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PAPER

Comprehensive Cardiac Ischemia Classification Using Hybrid CNN-Based Models

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ABSTRACT

This study addresses the critical issue of classifying cardiac ischemia, a disease with significant global health implications that contributes to the global mortality rate. In our study, we tackle the classification of ischemia using six diverse electrocardiogram (ECG) datasets and a convolutional neural network (CNN) as the primary methodology. We combined six separate datasets to gain a more comprehensive understanding of cardiac electrical activity, utilizing 12 leads to obtain a broader perspective. A discrete wavelet transform (DWT) preprocessing was used to eliminate irrelevant information from the signals, aiming to improve classification results. Focusing on accuracy and minimizing false negatives (FN) in ischemia detection, we enhance our study by incorporating various machine learning models into our base model. These models include multilayer perceptron (MLP), support vector machines (SVM), random forest (RF), long short-term memory (LSTM), and bidirectional LSTM (BiLSTM), allowing us to leverage the strengths of each algorithm. The CNN-BiLSTM model achieved the highest accuracy of 99.23% and demonstrated good sensitivity of 98.53%, effectively reducing false negative cases in the overall tests. The CNN-BiLSTM model demonstrated the ability to effectively identify abnormalities, misclassifying only 25 out of 1,673 ischemic cases in the test set as normal. This is due to the BiLSTM's efficiency in capturing long-range dependencies and sequential patterns, making it suitable for tasks involving time-series data such as ECG signals. In addition, CNNs are well-suited for hierarchical feature learning and complex pattern recognition in ECG data.

KEYWORDS

ischemia classification, electrocardiogram (ECG), convolutional neural network (CNN), hybrid CNN models

1 INTRODUCTION

Heart ischemia, a condition characterized by an inadequate supply of blood and oxygen to the heart muscle, has significant global implications. According to the

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2019 statistics from the World Health Organization (WHO), ischemic heart disease and stroke were the primary causes of death globally. They accounted for a significant portion of the global disease burden, leading to millions of deaths and posing substantial economic challenges due to healthcare costs and reduced productivity [1]. The impact of ischemia extends far beyond mortality, as survivors often suffer from debilitating disabilities. Ischemic heart diseases encompass a group of serious cardiovascular conditions. These diseases primarily include angina and myocardial infarction, which is known as a heart attack. They pose a significant global health concern, contributing to high rates of illness and death. Timely diagnosis and intervention are crucial for managing heart ischemic diseases and reducing their impact on individuals' lives.

Heart ischemia can often be detected through changes in an electrocardiogram (ECG). An ECG is a non-invasive test that records the electrical activity of the heart. When a region of the heart does not receive enough blood and oxygen due to ischemia, it can result in specific ECG changes. These changes typically include ST-segment depression or elevation and T-wave abnormalities [2]. ST-segment depression can indicate subendocardial ischemia, while ST-segment elevation is more indicative of transmural or severe ischemia [3]. T-wave changes may also occur in response to ischemia, reflecting alterations in repolarization patterns. ECG is a crucial tool for diagnosing and monitoring ischemic heart conditions. It helps healthcare professionals assess the extent and location of ischemia and make informed treatment decisions. Specific leads are typically examined to assess for signs of ischemia. The most commonly used leads for this purpose include standard limb leads (I, II, and III) and precordial leads (V1 to V6). ST-segment depression or elevation in these leads can be indicative of myocardial ischemia [4]. Changes in any lead over time can provide crucial information. Continuous monitoring is particularly crucial in critical care settings.

Researchers and healthcare professionals utilize artificial intelligence (AI) to classify ECG signals, aiming for improved precision and efficiency. This is particularly valuable in the context of ischemia, where timely and accurate diagnosis is crucial. It can enhance the speed and accuracy of diagnosis, making it especially beneficial in critical situations such as heart attacks or strokes. Deep learning techniques have revolutionized the field of ECG signal classification. Deep learning models, particularly convolutional neural networks (CNNs), are adept at automatically extracting intricate features from raw ECG data. This capability enables these models to identify intricate patterns and anomalies that are indicative of various cardiac conditions, including ischemia, thereby improving diagnostic accuracy.

In recent times, there has been a growing trend in the widespread use of deep neural networks for classifying ECG signals, with a notable focus on CNNs. These networks have shown impressive levels of accuracy in their results. In this study, the authors [5] propose a deep learning approach for classifying arrhythmias in ECG signals according to AAMI standards [6]. The method employs a CNN model that contains feature extraction and classification. A distinctive ECG heartbeat segmentation method is employed, commencing at R-peaks and concluding after 1.2 times the median RR interval. To tackle imbalanced datasets, the model incorporates a focal loss function to prioritize minority heartbeat classes. The evaluation, conducted on the INCART and MIT-BIH datasets, achieved an accuracy of 98.41%.

The authors of the study [7] introduce a deep learning approach for inter-patient ECG classification. It employs a specialized symbolization technique for ECG signals, effectively capturing the morphology and rhythm of heartbeats while mitigating inter-patient variations through baseline correction. A multi-perspective convolutional neural network (MPCNN) uses this representation to automatically extract features and classify the signals. The method's performance was evaluated for classifying ventricular ectopic beats (VEB) and supraventricular ectopic beats (SVEB) using the MIT-BIH arrhythmia dataset, achieving an accuracy of 96.4%. Additionally, it achieved F1 scores of 76.6% for SVEB and 89.7% for ventricular ectopic beats.

In another study [8], the authors focused on classifying arrhythmias in ECG signals. They developed a multistage deep learning classification model to automate the arrhythmia classification process. The model used second-order difference plot (SODP) features and ECG waveforms. It employed a deep belief network (DBN) classifier with a greedy layer-wise training approach using restricted Boltzmann machines. To eliminate baseline wander, the ECG signals were preprocessed using median filters, and the waveforms were segmented using a specific windowing technique. Based on ANSI/AAMI standards, they have achieved an impressive accuracy rate of 96.10%.

The study [9] presents a CNN-based approach for automatically detecting myocardial infarctions (MI) using ECG signals. The approach utilizes a CNN model to classify normal and MI ECG beats with and without noise. They achieved 95.22% accuracy for ECG beats without noise and 93.53% accuracy with noise.

This paper [10] presents an ECG beat classification system that uses CNN for clinical cardiac disease diagnosis. The model achieves a classification accuracy of 92.7% across five classes based on the AAMI standard, using 44 recordings from the MIT-BIH database.

The study [11] proposes a 12-layer deep one-dimensional CNN for arrhythmia classification using the MIT-BIH Arrhythmia database. By utilizing a wavelet self-adaptive threshold denoising method, the study achieved 97.41% accuracy and 97.05% sensitivity.

The study [12] addresses the classification of atrial fibrillation using the MIT-BIH atrial fibrillation database. The authors proposed an 11-layer neural network consisting of a combination of CNN and a modified Elman neural network (MENN). The model achieved an accuracy of 97.4%, a sensitivity of 97.9%, and a specificity of 97.1%.

[13] proposes a cascaded CNN and expert features combined with a random forest (RF) for classifying 12-lead ECG arrhythmias into nine categories with multiple labels. Validated against the China ECG Intelligence Challenge (CEIC), the method achieved a score of 86.5%.

While many recent studies in the field of cardiovascular disease have primarily focused on arrhythmias, our research takes a unique and essential direction towards ischemia. Ischemia is the primary cause of death worldwide. Our study aims to tackle a pressing global health issue by employing innovative approaches to diagnosis, prevention, and treatment. This will contribute to saving lives and reducing the number of ischemia-related deaths.

In our study, we present a comprehensive approach to classify ischemia using seven diverse datasets, employing a CNN model as the central component of our methodology. Emphasizing the significance of accuracy and reducing the false negative (FN) rate in detecting ischemia, we expanded our analysis by incorporating multilayer perceptron (MLP), support vector machines (SVM), RF, long short-term memory (LSTM), and bidirectional LSTM (BiLSTM) models into our CNN framework. This combination of hybrid models was designed to leverage the strengths of each algorithm, improving both classification accuracy and minimizing false negatives.

This paper is organized into four sections, offering a cohesive flow of information. Section 2 explains the research methodology used in this approach. In the following Section 3, we will present the outcomes and engage in relevant discussions. The conclusive findings of this study are presented in Section 4.

2 METHODOLOGY

2.1 Dataset

In our research, we utilize a dataset comprising individuals with ECG readings that have been annotated and diagnosed with ischemic heart disease by experts. The dataset is a combination of six distinct databases, including:

- St. Petersburg INCART 12-lead Arrhythmia Database [14]
- Chapman university, Shaoxing people's hospital, and Ningbo First Hospital ECG Database (CSNDB) [15]
- PTB-XL Electrocardiography Database [16]
- PTB Diagnostic ECG Database (PTBDB) [17]
- The China Physiological Signal Challenge 2018 (CPSC2018) [18]
- The Georgia 12-Lead ECG Challenge Database (G12EC) [19]

Only individuals identified as having ischemic heart disease from these datasets were included in this compilation.

2.2 Preprocessing

To enhance the accuracy of classification algorithms, it is often crucial to eliminate or minimize irrelevant or noisy information within the signals. The useful range is typically considered to be around 0.5 to 45 Hz. Frequencies below 0.5 Hz are associated with baseline wander and slow drifts, which can cause analysis problems [20], while frequencies above 45 Hz are often considered to contain less significant information for ECG analysis [21]. To achieve this, we applied discrete wavelet transforms (DWT) using the Daubechies D6 ('db6') wavelet to decompose the ECG signals. Sampled at 250 Hz, the ECG signals were decomposed up to 8 levels using MATLAB. The 8th sub-band, which primarily contained the baseline wander (frequency range of 0–0.488 Hz), was excluded from the denoising process (see Figure 1). Additionally, as the ECG signal did not contain significant information beyond 45 Hz, the first-level detail coefficients corresponding to frequency bands of 62.5–125 Hz were also excluded. The denoised ECG signal was reconstructed using sub-band coefficients from the 2nd to the 8th level, while the coefficients from other sub-bands were set to zero before performing the inverse wavelet transform, resulting in the final denoised ECG signal.

In this preprocessing context, the R-peaks, which are crucial points in the cardiac cycle, were detected. Afterwards, we segmented individual beats from the ECG signals and computed median beats for each of the 12 leads, ensuring a consistent duration of 250 data points per beat (see Figure 2). Overall, this comprehensive approach to ECG preprocessing is beneficial for creating a standardized and cleaned dataset ready for precise and meaningful analysis of cardiac signals.

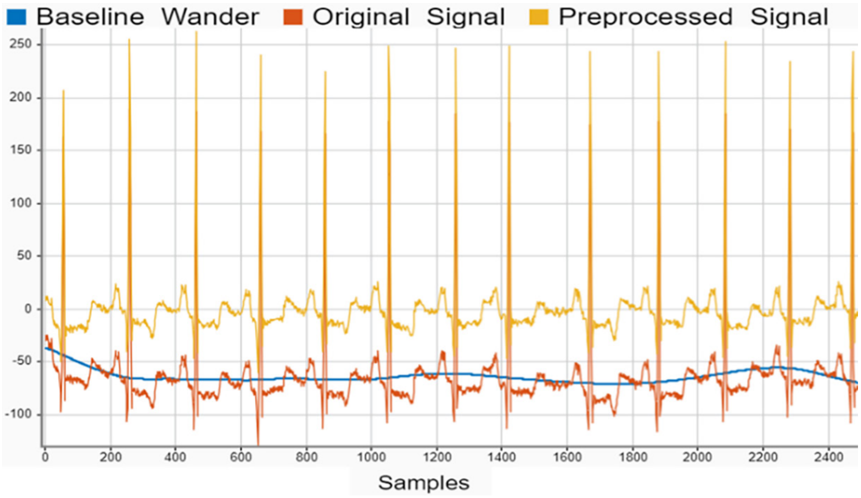

Fig. 1. ECG signal before and after applying the DWT

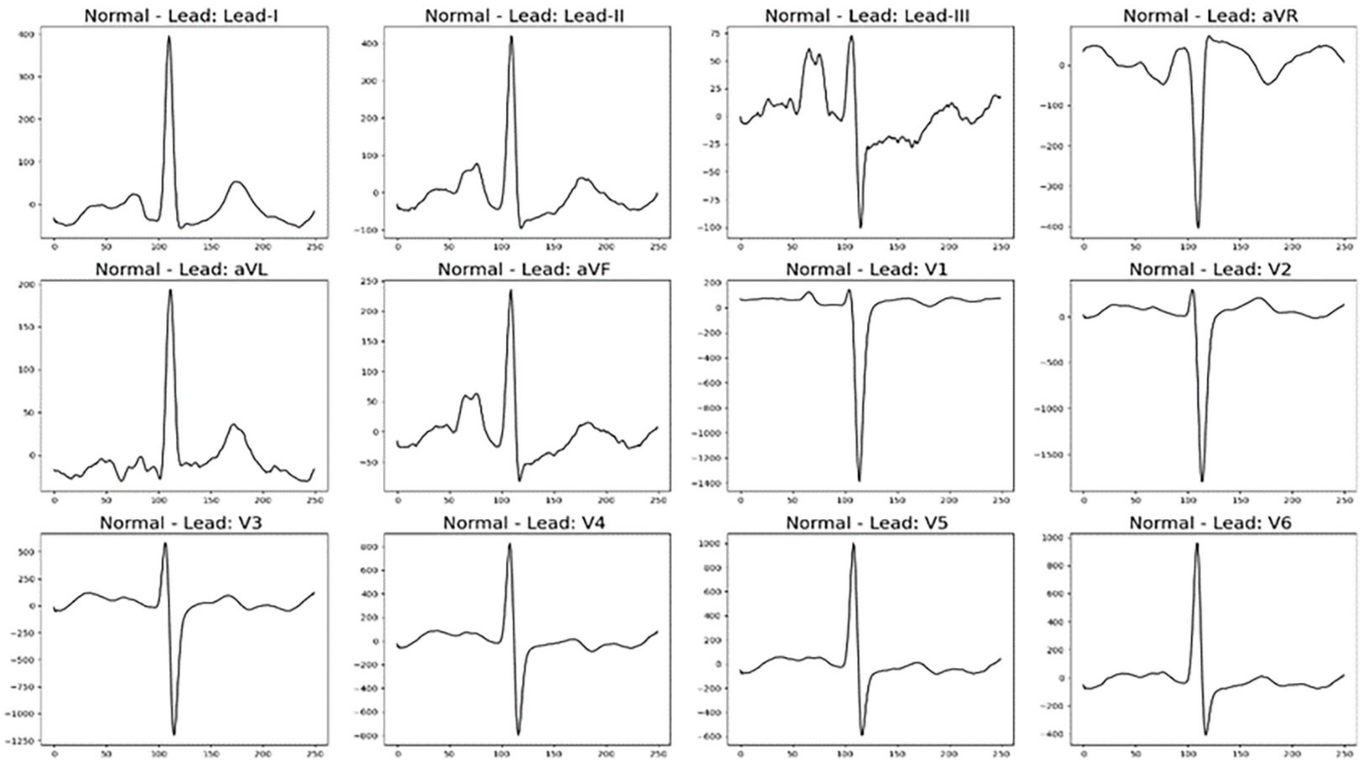

Fig. 2. Heartbeats of each lead

2.3 Data balance

To address the data imbalance issue, where one class has 8,431 samples and the other has only 1,502, representing 15% and 85% of the data, respectively, we implemented a random oversampling technique. This technique is efficient in achieving data balance. Oversampling involves creating artificial samples for the minority class to equal the size of the majority class. This approach offers several advantages, most notably improved model training and generalization. By increasing the dataset for the minority class, we established a more balanced training environment for our deep learning models. This prevented the classifier from becoming overly biased towards the majority class [22], enabling it to better learn the characteristics of both classes, and leading to a more equitable classification system for our dataset. The new balance is achieved with 8,431 samples in each class.

2.4 Classification methods

A) Convolutional neural network

A CNN has proven to be efficient in ECG analysis for feature extraction and classification tasks. Figure 3 depicts the proposed CNN standard model. We begin our architecture with two convolutional layers to apply filters to the ECG signal, extracting features and enabling the model to learn and capture local patterns within the signal. Then, we add a max-pooling layer to downsample the features while retaining the most significant information. This is particularly useful for reducing the size of the feature map [23]. After that, we add another two convolutional layers, each followed by a max-pooling layer. Finally, we add a fully connected layer.

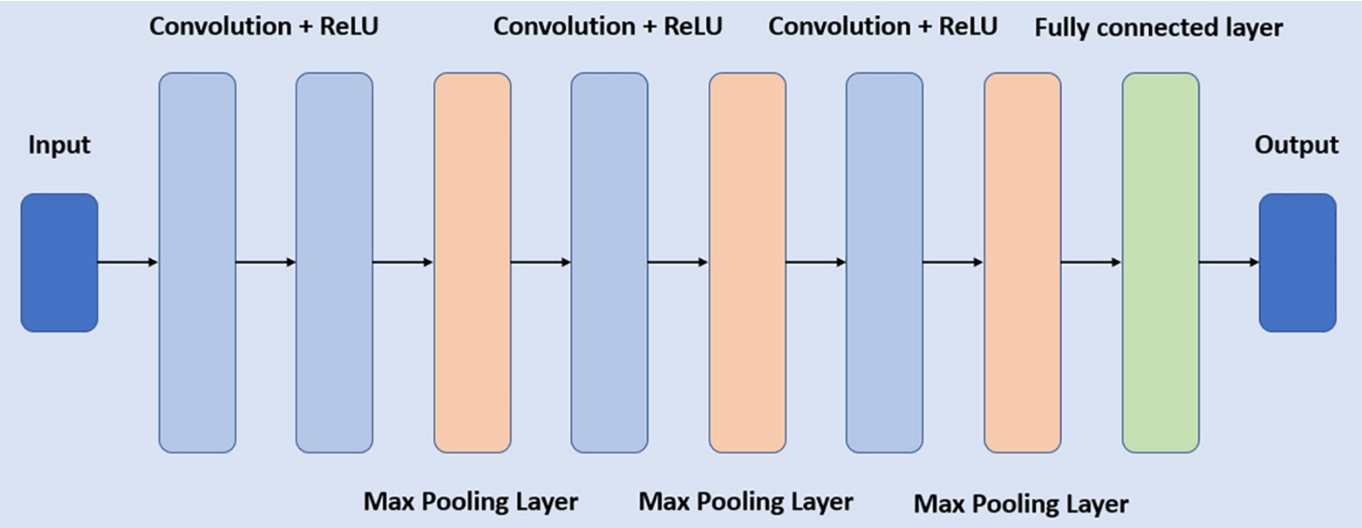

Fig. 3. Architecture of the proposed standard CNN

B) Support vector machine

The SVM is a supervised machine learning algorithm that plays a valuable role in improving classification tasks, particularly when used in combination with a CNN model as previously described. SVM is designed to find the most effective hyperplane that efficiently separates data points belonging to different classes in a high-dimensional space [24]. After CNN extracts complex features from ECG signals, SVM can further enhance classification accuracy by refining the decision boundary.

C) Random forest

The RF is a frequently used ensemble learning method that can improve classification tasks when combined with a CNN-based model. The RF algorithm operates by creating multiple decision trees (in this case, 100 estimators) during training and then combining their predictions to make a final classification [25]. When integrated into ECG classification, RF can serve as a complementary classifier following feature extraction by the convolutional neural network.

D) Multilayer perceptron

The multilayer perceptron (MLP) classifier is a type of neural network architecture renowned for its effectiveness in performing classification tasks. When used with a CNN model, it plays a crucial role in improving classification performance. Unlike ensemble methods such as RF, MLP is a neural network, and its integration with CNN offers certain advantages.

E) LSTM and BiLSTM

Long short-term memory and BiLSTM are recurrent neural network (RNN) architectures that are extensively utilized in natural language processing, speech recognition, and sequential data analysis. When used as supplementary classifiers after a CNN model, they have distinct roles in improving classification performance. The LSTM model is designed to capture temporal dependencies in sequential data [26], making it effective at modeling the context and long-term dependencies within the extracted features from the CNN. LSTM can learn from previous data and provide valuable context for making classification decisions. On the other hand, BiLSTM extends the capabilities of LSTM by processing sequences bidirectionally, taking into account both past and future contexts.

3 RESULTS AND DISCUSSION

The proposed models were trained under identical conditions to ensure a fair comparative study. The data was randomly partitioned into 80% training data and 20% testing data, with an additional 10% validation data subset from the training data using the train-test validation split technique. Each model was trained for 50 epochs.

The models' performance was evaluated using three evaluation metrics: accuracy, sensitivity, and precision. In addition to the confusion matrix (see Figure 4), which is an essential tool for evaluating the performance of classification models, where TP represents true positive, TN represents true negative, FP represents false positive, and FN represents false negative.

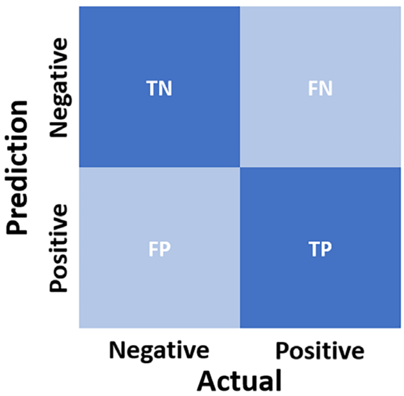

Fig. 4. Confusion matrix

Table 1 presents the performance of different hybrid CNN models. The standard CNN model demonstrated an impressive accuracy of 98.96% and a sensitivity of 98.00%. Moving to the hybrid models, the CNN-RF model had a slight advantage compared to the standard model, enhancing the sensitivity to 98.23%, which means fewer FN cases. The CNN-SVM model achieved a higher accuracy rate of 99.05% while maintaining the same sensitivity score. Furthermore, the model also outperformed the CNN-RF model in terms of precision. The CNN-MLP model improved the accuracy to 99.02% and achieved a sensitivity of 98.11%. In comparison, the CNN-SVM model experienced a decrease in both accuracy and sensitivity, losing some TP cases and resulting in FN cases. Meanwhile, the CNN-LSTM model achieved an accuracy of 99.08% and a sensitivity score of 98.29%. Finally, the CNN-BiLSTM model demonstrated the highest accuracy of 99.23% and a commendable sensitivity of 98.53%, resulting in a reduction of FN cases to 25 out of 3373 in the total test set, as depicted in the model's confusion matrix in Figure 5. This performance was superior to that of the other models considered, and as a result, this model will be referred to as the proposed model throughout the rest of the paper.

Table 1. Classification results the proposed hybrid models

Proposed Models	Sensitivity	Precision	Overall Accuracy
CNN	98.00%	99.94%	98.96%
CNN-SVM	98.24%	99.88%	99.05%
CNN-RF	98.23%	99.70%	98.96%
CNN-MLP	98.12%	99.94%	99.02%
CNN-LSTM	98.29%	99.88%	99.08%
CNN-BiLSTM	98.53%	99.94%	99.23%

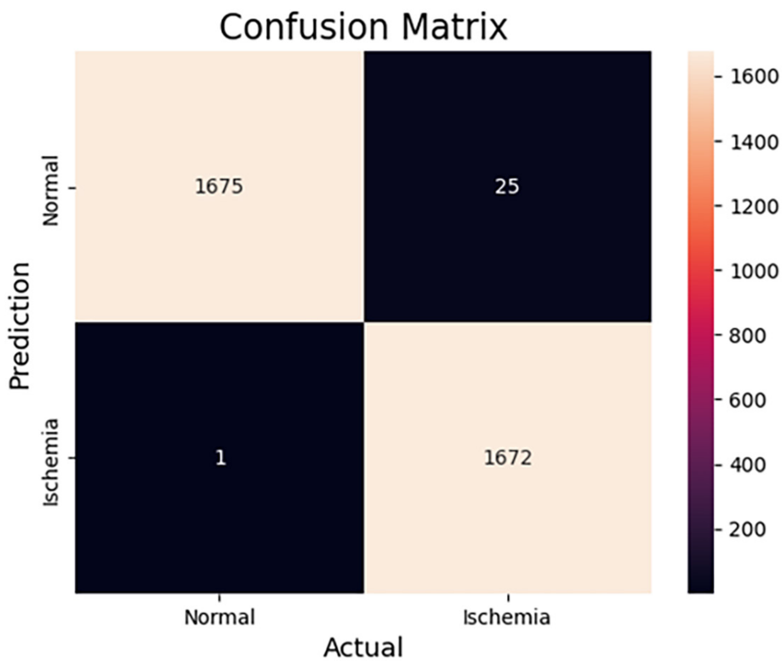

Fig. 5. Confusion matrix for the CNN-BiLSTM model

Our focus was consistently on evaluating the accuracy and true positive rate of the compared models. Sensitivity (true positive rate) measures the accuracy of the positive predictions made by a model, indicating how well it distinguishes true anomalies from normal data. In anomaly classification, high sensitivity indicates that a low number of true anomalies are incorrectly classified as normal. This is crucial in situations such as fraud detection or medical diagnosis, where incorrect negative results can have serious consequences. In our study, we identified 1673 cases of ischemia in our test set, and the CNN-BiLSTM model only classified 25 of them as normal. This demonstrates the model's ability to effectively identify anomalies.

However, the selection of the training-validation split can impact the reported accuracy and sensitivity levels. To evaluate the performance of our model with this approach, we also conducted experiments using a 60%–40% training-validation split on the CNN-BiLSTM model. The results depicted in the confusion matrix of the model in Figure 6 indicate that the model's performance remained consistent across different splits, with only slight variations in accuracy and sensitivity, which are 98.92% and 98.19%, respectively. This suggests that the reported accuracy and sensitivity are not significantly influenced by the specific choice of the training-validation split.

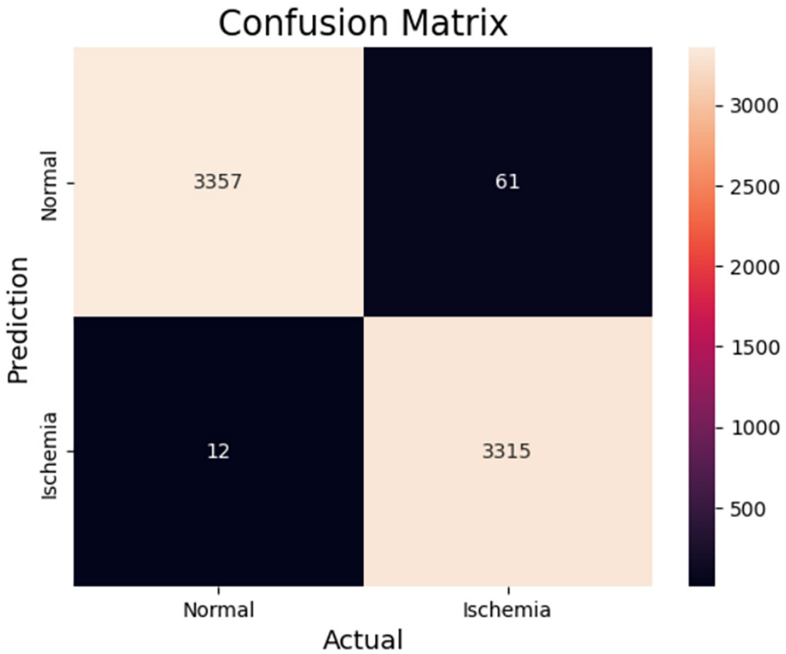

Fig. 6. Confusion matrix of the CNN-BiLSTM model with a 60%–40% training-validation split

Table 2 presents a compelling comparison between our approach and state-of-the-art methodologies. Notably, our most frequently used model achieved the highest classification accuracy when working with two classes across six diverse datasets using 12 leads. All of these studies [7], [8], [9], [10], [11], [12], [13] have achieved good results by working with just one dataset, except for [5], which used two datasets and achieved an accuracy rate of 98.41%. [9] focused on classifying MI as an ischemic disease, based solely on lead II. They achieved an accuracy rate of 95.22% without noise. The challenge in [13] was also significant, involving the classification of nine classes using a 12-lead ECG and achieving a final score of 86.5%.

Unlike many state-of-the-art studies that rely on one or two datasets, our approach involves merging six distinct datasets. This approach enabled us to capture a wider range of information. Unlike the typical single-lead datasets, using 12 leads presented a challenge in terms of incorporating various patterns. However, it offers a more comprehensive perspective on cardiac electrical activity, facilitating a better understanding of ischemic events. Additionally, removing unwanted artifacts and balancing the data ultimately enhanced the classification. This perspective not only enriched our analysis but also enhanced the reliability of our results.

Table 2. The comparison between our proposed model and state-of-the-art methodologies

Study	Database	Application	Number of Classes	DL Technique	Results
[5]	MIT-BIH INCART	Arrhythmias classification	5	CNN + focal loss	Acc = 98.41%, Prec = 98.37% F1-score = 98.38%
[7]	MIT-BIH	Arrhythmias classification	5	MPCNN	Acc = 96.4%, F1 score SVEB = 76.6%, F1 score VEB = 89.7%
[8]	MIT-BIH	Arrhythmias classification	5	DBN	Acc = 96.10%
[9]	PTBDB	MI classification	2	CNN	With noise: Acc = 93.53%, Sen = 93.71%, Spec = 92.83% Without noise: Acc = 95.22%, Sen = 95.49%, Spec = 94.19%
[10]	MIT-BIH	Arrhythmias classification	5	CNN	Acc = 92.7%
[11]	MIT-BIH	Arrhythmias classification	5	CNN	Acc = 97.41%, Sen = 97.05%, Spec = 99.35%
[12]	MIT-BIH	Atrial fibrillation classification	2	CNN + MENN	Acc = 97.4%, Sen = 97.9%, Spec = 97.1%
[13]	CEIC	Arrhythmias classification	9	Cascaded CNN	Acc = 86.5%, Sen = 85.3%, Spec = 82%
Proposed model	**INCART CSNDB PTBDB PTB-XL CPSC2018 G12EC**	**Ischemia classification**	**2**	**CNN-BiLSTM**	**Acc = 99.23%, Sen = 98.53%, Prec = 99.94%**

4 CONCLUSION

In this study, we present a comparison of six hybrid CNN-based models, evaluating their individual and collective contributions to ischemia classification. We improved the classification performance by eliminating and reducing irrelevant and noisy information in the data using DWT decomposition based on db6. Then, we utilized random oversampling to rectify a substantial data imbalance, resulting in a more balanced dataset and preventing classifier bias toward the majority class. By enhancing the CNN with various machine learning techniques, we achieved significant improvements in classification accuracy while reducing the number of false negative cases. Trained on six different datasets processed using DWT, the CNN-BiLSTM model achieved the highest accuracy of 99.23% and a good sensitivity of 98.53%. The proposed model was one of the best compared to related studies, thanks to the efficiency of BiLSTM in capturing long-range dependencies and sequential patterns within time-series data, such as ECG signals. This is complemented by CNN's ability to perform hierarchical feature learning and complex pattern recognition on ECG data. This approach demonstrates the benefits of using CNN hybrid models to improve diagnostic outcomes and reduce errors in clinical practice.

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6 AUTHORS

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