

CNN Based ECG Dual Heart Beat Arrhythmia Detection

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Abstract

Electrocardiogram (ECG) signals are crucial in the process of cardiac diagnosis as well as ongoing monitoring of health. However, achieving best performance is difficult due to factors such as large variations between patients, imbalanced heartbeat classes, and very subtle differences between certain abnormal beats. Although convolutional neural networks (CNNs) have become popular for ECG classification because of their strong ability to learn features, models based on singlebeat ECG representations often fail to capture important beattobeat information. To address these limitations, this work proposes a dualheartbeat CNNbased framework for ECG arrhythmia classification. Instead of analyzing each heartbeat independently, the method combines neighbouring heartbeats to capture both waveform characteristics and temporal relationships between beats. ECG signals are segmented around detected Rpeaks, and adjacent beats are transformed into twodimensional coupling matrices that serve as inputs to the CNN. In addition, a systematic training beat selection strategy is applied to improve learning for less frequent arrhythmia types. The proposed framework is evaluated using the MITBIH Arrhythmia Database following AAMIrecommended evaluation protocols. Performance is assessed using standard metrics such as sensitivity, precision, and overall accuracy. Experimental results show that the dualheartbeat CNN approach outperforms conventional single-beat CNN models, particularly in detecting supraventricular ectopic beats, where sensitivity improves by approximately 5%to12% while maintaining consistent performance for other heartbeat classes. The suggested approach offers an entirely automatic and stable ECG analysis framework that does not require manual feature eliciting or professional assistance.

Keywords: Electrocardiogram, Arrhythmia, Dual- Heartbeat Coupling, Convolutional Neural Network, Beat Segmentation.

I. INTRODUCTION

The ECG analysis is usually employed to identify Cardiac and Arrhythmias can play an important role in the clinical diagnosis. Proper automatic classification of ECG remains a challenge due to dissimilarity in patients, noises in ECG Signals, and the unequal distribution of the heart-beats of various kinds. There are many traditional ECG classification methods in which that depend on manually designed futures, determined characteristics or deconstruct individual heartbeats, which makes the temporal relations of consecutive difficult to seize. Recently, through the development of deep learning, in particular convolutional ECG analysis has been enhanced by neural networks (CNNs) learners useful

features directly out of data. Those models that are based on single heartbeat inputs are prone to poor performance. When rare arrhythmias are being detected, including supraventricular ectopic beats. In order to overcome these difficulties, this work explores a dual-heartbeat coupling method with a CNN based classifier. It has added both the shape of heartbeat and beat to beat along with the temporal information, the suggested approach is supposed to get better in general performance in arrhythmia detection.

1. Research Background

The cardiac arrhythmia detection is a very vital aspect of clinical diagnosis and long term cardiac assessment because the irregular heart rhythms may reflect underlying severe conditions. The automation of cardiac signal classification has thus received a lot of research interests in the last few decades. Original research mainly depended on handcrafted features based on the signal morphology, temporal interval, or spectral properties, then on traditional machine learning classifier. Even though the methods gained acceptable performance on common rhythm patterns, feature dependency and hence lower adaptability among patients limited their effectiveness. With the development of the deep learning methods and specifically the convolutional neural networks (CNNs), automated arrhythmia classification has been changed since now it is possible to directly learn features by providing end-to-end signal data. With this development, several CNN based methods still utilize single beat representations which ignore the time-dependence between the successive heartbeats. This is particularly problematic in the detection of arrhythmias that possess supraventricular ectopic beats, where rhythm anomaly and slight beat variations are important in clinical interpretation. According to recent studies, contextual and beat- to-beat information has been discovered to be essential to improve the reliability of classification. Due to such observations, this study discusses a dual-heartbeat coupling scheme that is built upon a CNN based framework to learn both morphological and temporal features of cardiac signals to enhance the performance of detecting difficult categories of arrhythmia.

2. Problem Definition

Automatic recognition and classification of cardiac arrhythmias based on ECG signals is a difficult task to get correct. ECG recordings are known to be very different among patients and are most of the time influenced by noise and artifacts. Moreover, arrhythmia data is extremely unbalanced where some of the abnormal cardiac beats are much rarer than normal heartbeats. Most of the current techniques study the beats of the heart separately or use features that are designed manually, which restricts their potential to depict the time correlation between the successive beats. This has led to misclassification of rare yet clinically important arrhythmias, e.g. supraventricular ectopic beats. This demands a requirement of an ECG classification methodology that is able to efficiently model the morphology of the heartbeat and the temporal variations between beats and is completely automatic and reliable across a variety of patients.

3. Key Challenges

The correct classification of ECG arrhythmias is not an easy task due to a number of reasons. The biggest problem is that arrhythmia datasets have a high class imbalance with abnormal heartbeats being significantly less frequent compared to normal heartbeats. This complicates pattern learning of the meaningful patterns of rare arrhythmias in models. The other problem is that there is a high disparity among patients, as the waveforms in an ECG and heart rhythms can vary radically among the patients, which means that a model can generalize itself to new patients only to a limited degree. Supraventricular ectopic beats are another problem since they have similar waveforms to those of normal beats, hence they are difficult to detect when the heartbeats are recorded independently. Noise and artifacts can also

tend to influence ECG recordings, and decrease signal quality as well as worsen classification accuracy. Finally, the use of deep learning models can lead to unstable and unreliable performance since the training is random, and data is split into two parts, and it is hard to achieve stable and reliable results.

4. Review of Existing Models

Various models of arrhythmia classification in the ECG have been suggested based on both the traditional machine learning and the deep learning approach. The initial methods used were based on features that were handcrafted as well as the use of such classifiers as support data machines and decision trees that needed specialized expertise and had poor generalization. The new models based on deep learning, especially convolutional neural networks, have shown even better results along with learning features directly dependent on ECG signals. Nevertheless, the majority of the currently available CNN based techniques utilize single beat representations and do not incorporate beat-to-beat time correlations. Consequently, they reduce their performance by failing to detect rhythm dependent arrhythmias including supraventricular ectopic beats. These limitations shows the need for models that use temporal context with morphological analysis.

5. Research Objective

The core objective of this study is to come up with an automated ECG arrhythmia classification system capable of capturing the shape of heart beats as well as the timely relationship between heartbeats. The paper is aimed at enhancing the accuracy of difficult arrhythmia types, in particular, supraventricular ectopic beats detection, through a dual-heartbeat coupling method combined with deep learning. The other significant goal is to minimize the effect of a class imbalance and variation between the patients through implementation of an organized approach to identifying training heartbeats. The proposed system is expected to operate without any handcrafted feature extraction but with a decent amount of both reliability and consistency in classification. Altogether, the purpose of this work is to enhance the precision and reliability of arrhythmia detection using the ECG data with the goal of a data-driven approach.

6. Contributions of this paper

This work has a number of contributions. Dual heartbeat coupling ECG presentation is presented to record morphological information about each heartbeat, as well as the temporal association between successive heartbeats, both of which single-beat analysis cannot provide. According to this representation, a two dimensional convolutional neural network (CNN) structure is developed to acquire discriminative features in a better way. Additional performance is achieved by use of systematic beat selection strategy of training to minimize the effects of class imbalance and improve sensitivity to rare arrhythmias, especially supraventricular ectopic beats. The suggested framework is fully automatic, and it does not require any manual feature extraction or human participation. Experimental assessment of a generic ECG arrhythmia database shows that the proposed method has a better performance in arrhythmia classification than a conventional single-beat CNN method.

II. LITERATURE REVIEW

Early methods of heartbeat categorization on the ECG had largely relied on features that were manually designed, including RR intervals, waveform morphology, and frequency domain. Llamedo and Martinez (2012) suggested a database generalization feature selection technique to enhance the heartbeat classification performance. Despite the reasonable outcomes of such methods, they depended on handcrafted characteristics, which restricted their applicability to new patients as well as their ability to

scale to large and heterogeneous data. However, the emergence of deep learning saw the use of convolutional neural networks (CNNs) become popular in the analysis of ECG signals. Kiranyaz et al. (2016) proposed a one-dimensional CNN model with patient-specific parameters with the ability to classify ECGs in real-time without requiring manual feature extraction. Subsequent research by Xu and Liu (2018) and Xie et al. (2019) also showed that CNNs were capable of automatically extracting meaningful representations directly out of raw ECG signals, which resulted in significant increases in the accuracy of classifications. Ensemble-based learning strategies were investigated by some researchers to make them more robust and diverse. Essa and Xie (2021) suggested using a multi-model deep learning approach, which included a number of CNN models to classify arrhythmia. Although the ensemble methods typically enhanced the detection performance, they added complexity to computation and inference time, and hence may be prohibitive in real-time or resource-constrained application. A number of investigations aimed at enhancing CNN designs to obtain more ECG features. Xie et al. (2019) suggested an enrichment method of CNN learning, and Paryma et al. (2018) suggested a pyramid-like CNN architecture to learn multi-scale ECG features. Despite the fact that these approaches improved performance in classification, they mainly used single beat representations and thus could not represent temporal dynamics between successive heartbeats. 1D CNN models were not effective at modelling beat-to-beat temporal relationships, which is important to detect difficult arrhythmias like SVEB, although they were effective at capturing the morphology of waveforms. More recent studies have also highlighted patient-specific learning methods in order to overcome inter-patient differences in ECG signals. The classification system introduced by Malik et al. (2022) is based on self-organizing operational neural networks and is designed as a real-time patient-specific one, which attains higher personalization and accuracy. Although it has these merits, patient-specific models can be very demanding in terms of additional training data and computation, which poses a constraint on their practical use. Despite the fact that the deep learning-based approaches have contributed significantly to the ECG arrhythmia classification, a number of challenges still exist. Most of the current methods also have difficulties in addressing extreme class imbalance, temporal dependency between beats, and high sensitivity on rare arrhythmia patterns. The vast majority of techniques are based on the analysis of a single beat or use complicated ensemble architectures. These shortcomings demonstrate the necessity to have a single and effective framework that will integrate dual-heartbeat temporal modeling with systematically chosen training beats and deep learning-based classification. Initial methods were based on manual feature engineering and human effort, which could be scaled out, whereas CNN-based models made end-to-end learning and a higher degree of automation possible. Ensemble and patient-specific models also improved the performance but added complexity to computations and deployment. Although these advances have been made, the majority of techniques continue to be based on a single-beat analysis and are less sensitive to rare arrhythmias, particularly supraventricular ectopic beats, and it is clear that both morphological and temporal heartbeat data should be modeled. Even though 1D CNN models are effective in capturing the morphology of the waveforms, they suffered in capturing of beat-to-beat temporal relationships, the work proposed or this approach uses dual-beat coupling matrices to record morphology and rhythm and a 2D CNN architecture to extract more features. It also includes selection of training beats. The main focuses is on improving S beat detection at low cost.

III. METHODOLOGY



Fig 1 Block Diagram Proposed block diagram is shown in Fig 1

1. Raw ECG Data

In this paper, the Arrhythmia Database of MIT-BIH was used to develop and test the proposed framework of arrhythmia classification using ECG. It is a publicly available database that is one of the most popular to test ECG-based heartbeat classification algorithms, and it has high-quality expert annotations to test algorithms. Data in the database comprised of 48 half-hour ECG records of 47 subjects where 2channel ECG records were digitized at a rate of 360 Hz. This study has applied only one channel of ECG data to analyze data to mimic the conditions of practical monitoring and minimize computational complexity. All ECGs were annotated individually by senior cardiologists and the exact R-peak positions of each heartbeat were given, allowing the segmentation of heartbeats. The ECG beats were all classified in accordance with Association of the Advancement of Medical Instrumentation recommendation (AAMI) into five classes of heartbeat: normal (N), supraventricular ectopic (S), ventricular ectopic (V), fusion (F), and unclassifiable (Q). As the practice dictates, the beats that were not categorizable were not part of the analysis. Heartbeat records that had paced heartbeats were also excluded to prevent bias in classification performance. The dataset was patient based, and using AAMI evaluation protocol, the data was split into a training and testing subset. Each subject had a small section of ECG record that was utilized during training and the remaining section was to be used during testing in order to provide subject independence. The dataset obtained is characterized by a wide variety of ECG morphologies, rhythm variations, and signal qualities, which causes considerable challenges in automated arrhythmia detection.

2. Data Preprocessing

This paper is equipped with the modified lead II ECG channel only since single channel ECG recording is typical in portables and wearable-based monitoring equipment. The database contains annotated position of R-peaks on each heartbeat which makes it possible to calculate directly R intervals in order to perform segmentation. Though good R-peak detecting algorithms are well developed, this paper is not within their scope of implementation. The electrocardiogram waveform is composed of various parts such as P wave, QRS complex, T wave as shown in Fig 2 among others that reflect particular electrical activities on the heart. The R-peak is one of them, and this feature can be considered a good reference point since it has a high amplitude and is always detected. Heartbeat segmentation in this work is performed based on centering the heartbeat segment around the cardiac cycle R-peak, with both the morphological and temporal properties of a cardiac cycle being maintained. This segmentation approach allows to produce single heartbeats that can be further analyzed.

a. Heartbeat Segmentation

Proper segmentation of heartbeats is a condition to classify arrhythmia. The fixed-length segmentation can also affect the beat morphology as different subjects exhibit different heart rates and change in time. In response to this, heartbeats are divided dynamically, and R-peak centred. In the case of the common training data, the length of the segments is selected based on the average R R interval computed over 10 s window around each beat, which makes the length of the segments variable. In case of subject-specific data, the average R R interval calculated out of the first five minutes of the record is taken, which ensures that the beat length remains consistent throughout the subject. When the time windows were averaged, the same performance was noted.

b. Segment Length Normalization

In order to make the input size the same across all the CNNs, all heartbeat segments are rescaled to the same fixed length. All the beat extraction results are then up sampled to the CNN input size through interpolation. The signal is then down sampled with an average over constant intervals so as to have an equal length representation no matter the original length of the heartbeat. The process maintains morphological features at the expense of uniformity in input dimensions that are used to classify. Upon normalization, a coupling matrix that is the input to the classifier is computed using both dual-beat vectors. The outer product of the 2 vectors of the dual beats yields the coupling matrix which is represented in (6)

$$CM = Dual_{i-1} \times Dual_i^T \tag{6}$$

3. R-Peak Detection

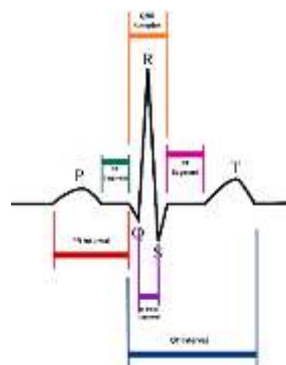


Fig 2. ECG wave form.

where $CM \in \mathbb{R}^{M \times M}$

The resulting coupling matrix is a combination of the morphological attributes of the heartbeat waveform and time- dependent features associated with rhythm variation. Patterns of amplitude in the matrix code morphology of the waveform, and a relative distribution of high-energy regions can be used to encode beat-beat timing relationships. This encoding allows the convolutional neural network to acquire discriminative visualizations to both normal and abnormal cardiac rhythms. The proposed input formulation, which converts sequential heartbeat data into a two dimensional format, enables the proposed classifier to effectively utilize convolutional neural networks spatial feature extraction features without the need to manually design features.

R-peak identifications are an important process when analyzing the ECG as they identify the point of position of each heartbeat. R peak is the maximum amplitude of the QRS complex of an ECG signal as shown in Fig 2. A peak detecting algorithm is used in our implementation to locate the R peaks of the ECG signal that has been pre-processed. After R peaks have been identified, a segment around each R

peak is extracted with respect to the R peak with a fixed window size.

4. Sample Classification

On identifying the R-peaks, the ECG signal is divided into heartbeat samples. Every piece is concentrated on the R-peak and includes a predetermined amount of samples (M). The input representation in this study is a dual-beat coupling matrix to the classifier. The analysis of arrhythmia is not limited to the morphology of a single heartbeat, but the correlation of the successive heartbeats in time. To represent the two simultaneously, the suggested approach incorporates the information of waveforms and beat-to-beat correlation in a two-dimensional input. The series of three beats is taken in each of the target heartbeats: the last beat, the beat, and the next beat. The segmentation of heartbeats is carried out by the same process as the preprocessing stage, with all the beats normalized in terms of the R-peak and equalized in terms of length.

Let the normalized heartbeat signals be represented as: $Beat_{i-1} = [bi-1(1), bi-1(2), \dots, bi-1(M)]$ (1)

$Beat_i = [b(1), bi(2), \dots, bi(M)]$ (2)

$Beat_{i+1} = [bi+1(1), bi+1(2), \dots, i+1(M)]$ (3) Here, (1),(2),(3) are the previous, current and next beats where

M denotes the fixed length of each normalized heartbeat segment. Two dual-beat vectors will be known constructed where, the first vector integrates the previous beat and the current beat:

$$Dual_{i-1} = [Beat_{i-1} \quad Beat_i] \quad (4)$$

Here, Integration of previous and current beats give first dual-beat vector (4)

Similarly, the second vector (5) combines the current beat and the next beat:

5. Splitting Data

The data is segregated as training and testing based on AAMI standard. This helps in making a fair comparison to the past research. The strategies used in class balancing, i.e., oversampling and loss of class-weighted, are used to balance the class-imbalance. Normal beats in ECG data occur far much more frequently than arrhythmic beats, and can lead to bias during training. Through controlled sampling, we will be able to make the classifier learn meaningful patterns of minority classes like S and V beats. Patient based data split is employed to make certain that ECG data of the identical subject are not present in both training and testing data. The training data are of two types a common training set and subject specific training set. The common training set is a representative set of heartbeats, which have been chosen within a fixed collection of ECG records, and are common to all subjects. The subject specific training set consists of heartbeats of the first portion of each ECG record of the subjects. According to this approach, the model can learn the general patterns of arrhythmia and adjust to the peculiarities of the patients. The rest of the ECG record is utilized just in testing. This arrangement has the benefit of testing the model on unknown data and give a strong indication of the power of the model to generalize. Standard evaluation measures used by AAMI are used to measure performance.

6. Classifier

The dual-heartbeat coupling matrices generated in the prior step are classified with the help of a two dimensional convolutional neural network (CNN). Architecture of the model is shown in Fig 3. The CNN automatically discovers significant patterns within the two-dimensional input and hence requires no features to be designed manually. The network consists of a number of convolutional layers that gather meaningful information on the inputs matrices and this is followed by activation functions, which induce nonlinearity. The size of the feature maps is shrunk during pooling layers so as to make the model more

resistant to small signal perturbations.

$$\text{Dual}_{i,+1} = [\text{Beati}$$

$$\text{Beati}+1]$$

(5)

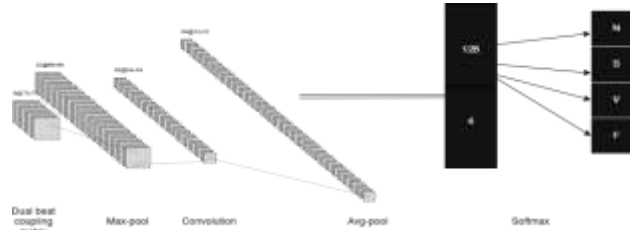


Fig 3. CNN architecture of the model.

The learned features are then fully connected and mapped to the various classes of heartbeat. ReLU activation is used all over the network to accelerate learning and enhance the stability of learning. A softmax layer is used to perform the last classification by giving probability values of every heartbeat class. The CNN is trained on the labeled ECG data and this enables the model to differentiate between normal and abnormal heartbeats using both the shape and timing of the waveform as reported in the two-beat representation of the heart. A 2 D CNN comprising of two convolutional layers, two pooling operations and fully connected layer is fed with the dual-beat coupling matrix of size 73 73. The last Softmax layer has probabilities of four AAMI heartbeat classes.

7. Evaluation Metrics

In an attempt to measure the performance of the proposed classifier, four widely used statistical measures are used, which include classification accuracy, sensitivity, specificity, and positive predictive rate. The metrics are very common in past cases of arrhythmia in ECG and those are very effective in giving an overall measure of the classification performance. The rate of accuracy of classification describes the general accuracy of the model to all heartbeat types. Nevertheless, since there are usually imbalanced datasets of arrhythmias, accuracy might be insufficient to reflect the effectiveness of the classifier. Thus, Sensitivity, specificity, and positive predictive rate are also taken into account since they create a more balanced analysis of various classes of heartbeats. Sensitivity is how well the abnormal beats are identified, whereas specificity is how well normal beats are detected. Positive predictive rate indicates the accuracy of positive hits of the classifier. These measures are computed based on the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), as it is customarily defined. The performance of classification is specifically compared in this study as ectopic beat detection of supraventricular and ventricular ectopic beating detection, as per the existing evaluation practices.

Xie et al. (2019)	CNN	MITBIH	<75%
Paryma et al. (2018)	Pyramid- like CNN	MITBIH	N/A
Xu & Liu (2018)	CNN	MITBIH	~70–78%
Xie et al. (2019)	Feature- enriched CNN	MITBIH	<78%
Kiranyaz et al. (2016)	1-D CNN	MITBIH	~70–75%
Proposed Method	Dual- heartbeat coupling + 2-D CNN + systematic S-beat selection	MITBIH	~78–85%

Table.2 SVEB sensitivity comparison.

IV RESULT

The effectiveness of the recommended ECG arrhythmia classification framework was judged in accordance with the recommended practice of AAMI utilizing typical evaluation pointers, such as the sensitivity and precision of every heartbeat category. After preprocessing, dual-beat coupling generation, as well as CNN-based classification, the evaluation was done on the test set based on the MIT-BIH arrhythmia database. Table below shows the classification results of the AAMI heartbeat classes using the proposed classification method. The findings show that the classifier has a good performance with regard to the Normal (N), Supraventricular Ectopic (S) and Ventricular Ectopic (V) beats. Specifically, the sensitivity to the S beats is known to be significantly enhanced over traditional single-beat and featurebased methods as showing the utility of dual-beat heartbeat coupling and systematic selection of training beats. The misclassification rate is lower in general when compared to the other CNN-based methods that do not explicitly model beat-to-beat relationships. The fact that S beats are very precise shows that the suggested model is dependable in the detection of supraventricular arrhythmias after identification. The performance of V beats in terms of classification is always high, which should be expected because of the morphologically peculiar features of ventricular ectopic beats. Altogether, the findings illustrate that the suggested framework has balanced and robust classification rates despite the overall big arrhythmia types, and the Sbeat detection is obviously better than traditional techniques. The results prove that dual-beat coupling of morphological and temporal information has a significant benefit in classifying ECG arrhythmia. From the confusion matrix Fig4 we can say that the model is not making guesses it actually acquired valuable ECG morphology. And sensitivity and precision of the proposed model are give below in the table 3.

Author & Year	Model Type	Dataset	SVEB Sensitivity
Malik et al. (2022)	Deep Learning models built using Self-Organizing Operational Neural Networks	MITBIH	N/A
Essa & Xie (2021)	Ensemble DL model	MITBIH	N/A



Fig 4. Confusion Matrix

Confusion matrix indicates that largest errors made are between S and N beats and this is also clinically explainable as supraventricular beats are similar to normal sinus beat. The beats of the ventricles are easily identified and determined with high precision. This proves the fact that the dual-beat coupling matrix is efficient in recording the morphological and rhythm information.

Class	Sensitivity	Precision
N(normal)	0.8699	0.9918
S(supraventricular)	0.8034	0.2911
V(ventricular)	0.9475	0.7794
F(Fusion)	0.7686	0.1136

Table.3 Results of sensitivity and Precision of proposed model.

V CONCLUSION AND FUTURE WORK

This paper suggested a CNN based model in ECG arrhythmia classification using a dual-heartbeat coupling representation. The technique integrates sequential heartbeats in a two-dimensional array to both extract morphological and temporal data. To minimize confusion of normal and supraventricular beat during training, an automatic beat selection strategy was introduced. Experiments on the MIT BIH Arrhythmia Database that were based on AAMI guidelines showed a higher sensitivity and accuracy in detecting supraventricular beats. The findings validate dual-heartbeat representation at the expense of no manual feature extraction improves the performance of classification. Appropriate input sizing and representative beat out picking were demonstrated to be of great importance in enhancing robustness and consistency. Even on a small and balanced dataset, the proposed model had a high generalization. The next steps in the work are improvement of the management of the imbalance between the classes, loss functions, and the detection of unusual arrhythmias. More challenging and sophisticated ECG datasets and bigger and more diverse samples will further improve clinical reliability and diagnostic accuracy.

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