

# **CLASSIFICATION OF ARRHYTHMIA BY USING DEEP LEARNING WITH 2-D ECG SPECTRAL IMAGE REPRESENTATION**

## **ABSTRACT:**

The electrocardiogram (ECG) is one of the most extensively employed signals used in the diagnosis and prediction of cardiovascular diseases (CVDs). The ECG signals can capture the heart's rhythmic irregularities, commonly known as arrhythmias. A careful study of ECG signals is crucial for precise diagnoses of patients' acute and chronic heart conditions. In this study, we propose a two-dimensional (2-D) convolutional neural network (CNN) model for the classification of ECG signals into eight classes; namely, normal beat, premature ventricular contraction beat, paced beat, right bundle branch block beat, left bundle branch block beat, atrial premature contraction beat, ventricular flutter wave beat, and ventricular escape beat. The one-dimensional ECG time series signals are transformed into 2-D spectrograms through short-time Fourier transform. The 2-D CNN model consisting of four convolutional layers and four pooling layers is designed for extracting robust features from the input spectrograms. Our proposed methodology is evaluated on a publicly available MIT-BIH arrhythmia dataset. We achieved a state-of-the-art average classification accuracy of 99.11%, which is better than those of recently reported results in classifying similar types of arrhythmias. The performance is significant in other indices as well, including sensitivity and specificity, which indicates the success of the proposed method.

## **INTRODUCTION:**

Cardiovascular diseases (CVDs) are the leading cause of human death, with over 17 million people known to lose their lives annually due to CVDs [1]. According to the World Heart Federation, three-fourths of the total CVD deaths are among the middle and low-income segments of the society [2]. A classification model to identify CVDs at their early stage could effectively reduce the mortality rate by providing a timely treatment [3]. One of the common sources of CVDs is cardiac arrhythmia, where heartbeats are known to deviate from their regular beating pattern. A normal heartbeat varies with age, body size, activity, and emotions. In cases where the heartbeat feels too fast or slow, the condition is known as palpitations. An arrhythmia does not necessarily mean that the heart is beating too fast or slow, it indicates that the heart is following an irregular beating pattern. It could mean that the heart is beating too fast—tachycardia (more than 100 beats per minute (bpm)), or slow—bradycardia (less than 60 bpm), skipping a beat, or in extreme cases, cardiac arrest. Some other common types of abnormal heart rhythms include atrial fibrillation, atrial flutter, and ventricular fibrillation.

The electrocardiogram (ECG) recordings are widely used for diagnosing and predicting cardiac arrhythmia for diagnosing heart diseases. Towards this end, clinical experts might need to look at ECG recordings over a longer period of time for detecting cardiac arrhythmia. The ECG is a one-dimensional (1-D) signal representing a time series, which can be analyzed using machine learning techniques for automated detection of certain abnormalities. This representation could allow the application of CNN architectures (designed to operate on 2-D inputs) for development of automated systems related to CVDs.

### **CONTRIBUTION:**

1. Spectrograms (2-D images) are employed, which are generated from the 1-D ECG signal using STFT. In addition, data augmentation was used for the 2-D image representation of ECG signals.
2. A state-of-the-art performance was achieved in ECG arrhythmia classification by using the proposed CNN-based method with 2-D spectrograms as input.

### **PROBLEM STATEMENT:**

- Reviewing advanced machine learning methods for an important medical application.
- Summarizing notable deep learning-based methods for detecting heart arrhythmia.
- Categorizing widely accepted datasets and evaluation metrics within the community.
- Reviewing mostly considered heart arrhythmias published in the recent years.
- Analyzing the advanced methods and comparing them based on their performance.
- The symptoms of the arrhythmia might not be seen during the ECG signal capturing period.
- ECG signal properties (such as period, and amplitude) vary from person to person and depends on different factors such as age, gender, physical conditions, and lifestyle. Finding a generalized framework along with the related standards to be functional for general population is problematic.
- Morphology of ECG signal is often not stationary even for one testing person because physical state such as running, walking, and sleeping.
- The volume of data to be considered for ECG signal analysis is large. Hence there is a higher probability of having a false diagnosis of arrhythmia.
- The noise, artifacts and interference can result in morphological variations and discrepancies in the captured ECG signal.

### **RESULT:**

The two significant optimization parameters in the proposed 2-D CNN model are the learning rate and the batch size of the data used. To improve the performance, these two optimization parameters must be selected carefully to obtain the best accuracy in the automatic classification of arrhythmia using the ECG signals. The proposed model was evaluated in different experiments with various values of learning parameters. For a smaller value of the learning rate (i.e., less than 0.0005), the speed of the convergence was very slow. However, when the value of the learning rate was large (i.e., greater than 0.001), the speed of convergence improved. At the same time, asymmetrical changes were observed in the accuracy rate. Henceforth, we selected an optimum value of 0.001 for the learning rate, as this value can attain better accuracy for the proposed model (i.e., optimum value).

| Model          | Native/Augmentation | Classes | Accuracy % | Sensitivity % | Specificity % | Precision % | F1 Score |
|----------------|---------------------|---------|------------|---------------|---------------|-------------|----------|
| FFNN [59]      |                     | 4       | 96.94      | 96.31         | 97.78         | -           | -        |
| PNN [60]       |                     | 8       | 98.71      | -             | 99.65         | -           | -        |
| SVM [61]       |                     | 6       | 91.67      | 93.83         | 90.49         | -           | -        |
| RNN [52]       |                     | 4       | 98.06      | 98.15         | 97.78         | -           | -        |
| LS-SVM [53]    |                     | 3       | 95.82      | 86.16         | 99.17         | 97.01       | 0.91     |
| RFT [54]       |                     | 3       | 92.16      | -             | -             | -           | -        |
| KNN [55]       |                     | 17      | 97.00      | 96.60         | 95.80         | -           | -        |
| 1-D CNN [56]   |                     | 5       | 96.40      | 68.80         | 99.50         | 79.20       | 0.73     |
| AlexNet [48]   | Augmented           | 8       | 98.85      | 97.08         | 99.62         | 98.59       | 0.97     |
| AlexNet [48]   | Native              | 8       | 98.81      | 96.81         | 99.68         | 98.63       | 0.97     |
| VGGNet [48]    | Augmented           | 8       | 98.63      | 96.93         | 99.37         | 97.86       | 0.97     |
| VGGNet [48]    | Native              | 8       | 98.77      | 97.26         | 99.43         | 98.08       | 0.97     |
| 2-D CNN [57]   |                     | 5       | 97.42      | -             | -             | -           | -        |
| 1-D CNN [58]   |                     | 7       | 93.60      | -             | -             | -           | -        |
| Proposed (1-D) | Native              | 8       | 97.80      | -             | -             | -           | -        |
| Proposed (2-D) | Augmented           | 8       | 99.11      | 97.91         | 99.61         | 98.58       | 0.98     |
| Proposed (2-D) | Native              | 8       | 98.92      | 97.26         | 99.67         | 98.69       | 0.98     |

## **CONCLUSION:**

In this study, we proposed a 2-D CNN-based classification model for automatic classification of cardiac arrhythmias using ECG signals. An accurate taxonomy of ECG signals is extremely helpful in the prevention and diagnosis of CVDs. Deep CNN has proven useful in enhancing the accuracy of diagnosis algorithms in the fusion of medicine and modern machine learning technologies. The proposed CNN-based classification algorithm, using 2-D images, can classify eight kinds of arrhythmia, namely, NOR, VFW, PVC, VEB, RBB, LBB, PAB, and APC, and it achieved 97.91% average sensitivity, 99.61% specificity, 99.11% average accuracy, and 98.59% positive predictive value (precision). These results indicate that the prediction and classification of arrhythmia with 2-D ECG representation as spectrograms and the CNN model is a reliable operative technique in the diagnosis of CVDs. The proposed scheme can help experts diagnose CVDs by referring to the automated classification of ECG signals. The present research uses only a single-lead ECG signal. The effect of multiple lead ECG data to further improve experimental cases will be studied in future work.

## **REFERENCE:**

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