Prediction of Coronary Artery Blood Flow Abnormalities Using MultiCNN-BiLSTM Model with Magnetocardiogram

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Abstract

The utility of magnetocardiography (MCG) analysis in detecting blood flow abnormalities is hindered by the accuracy limitations of current models. In this study, we propose an image-based MCG signal classification method employing the MultiCNN-BiLSTM model to differentiate between normal and abnormal blood flow patterns. Initially, MCG time series data from various cardiac cycles are segmented and concatenated to thoroughly investigate and analyze the periodic trends in cardiac blood flow. Subsequently, a combination of sliding window and CNN techniques is utilized to extract significant features from the time series data, thereby capturing the interrelationships among variables. Furthermore, BiLSTM is employed to further extract features, and the features derived from CNN and BiLSTM are integrated via a fully connected layer, culminating in the final prediction output. In order to mitigate the overfitting issue encountered in 2D networks, we initiate an AlexNet-like network utilizing weights pretrained on ImageNet. Evaluation conducted on the MCG database reveals that our proposed approach achieves an accuracy level of 94.5%. Additionally, the predictive efficacy of the MultiCNN-BiLSTM model introduced in this study surpasses that of three deep learning models and four machine learning models trained using extracted features.

1. Introduction

Coronary artery blood flow abnormalities serve as critical indicators of cardiovascular health, significantly influencing conditions such as myocardial infarction and heart failure. Accurate prediction of these abnormalities is essential for facilitating early intervention and improving patient care [1,2]. Magnetocardiography (MCG), a non-invasive technique that measures the magnetic fields generated by cardiac electrical activity, shows considerable promise for enhancing predictive models [3]. Unlike electrocardiography (ECG), MCG is less susceptible to interference from the body's conductive environment, enabling the detection of weaker electrical currents and yielding more precise diagnostic information. Moreover, the non-contact nature of MCG measurement enhances the overall experience for both patients and practitioners, presenting substantial clinical potential [4].

Current automated MCG diagnostic models can be categorized into traditional and deep learning-based approaches [5]. Traditional methods typically rely on manually engineered features and machine learning classifiers; however, they often face limitations stemming from the necessity of high-quality data and domain-specific expertise [6]. In contrast, deep learning techniques provide an end-to-end modeling approach that has demonstrated efficacy in disease detection and other applications utilizing MCG data [7,8]. This study proposes the MultiCNN-BiLSTM model as a novel solution for predicting coronary artery blood flow abnormalities using MCG data. By integrating Convolutional Neural Networks (CNNs) for spatial feature extraction with Bidirectional Long Short-Term Memory (BiLSTM) networks for capturing temporal dependencies, this model aims to enhance predictive accuracy and robustness in clinical settings [9].

2. Methods

2.1 MCG Data Collection

The dataset for this study was obtained from a prospective investigation of cardiovascular disease conducted at Qilu Hospital of Shandong University. All participants underwent either coronary angiography or computed tomography angiography (CTA), and comprehensive medical records were meticulously documented. Data collection was facilitated using the magnetocardiography (MCG) system (QMCG-360-MSE; Hangzhou Nuochi Life Sciences, China) [10], which comprises an optically pumped magnetometer (OPM) array, a magnetic shielding chamber, a non-magnetic bed, and a data acquisition device.

During the data acquisition process, participants

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were positioned in a supine posture on the non-magnetic bed, with the OPM array positioned 2 cm above their bodies, aligned precisely with the xiphoid process. Both the participants and the OPM array were enclosed within the magnetic shielding chamber to minimize external interference, allowing for the accurate recording of MCG data for a duration of 3 minutes per participant.

The dataset included recordings from 956 patients diagnosed with blood flow abnormalities and 1,000 healthy volunteers. Analysis revealed that 1-minute MCG recordings effectively captured complete cardiac cycles, making them suitable for diagnostic purposes. Consequently, the data from each participant were segmented into 0.5-minute intervals, resulting in 5 segments per individual. This approach yielded a total of 4,780 segments for patients with blood flow abnormalities and 5,000 segments for healthy individuals, providing a robust dataset for subsequent analysis.

2.2 Network Architecture

Building upon the foundational principles of Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs), we developed the MultiCNN-BiLSTM model for the classification of coronary artery blood flow abnormalities versus normal conditions, as illustrated in Fig. 1. This innovative architecture integrates a dual-layer one-dimensional convolutional network with a dual-layer bidirectional LSTM network. The CNN is responsible for extracting local features from the input data, while the BiLSTM effectively captures both forward and backward temporal dependencies, thereby enhancing the model's capacity to identify both periodic and aperiodic patterns in the magnetocardiography (MCG) signals.

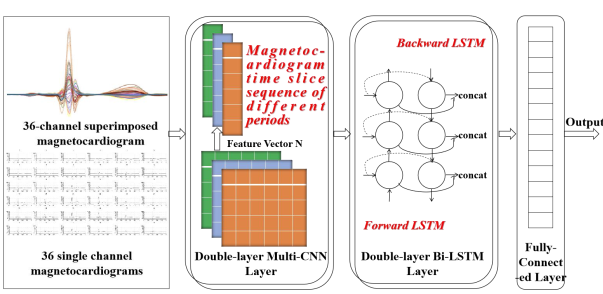

Figure 1. The diagram illustrating the structure of the MultiCNN-BiLSTM model.

To leverage the inherent periodicity of MCG data, we implement a strategy of segmenting and concatenating time series from various temporal intervals. This approach utilizes a sliding window mechanism in conjunction with the CNN to extract pertinent features from these time series. Subsequently, these features undergo further processing through the BiLSTM layers. The final classification outcomes are generated by integrating the extracted features via fully connected layers, ensuring a robust and accurate classification of the coronary artery conditions.

2.3 Transfer Learning and Fine Tuning

To address the issue of overfitting in the MultiCNN-BiLSTM model, we utilized a large, labeled dataset from a different application, such as ImageNet, for training. By employing weights pretrained on ImageNet, we fine-tuned the MultiCNN-BiLSTM model. This approach leverages the robust feature extraction capabilities of the two-dimensional image input method, enhancing the model's performance and reducing overfitting in the context of MCG data analysis.

2.4 Evaluation Metrics

The proposed method's performance is assessed using widely employed metrics: sensitivity (Sen), specificity (Spe), and accuracy (Acc), defined as follows:

$$
\begin{aligned}
Sensitisity &= \frac{TP}{TP+FN}\times 100\% \\
Specificity &= \frac{TN}{TN+FP}\times 100\% \\
Accuracy &= \frac{TP+TN}{TP+TN+FN+FP}\times 100\%
\end{aligned}
\tag{1}
$$

where TP, TN, FP, and FN denote the number of true positive, true negative, false positive, and false negative samples, respectively. Sensitivity assesses the model's ability to correctly identify all true positive cases, specificity evaluates its capability to accurately exclude all true negative cases, and accuracy represents the overall performance of the system in classifying both positive and negative instances.

3. Results

In this study, we employ the MultiCNN-BiLSTM model to train the pre-processed MCG signals. Each one-dimensional MCG waveform is converted into a two-dimensional image represented as a 256×256 pixel matrix. The dataset is split into training (80%) and testing (20%) subsets, ensuring each sample is included in either the training or testing set. To evaluate the model's performance, we utilize ten-fold cross-validation and report the average results across all folds. The training process involves 2,000 iterations and uses stochastic gradient descent (SGD) with a variable learning rate strategy. This approach ensures rapid convergence of the model while mitigating the issue of vanishing gradients.

3.1 MultiCNN-BiLSTM with Fine Tuning

To mitigate the risk of overfitting, we initialized the model using weights that were pre-trained on the ImageNet dataset and subsequently fine-tuned these weights to suit the specific characteristics of magnetocardiography (MCG) images. This approach allowed us to leverage the rich feature representations learned from a vast array of images, enhancing the model's performance on our specific task.

Figure 2 illustrates the relationship between accuracy and the number of iterations for the testing set, highlighting the improvements achieved during training. The utilization of ImageNet-initialized weights resulted in a notable increase in the model's accuracy, reaching an impressive 94.5%. This performance clearly demonstrates the effectiveness of our approach, positioning it as superior to alternative methods employed in the field.

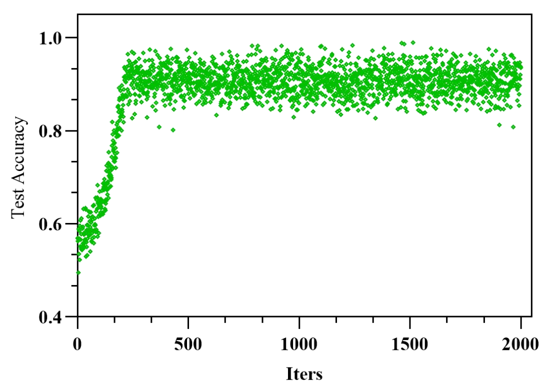

Figure 2. The accuracy vs number of iteration curve for testing set.

3.2 Evaluation Performance

Figure 3 presents a comprehensive comparative analysis of the prediction results from the MultiCNN-BiLSTM model in relation to several other pertinent models, encompassing both prominent deep learning and traditional machine learning approaches. The deep learning models evaluated in this study include Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), and the combined CNN-LSTM architecture.

Building on insights from prior research [11-14], we developed several baseline models for comparison, utilizing features extracted by domain experts. We focused on two primary categories of features: statistical features and signal processing features. These features were carefully extracted and concatenated, serving as inputs for various machine learning classifiers. This systematic approach allowed us to rigorously evaluate the performance of the MultiCNN-BiLSTM model against a well-defined set of baseline models.

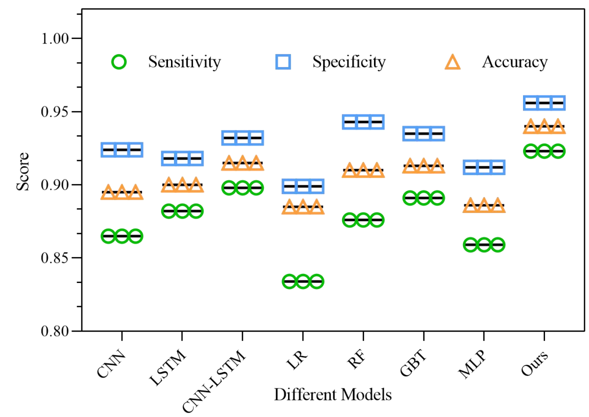

Figure 3. Comparison of prediction results of different methods

4. Discussion and conclusion

In this study, we introduce the MultiCNN-BiLSTM model, a novel approach for predicting coronary artery blood flow abnormalities using MCG data. This model integrates CNN with BiLSTM networks to effectively capture both spatial and temporal features of MCG signals. Our findings indicate that the MultiCNN-BiLSTM model significantly surpasses traditional methods and other deep learning approaches in terms of accuracy and robustness.

Traditional MCG analysis often relies on manual feature extraction and signal processing techniques, which require high-quality data and extensive domain expertise. While rule-based criteria and signal processing features have shown potential for cardiac diagnosis, they are constrained by the manual effort required and their limited capacity to handle large, complex datasets. In contrast, deep learning techniques offer an end-to-end solution by automatically learning features from the data. Recent advancements have demonstrated that models such as CNNs and LSTMs excel in various healthcare applications, including disease detection and signal denoising. The MultiCNN-BiLSTM model harnesses the strengths of both CNNs and BiLSTMs to extract comprehensive features from MCG data. Additionally, the use of transfer learning with ImageNet pretrained weights addresses overfitting issue.

In this study, we provide an extensive comparison of classification performance between the MultiCNN-BiLSTM model and several alternative methods, including CNN, LSTM, CNN-LSTM, LR, RF, GBT, and MLP. Our experiments demonstrate that the MultiCNN-BiLSTM model achieves superior results compared to these methods, particularly in terms of classification accuracy.

Our optimization efforts reveal that initializing the MultiCNN-BiLSTM model with weights pretrained on ImageNet effectively mitigates overfitting, outperforming models initialized with random weights. This approach yields an impressive accuracy of up to 94.5%. Furthermore, the utilization of image input in the MultiCNN-BiLSTM model provides notable advantages. It eliminates the need for manual feature extraction and allows for fine-tuning with extensive databases, thereby enhancing both accuracy and robustness. Comparative analyses against state-of-the-art methods underscore the exceptional performance of our proposed approach.

In conclusion, our study presents a thorough comparison and optimization of the MultiCNN-BiLSTM model for MCG classification tasks. We highlight its superiority over traditional methods, demonstrating significant improvements in both accuracy and robustness. These findings offer valuable insights for researchers and practitioners in medical image analysis and suggest promising avenues for advancing automated diagnosis and treatment of cardiac abnormalities.

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