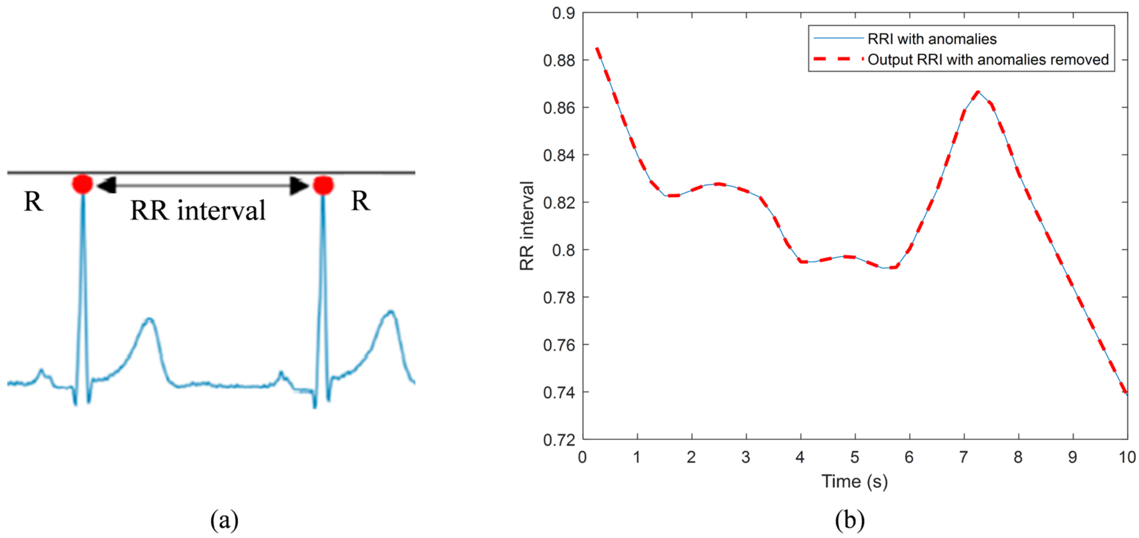

Fig. 5. (a) RR Intervals, (b) RRI anomalies.

D. Heart Rate Variability (HRV) Feature Extraction

Feature extraction is one of the important steps for diagnosis the heart disease. Different features are extracted for the given ECG signal. The following is the detailed expression of HRV analysis of ECG signal. HRV analysis is widely utilized in identification of CVD. This HRV extracts various genre of features which includes Short-Time Fourier Transform (STFT), Temporal, Frequency, fragmentation, Poincare plots. The HRV analysis is based on the variation of time intervals in the heartbeats in which RRI is considered for its analysis. These are evaluated for the given input signals. The values of the extracted features are tabulated in Tables I–VI.

1) Sample entropy

The value of sample entropy needs to obtained which helps in predicting the level of complexity and range of predicting the echo signals. If the sample entropy value is low, then the ECG signal is clean and stable with minimum variations in the heartbeat, whereas the higher entropy value indicates high complexity and the heartbeat is irregular.

2) Short-Time Fourier Transform (STFT) features

The STFT features are extracted by converting the ECG signal to time frequency domain. The STFT divides the signal into an overlapping time window. Late a Fourier transform is applied by which a 2D representation is done by showing the spectral content changes over time. The extracted features and its values are presented in Table I.

TABLE I. STFT FEATURE VALUES

Features	**Total energy**	**STFT energy**	**Low band energy**	**Mid band energy**
Value	1.677e+05	10.452	1.645e+05	3059.8
Features	Mean STFT	Variance STFT	Mean Peak Freq	STD peak Freq
Value	0.153	0.292	1.063	2.181

3) Temporal features

These features focus on the timing, shape, and duration of the signal components which are derived from the time domain signal. These features describe the timing intervals and amplitudes of ECG signal with components like P, QRS, and T. The temporal features and its values are shown in Table II.

TABLE II. TEMPORAL FEATURE VALUES

Features	**Mean**	**Std**	**Skewness**	**Kurtosis**
Value	$2.107e^{-18}$	0.179	−0.539	11.84

4) Frequency features

The frequency features are achieved by analysing the ECG signal in different frequency bands. These features suggest how the ECG signal in frequency domain have its energy, power, and the signal distribution. The extracted main features and its values is shown in Table III.

TABLE III. FREQUENCY FEATURE VALUES

Features	Mean frequency	Peak frequency	Spectral entropy
Value	0.1425	0.893	0.02

5) Heart Rate Variability (HRV) frequency domain

In this domain the analysis is done to evaluate the values of very low frequency, low frequency, high frequency, and the ratio of low frequency by high frequency. The power of ECG signal in these bands are evaluated and is shown in Table IV.

TABLE IV. HRV FREQUENCY DOMAIN FEATURE VALUES

Features	VLF	LF	HF	LF/HF
Value	0.167	0.276	0.0069	39.55

6) Heart Rate Variability (HRV) fragmentation features

The irregular beat to beat in HRV indicates the HRV fragmentation features. The sudden change in the series of RR interval is noticed which indicates abnormal functioning of heart leads to CVD. The features like Poincaré Index of Phase (PIP), Index of Average Length of Segments (IALS), Percentage of Short Segments (PSS), Percentage of Alternation Segments (PAS) are evaluated and is shown in Table V. The switching patter of heart rate and the frequency of switching is observed with the help of these features.

7) Poincaré plot features

These features are achieved by showcasing the scatter plot of every RR interval. The Poincare plot is shown in Fig. 6. The shape and the region of spreading in the plot offers the functioning of heart. The features values like SD1, SD2, entropy, and Detrended Fluctuation Analysis are evaluated and shown in Table VI.

All the feature values evaluated utilize recurrence plots to transform 1D HRV feature sequences into 2D images, which were then fed to EfficientNet-b0. This method preserves the temporal dynamics of HRV features while making them compatible with 2D CNN architectures.

TABLE V. HRV FRAGMENTATION FEATURE VALUES

Features	PIP	IALS	PSS	PAS
Value	26.76	3.64	26.76	0.02

TABLE VI. HRV NON-LINEAR FEATURE VALUES

Features	SD1	SD2	SampEn	DFA
Value	0.1425	0.893	0.02	0.0713

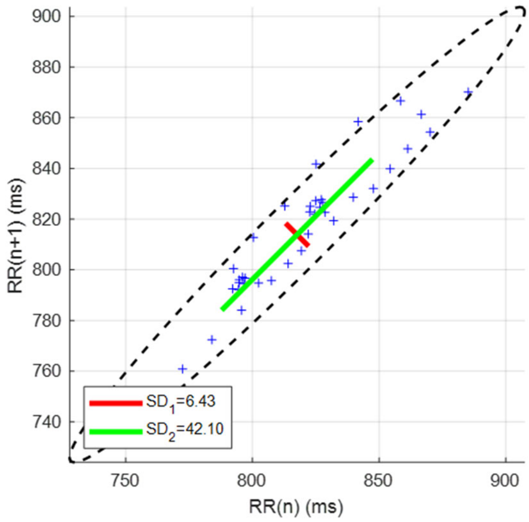

Fig. 6. Poincare plot.

E. Feature Extraction and Classification

The features are extracted and classification of data is performed using ENb0 model. The working of ENb0 is discussed below. The time frequency representation of input ECG signal is fetched to the deep learning model. The ENb0 have 9 layers and process of proposed model is shown in Fig. 7.

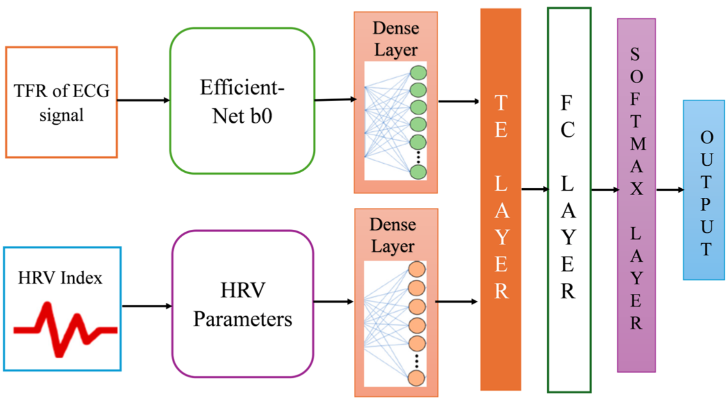

Fig. 7. Process of ENb0 model.

Initially the input is passed through the input layer in which image is normalized and fetched to the network. The feature extraction starts from the second layer i.e., convolutional layer. The Efficient-Net b0 utilizes Mobile Inverted Bottleneck Convolutional blocks (MB Conv), which are efficient and powerful in processing the desired output. In ENb0 seventeen number of MB Conv blocks are utilized and grouped into different stages by increasing the depth and reducing the resolution in spatial region. The Transform Encoder (TE) layer is added to boost the performance of the proposed model. In this transform encoder two layers are involved i.e., multi-head self-attention and feed forward MLP. This TE layer captures the temporal and contextual relationships in the features extracted by Efficient-Net b0.

All the details are fetched to fully connected dense layers and softmax layer is applied to achieve the class probability. Finally, the class with high probability is the output label that is predicted. The layers and its size utilized is shown in Table VII.

TABLE VII. LAYERS AND SIZE UTILIZED IN ENB0

Stage	Layer and kernel size	Size	Number of channels	Number of layers
1	Conv 3×3	224×224	32	1
2	MB Conv1, 3×3	112×112	16	1
3	MB Conv6, 3×3	112×112	24	2
4	MB Conv6, 5×5	56×56	40	2
5	MB Conv6, 3×3	28×28	80	3
6	MB Conv6, 5×5	14×14	112	3
7	MB Conv6, 5×5	14×14	192	4
8	MB Conv 6, 3×3	7×7	320	1
9	Conv 1×1, pooling, FC	7×7	1280	1

After building the efficient net b0 model, the data is split into training set, validation set and testing set. 70% of data is used to train the model, 10% for validation set for tuning the parameters and avoid overfitting, 20% of data is used for testing which evaluate the final model performance.

The Binary Cross Entropy (BCE) loss is calculated at the output layer and gradients are backpropagated through both the Transformer and Efficient-Net, updating their weights during training.

The loss function is given as,

$$L_{BCE} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \cdot \log(\hat{y}_i) + (1-y_i)\cdot \log(1-\hat{y}_i)\right] \quad (2)$$

where,

$y_i \in \{0,1\}$ is the ground truth (0 is no disease and 1 is disease)

$\hat{y}_i \in [0,1]$ is the predicted probability, N is the size of the batch.

The main goal is to minimize the loss during the process of training.

After performing classification, the output class is predicted. Parameters are used to evaluate how well EfficientNet-b0 predicts heart disease. The results evaluated is discussed in Section IV of the paper.

IV. RESULTS AND DISCUSSION

The CPSC 2018 dataset [29] is processed using matlab tool. The implementation of proposed model is performed on windows 11 OS with intel i10 processor. The design utilizes all the neural network tools which are inbuilt in Matlab version 2024. A large system space with 1 TB is utilized for storage and processing of large data. To speed up the processing speed of system a 64 GB RAM is installed. All the system environments help in developing an automatic system for detecting of heart disease by utilizing the ECG signals. The metrics evaluated and the experimental findings are discussed in this section.

The metrics are calculated to find the efficiency of the proposed model in identification of heart disease. Some of the commonly utilized for evaluating the performance is accuracy, precision, recall, F1-Score and hamming loss. The mathematical formulation of the metrics depends on the True Positive (TP), False Positive (FP), True Negative (TN), False Negative (FN) respectively. Here TP, TN, FP and FN denote the classification process done correctly or incorrectly. The metric and its formula are shown in Table VIII.

TABLE VIII. METRICS AND ITS FORMULA

Parameter	Formula
Precision	$Pe = \frac{TP}{TP+FP}$
Recall	$Re = \frac{TP}{TP+FN}$
F1-Score	$F1 = 2\times\frac{Pe\times Re}{Pe+Re}$
Accuracy	$Acc = \frac{TP+TN}{TP+TN+FP+FN}$
Hamming Loss	$H_l = \frac{1}{\lvert X\rvert}\sum_{x\in X}\frac{1}{\tau}\sum_{j=1}^{l}\left[\left(L_j \in HL(x)\right)\otimes\left(L_j \in y\right)\right]$

The hyperparameters utilized in this work is shown in Table IX. The experimental findings of proposed model are shown and discussed below. The parameters evaluated are shown in Table X. The proposed model parameters achieved higher values when compared to VGG-16 model.

TABLE IX. UTILIZED HYPERPARAMETERS

Number of epochs	50
Batch size	32
Learning rate	0.0001
Image Size	224×224×3
Data split	70% train, 10% validation, 20% test

TABLE X. COMPARISON OF METRIC EVALUATED

Parameter/ Method	Modified VGG-16	Efficient-Netb0
Accuracy	96.61	**98.71**
Recall	95.49	**98.98**
Precision	95.99	**98.76**
F1-Score	95.45	**98.86**
Hamming Loss	0.27	**0.088**

The confusion matrix shows the effectiveness and efficiency of the proposed model in classifying nine types of diagnosis classes in detection of heart disease. The confusion matrix using ENb0 is shown in Fig. 8.

The matrix provides a visual and numerical summary of how well the model is performing in terms of true and false predictions. From Fig. 8 it is shown that the true prediction of STD is 97% in which 1.8% is falsely predicted as normal, 0.6% is falsely predicted as AF and Right Bundle Branch Block (RBBB). In case of AF the true prediction is 98.9% in which 0.6% is falsely predicted as normal and 0.2% is predicted as STD. The class-wise analysis using the confusion matrix, highlighting the model's robustness across nine diagnostic categories, and discuss activation maps to interpret class-specific performance.

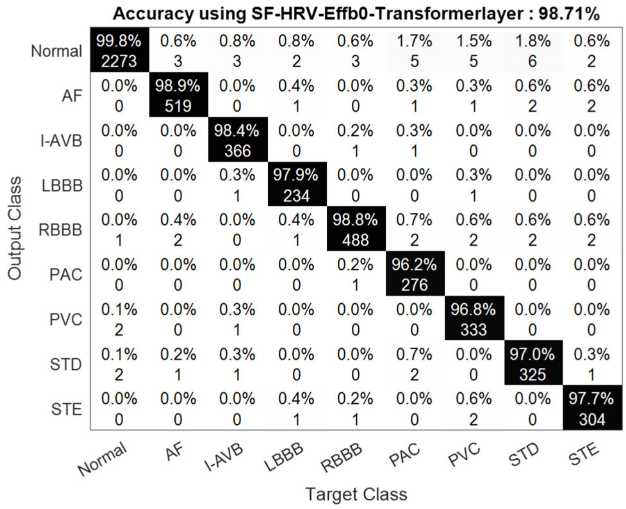

Fig. 8. Confusion matrix using HRV-ENb0-TE.

In processing of ECG signal nine different classes are considered and the plots obtained using different class when performed deep learning are shown individually. The classes considered are Atrial Fibrillation (AF), First order Atrioventricular Block (I-AVB), Left Bundle Brunch Block (LBBB), Premature Atrial Contraction (PAC), normal signal, ST segment depression, ST segment elevation, RBBB, and Premature Ventricular Contraction (PVC). The validation of results is performed using the explainable AI. The results achieved using the deep learning ENb0 model for each class is shown from Figs. 9–17.

Fig. 9 shows the behaviour of activation of ECG sample w.r.t AF. The end of beat is observed near 400 ms. The ECG points with AF is identified by the deep learning model. The highest peak of activation is observed at 0.55 mv.

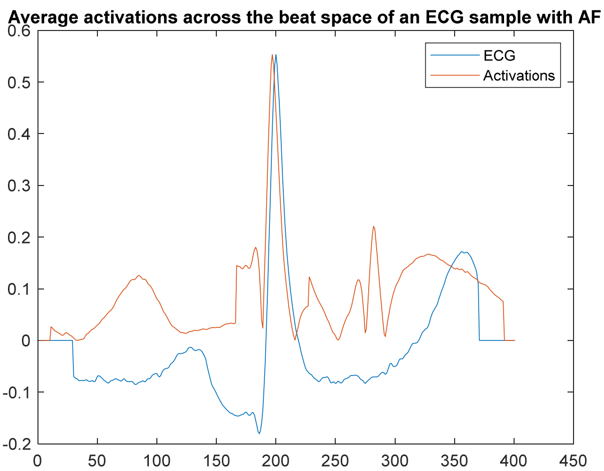

Fig. 9. AF- ECG signal activation compared to DL activated samples.

Fig. 10 shows the behaviour of activation of ECG sample w.r.t I-AVB. The end of beat is observed near 400 ms. The ECG points with AF is identified by the deep learning model. The highest peak of activation is observed at 0.6 mv. The deep learning is perfectly activated in the prolonged region of P wave.

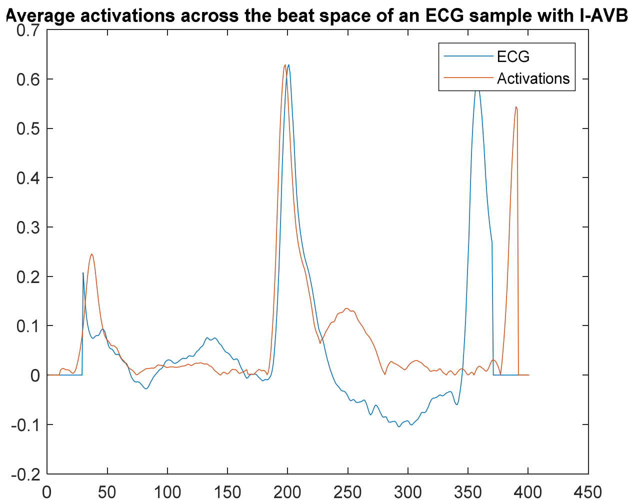

Fig. 10. I-AVB-ECG signal activation compared to DL activated samples.

The average activations across the beat space of an ECG samples with LBBB class is shown in Fig. 11. The peak activation is observed at 4.5 mv and the end beat observed at 400 ms. The activation of DL model is well in advance compared to actual ECG signal.

The QRS complex and T wave of an ECG signal with PAC are normally normal, but the P wave is aberrant. The average activations throughout the beat space of an ECG data using PAC are displayed in Fig. 12. The traits of PAC are correctly activated while performing DL model in case of P-wave, normal QRS and a normal T-wave as shown in Fig. 12.

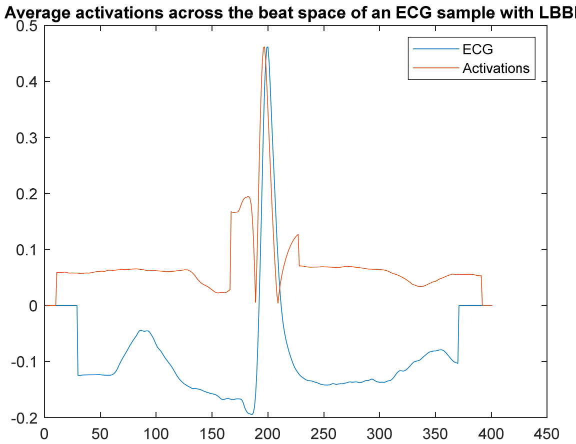

Fig. 11. LBBB-ECG signal activation compared to DL activated samples.

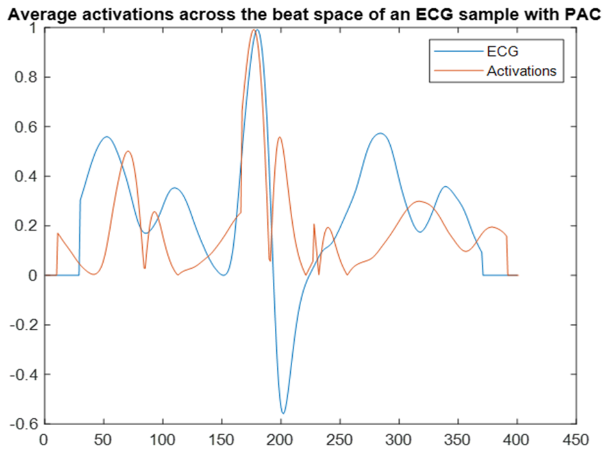

Fig. 12. PAC- ECG signal activation compared to DL activated sample.

In case of normal condition of heart, the ECG signal have a normal P, QRS and T waves. The activation of beat space shown in Fig. 13 is for normal ECG signal and the model performance is also shown good.

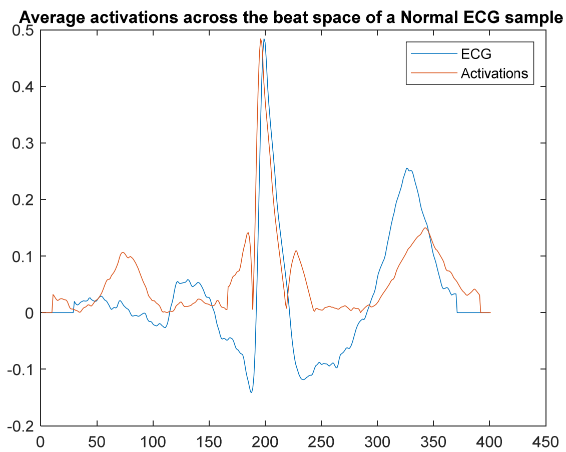

Fig. 13. Normal-ECG signal activation compared to DL activated samples.

For any ST segment depression class, the ECG signal have a normal P and T wave. A depressed trait is found in the ECG signal in the ST segment. The Fig. 14 shows the activation of signal using DL model which is pretty accurate and set to the conditions of ST segment depression, as the ST segment depression is clearly shown in Fig. 14.

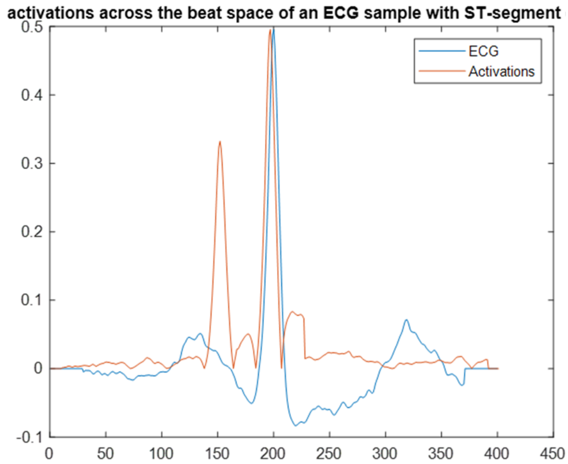

Fig. 14. ST segment depression- ECG signal activation compared to DL activated samples.

In the class of ST segment elevation, the signal traits have a normal QRS and normal T wave and an elevated ST segment. The model performance shown in Fig. 15 have an activation of right features and classifying the ECG signal.

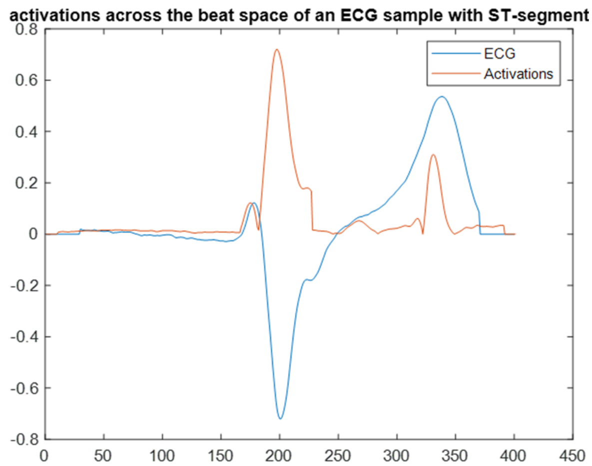

Fig. 15. ST segment elevation- ECG signal activation compared to DL activated samples.

In case of RBBB class the features considered are wide S wave, I, V5 and V6. The average activation of beat space of ECG sample with RBBB is shown in Fig. 16. The performance of model activation is wide in S wave region which shows the classification accuracy is good.

Let us consider the case of PVC and evaluate the beat space activation of ECG sample with PVC and is shown in Fig. 17. The PVC of ECG signal have abnormal condition of QRS. The DL model is activated in the QRS complex region which gives the better classification performance.

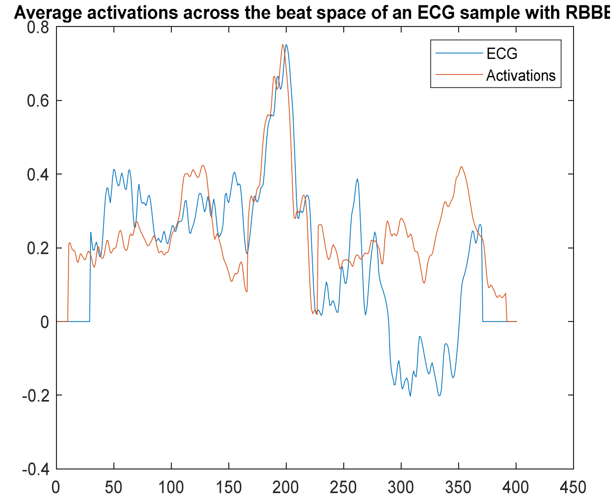

Fig. 16. RBBB- ECG signal activation compared to DL activated samples.

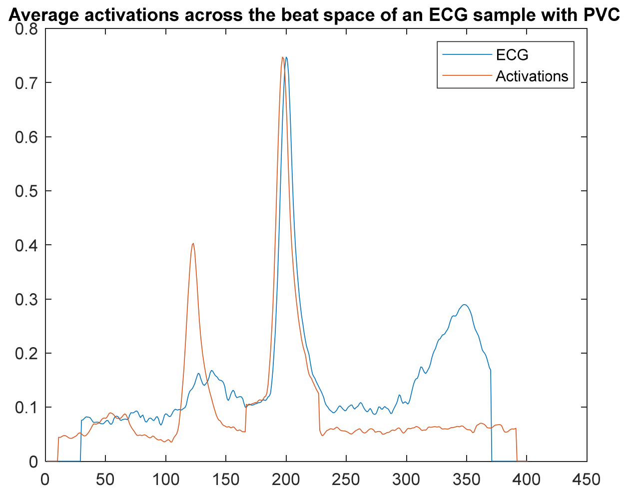

Fig. 17. PVC-ECG signal activation compared to DL activated samples.

The two major metrics used for comparison of existing results with our proposed work is accuracy and F1-Score. Most of the authors evaluate these two metrics to find out the efficiency of the model designed. The comparison results of accuracy and F1-Score with existing models is shown in Figs. 18 and 19.

The analysis observed from Fig. 18 is proposed approach having a highest accuracy of 98.71% when compared to existing models suggested by different authors. The ECG signals are processed and performed voting model to achieve 93.25% accuracy [34], using harmonic phase distribution [35] accuracy achieved is 95.6%, combination of CNN and RNN [36] achieved 94.6% accuracy, deep learning [37] achieved a lower accuracy with 81%, deep convolutional neural network [38] having an accuracy of 95%, artificial intelligence [39] achieved an accuracy of 94%, transferred deep learning CNN [40] achieved an accuracy of 95.6%.

From Figs. 18 and 19, proposed model performance is better when compared to other existing techniques. The model of HRV-Deep learning gives promising results and is helpful for diagnosis of heart disease.

Finally, the novel contribution of work is stated as: HRV analysis and CNN-based ECG classification have been individually explored, our work integrated handcrafted HRV features (spatial, frequency, Poincaré, fragmentation) with a hybrid ENb0–Transformer Encoder (TE) model trained on recurrence plots of HRV features. The use of recurrence plots to convert 1D HRV features into 2D representations for CNN-based feature extraction is a novel methodological step that enables the fusion of physiological signal variability and deep learning feature hierarchies. The inclusion of a Transformer Encoder on top of EfficientNet-b0 is a unique architectural enhancement to capture long-range dependencies in ECG derived features an innovation for HRV-ECG works.

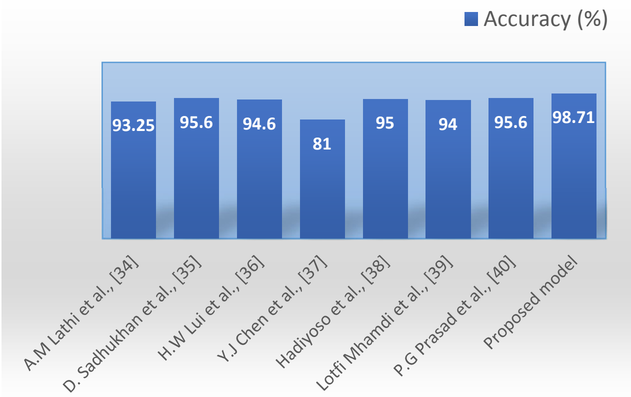

Fig. 18. Comparison of accuracy parameter.

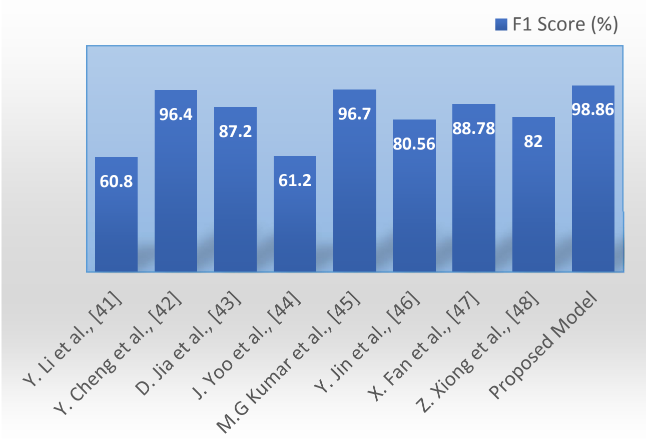

Fig. 19. Comparison of F1-Score parameter.

V. Ablation Study

The study aims to identify how every technique is useful in improving the detection accuracy. In this study the experiment conducted on different cases and evaluated the accuracy result.

Case1. Accuracy in detection of heart disease without using Transformer Encoder (TE) and tested the contribution of TE. The accuracy obtained is 97.3%.

Case2. No Efficient net b0. Directly utilized raw HRV features with transform encoder. The rate of accuracy achieved is 88.6%.

Case3. No HRV features. The model designed without extracting HRV features, utilized only ENb0 and TE model for detection of heart disease. The rate of accuracy obtained is 97.4%.

The importance of HRV features is studies by performed controlled ablation experiments by retraining the classifier after removing: (i) each HRV feature group (time-domain, frequency-domain, Poincaré, LF/HF).

- Removing time-domain features (all) the accuracy achieved is 95.5%.
- Removing frequency-domain features (all) the accuracy achieved is 95.99%.
- Removing Poincaré features (all) the accuracy achieved is 96.8%.
- Removing LF/HF the accuracy achieved is 97.7%.

From this study the combination of HRV-ENb0-TE provides better detection accuracy with 98.7%.

VI. Conclusion

In this work, the ECG signal database is gathered and pre-processed. The RR intervals in the 12-lead ECG signal is identified which helps in notifying the cardiac activity. The patterns of RR are irregular denotes the irregular activity of heart. The HRV analysis is performed by extracting features like STFT, temporal, frequency domain, Poincare plots. All these features help in identifying the nature of ECG signal. A pretrained deep convolutional neural network model efficientNet-b0 is proposed and evaluated for the task of classification in identification of heart disease. The transformer encoder layer added with ENb0 gives better results in training and performing validation of results when compared to VGG-16 model. The efficiency of ENb0 is shown by evaluating parameters like accuracy, recall, precision and F1-Score. The overall accuracy achieved in identification of heart disease is 98.71% and is better compared to other existing models. These results boost medical field and doctors to utilize the model for early diagnosis of heart disease. The work in future need to concentrate on the computational time and improving the accuracy by using optimization techniques performing features optimization. Based on the performance, the suggested model can be utilized in many disease identification applications.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Munji Gayathri conducted the research work, collected the data, and wrote the paper. Chittineni Suresh supervised the work and all authors had approved the final version.

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