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Deep Learning Techniques to Detect Coronary Artery Disease by Analyzing the ECG Signal

Avishek Choudhury

Department of Computer Science, New Alipore College, Kolkata, WB, India

avishek.nac.cs@gmail.com

ABSTRACT: Coronary artery disease (CAD), which restricts blood flow to the heart muscle and may result in a myocardial infarction, or heart attack, is brought on by plaque accumulation on the inner lining of the coronary arteries. An essential tool for evaluating heart function is the electrocardiogram (ECG). However, because ECG signals are inherently complex and exhibit nonlinear and nonstationary patterns, disease signs can appear in unexpected ways. This makes it challenging and prone to error to manually recognize irregular heartbeats. To address these issues, automated diagnostic methods have been developed. By examining ECG signal segments, convolutional neural networks (CNNs) have shown potential in detecting CAD symptoms. These deep learning algorithms are quite good at distinguishing between normal and abnormal cardiac rhythms by gathering complex morphological components from ECG data. Additionally, by combining CNNs with Long Short-Term Memory (LSTM) networks, performance is enhanced, leading to a hybrid CNN-LSTM framework that can more precisely and successfully classify cardiac abnormalities.

I. INTRODUCTION

Cardiovascular diseases (CVDs) are a major cause of death, accounting for 31% of all deaths globally in 2016 [1]. Coronary artery disease (CAD) is one type of CVD that affects millions of people every year. CAD is brought on by the accumulation of cholesterol and other fatty substances on the inner walls of coronary arteries over time [19]. This limitation of normal blood flow to the coronary arteries may cause a stroke or severe cardiac arrest [20]. Coronary angiography, an invasive procedure that requires hospitalization, is the gold standard for diagnosing CAD [21]. Early detection can often prevent the deadly consequences of many life-threatening CVDs. For the treatment of the elderly population, where the doctor-to-patient ratio is below optimal, interest in AI-based screening systems is consequently rapidly growing in both industrialized and developing nations. These screening instruments need to be low-cost, non-invasive, and require the least amount of clinician involvement. However, the subject of non-invasive CAD diagnosis remains unanswered.

Despite the fact that CAD is often asymptomatic in its early stages, the existing research has discovered several non-specific biomarkers. Many consider Heart Rate Variability (HRV) to be an important surrogate indicator [2, 3, 4, 5]. Numerous studies have shown that individuals with CAD had lower and more irregular heart rate variability (HRV) than those without the condition. HRV may be accurately computed from the electrocardiogram's (ECG) waveform. A typical ECG cycle consists of three primary components, as seen in Fig. 1. The P wave represents the depolarization of the atria, the QRS complex represents the depolarization of the ventricles, and the T wave represents the repolarization of the ventricles. The PR interval measures how long it takes an electrical impulse to travel from the sinus node through the AV node. The ST segment measures how long it takes for the ventricles to depolarize and repolarize. The distance between the R peaks indicates the heart rate.

Dua et al. [5] proposed novel HRV features based on Poincare plots, recurrence plots, and de-trended fluctuation analysis of the RR intervals to categorize CAD. The non-linear dynamics of the ECG were studied in [6]. The study in [2] revealed a noteworthy distinction between CAD and non-cardiac participants in terms of the average

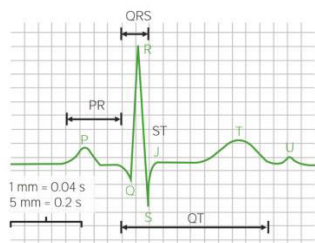
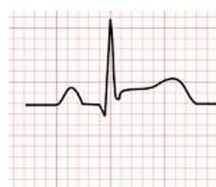


Fig. 1: Components of ECG [1]



(a) ST elevation



(b) ST depression



(c) T wave inversion

Fig. 2: Morphology changes in ECG cycles due to CAD [1]

heart rate and standard deviation of the RR intervals. Another approach [7] employed discrete wavelet transform, discrete cosine transform, and empirical mode decomposition on ECG beats for HRV. However, abnormal HRV may be associated with a range of clinical conditions that are not cardiac in character, such as mental stress.

Morphological alterations in the standard ECG pattern have been discovered as another sign of CAD [22]. As Fig. 2 shows, the changes take place in terms of T wave inversion, ST depression, or ST elevation myocardial infarction (STEMI) [1], [8], and [9]. However, because they are sporadic markers, they cannot be guaranteed at every stage of CAD. Moreover, computing such features on noisy ECG signals is challenging. Because of this, the great majority of AI methods now in use look for CAD in HRV. Recently, deep learning applications in biomedical engineering have become more common [23]. In these applications, relevant information is automatically extracted from the raw signal by a deep architecture. Such techniques have been successfully used to identify arrhythmias and atrial fibrillation, where the biomarkers are well-known and prominent in the input [24]. Using medical domain knowledge, two non-specific surrogate CAD markers are proposed: irregular HRV and abnormal ECG shape [25]. The markers complement each other in terms of CAD detection sensitivity and specificity, increasing the overall accuracy of a screening system.

A Convolutional Neural Network (CNN) structure is recommended for efficient morphological feature extraction from ECG. A hybrid CNN-LSTM framework and manually created features are used to merge the two distinct CAD markers into a single architecture for sickness categorization. An HRV-related algorithm for picking pertinent hand-crafted attributes. A pre-processing technique is also needed to extract time series from digital ECG images that can be clinically evaluated and recorded by an inexpensive, commercially available ECG sensor.

II. LITERATURE REVIEW

Numerous automated algorithms have been developed over time to categorize ECG and heart rate data in order to detect myocardial infarction (MI) and coronary artery disease (CAD).

Higher Order Statistics and Spectra (HOS) were first used by Acharya et al. [10] to automatically distinguish between ECG signals that are normal and those that are impacted by CAD. In order to reduce dimensionality, the collected characteristics were subsequently analyzed using Principal Component Analysis (PCA). To attain the best classification accuracy, these ranked features were assessed using k-Nearest Neighbors (KNN) and Decision Tree (DT) classifiers. The Coronary Artery Disease Index (CADI), an integrated measure, was also created to offer a single-value representation for differentiating between ECG recordings that are healthy and those that are impacted by CAD.

An accurate, effective, and totally automated method for the non-invasive identification of coronary artery disease using ECG data was developed by Kumar et al. [11]. The first step in the procedure is to separate the ECG signals into distinct heartbeats. The Flexible Analytic Wavelet Transform (FAWT), which divides the signal into approximation and detail coefficients, is then used to evaluate each segmented beat. Cross Information Potential (CIP) features are extracted from the detail components. Lastly, a classifier based on the Least Squares-Support Vector Machine (LS-SVM) architecture is trained using these features. For best results, both Radial Basis Function (RBF) and Morlet wavelet kernels are utilized.

A Convolutional Neural Network (CNN) model was presented by Reasat et al. [12] in order to categorize raw ECG signals from leads II, III, and AVF and differentiate between cases of inferior myocardial infarction (IMI) and normal

cardiac function. The efficacy of the model was evaluated by comparing IMI and healthy recordings using data from the Physikalisch-Technische Bundesanstalt (PTB) database. A subject-oriented testing approach was used to assess the model's generalizability across many individuals. This involves training the network using data from all patients but one, and then testing it on the data from the omitted patient. The model's performance was compared to current state-of-the-art techniques using this tactic.

For usage with wearable ECG monitors that record data from a single lead, Lui et al. [13] presented a myocardial infarction (MI) classification model that combines convolutional and recurrent neural network components. The system can efficiently discriminate between ECG data from MI patients, healthy people, those with chronic heart diseases, and even recordings impacted by noise interference thanks to its multiclass classification capabilities.

Using a hybrid deep learning architecture that combines a 16-layer Convolutional Neural Network (CNN) with an LSTM network, Feng et al. [14] presented an automated classification technique for single-lead myocardial infarction ECG signals. Preprocessing the raw ECG data to separate distinct heartbeat segments is the first step in the procedure. After that, these segments are given into the CNN-LSTM model, which classifies myocardial infarction signals and automatically extracts pertinent features.

The multiple-feature-branch convolutional bidirectional recurrent neural network (MFB-CBRNN), a sophisticated hybrid architecture, was presented by Liu et al. [15] with the goal of identifying myocardial infarction (MI) from 12-lead ECG data. Convolutional and recurrent neural network components are combined in this model to capture all aspects of the data. A separate feature branch made up of several one-dimensional convolution and pooling layers processes each lead. A bidirectional long short-term memory (BiLSTM) network is then used to aggregate the outputs from these branches in order to efficiently capture temporal relationships across all leads.

Using a CNN-based classification model that processes ECG signals directly without transforming them into alternative representations like wavelet transforms or Mel-Frequency Cepstral Coefficients (MFCC), Avanzato et al. [16] provided a simplified method for automatic detection of cardiac conditions. This approach works just in the time domain, which streamlines the classification workflow. Three criteria were used to evaluate the system's efficacy: "normal rhythm," "atrial premature beat," and "premature ventricular contraction."

Darmawahyuni et al. [17] used deep learning, namely recurrent neural networks (RNNs) with long short-term memory (LSTM) units, to create a diagnostic framework. The goal was to create a model that could provide high diagnostic accuracy with automatically produced characteristics and little input data. ECG recordings from publicly accessible PhysioNet databases were used in the study. Twenty-four LSTM models were refined by carefully adjusting their hyperparameters in order to determine the optimal setup.

III. METHODOLOGY

As previously stated, this study assessed the effectiveness of automated ECG-based cardiac pathology classification systems using the PhysioNet database, a well-known benchmark dataset. This dataset was used to extract the neural network's training and testing data in order to evaluate its classification capabilities. The model showed good accuracy in differentiating between normal heart activity and two aberrant cardiac rhythms: premature ventricular contractions and atrial premature beats. Metrics such as sensitivity (true positive rate), specificity (true negative rate), false positive rate (Fall-Out), and total classification accuracy were obtained from the confusion matrix and used to evaluate performance, as described in [18].

As a result, the following interpretations might be made of each statistical indicator utilized for categorization evaluation: The percentage of ECG signals from a specific class that the model properly classified is known as sensitivity. The classifier's capacity to accurately identify ECG signals that do not belong to the target class is reflected in its specificity. The percentage of ECG recordings that are mistakenly classified as belonging to a class they don't truly belong to is known as the false positive rate, or fall-out. The false discovery rate, on the other hand, displays the percentage of signals that were incorrectly excluded from a category when they actually ought to have been.

As a result, the following interpretations can be made of each statistical indicator used to evaluate classification: Sensitivity is the percentage of ECG signals from a specific class that the model properly detected. The classifier's specificity indicates how well it can identify ECG signals that are not part of the target class. The *false positive rate (FPR)*, also known as fall-out, is the proportion of ECG recordings that are mistakenly classified into a class to which they do not truly belong. On the other hand, the *false discovery rate (FDR)* displays the percentage of signals that were incorrectly excluded from a category when they should have been included. *Recall*, also referred to as sensitivity, is the ratio of true positives to all actual positives (true positives plus false negatives), whereas precision is the ratio of correctly predicted positive cases (true positives) to the total number of predicted positives (true positives plus false positives). The *F1 score* provides a balanced metric that takes into account both precision and recall. The evaluation metrics' equations are given below.

$$TPR = \frac{TP}{TP + FN} \quad (1)$$

$$TNR = \frac{TN}{FP + TN} \quad (2)$$

$$FPR = 1 - TNR, \quad (3)$$

$$FDR = \frac{FP}{FP + TP} \quad (4)$$

$$F_1 = \frac{2TP}{2TP + FP + FN} \quad (5)$$

A hybrid neural architecture is shown that combines abnormal ECG morphology and unusual heart rate variability (HRV), two indirect markers of Coronary Artery Disease (CAD), into a single CNN-LSTM framework. Figure 3 shows the entire structure, with the output tensor dimensions shown in brackets. The three main parts of this model are (1) a CNN segment that extracts morphological features from ECG signals, (2) an LSTM segment that records temporal relationships within RR intervals, and (3) a collection of statistical features that are manually engineered and calculated from the RR intervals. An aggregated HRV vector is created by combining these manually created characteristics with the final hidden state from the LSTM. The CNN-generated feature map is then merged with this vector. In order to optimize for unified classification, the hybrid model that is produced is trained.

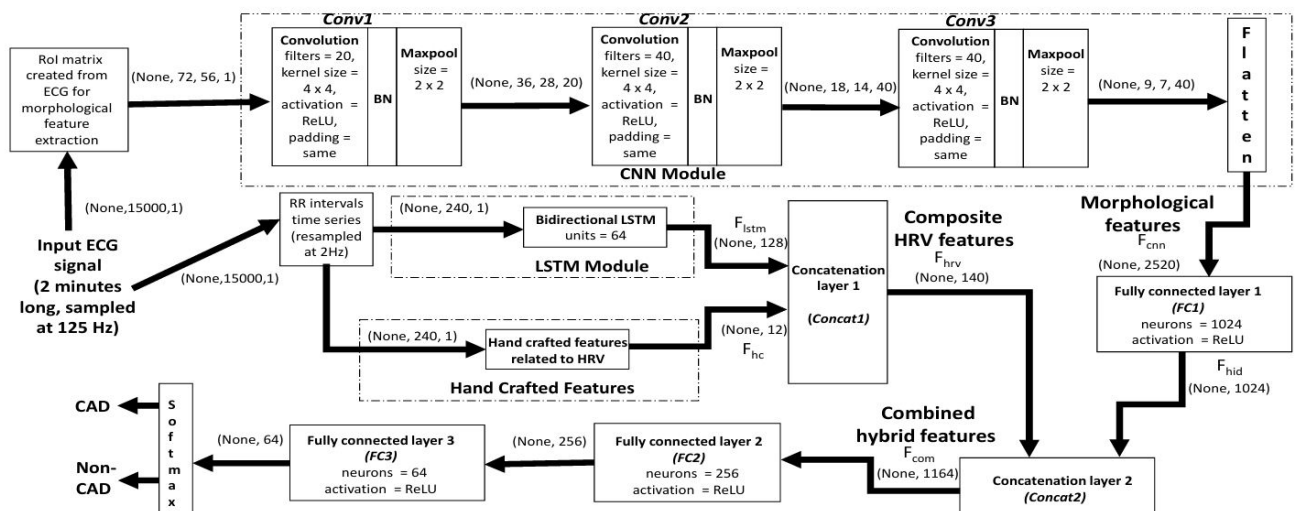


Fig. 3: Proposed hybrid CNN-LSTM neural network architecture for classification of CAD [1]

IV. RESULTS AND ANALYSIS

A system with an Intel Core i5-4590 processor operating at 3.30 GHz, 8 GB of RAM, and an NVIDIA GTX 750 GPU was used for the research in this study. Python 3.7 was used to create the model, with TensorFlow acting as the backend engine and Keras as the main framework. Different convolution kernel sizes were evaluated once the network's layer and channel counts were determined because kernel dimensions have a big influence on processing speed and classification performance. Various optimizers and learning rates were investigated in order to improve training accuracy and efficiency. In particular, by training the model at various learning rates, the study assessed three popular optimizers: RMSprop, SGD, and Adam. The main performance parameter was the average classification accuracy on the test dataset.

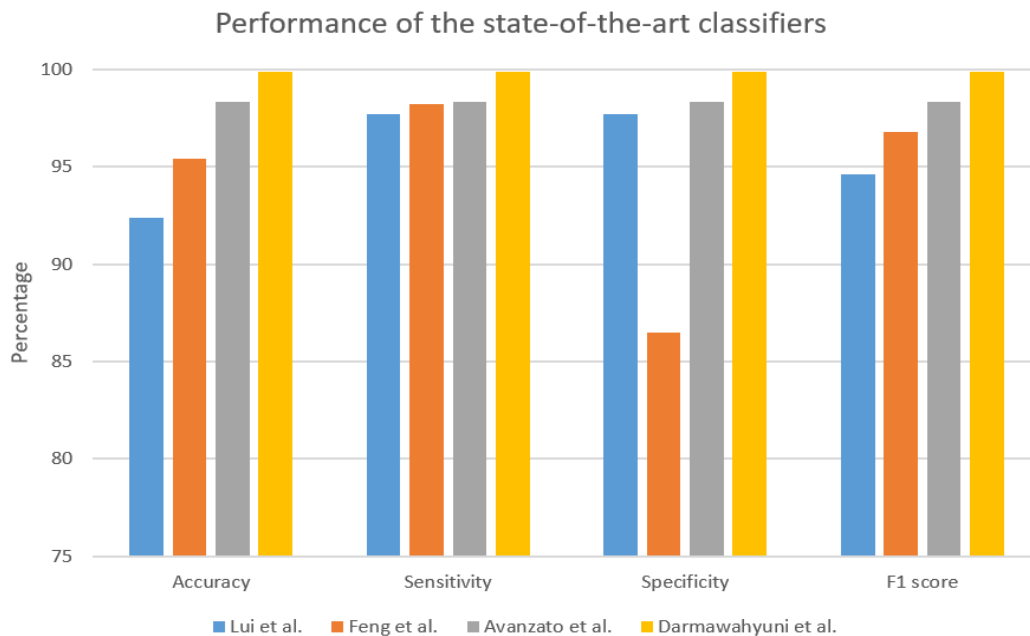


Fig.4: Performance of the state-of-the-art techniques on Accuracy, Sensitivity, Specificity and F1 score

Figure 4 presents a comparative review of contemporary approaches. The Darmawahyuni et al. model, which uses a recurrent neural network (RNN) with a long short-term memory (LSTM) structure, performs the best out of all the methods assessed.

V. FUTURE SCOPE OF WORK

The detection of Coronary Artery Disease (CAD) from ECG signals using deep learning offers several promising research opportunities.

Creating *multi-modal diagnostic frameworks* that integrate ECG with imaging data, blood biomarkers, and patient history to increase diagnosis reliability is a significant future goal. The shortcomings of ECG-only models can be addressed by incorporating a variety of clinical data, particularly when CAD symptoms are mild or sporadic.

The development of *wearable and real-time CAD detection systems* is another significant area. Future studies could concentrate on creating lightweight, noise-resistant deep learning models that can evaluate long-term ECG records from portable monitoring devices and smart watches. Continuous risk assessment and early ischemic event detection outside of clinical settings may be made possible by such systems.

Another crucial issue is enhancing *clinical acceptability and interpretability*. To emphasize ECG features that influence model decisions, such as ST-segment alterations or T-wave abnormalities, explainable AI strategies can be investigated. Increasing openness will promote clinician trust and make regulatory approval easier.

Robustness and generality should be included in future research. It is necessary to validate deep learning models in various clinical contexts, ECG devices, and demographics. Performance variability can be decreased by using methods like domain adaptation, transfer learning, advanced augmentation, and uncertainty estimation.

Furthermore, *privacy-preserving federated learning* has great promise for enabling cooperative model training across several hospitals without exchanging private patient information. Larger, more varied datasets and increased model accuracy are possible outcomes of this strategy.

Lastly, in order to assess how deep learning models affect diagnostic choices, patient outcomes, and healthcare efficiency, future research must prioritize *clinical trials and practical implementation*. Practical use will depend on the incorporation of CAD prediction models into clinical decision-support systems.

VI. CONCLUSION

One of the most important areas of research in medicine is the creation of low-cost, non-invasive techniques for the early identification of coronary artery disease (CAD). Accurate diagnosis is severely hampered by the lack of reliable non-invasive biomarkers. In order to improve screening efficacy, we introduce a hybrid CNN-LSTM model in this study that combines two different, indirect indications of CAD into a single design. Two clinical datasets were used to validate this system, one of which was gathered with an affordable ECG sensor in realistic settings. However, aberrant ECG morphology and irregular HRV, the surrogate markers used, might not consistently appear in the early phases of CAD. Because of this, the system sometimes misses borderline cases. Additional non-invasive indicators, like heart sound analysis, and categorical risk factors, like patient demographics, lifestyle choices, and family medical history, can be added to the architecture to enhance its diagnostic capabilities. These elements all play a part in cardiovascular risk assessment.

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