Proceedings of 9th IOE Graduate Conference
Peer Reviewed
ISSN: 2350-8914 (Online), 2350-8906 (Print)
Year: 2021 Month: March Volume: 9

Deep Learning to Detect Arrhythmia on Imbalanced ECG Dataset

Nabaraj Poudel [a], Laxmi Prasad Banstola [b], Surendra K.C. [c]

[a, b, c] *Department of Electronics and Computer Engineering, Paschimanchal Campus, IOE, TU, Nepal*
Corresponding Email: [a] nabarajpoudel14@gmail.com , [b] laxmiprasad.bastola@wrc.edu.np , [c] kcsurendra28@gmail.com

Abstract
Heart rhythm problems (Arrhythmia) occur when our heart beats are not synchronized with powerful impulses which cause our heart to beat too slowly or too quickly or irregularly. For testing the functionality of the cardiovascular system, Electrocardiogram (ECG) is used. The ECG has a significant role to play in reducing the high death rate due to cardiovascular disease (CVD). Because ECG Beat data falls in a highly imbalanced category, this task is approached from a Transfer Learning Perspective in order to define and classify five heart rhythm patterns. Here, time-series data is coded into 2-D images through the use of GAF and MTF. This approach uses MIT-BIH Arrhythmia data collection which consists of a sample rate of 360Hz record of ECG pattern obtained from 47 separate specimens. An efficient CNN architecture is implemented for the purpose of feature extraction and long short-term memory (LSTM) recurrence network model is deployed for the classification of heartbeats which is able to classify five different arrhythmias with high level accuracy. According to the results the suggested method is able to make 87% and 84% accuracy in VGG-LSTM and ResNet50-LSTM respectively.

Keywords
Arrhythmia, CVD, CNN, deep learning, ECG, GAF, LSTM, MTF, Transfer learning

1. Introduction

ECG recording is one of the most significant aspects cardiologists and medical practitioners use to monitor health status of heart. The identification of rhythmic diseases is essential [1]. Arrhythmia is very common and is handled predominantly by the cardiologists. The identification of arrhythmic beats is difficult manually so automatic learning algorithm is implemented for the detection. The result is finally evaluated and analyzed by the cardiologist. Arrhythmia thus detected and classified helps to diagnose the abnormality detected in a patient's ECG waveform. After identification of abnormality, appropriate treatment to the patient can be provided promptly. Precise ECG categorization into arrhythmia types comes up with adequate details to detect the diseases related to the heart which in turn assists the doctor to trace out suitable treatment therapy for subject. Several automatic ECG arrhythmia classification systems have been looked into using computational intelligence [2].

In this paper, effective diagnosis in detecting the arrhythmia using the deep neural network is used. Five ECG patterns are defined and categorized from a transfer learning perspective, which transfers information from the image classification domain into the ECG signal classification domain. For classification and prediction of the performance, the features retrieved from CNN architecture is provided to the LSTM network. The LSTM cells are capable to selectively accumulate information and supply it back. It is a particular type of RNN mostly used for study of time series data. Thus the combination of 2D-CNN and LSTM models improves the classification process.

This paper is principally concerned with encoding time series images using GAF and MTF approaches. The resulting image is combined into a larger 2-D image. CNN's (VGG16 and ResNet50) deep learning architecture is used to retrieve features that are fed to LSTM for classification.

2. Related Works

The ability to detect irregular heart conditions early through the ECG will help to extend life and improve quality of life. Sometimes even specialist cardiologists can't say the difference between normal and arrhythmic heartbeats. As a result, various machine learning and deep learning models for detecting arrhythmic beats in ECG are used to improve accuracy and effectiveness. Many approaches for classification of ECG signals have been suggested. The different methods include Time-domain, genetic algorithm, support vector machine (SVM), Wavelet transform, Bayesian. They are used for the distinguishing the beat [3].Various ap-proaches have been introduced over several years for working up with the motorized structure to absolutely label the ECG details.

Salem et al. [4] used arrhythmia classification where transfer learning approach was used with the aid of 2-Dimensional deep CNN features. Kohli et al [5] suggested SVM based arrhythmia classification where three different strategies: one against one, one against all, and fuzzy choice capacity were used for the purpose. Acharya et al [6] put forward a nine-layer convolutional neural network (CNN) in order to automatically recognize five ECG beat patterns. Yildirim et al [7] outlined an end-to-end 1D-convolutional neutral network (1D-CNN) prototype for arrhythmia recognition.

3. Methodology

3.1 Method Overview

Each time series of data are converted into an image using GAF and MTF methods in order to separate the ECG signal into five groups. The images are then fed into a CNN architecture (VGG16 and ResNet50) to extract features which are eventually categorized by LSTM. Usually, this translation is performed using a pattern recognition approach, the following two main steps are used:

Feature Extraction:The first signal processing is called "feature extraction" which attempts to define ECG signals by certain relevant values known as "feature". These features should take in the ECG signals which are necessary to classify the heart rhythms, while refusing noise and other irrelevant terms. The first signal processing is called "Feature Extraction." Typically all functions extracted are arranged into a vector, known as a feature vector.

Classification: The second step, known as "classification," assigns a class of the features derived from the signals (the feature vector). This stage may also be called a translation of the function. Algorithms for classification are called "classifiers."

The approach proposed is the transmission learning method used to extract the attribute from ECG signal using a pre-trained Convolution network. As an input to LSTM network serving as a classifier, the feature vector of the CNN network is being used. This is a common issue with the classification and our aim is to decide which class is the signal belongs to.The work-flow of proposed system is shown in Figure 2.

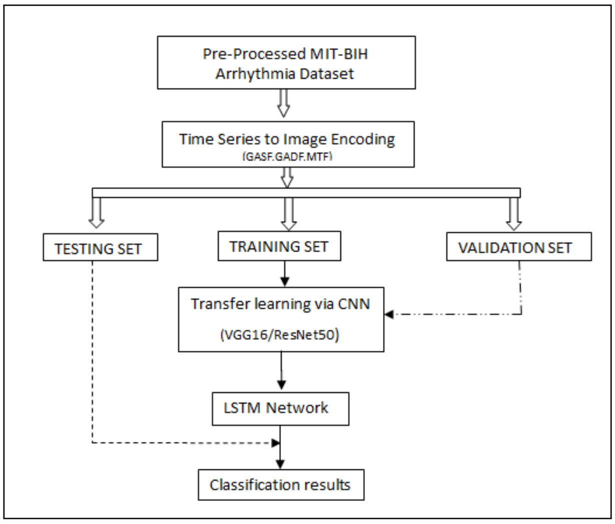

Figure 1: System Block Diagram

3.2 MIT-BIH Arrhythmia Dataset

In this study the data base for marked ECG records will be PhysioNet MIT-BIH Arrhythmia dataset. ECG lead II, resampled at 125 Hz sampling frequency, is used as source data in all experiments. The MIT BIH dataset is an EEG recording with a sampling rate of 360Hz from 47 different subjects. At least two cardiologists have annotated each beat. In compliance with the standard EC57 (Association for the advance of medical instrumentation) (AAMI), we use annotations in this dataset to define 5 separate beat classes [1].The different classes of dataset is shown in table 1. Arrhythmia classification in deep learning normally includes two basic categories:

- Preprocessing
- Classification

The Daubechies 6 (db6) discrete wavelet transform is used in preprocessing steps to omit noise from the waveform of the ECG. The ECG input denoted is fed to the CNN network. The ECG heartbeat is then retrieved using the sliding window explore technique on the sample map extraction. The MIT-BIH arrhythmia database yielded independent experts verified annotations for ECG beat class information. All ECG data were divided into sequences with a duration of 250 samples based on the annotated R-peaks. There is no general standard for the dimension. Normalization of data is done using Z-score.

Table 1: MIT-BIH Dataset Categories

Category	Annotation	No. of Instance
N	Normal Left/Right Bundle branch block Atrial escape Nodal escape	90589
S	Atrial premature Aberrant atrial premature Nodal premature Supra-ventricular premature	2779
V	Premature Ventricular contraction Ventricular escape	7236
F	Fusion of ventricular and norm	803
Q	Paced Fusion of paced and normal Unclassified	8039

3.3 Imbalance Process

The MIT-BIT ECG arrhythmia database is not-uniform distribution. There are approximately 80% hearts beats, in one class and the remaining 20% of the heartbeats to the other four classes. Thus this data is class imbalance [8]. The general approaches for improving the classification accuracy of class-imbalanced data include (1) oversampling, (2) undersampling, (3) threshold moving, and (4) ensemble techniques.

The class imbalance problem on multiclass tasks is much more difficult, where oversampling and threshold moving are less effective. In this paper, under sampling technique is used for the better performance. Under sampling is decreasing the number of negative datasets. It randomly eliminates datasets from the majority negative class until there are an equal number of positive and negative datasets.

3.4 Data Encoding as Images

The picture consists of pixels and is arranged in matrix. The combination of three channels also known as primary colors of light constitute a color image. This analysis includes time series data, which is translated to 2D images using a deep learning architecture in order to find the structure and the patterns via GASF, GADF and MTF methods are used for data encoding of images [9].

3.4.1 Gramian Angular Field(GAF)

A Gramian Angular field is a picture from a time series which reflects a time similarity between each point in time. Two approaches are available: Gramian Angular Summation field (GASF) Gramian Angular Difference field (GADF) Both these techniques are used to transform time-series signals into an image. The word 'Time Series' here is moved to a polar space for coordination. The grammatical matrix will then be generated in which the summed GASF angle Cosine or the GADF angle Sine are calculated for each factor.

First, let vector be represented by lower case bold character, scalers using lower case and matrices with uppercase bold characters. For n-real value reading in a time series X={x1, x2........xn} we resize X so that all values come under the interval [-1, 1] or [0, 1] by

$$\bar{x}^{\mathrm{i}}{}_{-1} = \frac{(x_{\mathrm{i}} - max(X)) + (x_{\mathrm{i}} - min(X))}{max(X) - min(X)} \tag{1}$$

$$\bar{x}^{\mathrm{i}}{}_{0} = \frac{(x_{\mathrm{i}} - min(X))}{max(X) - min(X)} \tag{2}$$

This provides angular value in the range $[0,\pi]$ which will aid in obtaining information granularity in the GAF. The next step is to obtain the polar co-ordinates which are the cosine angle ϕ , from the normalize amplitude values and the radius r, from the time stamp t, as present in below equation:

$$\phi = cos^{-1}(\bar{x}_{\mathrm{i}}), -1 \leq \bar{x}_{\mathrm{i}} \leq 1, \bar{x}_{\mathrm{i}} \in \bar{X} \tag{3}$$

$$r = \frac{t_{\mathrm{i}}}{N}, t_{\mathrm{i}} \leq N \tag{4}$$

In equation 4, N is constant used as a regularization factor for the polar space span and is set to N=1. Then the normalized data is converted into polar coordinates. After transformation, the GAF converted the vectors into a symmetric matrix called the Gramian Matrix. Since two ways are there to morph the vectors into a symmetric matrix. Gramian Angular Summation Field (GASF) and Gramian Angular Difference Field (GADF), they are stated in equations given below. Therefore the GAF relies on two techniques to encode time series information into images.

$$GASF = cos(\phi_{\mathrm{i}} + \phi_{\mathrm{j}}) = \bar{X}^{'}.\bar{X} - \sqrt{1-\bar{X}^{2}}^{'}.\sqrt{1-\bar{X}^{2}} \quad (5)$$

$$GADF = sin(\phi_{\mathrm{i}} + \phi_{\mathrm{j}}) = \bar{X}^{'}.\bar{X} - \sqrt{1-\bar{X}^{2}}^{'}.\sqrt{1-\bar{X}^{2}} \quad (6)$$

The GAF maintains temporal properties, so the image position proceeds from top-left to bottom-right as time advances. An image which is transformed by the GAF technique can be regenerated into time series data with the help of Gramian Matrix because the image embeds temporal correlations [10]

3.4.2 Markov Transition Field (MTF)

A Markov Transition Field is an image obtained from a time series, representing a field of transition probabilities for a discretized time series. Different strategies can be used to bin time series [10].

Given a time series X, we identify its Q quantile bins and assign each xi , to the corresponding bins q_{j} (j $\in$ [1,q]). Thus we construct a QxQ weighted adjacency matrix W by counting transitions among quantile bins in the manner of a first order Markov chain along the time axis. wij is given by the frequency with which a point in quantile qj is followed by a point in quantile qi. After normalization by $\sum_j w_{\mathrm{ij}}=1$. W is the Markov transition matrix. It is sensitive to the distribution of X and temporal dependency on time steps ti. However, our experimental results on W demonstrate that getting rid of the temporal dependency results in too much information loss in matrix W. To overcome this drawback, we define the Markov Transition Field (MTF) as follows

$$M = \begin{bmatrix} w_{\mathrm{ij}}|x_1 \in q_{\mathrm{i}}, x_1 \in q_{\mathrm{j}} & \ldots\ldots & w_{\mathrm{ij}}|x_1 \in q_{\mathrm{i}}, x_{\mathrm{n}} \in q_{\mathrm{j}} \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ w_{\mathrm{ij}}|x_{\mathrm{n}} \in q_{\mathrm{i}}, x_1 \in q_{\mathrm{j}} & \ldots\ldots & w_{\mathrm{ij}}|x_{\mathrm{n}} \in q_{\mathrm{i}}, x_{\mathrm{n}} \in q_{\mathrm{j}} \end{bmatrix} \quad (7)$$

3.5 Transfer Learning

Transfer learning is the improvement of learning in a new task through the transfer of knowledge from a related task that has already been learned. In transfer learning, we first train a base network on a base dataset and task, and then we repurpose the learned features, or transfer them, to a second target network to be trained on a target dataset and task. This process will tend to work if the features are general, meaning suitable to both base and target tasks, instead of specific to the base task [11]

Transfer learning is an important tool in machine learning to solve the basic problem of insufficient training data. It tries to transfer the knowledge from the source domain to the target domain by relaxing the assumption that the training data and the test data must be independent and identically distributed. This will leads to a great positive effect on many domains that are difficult to improve because of insufficient training data.

Transfer learning allows us to utilize state of the art networks that have been trained and tuned on large amounts of data for long periods of time. Two of the most popular models VGG16 and RESNET50 convolution neural network have been used to classify images in the IMAGENET competition. Models may be downloaded and use as feature extraction models. Here, the output of the model from a layer prior to the output layer of the model is used as input to a new classifier model.

3.6 Long Short Term Memory (LSTM)

Long Short Term Memory networks – usually just called “LSTMs” – are a special kind of RNN, capable of learning long-term dependencies. They were introduced by Hochreiter and Schmidhuber (1997), and were refined and popularized by many people in following work. They work tremendously well on a large variety of problems, and are now widely used [3]. In LSTM network, three gates are present is shown as in figure 2.

3.6.1 Input Gate

Input gate discover which value from input should be used to modify the memory. Sigmoid function decides which values to let through 0,1 and tanh function gives weightage to the values which are passed deciding their level of importance ranging from-1 to 1.

$$i_{\mathrm{t}} = \sigma(W_{\mathrm{i}}.[h_{\mathrm{t\text{-}1}}, x_{\mathrm{t}}] + b_{\mathrm{i}}) \quad (8)$$

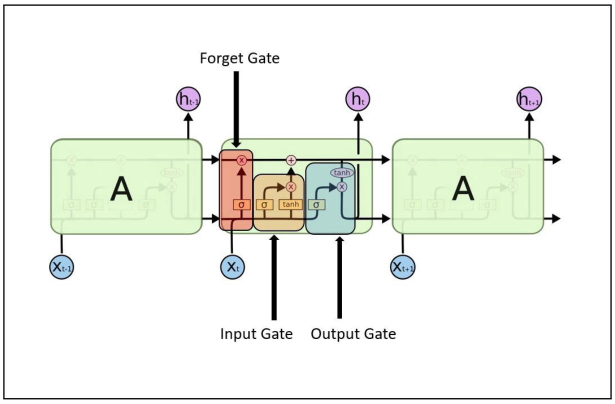

Figure 2: LSTM Gates

$$\bar{C}_t = tanh(W_c.[h_{t-1}, x_t] + b_c) \quad (9)$$

3.6.2 Forget Gate

Forget gate discover what details to be discarded from the block. It is decided by the sigmoid function. It looks at the previous state and the content input and outputs a number between 0(omit this)and 1(keep this)for each number in the cell state.

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \quad (10)$$

3.6.3 Output Gate

The input and the memory of the block are used to decide the output. Sigmoid function decides which values to let through 0,1. And tanh function gives weightage to the values which are passed deciding their level of importance ranging from-1 to 1 and multiplied with output of Sigmoid.

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \quad (11)$$

$$h_t = o_t * tanhC_t \quad (12)$$

3.7 CNN-LSTM Model

Many pertained models are provided us with many solutions to the problem. In this study VGG16 and other models such as ResNet50 have been used in the same manner and compared to each other for the classification of ECG arrhythmia. All the models are deep convolution neural network model. This model can extract ECG deep features well through convolution and pooling layers. It generates feature maps from the extracted features for learning and training. LSTM is good at capturing the characteristic of data related to time series [12]. In all models, learning rate of 0.001 was used and for optimization Adam optimizer was implemented.

4. Experiments and Results

This section explains the experiment settings and presents the results of the experiments. In this paper python 3.7 is used for coding the time series conversion, aggregation and transfer learning- LSTM models. The deep learning framework was constructed by using Tensorflow in Google Colab TPU with 12.72 GB RAM. The tools and software's that will be used in this project work are listed below

- Tensorflow Library
- Keras
- Python Imaging Library

4.1 MIT-BIH Data sets

MIT-BIH arrhythmia database is used for the classification of ECG beats. Originally the dataset was downloaded and studied for the normal and abnormal beats. This dataset is accompanied by annotation files which help finding the marked beats as normal and or arrhythmia. In total 48 recordings from 47 patients are available from MIT-BIH dataset. An individual record is approximately half hour in length. Basic preprocessing such as band pass filtering was already performed on these records prior to their availability for research usage.

It is the first standard test material that is generally available to evaluate arrhythmia detection. Since in 1980, this data was used 500 sites of the worldwide. The MIT-BIT data set consists of ECG recording from 47 different subjects recording at the sampling rate of 360Hz. Here in our project we used ECG lead II resampled to the sampling frequency of 125 Hz as the input. Each beat is annotated by at least two cardiologists. We use annotation in this dataset to create 5 different beat categories in accordance with Association for the Advancement of medical Instrumentation (AAMI) EC 57 Standard [1].

4.2 Image Encoding

The different three types of image encoding used here are GASF, GADF, and MTF. Plot of each encoding with classes is shown in figure 3.

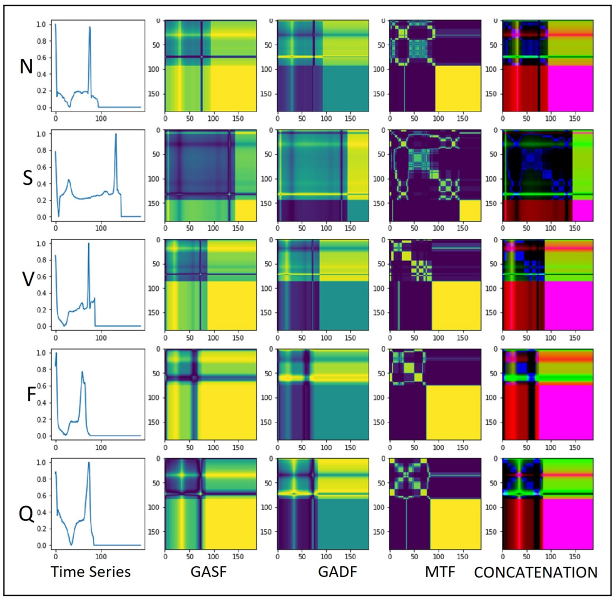

Figure 3: Image encoding GASF,GADF,MTF and Concatenation

4.3 Triple channel image

GAF encodes static information while MTF depicts information about dynamics. From this point of view, we consider them as three "orthogonal" channels, like different colors in the RGB image space. Thus, we can combine GAFs and MTF images of the same size (i.e. SGAF s = SMTF) to construct a triple-channel image (GASF-GADF-MTF). It combines both the static and dynamic statistics embedded in the raw time series, and we posit that it will be able to enhance classification performance

4.4 Model Output

4.4.1 VGG16-LSTM model

In VGG16-LSTM model each training epoch took approximately 20 minutes to complete. Figure 4 shows that after 15 epoch validation accuracy starts to plateau while the training accuracy continues to rise. In figure 5, it can be observed that U class is classified more accurately than other classes. The precision, recall and F1 score of VGG16-LSTM model is shown in table 2.

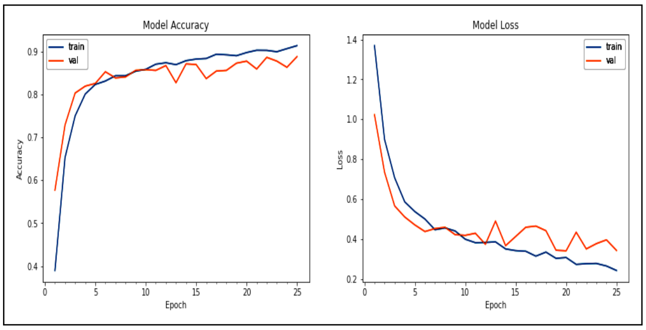

Figure 4: Accuracy and Loss (VGG16-LSTM)

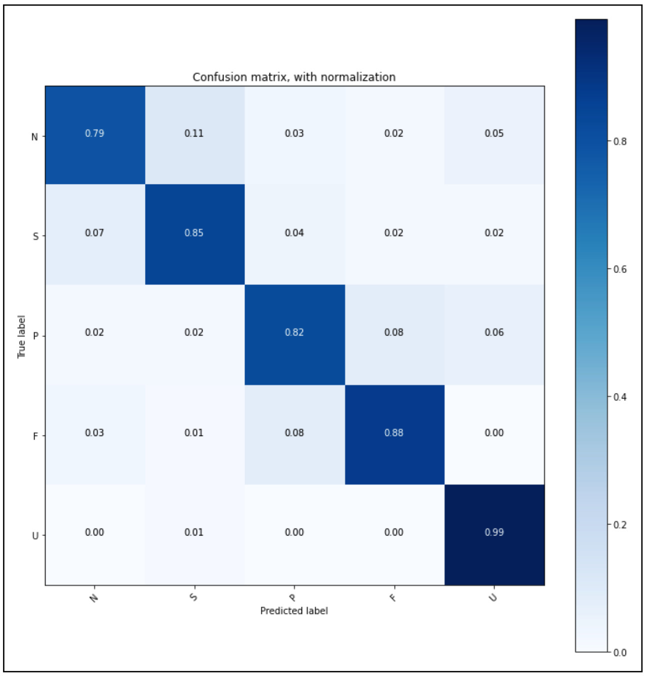

Figure 5: Confusion Matrix (VGG16-LSTM)

Table 2: precision, recall and fi-score of VGG16-LSTM model

class	precision	recall	f1-score
0	0.87	0.79	0.83
1	0.85	0.85	0.85
2	0.85	0.82	0.83
3	0.88	0.88	0.88
4	0.88	0.99	0.93
accuracy			0.87
macro avg	0.87	0.87	0.86
weighted avg	0.87	0.87	0.86

4.4.2 ResNet50-LSTM model

In ResNet50-LSTM model each training epoch took approximately 5 minutes to complete. Figure 6 shows that after 20 epoch validation accuracy starts to plateau while the training accuracy continues to rise. In figure 7, it can be observed that S class is misclassified more than other classes. The precision, recall and F1 score of ResNet50-LSTM model is shown in table 3.

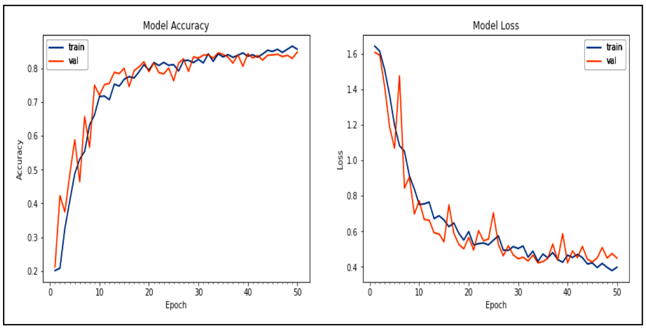

Figure 6: Accuracy and Loss (ResNet50-LSTM)

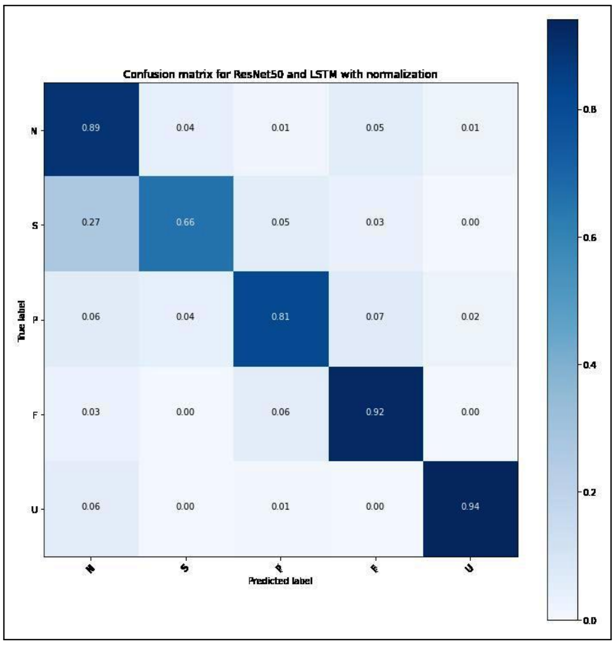

Figure 7: Confusion Matrix (ResNet50-LSTM)

Table 3: precision, recall and f1-score of ResNet50-LSTM model

class	precision	recall	f1-score
0	0.69	0.89	0.77
1	0.89	0.66	0.76
2	0.87	0.81	0.84
3	0.86	0.92	0.89
4	0.96	0.94	0.95
accuracy			0.84
macro avg	0.86	0.84	0.84
weighted avg	0.86	0.84	0.84

Table 4: Comparision of different classification approach

Approach	Precision	Recall	F1
VGG+LSTM	0.87	0.87	0.87
ResNet50+LSTM	0.86	0.84	0.84

Table 4 shows that classification of Arrhythmia using combination of different pre-trained model with LSTM. Better result was found using VGG16+LSTM than other approach. Therefore, via transfer learning and translation to 2D domain with LSTM cell, we were able to classify the ECG signal better.

5. Conclusion

In this study we have presented a method for ECG heartbeat classification based on the transferable representation. We use Gramian Angular Summation Fields (GASF), Gramian Angular Difference Fields (GADF) and Markov Transition Fields (MTF) to encode the time series as images. This work, to our understanding, is the first effort to used Concatenation encoded image in the deep CNN, pre-trained on millions of images to extract the features and LSTM for the classification purpose. We have obtained the classification accuracy of 87.0% in VGG-LSTM model. In future, we intend to use this model using ensemble method for better performance.

References

[1] Mohammad Kachuee, Shayan Fazeli, and Majid Sarrafzadeh. Ecg heartbeat classification: A deep transferable representation. In *2018 IEEE International Conference on Healthcare Informatics (ICHI)*, pages 443–444. IEEE, 2018.

[2] Shraddha Singh, Saroj Kumar Pandey, Urja Pawar, and Rekh Ram Janghel. Classification of ecg arrhythmia using recurrent neural networks. *Procedia computer science*, 132:1290–1297, 2018.

[3] Junli Gao, Hongpo Zhang, Peng Lu, and Zongmin Wang. An effective lstm recurrent network to detect arrhythmia on imbalanced ecg dataset. *Journal of healthcare engineering*, 2019, 2019.

[4] Milad Salem, Shayan Taheri, and Jiann-Shiun Yuan. Ecg arrhythmia classification using transfer learning from 2-dimensional deep cnn features. In *2018 IEEE Biomedical Circuits and Systems Conference (BioCAS)*, pages 1–4. IEEE, 2018.

[5] Narendra Kohli, Nishchal K Verma, and Abhishek Roy. Svm based methods for arrhythmia classification in ecg. In *2010 international conference on computer and communication technology (ICCCT)*, pages 486–490. IEEE, 2010.

[6] U Rajendra Acharya, Shu Lih Oh, Yuki Hagiwara, Jen Hong Tan, Muhammad Adam, Arkadiusz Gertych, and Ru San Tan. A deep convolutional neural network model to classify heartbeats. *Computers in biology and medicine*, 89:389–396, 2017.

[7] Özal Yıldırım, Paweł Pławiak, Ru-San Tan, and U Rajendra Acharya. Arrhythmia detection using deep convolutional neural network with long duration ecg signals. *Computers in biology and medicine*, 102:411–420, 2018.

[8] Saroj Kumar Pandey and Rekh Ram Janghel. Automatic detection of arrhythmia from imbalanced ecg database using cnn model with smote. *Australasian physical & engineering sciences in medicine*, 42(4):1129–1139, 2019.

[9] Chao-Lung Yang, Chen-Yi Yang, Zhi-Xuan Chen, and Nai-Wei Lo. Multivariate time series data transformation for convolutional neural network. In *2019 IEEE/SICE International Symposium on System Integration (SII)*, pages 188–192. IEEE, 2019.

[10] Chao-Lung Yang, Zhi-Xuan Chen, and Chen-Yi Yang. Sensor classification using convolutional neural network by encoding multivariate time series as two-dimensional colored images. *Sensors*, 20(1):168, 2020.

[11] Jenny Venton, Philip J Aston, Nadia AS Smith, and Peter M Harris. Signal to image to classification: Transfer learning for ecg. In *2020 11th Conference of the European Study Group on Cardiovascular Oscillations (ESGCO)*, pages 1–2. IEEE, 2020.

[12] Zhenyu Zheng, Zhencheng Chen, Fangrong Hu, Jianming Zhu, Qunfeng Tang, and Yongbo Liang. An automatic diagnosis of arrhythmias using a combination of cnn and lstm technology. *Electronics*, 9(1):121, 2020.