Classification of Arrhythmia in Time Series ECG Signals Using Image Encoding And Convolutional Neural Networks

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***Abstract*—Electrocardiograph (ECG) signal analysis has been used extensively to study a patient's heart and detect problems like arrhythmia for decades. Manual analysis of ECG in real time is laborious and therefore not practical for doctors. Deep learning helps make this job much easier due to quicker learning of signal features and event prediction. Deep Learning classifiers can help doctors differentiate between normal and abnormal ECG signals based on the basic and advanced features of ECG signals. This paper focuses on building a Convolutional Neural Network (CNN) to classify arrhythmia in dual channel ECG signals based on images generated by time series to image encoding techniques. The ECG time series signals were converted into images using Gramian Angular Fields (GAF) and Markov Transition Fields (MTF). These images were fed as input into the deep learning classifier which further classified the signals into various types. Our model achieved an accuracy of 97% for the GAF images and 85% per cent for the MTF images.**

***Index Terms*—Gramian Angular Fields, Markov Transition Fields, Convolutional Neural Networks**

I. Introduction

The classification of ECG signals for cardiac diagnosis is not a new concept. However, the popularity of deep learning and computational biology has encouraged scientists to use data science in analysing and classifying medical data. Moody and Mark depicted the impact of storing ECG records as an online catalogue in the form of the MIT-BIH Arrhythmia Database (mitdb) [1]. This paved the way for a plethora of classification algorithms for various kinds of ECG signals, especially those that represent arrhythmia, a condition involving irregular heartbeat. Krishnan et al in [2] developed an algorithm to classify cardiac arrhythmia using autoregressive modeling. They were able to perform classification for four kinds of arrhythmia. One of the most important features of an ECG signal is its RR interval(interval between the QRS peaks of two ECGs). Sideris et al in [3] were able to perform classification of arrhythmia based only on the RR intervals of the signals, which reduced computational complexity. Some methods also reduced the features of the signals and then performed classification, like Song et al in [4] who used Linear Discriminant Analysis (LDA) for feature reduction and Support Vector Machines (SVM) for classification. Singh et al [5] used Recurrent Neural Networks (RNN) for classifying multiple beats of ECG. The use of conventional Convolutional Neural Networks (CNNs) for arrhythmia classification was demonstrated by Jun et al. [6], where they used various deep learning methods such as data augmentation in order to prepare the ECG signals. These signals had to be converted to images for input. Most methods for classifying ECG deal with single channel recordings from datasets. In the case of multi channel ECG,the morphology of the signal might change from channel to channel and therefore single channel ECG classification might prove fallacious, as demonstrated by Sanchez et al. [7]. Kim [8] proved that multi-channel ECG classification yields higher accuracy than single channel ECG classification using conventional signal input. Since ECG is a time series signal, it is possible to use time series data analysis in order to encode the signals into images for classification. This is not the direct conversion of signals to images, rather a mapping of a one-dimensional time series ECG signal to a colored image, as depicted by Whang and Oates in [9]. This paper proposes to do the same, for the MIT-BIH Arrhythmia Database. However, for multiple classes, feature learning is important. For example, while analysing Atrial Fibrillation (AF), Christov et al. [10] were able to extract multiple features which could enhance detection of AF in future algorithms.

Analysing features is important to perform classification for various types of arrhythmia simultaneously. Gabbouj et al. in [11] performed patient specific analysis and found that inter patient variations also affect classifier performance. Nevertheless, multi channel ECG data from the mitdb dataset can be converted to images using Gramian Angular Fields (GAF) and Markov Transition Fields (MTF), which have been implemented in this paper for data preparation. In the case of multi channel ECG, Barro et al. [12] showed that the morphology of the signal might change from channel to channel and therefore single channel ECG classification might prove fallacious. So, here we propose to classify dual channel signals. Thiagarajan et al. [13] used an approach of generating the channels for the ECG signals and then classifying them accordingly. Zhang ,

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Xiao and Ji [14] were able to perform classification based on a faster region based Convolutional Neural Networks (CNN), which included image generation and a fast CNN architecture. Liang et al. [15] used a combination of CNN and a Long Short Term Memory (LSTM) networks, wherein the CNN performed as normal, but the LSTM was able to retain some feedback information which enhanced classification performance. Using wavelet transforms, morphological features of ECG signals were extracted by Coimbra et al. [16]. However, the episodic nature of ECG has contributed to limited applicability in classification due to small datasets and occasional anomalies in signal morphology Clifford et al.[17]. Nevertheless, there are multiple parameters that can determine the presence of AF, like f-waves, absence of P-waves etc. Images capturing the morphology of a heartbeat were implemented by Jiang et al. [18] using one-hot encoding. Sujit et al. in [19] used advanced methods like Synthetic Minority Over-Sampling Technique (SMOTE) to enhance detection ability in Phonocadiogram (PCG) signals.

Single lead signals of arrhythmia like AF can be classified without any pre-processing and still help obtain good classification performance, as exhibited by Sujit et al. [19]. Limitations of ECG arrhythmia classification include requiring to carefully select ECG recordings without cross validation, beat loss during denoising and feature extraction, fewer classes of arrhythmia and lesser classification accuracy for implementation as shown by Song et al [4]. However, these limitations can be overcome as more and more data is collected from patients, and the conversion of one-dimensional signals to two-dimensional images means that initial noise filtering and feature extraction can be avoided. Soman et al. in [20] were able to detect AF in single lead ECG with the help of RNNs with an accuracy of 95%. Since classification of all kinds of arrhythmia in the MIT database would not reap impressive results, major arrhythmia types can be selected like Ganesan et al. [21], who chose 7 classes and proceeded with the conventional CNN. Deep learning enables automated feature learning, which is much faster than manual extraction, which is important especially in the case of a random event like arrhythmia. Comparing models for classification performance is also abundant in the field of ECG analysis, as shown by Saiharsha et al. [22]. In this study, we use the MIT-BIH Arrhythmia Database (mitdb) for performing classification for normal and arrhythmic beats.

II. Methodology

The typical conventional classification algorithm for arrhythmia consisted of selecting one of the channels of the signal (V1 or V2), pre- processing the signal to remove artefacts or baseline wandering, splitting each sample into smaller bits, detection of Q peaks and presence of features unique to each arrhythmia, feature extraction and eventually classification. In this paper, however, we chose both the channels (V1 and V2 or MLII and V5) for each record and then converted them into images. The two dimensional nature of images enables us to color code each channel and map both signals onto the plot. Fig.1 shows an ECG signal where arrhythmia is present. This will also reflect in the image when the data is encoded using the GAF and MTF methods. Fig. 2 represents the steps involved in the entire project. Initially, the signal had to be pre-processed, so we performed median filtering and baseline wandering removal. This made learning of features for the images much easier.

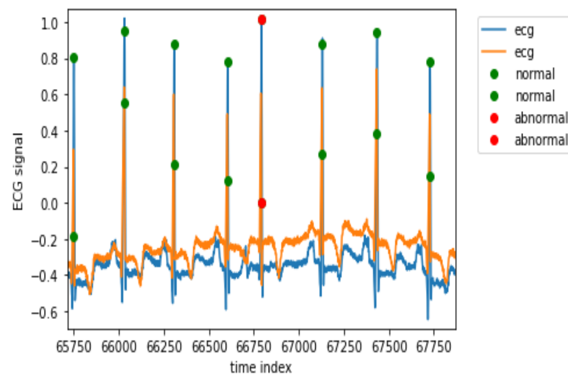

Fig. 1: Presence of an abnormal beat in the dual-channel ECG signal.

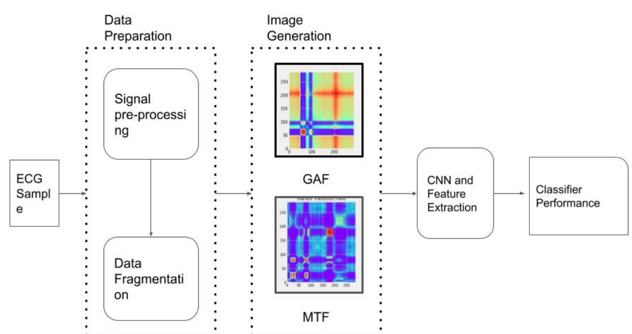

Fig. 2: The project workflow diagram representing the steps involved in the process.

A. Image Encoding

An ECG is a time series signal indexed in time order with timestamps for each value. There may be recordings from several channels for the same time interval. In this study, we use ECG time series signals consisting of two channels. Analysis of two channels at a single instance is difficult in the one- dimensional signal, but can be made much easier by converting the signal into a two-dimensional color image as demonstrated by Yang et al. [23]. This helps map temporal data of multiple channels (in this case, two) into a single image, which will hopefully help better find features that may not have been found if one-dimensional time series data had been used. This kind of imaging is not a direct conversion, rather an “encoding” of sorts, that is, a change in domain (like with the GAF) or a transition probability (with the MTF). Through this, we assume that the classifier performance will improve for the dual channel ECG data.

B. Gramian Angular Fields (GAF)

An image obtained from a time series signal, that contains some temporal correlations between each time point. Initially, time series data can be mapped onto the polar coordinate by computing the inverse cosine function (arccos) of the values. This representation based on polar coordinates is a new way of interpreting time series. The corresponding values warp on the spanning circles between different angular points, analogous to ripples in water, as time increases. The angular perspective can be used to define the temporal relation for each distinct time interval after translating the time series into the polar coordinate system by considering the trigonometric sum between each point.The matrix, referred to as the Gram matrix, is represented by G depicted in equation (1). It represents the polar coordinates of each value in the time series signal.

$$G = \begin{bmatrix} cos(\phi_1 + \phi_1) & .. & cos(\phi_1 + \phi_n) \\ cos(\phi_1 + \phi_1) & .. & cos(\phi_1 + \phi_n) \\ .. & \cdots & \cdots \\ cos(\phi_n + \phi_1) & .. & cos(\phi_n + \phi_n) \end{bmatrix} \quad (1)$$

Looking closely at the plot in Fig. 3, it is clear that the intersection of both lines represents the QRS peak. The x- axis represents the time and the y axis represents amplitude of the signal. The colors also vary as blue represents the first channel and orange represents the second. The GAF has different advantages. Temporal dependency can be preserved as time increases as the position moves from top-left to bottom-right. However, the size of the Gramian matrix could be large if the time series is long.

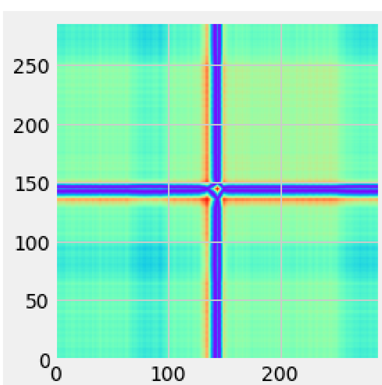

Fig. 3: The Gramian Angular Field of an interval of the ECG time series signal.

C. Markov Transition Fields (MTF)

In a first order Markov chain along the time axis, the elements of W constitute the transitions between quantile bins. W becomes a Markov transformation matrix after normalization. However, this matrix is time insensitive. The Markov Transition Field is therefore defined as shown in equation (2) in order to compensate for the loss due to lack of temporal dependence.

$$M = \begin{bmatrix} w_{ij|x_1 \epsilon qi, x_1 \epsilon qj} & .. & w_{ij|x_1 \epsilon qi, x_n \epsilon qj} \\ w_{ij|x_2 \epsilon qi, x_1 \epsilon qj} & .. & w_{ij|x_2 \epsilon qi, x_n \epsilon qj} \\ .. & \cdots & \cdots \\ w_{ij|x_n \epsilon qi, x_1 \epsilon qj} & .. & w_{ij|x_n \epsilon qi, x_n \epsilon qj} \end{bmatrix} \quad (2)$$

In fact, the MTF M codes the multi-span transition probabilities of the time series by assigning the probability at each pixel from the quantile at time stage ti to the quantile at time phase j. Each factor denotes the probability of transition with k-interval time between points. For instance, with a skip step, Mij=1 demonstrates the transition process along the time axis.. The key diagonal Mii, which is a special case when at time phase ti k = 0 captures the probability of each quantile to itself (the probability of self-transition). Fig. 3 illustrates the MTF over the same signal fragment as was selected for the GAF. A shift in amplitude over time is demonstrated by transition lines and color variations.

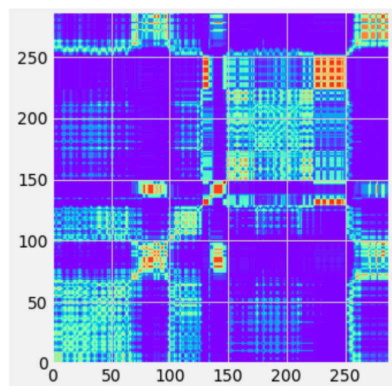

Fig. 4: The Markov Transition Field of an interval of the ECG time series signal.

D. Dataset

The recordings of ECG arrhythmia used in this paper are taken from the MIT-BIH arrhythmia database [1]. The database for this paper includes 8 ECG recordings (100 to 107), each 30 minutes long, that were chosen from 48 recordings. Each signal is sampled at 360 samples per second. For images, we needed only one waveform per image. Therefore, each sample contained about 288 fragments that contained roughly one cycle each. Therefore our primary goal was to split each sample into approximately 2250 fragments of length 288, which contain at least one PQRST signal containing one peak. This was to ensure that when the images are generated, feature extraction during classification becomes much simpler. Each fragment was then encoded using GAF and MTF. Time series requires that temporal dependency be preserved, which is accomplished by the above two methods. For this study, we selected 2700 images of each GAF and MTF. Beats with 15 distinct forms of arrhythmias are present in the MIT-BIH database, including Standard. For this paper, we combined all the 15 forms of arrhythmia into one big superclass called 'Abnormal' (A) and all the normal beats into 'Normal' (N). The database contains annotations for all signals. This means that information regarding the occurrence of arrhythmia is predetermined. The annotations give us exact points on the dataset where the arrhythmia has occurred.

E. Convolutional Neural Network (CNN)

Once the signals are converted to images, they could be labelled. The next step was to set up the classification model. In this study, we implemented a conventional CNN for classifying the dataset, with all the layers and hyper-parameters tuned to our needs. There is a trade-off between classifying for various types and obtaining enhanced classifier performance due to the small data size for some lesser recorded beat types. In this study, we decided to perform binary classification, which would help us achieve better classification performance. We implemented a basic 2D CNN, based on the convolution-pooling architecture. Each image was of size 224 x 224 at the input layer. Three convolution-pooling layers, along with a dense and flatten layer that uses a 'ReLU' (Rectified Linear Unit) activation function. For optimisation, we used the Adam optimiser and trained it at a learning rate of 0.000001. The model was run for 50 epoch for each image type and the classification report was obtained for each case. We implemented the 80:20 split for the training and testing data respectively.

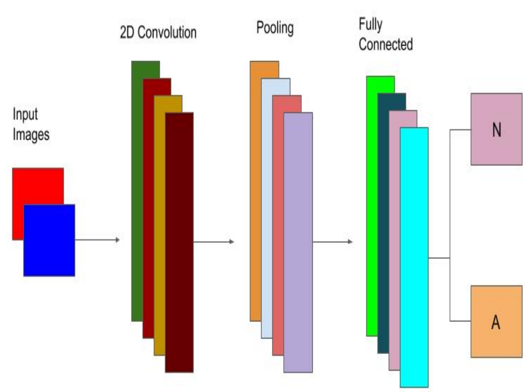

Fig. 5: The model used for this project It is a conventional 2D CNN that uses the ReLU activation function and Adam optimizer.

III. Results

Comparing the performance for both images, it was found that the model that used GAF images as input had achieved a training accuracy of 97%, as opposed to the model using the MTF images, which obtained 96%. This is most probably due to the lower error rate of the GAF, and the potential over-fitting that has been observed in previous studies conducted on time series encoding. As for testing, it was found that the model using the GAF images as input achieved an accuracy of 97%, which is higher than the model using MTF images, which could obtain only 84% as per Table I. Although MTF displays information about dynamics, GAF encodes static information. We consider them as two "orthogonal" channels from this point of view, like various colors in the RGB image space.

TABLE I: Evaluation parameters for both image types

Method	Accuracy (%)		Loss	
	Train	Test	Train	Test
GAF	97	97	0.34	0.38
MTF	96	84	0.22	0.51

TABLE II: Accuracy of models for both GAF and MTF

Method	Accuracy (%)		Loss	
	Train	Test	Train	Test
GAF	97	97	0.34	0.38
MTF	96	84	0.22	0.51

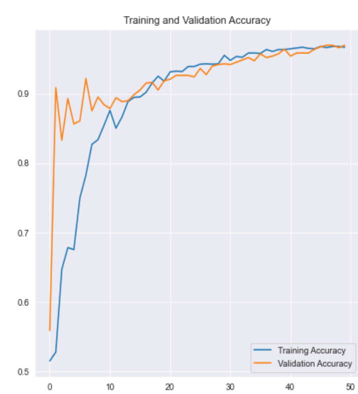

Fig. 6: The training and testing accuracy of the model(GAF).

Both GAF and MTF are not traditional 'natural' images; they have no image-making characteristics. They are color maps consisting of the ECG signal's different sets of amplitude values, the time representing the x-axis and the amplitude representing the y-axis. The intersection of lines in the GAF represents the QRS peak, and the color variations reflect the change in values. As for the MTF, each transition is recorded and color mapped for From Fig. 6 it is clear that the accuracy of the GAF model is high for both the training and testing phases. Fig. 7 shows a similar pattern for decrease in loss. The GAF model was able to obtain better precision, recall and F1 score as compared to the MTF model as illustrated by Table II, where N denotes 'Normal' and A represents 'Abnormal'. As observed in Fig. 8, the testing accuracy for the MTF images

Fig. 7: The training and testing accuracy of the model(MTF).

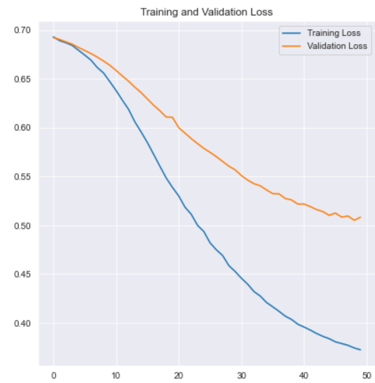

Fig. 9: The training and testing loss of the model(MTF).

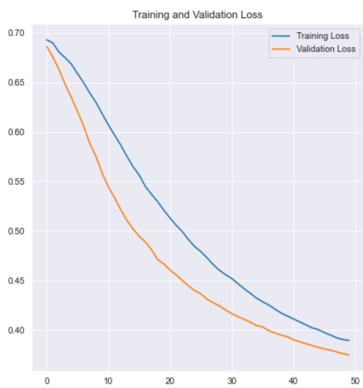

Fig. 8: The training and testing loss of the model(GAF).

was found to be much lower than the training accuracy. This could be due to the complexity of the MTF image due to its dynamic nature.

Fig. 9 also says the same story for loss, which does not decrease significantly over the epochs. The accuracy and loss curves for the GAF model are very low at the 50th epoch, which is not the case for the MTF model. These curves represent the performance of the models over time(epochs). The x- axis in each graph represents the epochs and the y-axis represents the value of accuracy or loss accordingly. The more the model gets trained, the better the graphs turn out to be eventually. This approach is used only for time series data due to the temporal dependency nature of the GAF and MTF methods used in this study.

Conclusion

The classification of dual channel ECG signals using time series encoding was performed successfully . Compared to Coimbra et al. [16], who obtained an accuracy of 96.5% for randomly chosen data from the MIT database(single channel), we were able to achieve 97% for the GAF image model. The potential prospect of multi class models for the MIT database performing well is difficult given the computational complexity involved, lack of adequate data for lesser known classes of arrhythmia, and the hardware constraints of the computer on which the model in this study was executed. However, advanced feature learning algorithms and increase in data recording will help improve classification and detection of various kinds of arrhythmia in the future.

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