Cardiac Arrhythmia Classification in Electrocardiogram Signals with Convolutional Neural Networks

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Abstract: Electrocardiography is a frequently used examination technique for heart disease diagnosis. 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 early diagnosis of 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. Heartbeats can be divided into five categories: non-ectopic, supraventricular ectopic, ventricular ectopic, fusion, and unknown beats. It is difficult to distinguish these heartbeats apart on the ECG as these signals are typically corrupted by outside noise. 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) to identify five categories 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 99.33% and an F1-score of 99.44% in the classification of ventricular ectopic beats (VEB).

1 INTRODUCTION

According to the World Health Organization, cardiovascular diseases (CVDs) are the leading cause of death in the world (McAloon et al., 2016). Arrhythmia, a heart rhythm disorder, is considered one of the most common disorders of the heart. Arrhythmia is a problem with the rate or rhythm of the heartbeat. During an arrhythmia, the heart may beat too fast, too slow, or with an irregular rhythm. Atrial fibrillation (AF) is the most prevalent case of arrhythmia. AF causes irregular heartbeats. In AF, the electrical activity of the atria (the heart's upper chambers) is irregular, inconsistent, and not synchronized with ventricles (Hagiwara et al., 2018).

AF is diagnosed by interpreting the ECG. Automatic diagnosis is useful in home settings, where an ECG interpretation specialist is not available to diagnose AF (Mant et al., 2007). Classification of ECG signals is necessary for the automatic diagnosis of arrhythmia. To improve AF detection, machine learning methods were used by various authors (Lown et al., 2020; Pollock et al., 2020; Shoemaker et al., 2020). Recently, Sanchez successfully experimented with the latest and most innovative convolutional neural networks (CNN) (Sánchez and Cervera, 2019). Deep convolutional neural networks have the capability of hierarchical feature learning, which allows the neural network to differentiate and generalize ECG signal patterns with higher accuracy than an expert (Chen et al., 2022; Kiranyaz et al., 2021). CNNs have been used to diagnose arrhythmias, and coronary artery diseases, and classify strokes (Zhiqiang and Jun, 2017).

Many approaches to arrhythmia heartbeat classification with CNN have been proposed. Han (Han and Shi, 2020) presents a method to detect and localize myocardial infarction by combining a multiple-lead residual neural network (ML-ResNet) framework with three residual blocks and feature fusion using 12-lead ECG recordings.

Qiyang Xie (Xie et al., 2021) used ResNet34 to train a model with the morphological characteristics of ECG signals and obtain meaningful information from ECG signals.

Xiong (Xiong et al., 2017) proposed a purely data-driven, deep learning pipeline, a 16-layer CNN, for the automatic classification of ECG signals from the

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Computing in Cardiology (CinC) Challenge 2017 into four categories, including AF. The large dataset of ECG data recorded from patients and labeled by experts provided a framework for developing and validating their approach to ECG diagnosis.

Zhi Li (Li et al., 2020) developed a deep learning method for cardiac arrhythmia classification based on ResNet. The design consists of a 1D 31-layer convolutional residual network. The algorithm includes four residual blocks, each of which consists of three layers of 1D convolutions, three layers of batch normalization (BN), three layers of the rectified linear unit (ReLU) activation function, and a structure of identity shortcut connections. The 2-lead ECG signals were used in combination with deep learning techniques to automatically identify the normal, left group, right group, premature atrial, and premature ventricular contraction heartbeats.

Zhu (Zhu et al., 2020) developed a deep learning approach for the automated diagnosis of multiple cardiac rhythm labels or conduction abnormalities by real-time ECG signal analysis. The dataset used was obtained from ECG data with 10s in length and 12-channel format. The data is from adult patients, with 21 distinct rhythm classes for the diagnosis of simultaneous cardiac arrhythmias, i.e., patients with multiple heart diseases.

Kiranyaz (Kiranyaz et al., 2017) proposed a personalized health monitoring system that can detect early occurrences of arrhythmias from a patient's ECG signal by modeling common causes of arrhythmias in the signal domain as degradation from normal ECG beats to abnormal beats. Using the degradation models, abnormal beats were created from the patient's average normal beat. A simple 1D convolutional neural network was trained using real normal beats and synthesized abnormal beats.

Han (Han and Shi, 2020) presented a method to detect and localize myocardial infarction by combining an ML-ResNet framework with three residual blocks and feature fusion using 12-lead ECG recordings. The single-lead feature branching network is trained to automatically learn local features of different levels between different layers, which can be used to characterize the spatial representation of the ECG. The main features are merged as global features. For the generalization and evaluation of the proposed method in clinics, intra-patient and inter-patient schemes were used.

Acharya (Acharya et al., 2017) developed a nine-layer deep convolutional neural network to identify five different categories of heartbeats in ECG signals: non-ectopic beat, supraventricular ectopic beat, ventricular ectopic beat, fusion beat, and unknown beat. The experiment was conducted on noise-attenuated and non-attenuated data sets from a public database, MIT-BIH. This set was artificially augmented to equal the number of instances of the five heartbeat classes and filtered to remove high-frequency noise.

Xiang (Xiang et al., 2018) proposed an accurate method for patient-specific ECG beat classification, which adopts morphological features and timing information. As to the morphological features of a heartbeat, attention-based two-level 1-D CNN is incorporated in the proposed method to extract different-grained features automatically by focusing on various parts of a heartbeat. The timing information, the difference between previous and post RR intervals, is computed as a dynamic feature. Both the extracted morphological features and the interval difference are used by multi-layer perceptron (MLP) for classifying ECG signals.

Ali Sellami (Sellami and Hwang, 2019) proposed a new type of deep convolutional neural network for heartbeat classification. A batch-weighted loss function was created to quantify the loss and decrease the imbalance between classes. The loss weights change dynamically as the distribution of classes in each batch changes.

Schwab (Schwab et al., 2017) proposed a machine learning approach based on recurrent neural networks (RNN) to analyze different cardiac arrhythmias with only a single lead and short ECG recordings, below 10s. To facilitate training dependencies on the temporal dimension, a new task formulation was introduced that takes advantage of the natural beat-based segmentation of ECG signals.

Rahhal (Al Rahhal et al., 2019) proposed a novel end-to-end architecture based on a dense convolutional network (DCN) for ECG signal classification. The architecture is based on two main modules: the first is a generative module and the second is a discriminative module. The generative module converts the one-dimensional ECG signal into an image through fully connected up-sampling layers and convolutional layers. The discriminative module receives the image from the generative module and performs feature learning and classification.

Zhai (Zhai and Tin, 2018) developed a high-performance ECG-based arrhythmic beat classification system. The classifier was designed based on a CNN. The single-channel ECG signal was segmented into heartbeats according to the change in beats. Zhai provided accurate ECG classification tools.

We believe that it is possible to further improve the accuracy, sensitivity, specificity, precision, and F1-score of CNN heartbeat classifiers. Our study aims to improve the classification metrics by increasing the number of convolution layers in the couple-convolution implementation and using a new architecture with triple-convolution (Uchida et al., 2018) for the classifier in conjunction with fine-tuning for further optimization. The classification of arrhythmia signals in public ECG datasets will generate more precise and accurate results. The improved classification of ECG signals will generate more accurate responses in the detection of cardiac arrhythmias, facilitating the health care of patients. Our neural network architecture was inspired by Xiong architecture design (Xiong et al., 2017), but with a faster architecture, fewer loops, more convolutions for feature extraction, and a higher resulting F1-Score.

2 METHODOLOGY

In this study, we created a classifier capable of distinguishing the different types of heartbeats and detecting cardiac arrhythmia. This architecture was fine-tuned so that the models achieved the highest validation accuracy and F1-score possible. Our model was evaluated in the test set. The ECG heartbeat classifier is composed of two main steps: preprocessing and classification. The network architecture is shown in Figure 1. The implementation of this methodology is publicly available [1] and was coded in Python using Tensorflow, Keras, and Numpy.

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 was 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.

[1] https://github.com/Igor-Lopes-Souza/VISAPP-2023
[2] https://www.kaggle.com/datasets/shayanfazeli/heartbeat

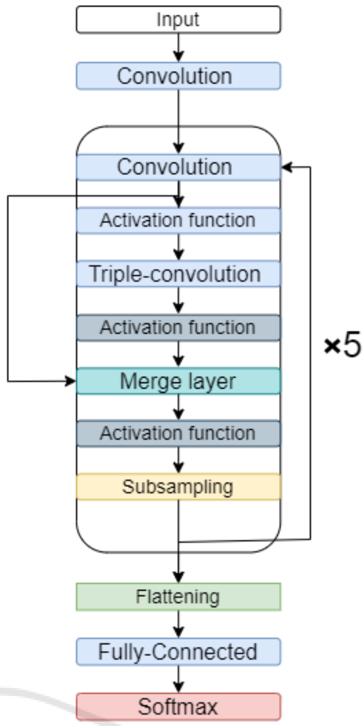

Figure 1: Neural network architecture.

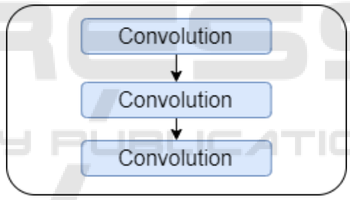

Figure 2: Triple-convolution.

2.2 Preprocessing

The raw MIT-BIH signal is corrupted by myoelectric interference, power line interference, and line drift. To remove these noises, the raw ECG signal is filtered using wavelet filters. 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). After noise removal, we segmented the signal for heartbeats by taking advantage of information from the positions of the R-peaks annotated in the MIT-BIH arrhythmia database. Each heartbeat consists of 300 samples: 149 before and 150 after the R-peak position.

2.3 Classifier Architecture

Figure 1 shows the schematic of our CNN classifier. The network is composed of convolutional lay-

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

Parameters	Values	Chosen Value
Dropout	0.10, 0.25, 0.30, 0.50	0.50
Optimizer	Adam, Adamax, SGD	Adam
Activation function	Relu, Selu, Elu, Softmax, Softplus	Relu
Batch size	100, 250, 500, 1000, 1500	500
Epochs	10, 25, 75, 125, 175, 300, 1000	75
Loss function	Binary cross-entropy, Categorical cross-entropy, Poisson, Kullback-Leibler divergence, Huber	Categorical cross-entropy
Learning rate	0.01, 0.001, 0.0001, 0.00001	0.0001
$\beta 1$	0.900, 0.990, 0.999	0.900
$\beta 2$	0.900, 0.990, 0.999	0.990

Table 2: Comparison of the proposed algorithm classification using ventricular ectopic beats (VEB).

	ACC	SEN	SPE	PRE	F1S
Martis (Martis et al., 2014)	99.45%	**99.61%**	**99.99%**	**99.99%**	**99.8%**
Proposed classifier	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%
Yande (Xiang et al., 2018)	99.20%	93.70%	99.60%	94.80%	94.20%
Jiang (Jiang and Kong, 2007)	98.80%	94.30%	99.40%	95.30%	94.70%
Ince (Ince et al., 2009)	97.60%	83.60%	98.10%	87.40%	85.40%

ers, subsampling layers, fully connected layers, and a softmax layer. The convolutional layers perform the convolution operations on the output of a previous layer using the current convolution kernel (ω_{ik}). The merge layer adds two layers, in our case the second convolution layer and the first activation function of each execution. Usually, each convolution layer is followed by a subsampling layer. However, 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). Figure 2 shows the structure of a triple-convolution layer sequence.

The subsampling layer was used to reduce by half the input size of the next layer, compressing the size of the ECG data, reducing the number of computations and extracting useful features, our max pooling size is set to 5 with a stride of 2 in all pooling layers. The function max-pooling was used to obtain the maximum value inside a region around each position in the input matrix (Murray and Perronnin, 2014). Fully connected layers were used to increase the number of nonlinear operations (Xu et al., 2019).

In this study, we use the ReLu function as an 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 activation function softmax to obtain the five heartbeat categories (non-ectopic beat, supraventricular ectopic beat, ventricular ectopic beat, fusion beat, and unknown beat) (Nwankpa et al., 2018).

2.4 Training Method

The goal of training is to reduce the value of the loss function L, i.e., to decrease the model 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):

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 256:

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

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. The m_t and v_t represent the first and second estimates of the moment of the gradient. The $\hat{m}_t$ and $\hat{v}_t$ are the corresponding bias corrections. The β_1 and β_2 are the decay rates for the moment estimates, set to 0.900 and 0.990.

The regularization dropout (Hinton et al., 2012; Srivastava et al., 2014) was used to avoid overfitting

Table 3: Comparison of proposed implementations.

			ACC	SEN	SPE	PRE	F1S
With preprocessing	With subsampling	Triple convolution	**99.33%**	**99.59%**	**99.30%**	**99.12%**	**99.44%**
		Simple convolution	95.32%	95.73%	98.83%	96.39%	95.40%
	Without subsampling	Triple convolution	95.40%	95.27%	94.70%	95.25%	95.35%
		Simple convolution	90.45%	90.14%	92.83%	90.89%	90.44%
Without preprocessing	With subsampling	Triple convolution	89.65%	89.00%	97.41%	91.63%	89.50%
		Simple convolution	87.85%	83.25%	96.06%	90.63%	87.56%
	Without subsampling	Triple convolution	86.68%	88.69%	96.80%	90.05%	86.67%
		Simple convolution	87.20%	90.40%	90.50%	89.20%	85.80%

and excessive specialization in the training dataset, in the convolutional layer, and in the fully connected layers. The dropout allows the weights of the hidden layer neurons to be randomly set to zero during training, causing these nodes to be ignored. After defining the architecture, fine-tuning was performed to obtain the best number of epochs. The hyperparameters that decreased the classifier training time and increased accuracy and F1-score were obtained and displayed in Table 1.

Since the best optimization method was obtained with the Adam function, we also needed to optimize the learning rate, β1 and β2 values. We tried the values 0.01, 0.001, 0.0001 and 0.00001 for the learning rate. Furthermore, to obtain a variable learning rate, we tested β1 and β2 with the values 0.900, 0.990 and 0.999. The best result was obtained with a 0.0001 learning rate, 0.900 β1 and 0.990 β2. We tested several other loss functions to optimize the classifier, and the categorical cross-entropy was the one that generated the best results. We needed to find the minimum number of epochs necessary to maximize the accuracy. Excessive training could cause overfitting and incapacity to generalize and evaluate new images. We started the test with 100 epochs and increased this value until 1500 epochs. This test showed that for 500 epochs or more, the accuracy remained stable.

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 375 representative beats, including 75 from each class: type-N, non-ectopic beats; type-S, supraventricular ectopic beats; type-V, ventricular ectopic beats; type-F, fusion beats and type-Q, unknown beats. The representative beats are randomly sampled from each class of the first 20 recordings (chosen in the range of 100 to 124) from the MIT-BIH database. The neural networks are trained with a total of 245 common training beats, and a variable number of beats depending on the patient's heart rate, so less than 1% of the total beats are used for training. The 24 unused recordings are used as test patterns for performance evaluation.

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 2.

Our model was implemented using the TensorFlow framework. The training time of each epoch was approximately 5s, and the maximum epoch number was set to 75. Table 2 shows that the implemented classification algorithm has an F1-score value comparable to those of other studies obtaining better results, presenting the second best in Table 2. We show only the VEB in the comparison as it is the most commonly used among other studies. Table 3 shows the results of different convolutional architectures. In this study, our best model achieved an accuracy of 99.33%, sensitivity of 99.59%, specificity of 99.30%, precision of 99.12% and F1-score of 99.44%.

Figure 3 shows the confusion matrix of the clas-

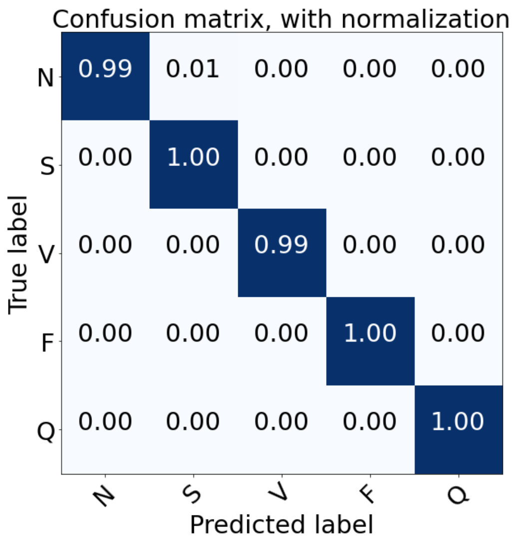

Figure 3: Confusion matrix for heartbeat classification on the test set.

sification results of the test set. The model is able to make accurate predictions and distinguish different classes. The main reason behind this might be the fact that we have used fine-tuning to optimize our model, which allows us to better train our classifier.

4 CONCLUSIONS

In this study, we designed an ECG signals classifier for cardiac arrhythmia detection using CNNs. The proposed model achieved an accuracy of 99.33% and an F1-score of 99.44% in the classification of ventricular ectopic beats (VEB). In order to optimize our model, we fine-tuned our variables and functions, the selected values compose our final version of the classifier and are displayed in Table 1. Compared with the methods in previous literature, our model performed better in terms of VEB classification accuracy, and F1-score.

The referenced authors in Table 2 achieved high accuracy, sensitivity, specificity, precision and F1-score with private datasets. On the other hand, our study managed to obtain high results for these metrics with a public dataset. Our trained CNN heartbeat classifier model can be used for real-life and real-time applications. It can also be used to analyze other biosignals by changing the training the dataset and input size before use. Future work may refine this approach with a better set of hyperparameter values and different augmentation strategies. An F1-score of 99.00% is accurate enough for cardiovascular disease detection in home devices. The method has the potential to be adapted to analyze other biosignals.

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