Cardiac Arrhythmia Detection in Electrocardiogram Signals with CNN-LSTM

Igor Lopes Souza[a] and Daniel Oliveira Dantas[b]
Departamento de Computação, Universidade Federal de Sergipe, São Cristóvão, SE, Brazil

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Abstract: Sudden cardiac death and arrhythmia account for a large percentage of all deaths worldwide. Electrocardiography is essential in the clinical evaluation of patients who have heart disease. Through the electrocardiogram (ECG), medical doctors can identify whether the cardiac muscle dysfunctions presented by the patient have an inflammatory origin and diagnose early serious diseases that primarily affect the blood vessels and the brain. The basis of arrhythmia diagnosis is the identification of normal and abnormal heartbeats and their classification into different diagnoses based on ECG morphology. Traditionally, ECG signals are classified manually, requiring experience and great skill, while being time-consuming and prone to error. Thus, machine learning algorithms have been widely adopted because of their ability to perform complex data analysis. The objective of this study is to develop a classifier capable of classifying a patient's ECG signals for the detection of arrhythmia in clinical patients. We developed a convolutional neural network (CNN) with long short memory (LSTM) to identify five classes of heartbeats in ECG signals. Our experiment was conducted with ECG signals obtained from a publicly available MIT-BIH database. The number of instances was even out to five classes of heartbeats. The proposed model achieved an accuracy of 98.12% and an F1-score of 99.72% in the classification of ventricular ectopic beats (V), and an accuracy of 97.39% and an F1-score of 95.25% in the classification of supraventricular ectopic beats (S).

1 INTRODUCTION

According to the World Health Organization, cardiovascular diseases (CVDs) are the leading cause of death in the world (Wold Health Organization, 2023). Arrhythmia, a heart rhythm disorder, is considered one of the most common disorders of the heart. Arrhythmias can lead to tachycardia or even sudden cardiac arrest. Heartbeat classification based on ECG signal has become a valuable and promising technique for early warning of arrhythmias. However, variations in ECG signals can be significant among different subjects. Under different circumstances, the waveform and rhythms produced by the arrhythmia symptoms can be quite different as well. Experienced cardiologists can easily distinguish abnormal heartbeats from normal sinus rhythms by observing the ECG. However, this is still challenging for patients who wish to accompany their clinical symptoms. Computer-driven signal processing is an important tool to diagnose arrhythmia in the field of biomedical engineering. Today, biomedicine has advanced to the stage of the practical application of signal processing and pattern analysis techniques.

Many approaches to arrhythmia heartbeat classification with convolutional neural networks (CNN) have been proposed. Ozaltin (Ozaltin and Yeniay, 2022) proposed a novel CNN architecture to detect ECG types. In addition, the proposed CNN can automatically extract features from images. He classifies an ECG dataset using a CNN with 34 layers. While this dataset is composed of 1D signals, these are transformed into images using continuous wavelet transform (CWT). In addition, the proposed CNN is compared to known architectures, AlexNet and SqueezeNet, for classifying ECG images. Ozaltin not only performed CWT but also implemented a short-time Fourier transform. Ozaltin obtained an accuracy of 99.21% from the proposed CNN–SVM when using CWT.

Li (Li et al., 2018) proposed a generic convolutional neural network (GCNN) trained first using heartbeats without distinguishing patients. Based on the GCNN, the fine-tuning technique is applied to

[a] https://orcid.org/0000-0002-2499-4607
[b] https://orcid.org/0000-0002-0142-891X

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modify the GCNN to a tuned dedicated CNN (TDCNN) for the corresponding individual. Fine-tuning is done in several seconds rather than dozens of minutes, necessary for the TDCNN to be used to monitor the long-term ECG signals in clinics. To accelerate the ECG classification, only the original ECG heartbeat is input to the CNN without other extended information from the adjacent heartbeats or FFT representation.

Cao (Cao et al., 2022) proposed a novel nonlinear adaptive noise-canceling framework (ANC) based on a temporal CNN to effectively extract fetal ECG signals from mothers' abdominal ECG recordings. The proposed framework consists of a two-step network, using the ANC architecture; one network is for the maternal ECG component elimination and the other is for the residual noise component removal of the extracted fetal ECG signal. Then, joint approximation diagonalization of eigenmatrices (JADE), one of the blind source separation algorithms, is applied as a post-processing step to produce a clean fetal ECG signal.

Kamozawa (Kamozawa et al., 2023) proposed a method for detecting atrial fibrillation (AF) from an electrocardiogram (ECG) measured by a 24-hour Holter electrocardiograph (Holter-ECG) using CNN. In the preprocessing step, artifacts and noises on Holter-ECG are removed by a bandpass filter. The detection method consists of extraction of abnormal waveforms using 1D CNN trained with segmented ECG waveform, spectral entropy, and identification of AF.

Xiong (Xiong et al., 2017) created a data-driven deep learning pipeline using a 16-layer CNN for the automatic classification of ECG signals. Xiong used a large dataset recorded from patients and labeled by medical experts in ECG for developing and validating his approach.

Kiranyaz (Kiranyaz et al., 2017) created a system that can detect early occurrences of arrhythmias, by modeling common causes of arrhythmias in a patient's ECG signal. The causes of arrhythmia are modeled as a degradation from normal ECG beats. The CNN was trained using real normal beats and synthesized abnormal beats.

Han (Han and Shi, 2020) proposed a multi-lead attention (MLA) mechanism integrated with a CNN to detect myocardial infarction (MI) in 12-lead ECG recordings. The MLA automatically assigns weights to different leads and a 2D CNN extracts discriminative features from all the 12 leads. The robustness of the MI detection was tested in both intra-patient and inter patient schemes.

Martis (Martis et al., 2014) investigated four different methods for atrial fibrillation and atrial flutter feature extraction: the principal components of discrete wavelet transform coefficients, independent components of discrete wavelet transform coefficients, principal components of discrete cosine transform coefficients, and independent components of discrete wavelet transform coefficients methods. Martis explored three different classification techniques: K-nearest neighbor, decision tree, and artificial neural network. The methodology used data from MIT-BIH arrhythmia and atrial fibrillation databases. Discrete cosine transform coupled with independent component analysis and K-nearest neighbor yielded the highest average sensitivity of 99.61%, average specificity of 99.99%, and classification accuracy of 99.45% using tenfold cross-validation.

We believe that it is possible to further improve the accuracy, sensitivity, specificity, precision, and F1-score of CNN heartbeat classifiers of our previous works. Our study aims to improve the classification metrics of our previous study by using LSTM combined with CNN models (Souza and Dantas, 2023). We used a fine-tuning step for further optimization of the classification of arrhythmia. The improved classification of ECG signals will generate more accurate responses in the detection of cardiac arrhythmias, facilitating the health care of patients. The proposed neural network architecture provides a better F1-score when compared to the previously listed works, and provides a higher F1-score and less training time when compared to our previous work.

2 METHODOLOGY

In this study, we created classifiers based on CNN-LSTM and AlexNet capable of distinguishing the different types of heartbeats and detecting cardiac arrhythmia. Their architecture was fine-tuned so that the models achieved the highest validation accuracy possible and were compared to the decision tree, random forest and extra trees classifiers (Kumar, 2022). Our models were based on a previous study (Souza and Dantas, 2023) and evaluated in the test set. The ECG heartbeat classifier is composed of two main steps: preprocessing and classification. The CNN-LSTM and AlexNet network architectures are shown in Figure 1 and Figure 2 respectively. The implementation of this methodology is publicly available[1] and was coded in Python using Tensorflow, Keras, and Numpy.

[1]https://github.com/Igor-Lopes-Souza/2023-CNN-LSTM

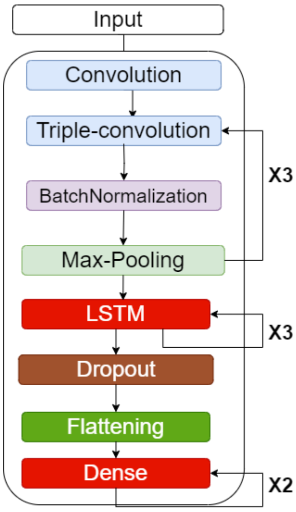

Figure 1: CNN-LSTM architecture.

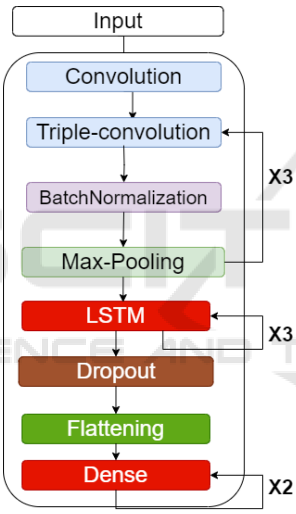

Figure 2: AlexNet architecture.

In the following subsections we will describe the dataset used, the preprocessing step, which includes filtering and data augmentation, the classifier architecture, and classifier training.

2.1 Dataset

In this study, we used the ECG Heartbeat Categorization Dataset, freely available in the Internet[2]. We used only the portion of the dataset derived from the Physio Bank MIT-BIH Arrhythmia database (Mark and Moody, 1988). This database consists of a 48 half-hour long ECG recordings from 47 subjects—obtained with a Lead II ECG configuration—that

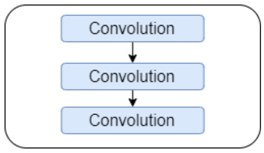

Figure 3: Triple-convolution.

were band-pass filtered over the frequency range from 0.1 to 100Hz and digitized at 360 samples per second. Furthermore, these recordings were interpreted and validated by at least two cardiologists. The database consists of annotations for both heartbeat class information and R-peak position information verified by two or more expert cardiologists. The 17 beat types can be grouped into five beat classes defined by the Association of Advancement for Medical Instrumentation (AAMI) which follows the American National Standard for Ambulatory ECGs (ANSI/AAMI EC38:2007) recommendations. The five beat types are the non-ectopic beat (N), supraventricular ectopic beat (S), ventricular ectopic beat (V), fusion beat (F), and unknown (Q).

2.2 Preprocessing

The MIT-BIH dataset is unbalanced, difficulting the analysis of the signal. The original dataset contains a total of 109,446 data rows. Each data row contains a fraction of the ECG signal with duration of 10 seconds and its class, specified in the last column by a number from 0 to 4 representing N, S, Q, F, and Q. There are 70,043 data rows for training, 17,511 for validation and 21,892 for testing, making the proportions 65/15/20. We augmented the training and validation datasets to match the value of the biggest class from the five types of heartbeats.

The raw MIT-BIH signal is corrupted by myoelectric interference, power line interference, and line drift. We added noise through the Gaussian function, by creating a random variable and adding it to our train dataset in order to simulate the myoelectric interferences and better train our model (Yong et al., 2011). The noise serves to better train our model by adding a varying variable to our dataset, acting as a probability distribution. To remove the noise, the raw ECG signal is filtered using wavelet filters (Audhkhasi et al., 2016). The raw signal is decomposed by Daubechies wavelet 6(db6) at six levels, and wavelet coefficients from the third to the sixth level were retained and used for signal reconstruction (Shi et al., 2019).

[2]https://www.kaggle.com/datasets/shayanfazeli/heartbeat

Table 1: Hyperparameter values chosen in classifier fine-tuning.

Parameters	Values	Chosen Value
Dropout	0.10, 0.20, 0.30, 0.40, 0.50	0.50
Optimizer	Adam, Adamax, SGD	Adam
Activation function	Relu, Softmax, Softplus	Relu
Batch size	10, 32, 54, 76, 98	98
Loss function	Binary cross-entropy, Categorical cross-entropy, Poisson, Kullback-Leibler divergence, Huber	Categorical cross-entropy

Table 2: Number of samples in the training, validation, and test sets.

	Before data augmentation			After data augmentation		
	Training	Validation	Test	Training	Validation	Test
N	57974	14493	18118	57974	14493	N/A
S	1778	450	556	57974	14493	N/A
V	4630	1155	1448	57974	14493	N/A
F	520	127	162	57974	14493	N/A
Q	5141	1286	1608	57974	14493	N/A
Total	70043	17511	21892	289870	72465	N/A

2.3 Classifier Architecture

Figure 1 shows the CNN-LSTM classifier architecture, which comprises convolutional layers, subsampling layers, fully connected layers, batch normalization layers, LSTM layers and a dropout layer. Usually, each convolution layer is followed by a subsampling layer. In order to facilitate mapping between the heartbeat category and its waveform, we use a triple-convolution structure to achieve a more powerful fitting capability (Uchida et al., 2018) in our CNN model. Figure 3 shows the structure of a triple-convolution layer sequence.

Figure 2 show the schematic of our AlexNet classifier. The standard AlexNet classifier (Krizhevsky et al., 2012) is used for 2D image classification, while we modify its architecture for the analysis of ECG signals, which are 1D. The AlexNet classifier comprises convolutional layers, subsampling layers, fully connected layers, batch normalization layers, and dropout layers. We altered the convolution, max-pooling, and dropout layers to use their 1D versions. In our AlexNet architecture when compared to the standard format, we doubled the number of triple-convolutions to obtain better accuracy and used the batch-normalization layer to normalize the interlayer outputs into a standard format.

In order to compare the performance of the proposed models with standard classification algorithms, our CNN-LSTM and AlexNet models are compared with extra trees, random forest and decision tree classifiers (Alom et al., 2018; Yu et al., 2019) that were trained with the sklearn default configuration and our training dataset (Kramer and Kramer, 2016). The extra trees, decision tree, and random forest classifiers architecture use the following parameters in their default form:

- Minimal Number of Leaves: 1
- Minimal Number of Samples Split: 2
- Criterion: gini,
- Maximum Depth: None,
- Maximum Number of Features: sqrt,
- Maximum Number of Leaf Nodes: None,
- Maximum Number of Samples: None,
- Number of Estimators: 100

In this study, we use the ReLu activation function in both convolutional layers and fully connected layers (Nair and Hinton, 2010; Girosi et al., 1995). In the output layer, we use the softmax activation function to obtain the five heartbeat classes.

2.4 Training Method

The goal of training is to reduce the value of the loss function L, i.e., to decrease the CNN-LSTM and AlexNet models loss and adjust the weights and biases so that Equation 1 fits the model training set. The cross-entropy function is used as the loss function (Xu and Liu, 2020):

Table 3: Comparison of the proposed algorithm classification using ventricular ectopic beats (V).

	ACC	SEN	SPE	PRE	F1S
Martis (Martis et al., 2014)	99.45%	**99.61%**	**99.99%**	**99.99%**	**99.80%**
Proposed classifier: CNN-LSTM	98.12%	99.00%	98.85%	99.39%	99.72%
Souza (Souza and Dantas, 2023)	99.33%	99.59%	99.30%	99.12%	99.44%
Sellami (Sellami and Hwang, 2019)	**99.48%**	96.97%	99.87%	98.83%	97.80%
Acharya (Acharya et al., 2017)	94.03%	96.71%	91.54%	97.85%	97.27%
Zhai (Zhai and Tin, 2018)	99.10%	96.40%	99.50%	96.40%	96.40%
Jiang (Jiang and Kong, 2007)	98.80%	94.30%	99.40%	95.30%	94.70%
Xiang (Xiang et al., 2018)	99.20%	93.70%	99.60%	94.80%	94.20%
Ince (Ince et al., 2009)	97.60%	83.60%	98.10%	87.40%	85.40%
Proposed classifier: AlexNet	96.66%	99.45%	99.10%	96.85%	80.07%

Table 4: Comparison of proposed implementations using ventricular ectopic beats (V).

	ACC	SEN	SPE	PRE	F1S
CNN-LSTM	98.12%	99.00%	98.85%	99.39%	**99.72**%
Decision tree classifier	99.11%	99.22%	99.16%	99.00%	99.36%
Random forest classifier	95.32%	95.73%	98.83%	96.39%	95.40%
Extra trees classifier	95.40%	95.27%	94.70%	95.25%	95.35%
AlexNet	96.66%	99.45%	99.10%	96.85%	80.07%

We update the weights and offsets using the Adam optimizer (Kingma and Ba, 2014). First, a batch of samples was sent to calculate the gradient of the Equation 1, and we set the batch size to 98:

$$g = \left(\frac{1}{m} \nabla_{\theta} \sum_{i} L(f(x^{(i)};\theta), y^{(i)}) \right). \tag{1}$$

The g is the gradient value, m is the batch size, θ is the parameter to be updated, $f(x^{(i)};\theta)$ is the heartbeat type predicted by the i-th sample, $y^{(i)}$ is the actual type of the i-th sample, and L is the loss function.

After defining the architecture, fine-tuning was performed to obtain the best values of dropout, optimizer, activation function, loss function, and batch size. A grid search in the hyperparameter space tested each possible combination with 20 epochs. Table 1 shows the tested hyperparameter values and the ones that maximized accuracy.

3 RESULTS AND DISCUSSION

We performed classification experiments on 44 recordings from the MIT-BIH arrhythmia database, among the 48 recordings obtained from 47 patients studied by the BIH arrhythmia laboratory, and the heartbeats were classified according to the recommendation of the AAMI.

The training dataset contains a total of 109,466 data rows of representative beats from all classes: type-N, non-ectopic beats; type-S, supraventricular ectopic beats; type-V, ventricular ectopic beats; type-F, fusion beats; and type-Q, unknown beats. Classification performance is measured using the statistical error metrics found in the literature (Chen et al., 2022): accuracy (ACC), sensitivity (SEN), specificity (SPE), precision (PRE), and F1-score (F1S). The F1-score measures the overall performance of the beat classification, as shown in Table 3.

Our CNN-LSTM and AlexNet models were implemented using the TensorFlow framework. The CNN-LSTM and AlexNet models training time of each epoch was approximately 20s, and the maximum epoch number was set to 100. Table 3 shows that the CNN-LSTM model has an F1-score value comparable to those of other studies, presenting the second best results. Table 4 shows the results of the different proposed architectures. In this study, our CNN-LSTM model achieved an accuracy of 98.12%, sensitivity of 99.00%, specificity of 98.85%, precision of 99.39%, and F1-score of 99.72% and our AlexNet model achieved an accuracy of 96.66%, sensitivity of 99.45%, specificity of 99.10%, precision of 96.85%,

Table 5: Comparison of the types of heartbeats.

	ACC	SEN	SPE	PRE	F1S
Normal (N)	99.45%	99.98%	92.83%	90.89%	99.44%
Supraventricular ectopic beats (S)	97.39%	88.61%	98.92%	88.92%	95.25%
Ventricular ectopic beats (V)	98.12%	99.00%	98.85%	99.39%	99.72%
Fusion Beats (F)	87.40%	77.27%	84.70%	95.25%	82.35%
Unknown Beats (Q)	99.32%	99.65%	98.72%	97.20%	99.10%

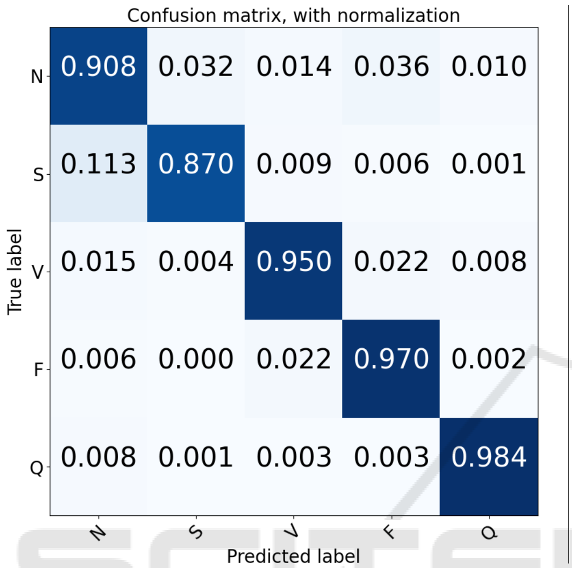

Figure 4: Confusion matrix for heartbeat classification on the test set.

and F1-score of 80.07%.

Figure 4 shows the confusion matrix of the classification results of the CNN-LSTM test set. The model is able to make accurate predictions and distinguish different classes. The main reason behind this might be that we have fine-tuned our model, as unrefined tests with ventricular ectopic beats (V) obtained an average accuracy of 89.99% and an F1-score of 88.54%.

4 CONCLUSIONS

In this study, we designed an ECG signals classifier for cardiac arrhythmia detection using CNN-LSTMs. The proposed model achieved an accuracy of 98.12% and an F1-score of 99.72% in the classification of ventricular ectopic beats (V), and an accuracy of 97.39% and an F1-score of 95.25% in the classification of supraventricular ectopic beats (S) as shown in Table 5. In order to optimize our model, we fine-tuned the hyperparameters. The selected values compose our final version of the classifier and are displayed in Table 1. Compared with the methods in the literature, our model performed better in terms of ventricular ectopic beat classification precision and F1-score, only being surpassed by Martis (Martis et al., 2014).

Our trained CNN heartbeat classifier model can be used for real-life and real-time applications. It can also be used to analyze other 1D biosignals. Future work may refine this approach with a better set of hyperparameter values and different augmentation strategies and training methods.

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