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Multi Classification of ECG Signals based on Convolution and Residual Neural Networks for Effective Forecasting of Cardiovascular Disease

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Abstract: Cardiovascular disease (CVD) is a major contributor to death rates around the globe. Early diagnosis of cardiac illnesses is critical for efficient therapy, and an electrocardiogram (ECG) is vital for identification. Deep learning techniques have made significant advancements in the classification of ECG signals, achieving a level of accuracy comparable to that of cardiologists. In a medical situation, a cardiologist uses conventional 12-lead ECG data to determine a diagnosis. This work describes a multi-class classifier that can identify five distinct forms of cardiovascular illnesses: NORM, hypertrophy, myocardial infarction, ST-T abnormalities, and conduction disturbances. The model utilizes the abundant input from the usual 12-lead ECG data and acquires knowledge of patterns at the beat, and rhythm, and uses the dataset PTB-XL. Convolution with residual connection with Bi-LSTM performance at different filter sizes, when the filter size increases, we get a little more improvement in the model performance. The comparative study of the performance of 3 different classifiers LSTM, RNN, and Bi-LSTM, evaluates the performance of Accuracy, f1-score, recall, and precision. The performance at CRDM at filter size 11 accuracy, precision, F1-score &recall is 95.34%,91.54%,93.67% and 92.99%.

Keywords: CVD, ECG, PTB-XL dataset, Bi-LSTM, LSTM, RNN

1. Introduction

Cardiovascular illness is the biggest reason for early death on a global scale, as stated by the World Health Organisation. Cardiovascular disease (CVD) accounts for around 31% of all deaths worldwide, resulting in approximately 17 million fatalities annually [1]. CVD was the leading cause of mortality worldwide in 2021, with low- and middle-income countries held accountable for 80% of all CVD deaths [2]. Mortality from cardiovascular illnesses increased sharply from 12.1 million in 1990 to 20.5 million in 2021, per a report published by the WHF (World Heart Federation) on May 20, 2023. Cardiovascular issues are prevalent in India, particularly among those in their late 40s and early 50s. [3].

Identifying cardiac illness in its initial stages is difficult because the symptoms are similar and cannot be easily distinguished [4]. An Electrocardiogram (ECG) or electrocardiograph (EKG) is a distinctive plot that displays the sequential heart rate monitoring. The electrocardiogram displays a time-voltage graph illustrating a heart rate. The ECG is a vital component that provides cardiac diagnosis and therapy due to its provision of significant information [5]. The ECG and its characteristics have been demonstrated to be highly effective techniques for the initial stages of the forecasting of cardiac illness. The widely accepted clinical norm that does not require an invasive procedures approach is used to evaluate the normal or abnormal performance of the cardiac. Additionally, it serves as a biomarker for forecasting cardiac problems [6, 7]. There are several ways to record an ECG, including single-lead, 3-lead, 5-lead, 6-lead, and 12-lead systems. Out of all 12 leads, electrocardiogram recording is still considered the most reliable for clinical use. In traditional clinical settings, the 12-lead ECG is the gold standard because it provides a comprehensive picture of the heart and may be employed to identify cardiac disease and pinpoint its exact location.

Additionally, it's beneficial for the cardiologist to proceed with additional evaluation and therapy [8].

ECG data is essential for monitoring heart rates and rhythms. This information enables medical professionals to remotely assess various health issues and develop tailored treatments for each patient. The world is constantly changing, and numerous medical problems arise as a result of the global epidemic. Therefore, the timely identification of many diseases using neural networks techniques might mitigate their impact [9]. Feature extraction from EEG signals is an essential method for analyzing and diagnosing neurological conditions [10].Cardiovascular disease has become one of the most critical health challenges in recent decades. Accurate prediction plays a pivotal role in determining the most effective treatment strategies and enabling early detection, which is essential for improving patient outcomes and mitigating long-term complications [11].

The objective of this paper is to design a robust and accurate multi-class classification model for diagnosing cardiovascular diseases (CVD) using ECG signals. This includes:

1 CR+Bi-LSTM model, to classify ECG signals into five categories: Normal ECG, Conduction Disturbances, Myocardial Infarction, Hypertrophy, and ST/T Changes.

2 Leveraging advanced techniques such as CNNs, Bi-LSTM, and attention mechanisms to effectively extract spatial and temporal features from ECG data.

3 Validating the model's performance using the PTB-XL dataset and achieving high accuracy, precision, recall, and F1-score.

Demonstrating the superiority of the proposed model compared to existing traditional and deep learning methods in ECG classification

2. Literature Review

The machine learning techniques employ traditional approaches to identify cardiac problems from a patient's ECG data. Most of the time, the best way to classify heart disease is to use supervised machine learning that includes ECG data or its characteristics in addition to certain demographic or laboratory information. A significant quantity of research is being done in unsupervised machine learning [12, 13]. It could be further employed for CVD diagnosis using various biomarkers. Gupta demonstrated the efficacy of different machine learning (ML) techniques, including KNN, DT, RF, and SVM, in forecasting cardiovascular disease (CVD) [14]. Sarah, *et.al.* Employed data from Cleveland to conduct a comparative analysis of several classifiers to predict the occurrence of cardiovascular illness. The results demonstrated that logistic regression (LR) exhibited the highest accuracy rate of 85.25%. Given that ECG is often considered the most reliable approach for the initial detection of cardiovascular illness, it is convenient to get PPG measurements [15].

Deep learning approaches have consistently surpassed traditional machine learning methods and achieved exceptional outcomes in terms of accuracy and efficiency. Deep learning methods employ algorithmic phases to develop models that are trained using the inherent qualities of the underlying data [16]. Deep learning methods, specifically convolutional neural networks (CNN) and recurrent neural networks (RNN), notably those incorporating LSTM networks, have achieved notable success in the processing of ECG signals [17]. Dang, H *et.al.* [18] Constructed a CNN with bidirectional long short-term memory (BiLSTM) to accurately categorize ECG signals by examining the characteristics of RR intervals, PR intervals, and QRS complexes (which encompass the Q, R, and S waves and indicate ventricular depolarization). The task involves classifying 100 samples of ECG signals into five distinct categories. The method attained a classification accuracy of 96.59% when applied to categorize five distinct types of ECG data. Jin, Y.*et.al*. [19] Built a method that employed attention with CNNLSTM to analyze multi-domain characteristics. The model achieved an accuracy of 97.51% in forecasting five distinct ECG signals, although it lacks strong flexibility. The study of work is divided into two ways: one is non-ECG-based and the other one is ECG-based.

2.1. CVD Detection Using ECG Data

An ECG manifests the electrical activity generated by the myocardium during its cyclic contraction and relaxation. It implies when the heart is not working properly, such as when there's ischemia, arrhythmia, hypertrophy, stenosis, or some other cardiovascular illness. It is a very efficient and economically viable approach to assessing cardiovascular well-being. Additionally, it serves as a vital marker for the prompt identification of cardiovascular illnesses. Given the significance of electrocardiography (ECG), numerous researchers have conducted various studies on the forecasting of cardiovascular disease (CVD). Sadasivuni, *et.al.* [20] Provides a reservoir-computing and fusion approach that utilizes ECG with clinical data to forecast ischemic cardiac disease, a condition characterized by the blockage of blood flow to various heart regions. Guo, C *et.al.* [21] Senthil Kumar Mohan et al. provide the Hybrid method (HRLFM) with LM (Linear Method) &RF (Random Forest). Using this model provided an accuracy of 88.7 percent for the forecast of heart disease and improved the accuracy performance to apply feature selection techniques. Mohan, S *et.al.* [22] Presented a hybrid approach, known as HRFLM, that employs both random forest as well as linear approaches to forecast heart illness using the UCI Cardiac illness dataset. Obayya, M., *et.al.* [23] the approach of a DNN classifier using a neural network, which incorporates Honey Badger optimization for selecting features along with Bayesian optimization for fine-tuning hyperparameters, to forecast CVD. Ghosh, P *.et.al*. [24] using UCI data, the identical information was extracted from the attributes by the application of LASSO and relief methods, subsequently employing these features for forecasting heart disease.

2.2. CVD detection using Non-ECG data

CVD is predicted using a variety of approaches, including ECG, PPG, EHR data, demographics, and behavioral characteristics [25]. Nikam, A., *et.al* [26] Utilise the prevalence of attributes found in Electronic Health Records (EHR) to forecast CVD. Body Mass Index (BMI) is recognized as a significant factor in predicting CVD. Simonyan, M.A *et.al.* [27] Features obtained from the spectrum analysis of PPG Indicators such as the power density of low and high-frequency signals, as well as their ratio, are employed for early forecasting of CVD. Qian, X. *et.al.* [28] They utilized machine learning algorithms, specifically an ensemble ML classifier consisting of LR as well as KNN techniques, and the SMOTE for data balance technique. The objective was to reliably predict cardiovascular disease using standard physical examination indicators. The Framingham dataset was employed for this purpose. Yang, H *et.al* [29] Employed identical data to train an Optuna hyper-parameter optimized LightGBM technique for classifier to forecast myocardial heart illness. Ghorashi, S., *et.al* [30] applied convenience sampling to UAE hospital patient data consisting of 2621 records and employed PCA-choosing attributes and the LSTM approach to forecasting CVD. SPSS was utilized to conduct simple LR and multiple LR for subsequent analysis. Joo, G., *et.al* [31] evaluated the efficacy of DNN, LR, Light GBM, and RF Approaches in predicting CVD between a two-year and ten-year timeframe. In addition, they conducted the SHAP feature importance analysis to determine the risk of CVD. Table 1 provides a summary of the methodology used in recent studies of cardiovascular disease.

3. Methodology

3.1 Dataset

This work uses the PTB-XL, a freely accessible dataset offering therapeutics, it contains 12-channel ECG signals from clinical environments (V1 to V6, a VL,aVR,aVF, I, II, III).

Table 1. Literature Review

Author	Year	Dataset	Methodology
Anand, A.*at.el* [32]	2022	PTB-XL dataset	Using CNN and SHAP(shapley additive explanations) based on this method to identify heart disease
Geweid, G. *et.al*.[33]	2022	PhysioNet	The hybrid approach of Dual SVM(HA-SVM) used for identify of atrial fibrillation
Liu, P, *et.al*. [34]	2022	MIT-BIH arrhythmia	An autoencoder can extract the temporal patterns of ECG data, while LSTM can be used for classification.
Li, Y *.et.al* [35]	2022	MIT-BIH arrhythmia	Subsequently, the discrete wavelet transform (DWT) is employed to remove noise from these segments, while the enhanced deep residual CNN is utilized for arrhythmia classification.
Nguyen, Q. H *et.al*.[36]	2021	PhysioNet	Using a CNN, generated segment-based identification units and extracted statistical characteristics from these units. Then SVM to forecast atrial fibrillation (AF) using the ECG data.
Wu, M., *et.al*.[37]	2021	MIT-BIH arrhythmia	CNN, DL, Ensemble classifiers, ML
Prasanna *et.al* [38]	2023	UCI Repository	BHHO is used for the feature selection and Deep bi-lstm for the classification
Nandy,S *et.al* [39]	2023	UCI Repository	An intelligent healthcare system employs the Swarm-ANN technique to forecast cardiovascular heart illness
García-Ordás, M.*et.al* [10]	2023	Switzerland,Cleveland, Hungarian, stalog, Long Beach.	Deep learning techniques are used with feature-augmentation approaches is sparse autoencoder to assess patients' risk for cardiovascular illness at early prediction.

Table 2. The PTB-XL data consists of both superclass & subclass information [28].

Super- classes	Sub-classes	Abbreviation
CD	Left Anterior/Left Posterior Fascicular Block	LAFB/LPFB
	Incomplete Right Bundle Branch Block	IRBBB
	Incomplete Left Bundle Branch Block	ILBBB
	Complete Left Bundle Branch Block	CLBBB
	Complete Right Bundle Branch Block	CRBBB
	AV block	_AVB
	Non-specific intraventricular conduction distur- bance (block)	IVCB
	WPW Wolff-Parkinson-White Syndrome	WPW
HYP	Left Ventricular Hypertrophy	LVH
	Right Ventricular Hypertrophy	RHV
	left atrial overload/enlargement	LAO/LAE
	Right Atrial Overload/Enlargement	RAO/RAE
	Septal Hypertrophy	SEHYP
MI	anterior myocardial infarction	AMI
	Inferior Myocardial Infarction	IMI
	Lateral Myocardial Infarction	LMI
	Posterior Myocardial Infarction	PMI
STTC	Ischemic in anterior leads	ISCA
	Ischemic in Inferior Leads	ISCI
	Ischemic (non-specific)	ISC
	ST-T changes	STTC
	Non-specific ST changes	NST
NORM	Normal ECG signal	-

Table 3. The illustration of diagnostic superclasses is depicted

Obervation	Super class	Records
Normal ECG	NORM	9464
Condution Distrurbance	CD	3988
ST/T Change	STTC	5345
Hypertrophy	HYP	21334
Myocardial Infarction	MI	5377

It includes 21837 ECG data from 18885 patients, with a median recording duration of 10 seconds. The dataset encompasses a diverse array of illnesses, including numerous co-occurring diseases. The ECG dataset contains multiple labels due to the annotations provided by two cardiologists. Subsequently, it was consolidated into super and subclass. The main categories are HYP, MI, STTC, Normal ECG, and CD. Every superclass, except NORM, is associated with several subclasses [40], which are detailed in Table 2.

In the dataset, Within the age range of 0 to 95 years, the sample contains 52% male and 48% female recordings. In Table 3 we can see how the data is distributed within the superclasses.

3.2 Data Preprocessing

During the preprocessing stage, multi-channel ECG data is divided into individual heartbeat segments towords a specific length, B, for each channel. The signal's initial and final spikes were removed using an intermittent approach, and may now be downloaded at a sample rate of 100 Hz. In the other residual blocks, the inputs undergo a down-sampling operation with a reduction factor of 2 following every other residual block. The data is accessible in two distinct categories. One category contains 10-second ECG data in its raw format for each patient, whereas the other file contains an SCP assertion [41]. The SCP assertions contain data regarding patient demographics, including age, sex, height, weight, etc., as well as diagnosis category and diagnosis superclass. Every ECG data is associated with a Python diagnosis superclass, which serves with a label.

3.3. Proposed Model

The proffered approach is an extremely priced CVD forecasting framework encompassing five distinct classes. Figure 1 illustrates the categorization of the operational aspects of the suggested model. The explanation for each step is provided in the subsequent subsections.

A framework of the method can be represented in two phases. The initial phase independently handles every channel to provide an encoding input signal. The individual heartbeats from multi-channel data are processed and analyzed by a beat level. The beat-level block results are processed to rhythm-level block to provide encodings specific to each channel. The channel-wise encoded data are inputted into the next component of the method, where they are pooled across every channel and used to obtain forecasts.

The CNN structure employed in the beat segment is illustrated in Figure 2. A batch normalization and a Leakey ReLU activation function follow each of the two convolutional layers. Dropout is utilized among two convolutional layers to regulate the training of the model and prevent overfitting. In the first two blocks of residuals, downsampling is not performed. After the other residual blocks, the inputs undergo a downsampling operation with a reduction factor of two after every other residual block. Each layer utilizes a filter length of -7 with an initial set of 28 filters. There is a doubling of the number of filters in each residual block that has input downsampling. In this model, CNN weights are distributed uniformly in all beat segments as well as in different channels. where L represents the duration of the ECG data for the Cth channel, and let B represent length of a single heartbeat. The total no.of beat intervals is represented by the variable $T = \frac{L}{B}$. Each $(bs_1^C, bs_2^C, bs_3^C, \dots . bs_T^C)$ beat intervals represent the Cth channel of ECG data. To train, the CNN is fed a time series with ith beat segments bs_i^Ceach of length B. CNN provides the output with an input bs_i^C Beat segment $\overline{bs_i^C}$ with an intermediate sequence length $\bar{L}$ .The different regions across a cardiac segment do not have equal significance in detecting an irregular heartbeat. The attention system enhances the ability to detect significant places inside a heartbeat fragment by assigning higher scores to them. The model consists of a 2nd-layer NN that receives inputs through the results of the CNN. It calculates the score for attention by adding the softmax function to the outcomes of the neural network, as described in the below 1&2 equations. In a similar manner to CNNs, the weights of the beat-level attention layer are utilized uniformly among all section corresponding to beats.

$$\alpha_i^C = softmax\left(V_{bs}\tanh\left(B_{bs}\overline{bs}_i^C + bs_{bs}\right)\right) \quad (1)$$

$$BE_i^C = \sum_{K=1}^{\bar{L}} \alpha_{i,K}^C \overline{bs}_{i,K}^C \quad (2)$$

V_{bs}, B_{bs}, bs_{bs} are beat-level attention metrics are acquired by training. This α_i^C represents the attention level of the ith beat fragment in a heart rhythm signal for Cth channel. The contextual vector BE_i^C represents the beat fragment in a heart rhythm signal in the Cth channel. Rhythm context vector BE_i^C is a weighted total $\overline{bs}_{i,K}^C$ with weights are determined by attention level $\alpha_{i,K}^C$.

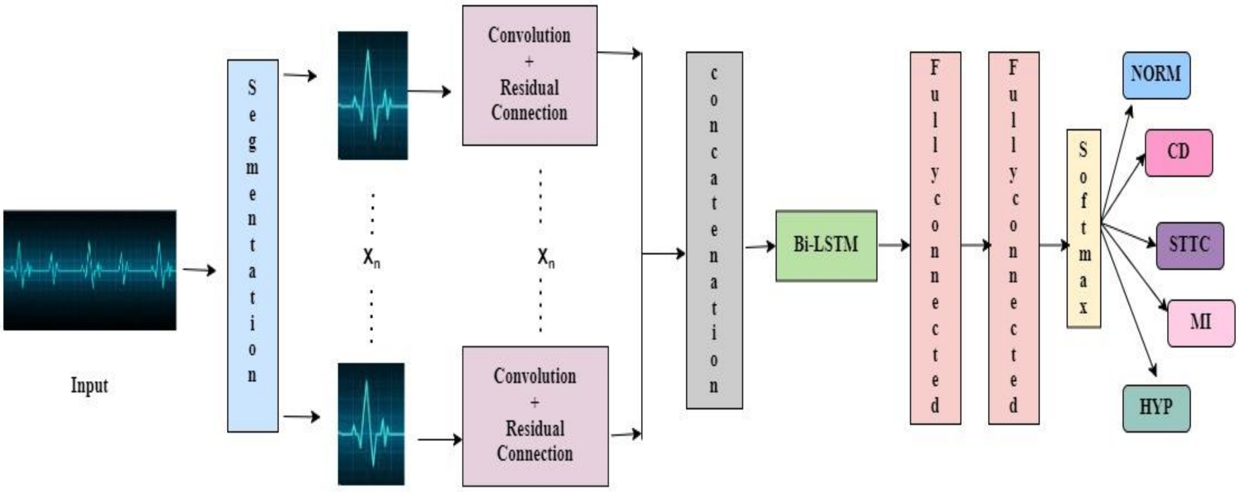

Figure 1. A framework design for the flow of work

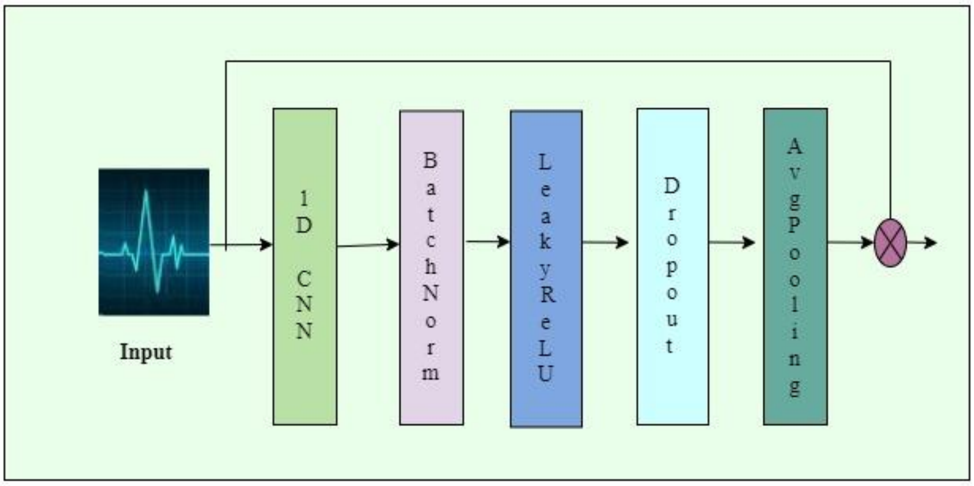

Figure 2. The structural framework of CNN is utilized at the beat level

The cardiac beat levels block the processing of the incoming ECG signal, which consists of multiple beat fragments. It has two layers: an attention layer at the rhythm level and a BI-LSTM. The use of BI- LSTM is based on its ability to handle the forward as well as backward directions for a sequence of input data.

$$\beta^c = softmax(V_R \tanh(B_R R^C + bs_r)) \quad (3)$$

$$RL^c = \sum_{k=1}^{n} \beta^c{}_k R^c{}_k \quad (4)$$

The Bi-LSTM receives a series of heartbeat contextual vectors BE_i^C for the Cth channel using W beat patterns as input. The Bi-LSTM concatenates both the forward and backward hidden states for the present stage i to produce the output $R^c{}_i$. The Bi-LSTM results R^C for the Cth channel, which has an order length of W, will be handled by a rhythm attention phase. This rhythm attention mechanism recognizes significant beat portions in an ECG rhythm by assigning more attention score.

There are multiple ECG channels, and the channel-level block processes the data from each. Each ECG channel has unique data. Only a small number of channels may have the specific data needed to make a diagnosis. We require a system to prioritize channels based on their relevance to specific aspects of exact heart conditions, rather than treating every channel similarly. This model utilizes a channel-level attention system that takes inputs (RL^1, RL^2,... RL^c... RL^Z), where Z represents the total no. of channels in Heart rate monitoring. Calculating channel-level attention scores is analogous to rhythm-level scoring by using equations 5 and 6.

$$\gamma = softmax\left(V_C \tanh(B_C RL^c + bs_C)\right) \quad (5)$$

$$ch = \sum_{k=1}^{m} r_k RL^c{}_k \quad (6)$$

4. Results & Discussions

The experimental setup involves the PTB-XL dataset, which contains 21,837 12-lead ECG recordings from 18,885 patients, categorized into five diagnostic groups. Data preprocessing includes down-sampling to 100 Hz, normalization, and segmentation into individual heartbeats. The CR+Bi-LSTM model combines CNNs with residual connections for spatial feature extraction, Bi-LSTM for temporal pattern analysis, and attention mechanisms at beat, rhythm, and channel levels. An 80:20 split is used for training and testing, with the model trained using the Adam optimizer and categorical cross-entropy loss. Metrics such as accuracy, precision, recall, and F1-score are used to evaluate performance, with implementation conducted using TensorFlow/Keras on high-performance.The data set is divided into 80% training as well as 20% testing. We used attention scores to analyze the model's performance the beat, rhythm, and channel levels. The training sets used to evaluate the model are grouped based on a single relative of pathologies; this training data is unsuitable for validating the findings at the channel level. The grouped ECG recordings being evaluated do not contain sufficient difference in abnormal heartbeat traits among various channels. To validate channel-level interpretations, we specifically selected a pair of sub-diagnostic illnesses of MI, which are ASMI (Anteroseptal Myocardial Infarction) and IMI (Inferior Myocardial Infarction), as well as NORM (normal) ECG recordings. We excluded the other variants of MI because of the limited no.of available ECG recordings for these particular subcategories.

4.1 Evolution Metric

Table 4 represent the no.of incorrected prediction made by the classifier, this confusion matrix summarizes the model's classification performance by mapping actual ('Disease'/'Non-Disease' rows) against predicted labels (columns).

Table 4. Confusion Matrix's

Actual	Predicted	
	Disease	Non-Disease
Disease	D11	D12
Non-Disease	D21	D22

It quantifies True Positives (D11/TP), False Negatives (D12/FN), False Positives (D21/FP), and True Negatives (D22/TN). These core counts are directly used to calculate essential performance metrics such as Accuracy, Precision, Recall, Specificity, and F1-score, evaluating both correct predictions and specific error types from Equations 7 to 12.

$$True\ Disease = \frac{D11}{D11+D12} \tag{7}$$

$$False\ Disease = \frac{D21}{D21+D22} \tag{8}$$

$$Accuracy = \frac{D11+D22}{D11+D12+D21+D22} \tag{9}$$

$$precision = \frac{D11}{D11+D21} \tag{10}$$

$$\text{Recall} = \frac{\text{D22}}{\text{D12+D22}} \tag{11}$$

$$F1-Score = 2\left(\frac{precision \times recall}{precision+recall}\right) \tag{12}$$

Table 5. Performance metrics of LSTM

Class	Precision	Recall	F1Score
NoRM	76	78	82
MI	84	84	84
STTC	88	89	89
HYP	90	91	91
CD	94	93	94

Table 5 represents The performance of a classification model is often evaluated using metrics such as precision, recall, and F1 score across different classes. In this particular study, the model's performance across various courses is presented. For the class "NoRM," which likely represents normal heart rhythm, the model achieved a precision of 76%, recall of 78%, and an F1 score of 82%. Moving to the class "MI" (Myocardial Infarction), the model demonstrated improved performance with a precision, recall, and F1 score of 84%. Similarly, for "STTC" (Suspected Transient Tachycardia), the precision, recall, and F1 score were higher at 88%, 89%, and 89%, respectively. The class "HYP" (Hypertension) showed further improvement, with precision, recall, and F1 score reaching 90%, 91%, and 91%, respectively. Finally, for the class "CD" (Cardiomyopathy), the model achieved the highest performance metrics, with a precision of 94%, recall of 93%, and an F1 score of 94%. These results indicate that the model exhibits strong predictive capabilities across various cardiac conditions, with particularly notable performance in detecting cardiomyopathy.

Table 6 represents the model's performance across different cardiac conditions was evaluated using precision, recall, and F1 scores. For "NoRM" (Normal Rhythm), precision was 74%, recall was 87%, and F1 score was 81%. "MI" (Myocardial Infarction) had precision of 84%, recall of 85%, and F1 score of 83%. "STTC" (Suspected Transient Tachycardia) showed 89% precision, 84% recall, and 88% F1 score. "HYP" (Hypertension) had 94% precision, 81% recall, and 92% F1 score. Lastly, "CD" (Cardiomyopathy) demonstrated 96% precision, 89% recall, and 93% F1 score. These results indicate the model's ability to accurately identify various cardiac conditions, with particularly strong performance in detecting cardiomyopathy.

Table 6. Performance metrics of RNN

Class	Precision	Recall	F1Score
NoRM	74	87	81
MI	84	85	83
STTC	89	84	88
HYP	94	81	92
CD	96	89	93

Table 7. Performance metrics of Bi-LSTM

Class	Precision	Recall	F1Score
NoRM	83	92	86
MI	91	88	93
STTC	93	90	95
HYP	95	96	97
CD	97	95	91

The table 7 shows Bi-LSTM performance at filter size 3, From table 4,5,6 give that Bi-LSTM achieved the highest accuracy (95.34%), precision (91.56%), recall (92.99%), and F1-score (93.67%), showcasing its robust handling of sequential ECG data and balanced performance across metrics. In comparison, LSTM delivered moderate results with accuracy at 89.63%, precision at 88.0%, recall at 85.35%, and F1-score at 86.76%, indicating less effective management of false positives and negatives. RNN underperformed with accuracy at 86.99%, precision at 85.0%, recall at 83.67%, and F1-score at 82.11%, reflecting its limitations in capturing temporal dependencies.

The integration of bidirectional processing, residual connections, and attention mechanisms makes Bi-LSTM the most reliable for multi-class ECG classification. when parameter tunned that is improve the filter size, we get little more improvement of the model performance. The filter sizes are 7, 9 and 11. Table 8 shows list the performance for all three classification the performance of Bi-LSTM at filter size 11 is best in terms of overall performance. When comparing the accuracy of the five classifiers, it becomes evident that Bi-LSTM with filter size 11 performs better than the others based on performance metrics.Different models combining convolutional and Residual (CR) were evaluated using various filter sizes. The CR+Bi-LSTM model consistently outperformed others, achieving the highest precision, recall, F1-score, and accuracy. As the filter size increased from 3 to 11, the model's performance improved steadily, indicating the effectiveness of larger filter sizes in capturing relevant features. Figure 3 & Figure 4 represents the code part.

4.2 Comparison with the existing work

The Comparison between the present and existing work in terms of overall accuracy the Table 9 shown below and Figure 3 represents the comparison of the accuracy. Several research groups have made significant advancements in recent studies focusing on cardiovascular disease (CVD) detection and diagnosis. Reddy et al. achieved an accuracy of 88.46% using the PTB-XL dataset. Similarly, Śmigiel et al. reported an accuracy of 87.89% also utilizing the PTB-XL dataset [42]. Tiwari et al., on the other hand, employed multiple datasets including Cleveland, Hungarian, Switzerland, and Long Beach, achieving an impressive accuracy of 92.34% [43]. Alqahtani et al. tackled CVD detection using the Kaggle dataset, achieving an accuracy of 88.70% [44]. Sinha et al. reported a noteworthy accuracy of 93.0% using the PTB-XL dataset. Our model, CR+Bi-LSTM, notably surpassed previous efforts, achieving the highest accuracy of 95.34% on the PTB-XL dataset. These findings underscore the progress made in CVD detection, with our model demonstrating promising potential for clinical applications.

5. Conclusion

In this study is the CR+Bi-LSTM, a hybrid approach that combines convolutional networks with residual connections and bidirectional long short-term memory (Bi-LSTM) networks. This integration leverages the strengths of both components: the convolutional layers effectively capture spatial features, while the residual connections enhance gradient flow during training, mitigating issues like vanishing gradients.

Table 8. Comparison the overall performance of classifiers

Model/metrics	Filter size	Precision	Recall	F1 -Score	Accuracy
CR+LSTM	3	88.0	85.35	86.76	89.63
CR+RNN	3	85.0	83.67	82.11	86.99
CR+Bi-LSTM(proposed Model)	3	90.0	87.98	89.93	91.12
CR+Bi-LSTM	7	91.0	89.99	90.33	92.0
CR+Bi-LSTM	9	90.23	91.08	91.82	93.11
CR+Bi-LSTM	11	91.56	92.99	93.67	95.34

Table 9. Comparison with existing benchmark datasets

Reference	Dataset	Method	Accuracy
Reddy, L., [45]	PTB-XL	Ensemble classifiers(Extra Tree,XGBoost,RF)	88.46
Śmigiel, S.*et.al* [42]	PTB-XL	Ensemble classifiers majority of voting	87.89
Hannun,A *et.al* [46]	Cardiologist-labeled test dataset	DNN	83.34
R. Banerjee *et.al* [47]	CVD from Kaggle	CNN+LSTM	93.00
Sinha, N..*et.al* [8]	PTB-XL	IMLE-Net	93.0
CR+Bi-LSTM(Proposed Model)	PTB-XL	CR+Bi-LSTM	95.34

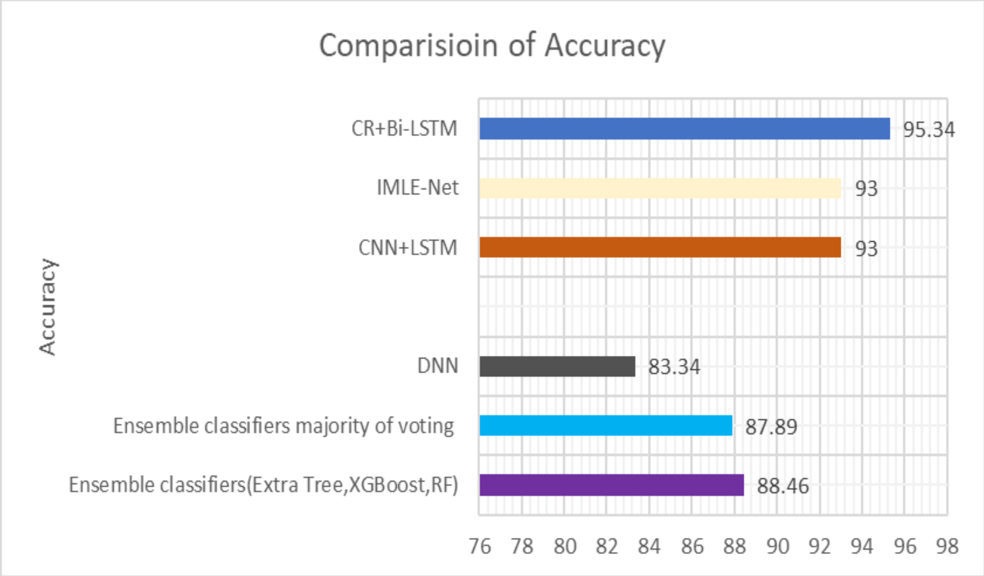

Figure 3. Comparison of Accuracy with Existing Models

The bidirectional LSTM, on the other hand, processes sequential data in both forward and backward directions, enabling the model to understand contextual information from both past and future inputs. This combination makes the CR+Bi-LSTM an optimal choice for tasks requiring robust feature extraction and temporal sequence modeling.The study employs the PTB-XL dataset, splitting it into 80% for training and 20% for testing, to evaluate the multi-classification of cardiovascular diseases (CVD) using 12-lead ECG signals. The target classes include myocardial infarction (MI), hypertension (HYP), ST-T changes (STTC), and conduction disturbances (CD). The analysis highlights a noticeable trend: increasing the filter size slightly enhances the classification accuracy. Among the five classifiers compared, the filter size of 11 demonstrated superior performance. The CR+Bi-LSTM model, in particular, outperformed the others, achieving an accuracy of 95.34%, precision of 91.54%, an F1-score of 93.67%, and a recall of 92.99%. These results underline the model's effectiveness in accurately identifying and classifying CVDs. The findings also suggest potential future directions, such as investigating the applicability of 1-lead and 3-lead ECG data for predicting cardiovascular diseases, which could offer more accessible and cost-effective diagnostic solutions.

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Kamepalli S L Prasanna; Conceptualization, Methodology and Writing original manuscript. Nagendra Panini Challa: Writing original manuscript, Supervision. Jajam Nagarju: Formal Analysis and validation. Bollapalli Althaph: Formal Analysis and validation. Rachakonda Subba Rao: Writing, review and editing. Venkata Sasi Deepthi Ch: Writing, review and editing. Beebi Naseeba: Writing, review and editing. All the authors read and approved the final version of the manuscript.

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The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Data Availability

The datasets mentioned in this paper are publicly accessible in the open-source framework, with supporting files accessible in https://physionet.org/content/ptb-xl/1.0.3/

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