RESEARCH PAPER

Channel Attention based 1D-CNN-LSTM Fully Connected Network for ECG Beat Classification using SE Block

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ABSTRACT

To automatically categorize ECG data for identifying cardiac arrhythmias, this thesis proposes a deep learning based technique. The proposed paradigm includes a convolutional neural network (CNN), long short-term memory (LSTM), and fully connected network (FCN) with channel attention mechanism. LSTM can capture temporal dependencies in the sequential data, conversely, CNN processes ECG signals and extracts spatial features. Feature selection is improved by introducing a Squeeze-and-Excitation (SE) block that gives importance to more relevant channels and suppresses the irrelevant ones. This model is trained and further tested on seven types of ECG beats taken from the MIT-BIH arrhythmia dataset. Segmentation and noise filtering is used to improve the data quality. The proposed hybrid architecture achieves a 99.68% success rate and outperforms other deep learning and traditional methods. The results reveal that combining attention-based learning with spatial and temporal learning improves the classification performance and is suitable for use in healthcare applications that require real-time data.

Keywords: CNN-SE-LSTM-FCN, Arrhythmia Classification, ECG beat classification.

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I. INTRODUCTION

Cardiac arrhythmia is one of the principal causes of global mortality. Irregular heart rhythms caused by irregularities in the electrical conduction system of the heart characterize cardiac arrhythmia. The electrocardiogram (ECG) signals provide essential information to analyze heart electrical activity and identify abnormalities. The automation of abnormal heart rhythm detection benefits significantly from machine learning(ML) and artificial intelligence(AI).

This problem has attracted a lot of applications from AI and ML approaches in recent years, and ECG classification is one of them. A good candidate is deep learning, where CNNs are a good vehicle for extracting the spatial aspects in electrocardiogram (ECG) data, such as waveform patterns of P waves, QRS complexes, and T waves. However, the temporal dependencies in a sequence pose challenges for CNNs. Many people resort to Recurrent Neural Networks (RNNs), and more specifically LSTM networks, to tackle this problem. LSTM networks are particularly suitable for analyzing ECG signals for their capability to learn sequential patterns and long-term dependencies in time-series data. Combining CNN and LSTM into hybrid models may lead to improved classification performance as they can leverage both spatial and temporal feature extraction. Attention techniques have also been introduced to enhance deep learning models to help them focus on the important bits in the input data. The Squeeze-and-Excitation (SE) block in particular enables adaptive channel-wise feature recalibration and enhances the capacity of this network.

In this paper, an attention-based hybrid CNN-SE-LSTM-FCN architecture for ECG beat classification is designed. A hybrid model with CNN and an SE attention mechanism and LSTM for extracting the temporal dynamics are developed for automated cardiac arrhythmia detection. This high accuracy system may be used in real clinical settings.

II. Literature survey

The classification of ECG signals has been a popular topic in the field of signal processing because they are essential for diagnosing cardiovascular diseases. Initially, the detection of arrhythmia automatically was mainly based on classic signal processing techniques and other machine learning techniques. In this type of approaches, ECG signals were first preprocessed to reduce noise generated by muscle artifacts, baseline drift and power line noise. The most typical filtering methods included linear filtering, adaptive filtering and wavelet denoising techniques in order to improve signal quality prior analysis[1]–[4]. After preprocessing, a set of feature extraction methods based on human-designed features was used to extract relevant features of ECG signals and then the features from time-frequency domain analysis including time-domain, frequency-domain were used for classification [5],[6]. Also, Standard machine learning techniques were commonly used for arrhythmia classification.[7]–[10]. While these approaches showed encouraging results, their performance was largely influenced by hand-crafted features and domain knowledge. Consequently, the conventional approaches often failed to generalize well on large and complex ECG data sets[11], [12].

Among many deep learning methods, CNNs has also been significant for their ability to capture spatial features from the input data. Several papers have shown that CNN architectures that can automatically capture morphological features such as peaks, intervals and waveform shapes in ECG signals. Acharya et al. showed that deep CNN models can achieve high accuracy in detecting arrhythmia by learning features directly from ECG signals[13], [14]. Similarly, Kiranyaz et al. developed a patient-specific 1D-CNN architecture for ECG classification that outperformed conventional classifiers[15]. Other works investigated deeper CNN architecture and end-to-end learning without handcrafted feature extraction [16], [17]. While their CNN models are powerful to learn spatial representations, these models are limited in capturing the temporal dependency within sequential ECG signals.

To address the limitation of CNNs in processing sequential data, RNNs or more specifically LSTM networks have been studied in recent years. By using memory cells in LSTMs and their gating mechanisms to control information flow, LSTM models are good at modeling time-series data. They are specially useful for the analysis of sequential biomedical signals such as ECG signals, where the temporal relationship between heartbeats is important for arrhythmia detection. Yildirim proposed a deep Bi-LSTM network for arrhythmia detection and reported promising classification accuracy [18]. Other studies have also used autoencoder models and LSTM networks to detect anomalies in ECG signals [19], [20]. Additionally, deep neural network architectures and recurrent models have also been studied extensively for large ECG datasets to automatically detect abnormal heart rhythms [21], [22]. Although LSTM models are great at modeling temporal dependencies, they cannot easily extract rich morphological features from raw ECG signals, which results in inferior performance when used in isolation.

To combine both the power of CNNs and RNNs, hybrid models consisting of both CNN and LSTM architectures have been proposed in recent years. These hybrid models use CNN layers to capture spatial and morphological features and LSTM layers to capture the temporal dependency among consecutive heartbeats. A number of studies have reported significant improvements in arrhythmia classification accuracy using such hybrid architectures. For example, Zhang et al. and a few other authors also proposed a CNN-LSTM based hybrid model for ECG beats classification and achieved better performance [23], [24], [25].

III. Methodology

The Principal aim of this system is to classify the different types of cardiac arrhythmias. The system utilizes the electrocardiogram (ECG) signals which are extracted from a public benchmark dataset, MIT-BIH Arrhythmia Database. This database has the ECG records with 30 minutes of length, sampled at 360 Hz. These records in the database have a variety of heartbeat types. In this paper, seven different classes of ECG beats were considered. Those classes are normal beat (N), atrial premature beat (A), fusion beat (F), left bundle branch block beat (L), right bundle branch block beat (R), paced beat (P), and premature ventricular contraction beat (V).

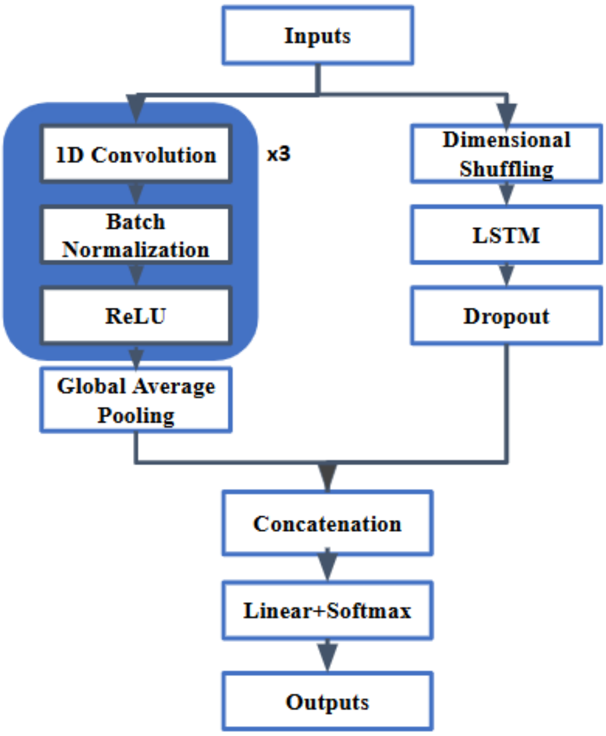

Fig 1 proposed system flow diagram

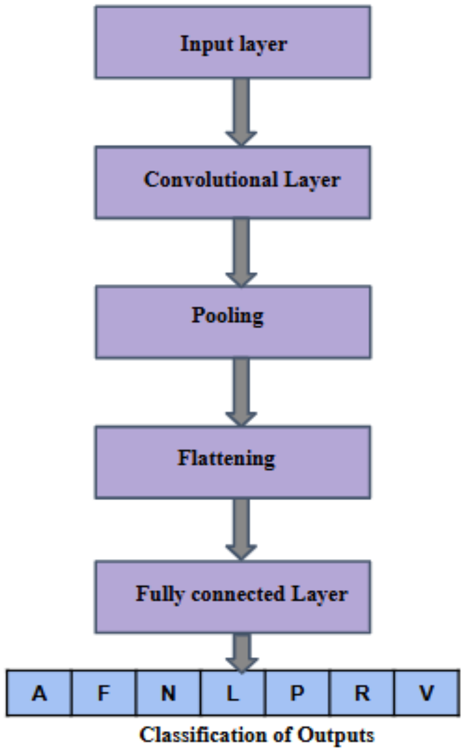

Fig 2. 1-D CNN Architecture

Data Preprocessing is important for the ECG signals in order to improve the signal quality before sending them into a deep learning model. ECG signals are prone to noise caused by baseline wandering, electrode movement, muscle activity, and power line interference. These noises and artifacts may influence the classification performance if not removed appropriately. Hence, preprocessing steps including noise-filtering, segmentation, and normalization of the raw ECG signals. The ECG signal is first filtered to eliminate baseline shift and high-frequency interference. Later, R-peak identification algorithms are used to further divide these noiseless ECG signals into individual heartbeats. The length and signal amplitude of the ECG beats are further normalized..

Later, Feature extraction and representation is performed using deep learning after preprocessing. The 1D-CNN architecture applies convolutional filters along the temporal axis of the ECG signal to extract characteristic waveform features like peaks and intervals. The convolutional layers are then followed by activation and pooling layers to help dimensionality reduction and feature representation. Batch normalization layers are also used to speed up training and convergence. The resulting feature maps contain morphological information about ECG signals which has been shown to help with classification of different arrhythmia types.

Later, We use an LSTM layer to learn the temporal evolution of the extracted features across heartbeats. The output of these LSTM layers is subsequently fed through the fully connected (FCN) layers to perform classification. A softmax activation function is used at the final layer to produce probability scores for each arrhythmia class. To measure the effectiveness of the suggested model, we train it and conduct additional testing. We assess measures like overall accuracy, precision, recall, specificity, and F-Score.

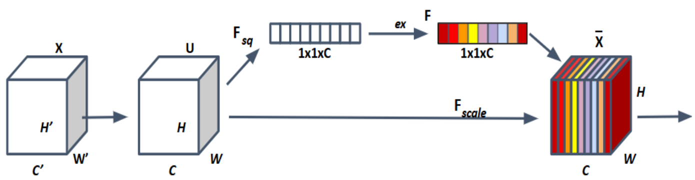

Fig 3. Channel Attention (SE) - Scale and Combine

IV. Proposed System

The proposed architecture combines a 1D-CNN network, the Squeeze-and-Excitation (SE) attention mechanism, and an LSTM Network in conjunction with the Fully Connected Network (FCN). The proposed system is characterized by a series of steps, including data preprocessing, feature extraction, channel attention using the SE blocks, and temporal modeling using the LSTM networks. Finally, the classification is done using fully connected layers.

The Initial step of this proposed system is extracting morphological features from ECG signals using 1D CNN. Multiple learnable filters are applied to the convolutional layers that slide across the temporal axis of the ECG signal to learn important features. The convolutional layers are then followed by an activation function, a Rectified Linear Unit (ReLU) in our model that introduces nonlinearity and helps the network learn complex patterns.

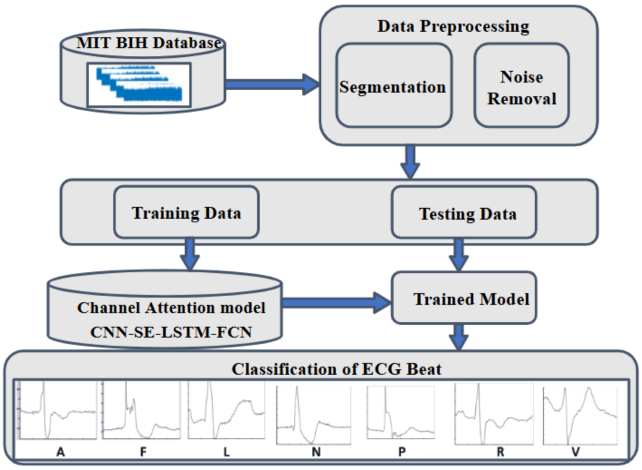

Fig 4. Block Diagram of model proposed

To further improve the feature representation, an SE attention mechanism is looped into the CNN network. During the squeeze operation, global average pooling is used to compact the spatial information into a single value. A compact channel descriptor that encapsulates each channel's global information is produced by the squeeze operation. In order to get attention weights, the channel descriptors are supplied through fully connected layers and activation functions during the excitation process. In order to teach the network to highlight the significant characteristics and minimize the irrelevant ones, the attention weights are then multiplied by the initial feature maps. This adaptive feature weighting mechanism greatly enhances the representational power of the CNN network and boosts the performance of classification.

After extracting spatial features and applying channel attention, our model includes an LSTM network .The ECG signal, as a sequential signal, has an inherent relationship between successive heartbeats. The temporal dynamics of the ECG signal contain important information for classification performed. This output from the LSTM layer is merged with the extracted spatial features and fed into a Fully Connected network (FCN). The FCN aggregates all learned features and performs the final classification using a softmax activation function. The output layer yields probability scores for each arrhythmia class. Our proposed system, which combines CNN-based feature extraction, attention mechanisms, and LSTM-based temporal modeling, has improved robustness, generalization, and classification accuracy when compared with conventional methods.

V. RESULTS

Testing is conducted with the aim of the accurate classification of seven arrhythmias namely N, F, A, L, R, P and V. The database consists of 10,556 ECG beat samples, out of which 9,568 were taken to train, and 988 were used to test the model.

Beat	Training	Testing
Normal - N	2356	241
Fusion - F	1034	108
Atrial - A	976	101
Left - L	1598	165
Paced - P	1239	129
Right - R	956	99
Ventricular - V	1409	145
Total	9568	988

Table 1. Summary of the ECG beats

Parameter	Value
Mini Batch Size	32
Maximum Epochs	15
LSTM Hidden Units	100
Initial Learn Rate	0.0001
Drop Factor of Learn Rate	0.2

Table 2. LSTM Learning parameter configuration

While the training iterations increase, the model gradually learns the feature information of ECG signals and enhances its classification performance. The training accuracy increases with training iterations, while the loss value decreases, which indicates that the model can be optimized to converge well. This deep neural network has the adaptive learning ability to learn the complex nonlinear information of ECG signals. The convolutional layer mixed with the SE block can make the model learn the important waveform information such as QRS complex and P wave, which are essential for arrhythmia classification. The stability of the training graph shows that the proposed architecture can learn the characteristic patterns well without overfitting the training data.

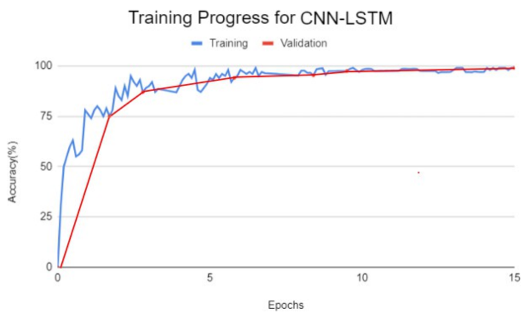

Fig 5. Training Process of CNN–LSTM–FCN Model

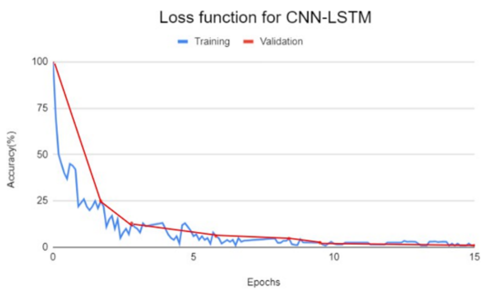

Fig.6 Loss Function of CNN–LSTM–FCN Model

True Class (Beats)

Predicted Class (Beats)	A	F	N	L	P	R	V
A	100			1			
F		107			1		
N			241				
L				164		2	
P			1		128		
R					1	98	
V							145

Fig.7 Confusion Matrix of CNN–LSTM–FCN Model

The above shown confusion matrix compares the actual class label with the predicted class label for each beat of ECG. The diagonal shows a large number of correctly classified samples indicating good classification performance.For example, the model has perfect accuracy for some classes such as atrial premature beats and premature ventricular contractions. Although a small number of misclassifications occur for some classes due to similar waveform patterns, the classification performance is highly accurate.

The proposed CNN–SE–LSTM–FCN model can classify the ECG beat accurately with an accuracy of 99.68%.

Performance Parameters	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F-score
CNN-SE-LSTM-FCN	99.68	99.7	99.5	99.6	99.6
A	100	100	99.01	100	99.5
F	100	100	99.07	100	99.53
N	99.8	99.59	100	99.87	99.79
L	99.5	99.39	98.8	99.88	99.09
P	99.8	98.46	99.22	99.77	98.84
R	99.8	98	98.99	89.99	98.49
V	100	100	100	81.7	100

Table 3. Performance parameters of the model

Model	Technique Used	Accuracy (%)
Sun J [20]	CNN+RNN+Attn.	Fscore:0.9082
Niu L [21]	CNN+RNN+Attn.	92.5%
Najia M [25]	CNN+BiLSTM+Attn	99.2%
Proposed model	CNN+LSTM-FCN+SE	99.68%

Table 4. Comparison with other previous models

Finally, we have compared this model with several other existing models. Reported classification accuracies reported in the literature range between 76% and 95% using CNN, MLP, and other machine learning models. However, the reported accuracy of 99.68% reported by the proposed CNN–SE–LSTM–FCN model is more than the reported models.

VI. Conclusion

In this paper, an efficient deep learning framework for ECG beat classification is proposed. The CNN component of our system is effective in extracting morphological structures such as local fluctuations and waveform patterns from ECG data and the LSTM net component is effective in extracting rhythm-related characteristics as well as time-related relationships. The SE attention block increases the significance of the separate channels, thereby enhancing the model's ability. This combination enhances both feature representation and classification accuracy. Experimentally, the model achieved an accuracy of 99.68%, outperforming many of the current approaches. This proposed CNN-SE-LSTM-FCN model can be applied as an effective system for arrhythmia detection. In the future, the model can be tested with large data sets and used in real-time ECG monitoring systems for cardiac health assessment.

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