Hybrid Deep Learning Models for Accurate ECG Classification in Cardiovascular Disease Diagnosis

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ABSTRACT

Electrocardiograms (ECGs) are very important for diagnosing Cardiovascular Diseases (CVDs) because they record important information about the electrical activity of the heart. As CVDs are so common and fatal, it is very important to predict them promptly using ECG signals. This study suggests a new type of hybrid deep learning architecture called CRNN (Convolutional Recurrent Neural Network), which combines the ability of CNNs to extract spatial features with the ability of LSTMs to model temporal one. The MIT-BIH Arrhythmia Database was used to train and test the model in classifying ECG beats. The proposed model uses convolutional operations, LSTM state transitions, and a softmax classification function. The CRNN does better than CNN or LSTM models on their own, with high classification accuracy and low false positive rates. This study shows that hybrid deep models can be used for robust ECG analysis and clinical decision support systems.

Keywords—Convolution Neural Network (CNN); Electrocardiograms (ECGs); Cardiovascular Disease (CVD); Long Short-Term Memory (LSTM); Recurrent Neural Networks (RNNs)

I. INTRODUCTION

Affecting 17.9 million people in 2016, Cardiovascular Diseases (CVDs) [1] is the leading cause of death worldwide. To improve patient outcomes, save lives, and reduce suffering, early identification and an accurate prognosis are essential [2]. Improvements in Deep Learning (DL) and artificial intelligence (AI) have allowed the automatic and more accurate interpretation of ECGs as complex cardiac signals, therefore increasing their use in predictive diagnosis [3, 4].

The early and accurate diagnosis of CVDs depends on reliable prediction tools to prevent strokes and heart attacks [5]. Using predictive models, therapies for each patient can be tailored to their risk profiles, optimizing the management of healthcare resources and improving patient outcomes [6]. By managing complicated high-dimensional data such as ECG

signals, DL can greatly help medical diagnosis. Often surpassing traditional methods and human specialists, models such as Convolutional Neural Networks (CNNs) automatically extract pertinent features from raw ECG data [7, 8].

Using MIT-BIH database ECG data, this study assessed and tested several DL algorithms for their ability to predict CVDs. The findings indicate that LSTMs and CNNs can precisely predict the onset of CVDs [3, 5]. However, significant constraints still exist in the form of interpretation issues, possible dataset biases, and problems including several data sources [8, 9]. ML applications for early CVD prediction and risk assessment have to be continuously investigated to be improved [10]. With CNNs being the most frequent method, DL is often used to find abnormalities in ECG signals [3, 4, 6]. Still, problems such as reliance on particular datasets, lack of openness, great computational needs, and the possibility of overfitting remain.

The diagnosis of CVDs depends on a crucial first step: the classification of ECG data. Dummy classifiers, linear discriminant analysis, logistic regression, random forests, and Gaussian Naïve Bayes are among ML classifiers used for this purpose. The efficacy of these algorithms varies greatly with the amount and quality of the ECG data. In addition, some models have low interpretability, which complicates clinical decision making.

Given interpretability issues and the lack of trained professionals, ECG-based heart disease diagnosis especially benefits from Interpretable Machine Learning (IML) models [8]. In [9], the deep convolutional neural network SEER achieved an AUC of 0.83 for 5-year mortality. However, its accuracy might change depending on patient demographics and ECG acquisition settings, necessitating more validation for general use.

Silent heart attacks are a major diagnostic difficulty due to their asymptomatic presentation. Poor feature selection causes many current prediction techniques to fail. In [10], a CNN architecture was suggested for silent heart attack classification to solve this problem, stressing the management of class imbalances. In [11], a Deep CNN and LightGBM (LGBM) model assessed heart failure risk from ECG data, achieving an AUC of 0.756, with performance increasing to 0.818 when combined with other risk factors. The range was restricted to baseline data from 1987–1989 and excluded those with current heart failure. In [12], ML algorithms, including CNN, SVM, KNN, Naïve Bayes, and Random Forest, were used for CVD detection using ECG images, with CNN achieving 94.1% accuracy. Most studies emphasise accuracy, sensitivity, and specificity while ignoring other performance measures, such as robustness or interpretability.

In [13], a MobileNet v2-based deep neural network used Single Shot Detection (SSD) on 12-lead ECG images, achieving 98% accuracy in detecting several cardiac anomalies. However, the training dataset might not be sufficiently varied, limiting real-world generalizability. On standard datasets, such as MIT-BIH and PTB-ECG [14, 15], ensemble techniques such as GAN-LSTM combinations outperformed single-model baselines. These studies, however, are frequently lacking in-depth analysis of the effects of unbalanced data and associated biases. In [16], single-lead ECG classification was improved by combining several leads, with lead-aVR and II performing the best. However, a dataset from one medical center could restrict outside validity.

In [17], a comparative assessment of DL algorithms for CVD risk prediction examined the Radial Basis Function Network (RBFN) and wekaDeeplearning4j. Other studies have examined different techniques, such as infinite feature selection, Recurrence Quantification Analysis (RQA), and the application of MLP and ExtraTrees classifiers, achieving great accuracy and sensitivity [18-22]. In [23], ECG signals were processed with transfer learning, using a pretrained CNN on ImageNet, achieving good results in arrhythmia classification.

Many studies have highlighted the need for more clinical validation, better model interpretability, and the importance of strong and varied datasets [6, 8, 10]. Although DL models predict CVD based on ECG with great accuracy, their clinical use requires addressing ethical issues, integration with current healthcare infrastructure, and consistency of performance between different populations [14, 24]. In [25], a hybrid DL model combined Bi-LSTM and CNN for precise CVD prediction. This model used ECC-based Diffi-Huffman encryption for safe data transfer and hybridized swarm optimisation to improve performance. High accuracy (97.716%) and good sensitivity and specificity metrics were achieved. However, its complexity increases computational needs and its understanding is poor. Security overhead and data dependency also create difficulties. For real-world deployment, real-world clinical validation and scalability require more investigation.

II. PROPOSED METHOD

The system architecture, as shown in Figure 1, provides module-specific details about the proposed model. It encompasses various processes such as data collection, preprocessing, model training and building, as well as model evaluation and performance analysis.

A. Dataset Description

This study uses the publicly available MIT-BIH Arrhythmia Database, provided by PhysioNet [26]. It includes 48 half-hour two-channel ambulatory ECG recordings from 47 subjects, sampled at 360 Hz with 11-bit resolution over a 10 mV range. It also includes annotations by expert cardiologists for beat types and arrhythmia episodes. The labels show which kinds of arrhythmias and other cardiac events are present in each record in the collection.

B. Preprocessing

Before training DL models, the data underwent a series of preprocessing steps:

- Noise Reduction: Filtering methods eliminated artifacts such as baseline noise and powerline interference.
- Normalization: The signals were normalized to ensure that all ECG samples had the same amplitude ranges.

- Segmentation: Continuous ECG recordings were split into windows of set length to generate input samples for the models.

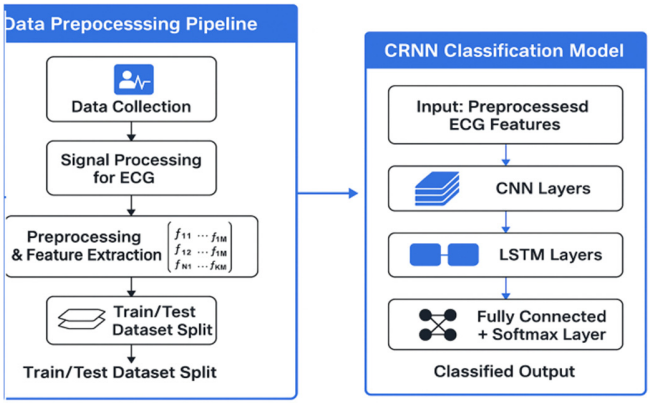

Fig. 1. Architecture of the proposed method.

C. Model Training and Building - CRNN (CNN + LSTM) Architecture)

The proposed CRNN is described in the following steps. The data input consists of ECG segments, which are provided as a two-dimensional array with the dimensions *segment_length* and *number_of_segments*.

1) Step 1: Extract features using convolutional layers.

Use a set of filters (f_1) with sizes (*filter_height*, *filter_width*) to apply the first convolutional layer. Appropriate stride and padding are used to keep the output size constant. A Rectified Linear Unit (ReLU) activation function is used to add non-linearity to the output step by step. The feature maps are downsampled using a max-pooling layer to reduce the dimensionality while maintaining significant characteristics. The number of filters (f_2, f_3, etc.) is gradually increased by repeating the convolutional, ReLU, and max-pooling procedures with additional convolutional layers. This approach may capture more intricate spatial patterns in the ECG data.

Given an input signal x and kernel/filter w, the 1D convolution operation is described as:

$$(y * w)[i] = \sum_{j=0}^{k-1} x[i+j].w[j] \quad (1)$$

The output of this step is a spatially reduced 3D tensor of feature maps.

2) Step 2: Reshape for LSTM (Temporal Sequence Creation)

This step reduces the 3D tensor of feature mappings to a 2D sequence that the LSTM layers can understand. Specifically, the reshaped data are represented as (*time_steps*, *feature_dimension*), where *time_steps* represents the number of segments (the temporal dimension), and *feature_dimension* represents the flattened spatial characteristics obtained by the CNN. The output is a two-dimensional series that depicts the change in spatial characteristics over time.

3) Step 3: LSTM Layers (Temporal Dependency Learning)

The reshaped sequence is processed through one or more layers of LSTMs, designed to capture long-term relationships within the temporal sequence. Each LSTM layer processes the sequence step-by-step, maintaining a hidden state containing information from previous time steps.

To enhance generalizability and avoid overfitting, dropout is added to the LSTM layers. LSTM updates are governed by:

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f \quad (2)$$

$$i_t = \sigma(W_f.[h_{t-1}, x_t] + b_i \quad (3)$$

$$\hat{C}_t = \tanh(W_C.[h_{t-1}, x_t], b_C \quad (4)$$

$$C_t = f_t * C_{t-1} + i_t * \hat{C}_t \quad (5)$$

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o \quad (6)$$

$$h_t = o_t * \tanh(C_t) \quad (7)$$

The last hidden state or LSTM output sequence contains the learnt temporal dependencies.

4) Step 4: Fully Connected (Dense) Layers

This step incorporates the characteristics learned by the CNN and LSTM components by passing their output through one or more dense layers that are completely linked. Non-linearity is incorporated by using a ReLU activation function after each dense layer. To avoid overfitting, dropout can be used between dense layers. The output is a feature vector that contains the integrated spatial and temporal data retrieved from the ECG.

5) Step 5: Output Layer (Classification)

The output layer assigns probability scores for each class by passing the final feature vector through an activation function. This layer produces the anticipated class labels, which indicate the presence or absence of various CVDs. For multi-class classification, a softmax layer can be used:

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_i}} \quad (8)$$

This layer outputs the type of CVD predicted by labels or class probability.

6) Step 6: Training and Optimization

This study employed categorical cross-entropy as the loss function because the classification task involved multi-class labels for different ECG beat types (e.g., N, L, R, A, V). Categorical cross-entropy effectively penalizes incorrect predictions across multiple classes and works well with softmax outputs.

In addition, the Adam optimizer was used with a learning rate of 0.001, selected for its efficient convergence and adaptive learning rate capabilities. To further reduce overfitting, L2 regularization and dropout (rate = 0.4) were applied to both CNN and LSTM layers. The model was trained for 50 epochs with early stopping based on validation loss.

D. Model Training and Evaluation

The study uses optimization techniques and parameters such as backpropagation to separate data into training, validation, and testing sets. Overfitting is avoided through regularization. In order to identify the most effective approach

for clinical applications, the study evaluated deep learning architectures for ECG-based CVD prediction.

III. RESULTS AND DISCUSSION

Figure 2 illustrates how various forms of noise and artifacts in the raw ECG signal may obscure the cardiac information. Due to these noise sources, the raw ECG signal plot may display noticeable oscillations and non-linearities. Important cardiac diagnostic signals, such as QRS complexes, P-waves, and T-waves, could be distorted or obscured by background noise.

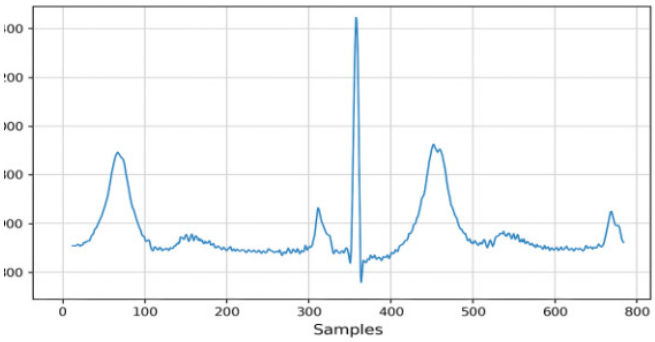

Fig. 2. Sample ECG signal before preprocessing.

The waveform of the denoised and normalized ECG is more apparent and distinct, with QRS complexes, P-waves, and T-waves standing out, as shown in Figure 3. With little baseline drift, the signal seems more regular and smoother. DL models enable improved feature extraction by accurately representing the essential properties of the ECG, such as the amplitude and length of the QRS complex.

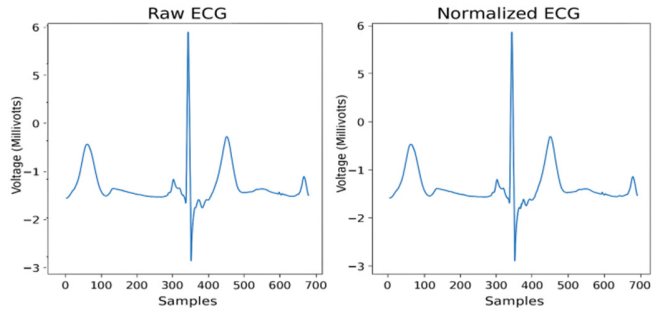

Fig. 3. Sample ECG signal after denoising and normalization.

Figure 5 shows a variety of ECG beat types, including Normal (N), Left Bundle Branch Block (L), Atrial Premature (A), Right Bundle Branch Block (R), and Premature Ventricular Contraction (V). The Left Bundle Branch Block Beat (L) is characterized by a widened QRS complex due to a blockage in the channel that supplies electrical impulses to the left side of the heart, whereas the Normal Beat (N) plot shows a regular heartbeat free of abnormalities. An abnormally early heartbeat is indicated by an irregularly shaped premature P-wave on the Atrial Premature Beat (A) plot.

Similarly to the L plot, the Right Bundle Branch Block Beat (R) plot shows an M-shaped QRS complex that affects the right side of the heart. An ectopic ventricular focus is indicated by an irregular heart rhythm with an abnormally broad QRS complex and no P-wave on the Premature Ventricular Contraction Beat (V) plot.

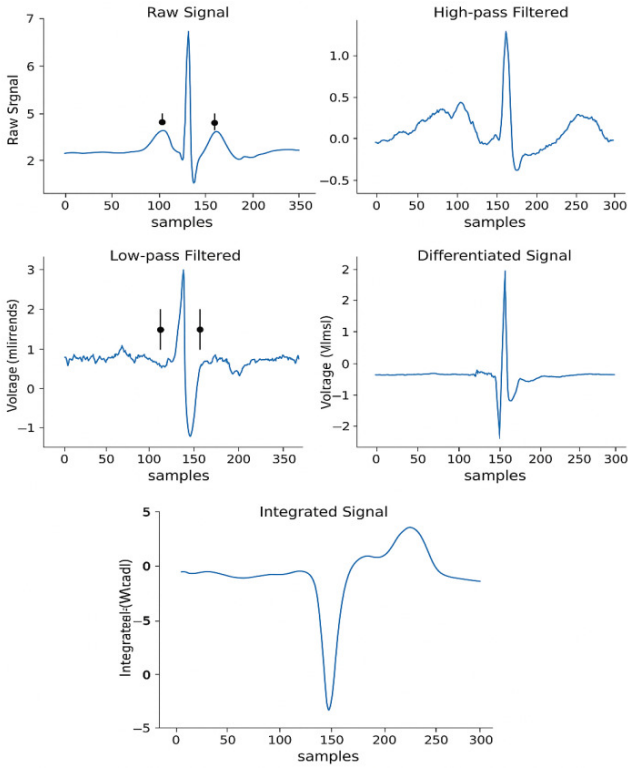

Fig. 4. ECG Beat types: N-type, L-type, R-type, A-type, and V type.

TABLE I. ECG BEAT TYPE DISTRIBUTION BEFORE RESHAPING

Beat Type	Count	Percentage
N	75000	72.2
L	8000	7.7
R	6500	6.3
A	6200	6.0
V	7500	7.8

TABLE II. ECG BEAT TYPE DISTRIBUTION AFTER RESHAPING (BALANCED)

Beat Type	Count	Percentage
N	12000	20.0
L	12000	20.0
R	12000	20.0
A	12000	20.0
V	12000	20.0

Tables I and II show the distribution of the types of ECG beats before and after data reshaping. These tables illustrate how data preprocessing impacts beat distribution and model training by displaying the percentage of each beat before and after the data was reshaped. With more data from minority

classes and less from majority classes, the reshaped chart depicts the beat distribution of the dataset.

Figure 5 shows the accuracy of the model on both the training and the test datasets. Figure 6 shows the loss graph, an essential tool for evaluating a model's performance on both training and test datasets that points out possible problems such as under- or overfitting. Figure 7 evaluates the accuracy of the proposed CRNN model, showing CVD predictions in a confusion matrix. This matrix contrasts the actual classes with the expected ones. The results clarify the capacity of the model to distinguish between several ECG beat categories.

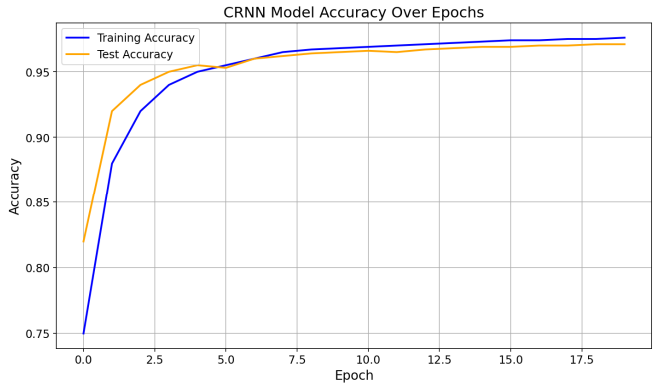

Fig. 5. CRNN model accuracy

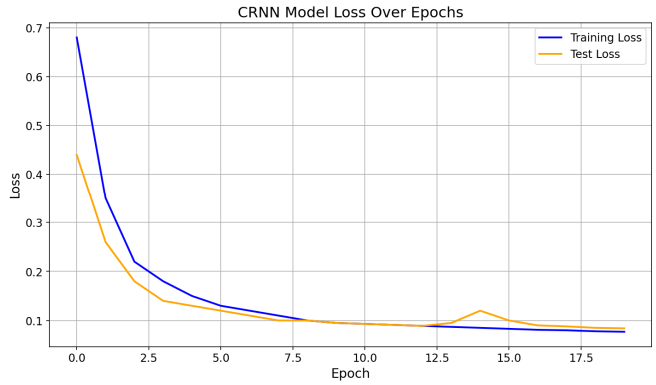

Fig. 6. CRNN model loss.

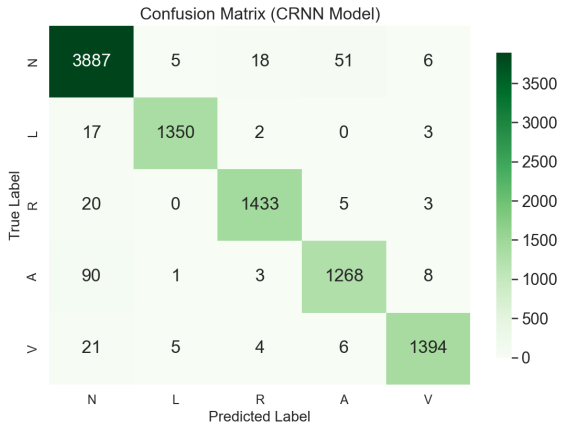

Fig. 7. Confusion matrix

IV. CONCLUSION

This paper presents a new hybrid CRNN architecture that combines convolutional layers with LSTM units to accurately classify ECG beats. The proposed model can learn both spatial and temporal features from ECG data, making it very accurate in predicting different types of CVD, including PVC, LBBB, and APB. The proposed method differs from previous works by emphasizing a well-engineered and scalable data preprocessing pipeline. First, band-pass filtering (0.5-40 Hz) was applied to eliminate baseline noise and powerline interference, preserving diagnostic features such as QRS complexes. Next, z-score normalization was applied to stabilize signal amplitudes across patients. Sliding window segmentation was implemented with overlap, ensuring that temporal transitions are not lost during fixed-length input slicing. Finally, the class imbalance problem was addressed by performing SMOTE-like oversampling for minority classes (A, R, L, V) and under-sampling the overrepresented normal (N) class. This balanced class representation improved model generalization and reduced the bias often observed in arrhythmia classification tasks.

These steps, although often overlooked, are essential for reproducibility and clinical scalability. The results on the MIT-BIH dataset show that generalization is better and overfitting is less. This study adds a model to predict CVD risk in the real world that is easy to understand, works well on computers, and is useful in clinic settings. However, more research is needed, using attention-based methods and larger and more diverse datasets.

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