Classification of ECG signals for detection of arrhythmia and congestive heart failure based on continuous wavelet transform and deep neural networks

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Article Info	ABSTRACT
	According to World Health Organization (WHO) report an estimated 17.9 million lives are being lost each year due to cardiovascular diseases (CVDs) and is the top contributor to the death causes. 80% of the cardiovascular cases include heart attacks and strokes. This work is an effort to accurately predict the common heart diseases such as arrhythmia (ARR) and congestive heart failure (CHF) along with the normal sinus rhythm (NSR) based on the integrated model developed using continuous wavelet transform (CWT) and deep neural networks. The proposed method used in this research analyses the time-frequency features of an electrocardiogram (ECG) signal by first converting the 1D ECG signals to the 2D Scalogram images and subsequently the 2D images are being used as an input to the 2D deep neural network model-AlexNet. The reason behind converting the ECG signals to 2D images is that it is easier to extract deep features from images rather than from the raw data for training purposes in AlexNet. The dataset used for this research was obtained from Massachusetts Institute of Technology-Boston's Beth Israel Hospital (MIT-BIH) arrhythmia database, MIT-BIH normal sinus rhythm database and Beth Israel Deaconess Medical Center (BIDMC) congestive heart failure database. In this work, we have identified the best fit parameters for the AlexNet model that could successfully predict the common heart diseases with an accuracy of 98.7%. This work is also being compared with the recent research done in the field of ECG Classification for detection of heart conditions and proves to be an effective technique for the classification.

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1. INTRODUCTION

An electrocardiogram also known as electrocardiogram (ECG) is a test that measures the electrical activity of the heartbeat. With each beat, an electrical impulse travel through the heart. This wave causes the muscle to squeeze and relax and hence pumping blood from the heart to the whole body. A normal heartbeat on ECG as shown in Figure 1 will show the timing of the top and lower chambers. There is a "P wave" which yields from a right and left atria or upper chambers. Then it is followed by a flat line when the electrical impulse goes to the bottom of chambers. The "QRS complex" is the next wave that is produced by right and left bottom chambers. The final wave or "T wave" represents electrical recovery or return to a resting state

for the ventricles. ECG serves as the basic and easy to implement method for the diagnosis of cardiac malfunctioning (or heart rhythm disorders). This is due to its non-invasive and simple technique of recording the signals whilst providing vital information on heart conditions.

Around 17.3 million people die each year globally due to cardiac diseases which accounts for over 37% of the total world deaths [1] and it has also been predicted that about 23.6 million might die due to heart diseases and failures [2]. The advancements in data mining and cloud computing allow huge amounts of medical data to be extensively analyzed without compromising the precision of its results. This is considered as a motivation to conduct a data driven research to predict, determine and detect the diseases at an early stage. Likewise, ECG signals generate huge chunks of data that has been used by researchers to develop prediction models based on machine learning and convolutional neural networks [3].
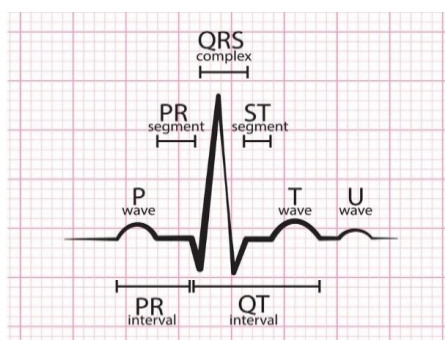

Figure 1. Electrocardiography wave [4]

Health care research has always aimed to identify the techniques to reduce the mortality rates in one form or another. Appropriate data mining and machine learning algorithms have played a pivotal role in developing the highly efficient prediction models for detection of disease and one among those diseases is the heart disease [2]. In retrospect, there are many types of heart diseases and the most common of heart conditions are arrhythmia (ARR) and congestive heart failure (CHF) [5]. What differentiates between one heart disorders from another is the electrical activities which reflect in its ECG signals. A normal sinus rhythm (NSR) represents a proper transmission of electrical signals from one's sinus nodes and is an indication of a normal heart [5].

This research makes use of the NSR, ARR, and CHF ECG data from the verified databases in order to build a prediction model based on convolutional neural networks. The proposed algorithm would be able to determine whether a person has any of the mentioned disorders or possesses a healthy heart rhythm. Accurate diagnosis and prediction of any disease is an extensive and challenging task and needs more accurate classification.

Algorithms do exist for ECG based automatic cardiac disorder detection which mainly rely on the morphological features of QRS complexes or heartbeats. But the analysis of QRS complexes is more popular in the scientific literature than the ECG signal fragments of long durations [6]. The problem with such methods arises due to the varied beat-to-beat variability among individuals and this prompted us to look beyond these morphological features and perform that analysis of long duration ECG signals with more data and features using deep neural networks.

Deep learning, a type of machine learning method, comprises a hierarchical architecture that includes multiple layers and stages for information processing [7]. The inner layers are utilized to extract the deep features whereas the outer layers help in performing the analysis and classification [8]. The classification of deep learning can be done based on the training methods involved in building up the networks and some of its prominent subtypes are: i) Convolutional neural networks (CNNs), ii) Recurrent neural networks (RNNs), iii) Deep neural networks (DNNs)

These subtypes fall in the category of deep discriminatory models. Another such category of deep learning includes unsupervised/generative models such as deep belief networks (DBNs), restricted Boltzmann machines (RBMs), deep Boltzmann machines (DBMs), and regularized autoencoders. Deep learning has gained pace from the past 10 years due to its ability to process huge chunks of processed data including 2D images with high efficiency. We will be using this feature of deep learning to train the model with 2D Scalogram images which have been derived from 1D ECG signal datasets. The goal is to train a convolutional neural network (CNN) so that it will be able to distinguish between these three types of ECG signals-NSR, ARR and CHF.

2. RELATED WORK

Heartbeat segmentation is essential for classification of heart diseases as few errors might have a definite impact on the classification results of ECG signals. Segmentation mainly involves detection of P-QRS-T waves. Research into the detection of QRS complexes in ECG signals has been carried for years by virtue of frequently used methods such template matching method [9], differential threshold method [4] and wavelet transform [10]. Some algorithms were also developed to extract features from P and T waves [11]. RR intervals are one of the most sought out features of ECG signals that have been used for classification [12]. In addition to RR intervals, morphological features such as wave amplitude and positive negative areas have been used. Apart from the morphological features obtained from P-QRS-T waves of ECG signals, signal processing methods such as higher order spectral cumulants [13], wavelet transforms both discrete and continuous and independent component analysis (ICA) have been widely used for ECG classification for heart diseases. Although, these features follow a particular mathematical interpretation, they certainly do lack the physiological meaning making it difficult for medical practitioners to understand plus computational cost to implement these methods.

The work proposed Kumar *et al*. in [14] for arrhythmic beat classification using the ECG dataset is based on discrete cosine transform (DCT) where the DCT converts time series plot of an ECG data into the corresponding frequency components. In this methodology the QRS complex of an ECG signal along with the RR interval are used to distinguish signals from one another followed by the classification using random tree technique. Data was obtained from the physiobank website and paper claims to achieve an accuracy of 90%. One of the backdrops of the proposed strategy is that the classification has been done using the random forest which works well for the limited dataset only and slows down for huge chunks of data.

Thomas *et al*. [15], the work proposed extracts the features based on the dual tree complex wavelet transform (DTCWT) and results in the automatic classification of cardiac arrhythmias. DTCWT technique was preferred over DWT due to the property of shift invariance present in former. DWT is no doubt a powerful tool for ECG signal analysis but suffers from problems like aliasing and oscillation apart from shift variance. DTCWT technique proposed Manu *et al*. in [15] simply overcomes the limitations of DWT technique by implementing Fourier transform as the magnitudes do not oscillate from positive to negative and are perfectly shift invariant. However, limitation of such a strategy is that there is no means of identifying where an event has occurred as the time information is missing.

Zhu *et al*. [16] proposes a method for arrhythmia recognition and classification using ECG morphology and Segment Feature Analysis. It begins with the extraction of morphological features from P-QRS-T waves followed by principal component analysis (PCA) and dynamic time warping (DTW) to extract ECG segment features. In the last section of their proposed methodology support vector machines (SVM) has been applied to the features extracted and the classification results are obtained. Though the efficiency obtained is higher than the other proposed methodologies, however, it is a known fact that SVM has limitations when it comes to the size of the dataset and is simply not suitable for large datasets. SVMs do not perform at par with other highly efficient classifiers when the noise in the signal is high. There is no mention of the size of the dataset eventually used for training and testing using SVM classifiers. Work proposed Saini *et al*. [17] also uses PCA to compute the statistical features directly from ECG signals followed by the use of supervised machine learning classifier k-nearest neighbors (KNN) resulting in an overall accuracy of 87.5% for 10 different classes.

From the past few years, deep learning techniques have shown a positive trend and outperformed the traditional ECG classification methods for pattern recognition applications [18] and as a result, researchers are focusing more on the deep learning models for ECG classification problems for several heart diseases. Recurrent neural networks (RNNs) were proposed by Salloum and Kuo [19] for the identification and authentication problem in ECG-based biometrics. Mostayed also used RNN for the detection of pathologies in 12-lead electrocardiogram signals that consisted of bi-directional short-long-term-memory layers [20]. 1D convolutional neural networks (CNNs) were used to propose a real time patient specific electrocardiogram classification technique for classifying long ECG signal records of patients [21]. Li also proposed a model for the classification of 5 types of arrhythmias based on the 1D-CNN method [22]. Impulse radio ultra-wideband (IR-UWB) radar integrated with ECG monitoring was proposed by Yin *et al*. [23] and implements a cascade CNN for analysis of ECG signals and radar data. The overall accuracy achieved was 88.89% and the proposed model maintains a stable accuracy in classifying normal and abnormal heart signals in the slight motion state.

A recent trend in the classification of ECG signals has been the use of 2D CNN architectures that have shown promising results when compared with the results from 1-D CNN. One such method has been proposed Elif *et al*. in [24] where a deep learning based 2-D CNN model classifies five distinct arrhythmia types. In this approach each of the heartbeats that were collected from Massachusetts Institute of Technology-Boston's Beth Israel Hospital (MIT-BIH) database were converted to 2-D grayscale images as an input to the CNN model and the model could reach to an overall accuracy of 97.42% on the training results.

The proposed CNN architecture included 2 convolutional layers, 2 pooling layers and a fully connected layer in which the first two layers (convolutional and pooling) are responsible for feature extraction whereas fully connected layer helps in the classification steps. So, this way 2-D images are directly used as an input and thereby do not require separate feature extraction methods for varied features of ECG Signals. Another study [25] proposes a ten-layer model consisting of four convolutional layers, four pooling layers followed by a single fully connected layer and an output layer to transform the ECG signals into 2-D spectrograms. This transformation is done using a short-time Fourier Transform and the classification accuracy obtained is also very high. Though the final average accuracy as claimed in this research is above 99% but there two classes with individual frequencies of less than 90% and one class accuracy reaching as low as 77.6%.

3.   MATERIAL AND METHODS
3.1. ECG signal dataset and database processing
Here, we used three categories of ECG signals for modelling a deep CNN: i) Cardiac arrhythmia (ARR), ii) Congestive heart failure (CHF), iii) Normal sinus rhythm (NSR). These signals are obtained from 162 ECG recordings from three Physionet databases: MIT-BIH arrhythmia database (96 recordings of ARR signals), MIT-BIH normal sinus rhythm database (30 Recordings of NSR signals and BIDMC congestive heart failure database (36 recordings of CHF signals). The data matrix is of size 16*65536 which means it carries a total of 162 ECG signals of size 65536 samples each. Each signal has been labelled from which the information about the type of the ECG signal is gathered. Rows 1:96 of the database are ARR signals, rows 97:126 of the database are CHF signals and rows 127:162 of the database are NSR signals.

Data preprocessing for our problem statement is first started at the database level. Each record is of length 65536 samples or simply data points and is thereby broken into small signals of lengths 500 samples to increase the size of the database to make it appropriate to train a convolution neural network-in our case AlexNet. We also take 30 recordings of each type (ARR, CHF, and NSR) to have equal distribution. Each recording has been broken into 20 pieces of length 500 samples and therefore each category will provide 600 (30*20) recordings of size 500 samples and thus the total will be 1800 recordings.

3.2. ECG signal to image conversion using continuous wavelet transform
Here we were able to convert one-dimensional ECG signal into a new two-dimensional RGB image by extracting ECG signal features that appeared in a certain frequency band. The resultant images were obtained via time-frequency representation of their corresponding ECG signals. Short time fourier transform (STFT) which has been commonly used for the time-frequency representation is less effective for ECG signals due to time and frequency trade-off in resolution [26]. Small window size in STFT results in good time but poor frequency and the results are quite opposite when the window is wide. To resolve this issue, we make use of continuous wavelet transform (CWT) [27] to develop a two-dimensional RGB image of an ECG signal. Fourier transform (FT) and continuous wavelet transform (CWT) have similar methodologies where FT generates correlation coefficients between the sinusoidal signal and the original signal. Similarly, CWT also generates coefficients like FT, however, the difference between two transforms is the domains in which those correlation coefficients are generated. While FT deals with frequency domain, coefficients in CWT are generated in time domain. We chose CWT due to the reasons many relevant useful details could be extracted from the signals in the time domain. The shape of the CWT waveform can be easily controlled by shifting and scaling parameters. The mathematical formula of CWT for a function x(t) has been given in (1):

$$CWT\ (s, \omega) = (1/\sqrt{s}) \int x\ (t).\ \Psi\ ((t-\omega)/s).\ dt \tag{1}$$

Here s and ω are called dilation (scale) and translation (position) parameters, respectively. Scale parameters are responsible for either stretching the wavelet or compressing the wavelet. Ψ represents a wavelet function and in our experiment, we are using Morlet wavelet as given in (2). x(t) represents the ECG signal in this paper and CWT (s, ω) denotes the coefficients obtained by performing continuous wavelet transform.

$$\Psi(t) = e^{j\omega o t}.e^{t^2/2} \tag{2}$$

The results of CWT are many wavelet coefficients, which are a function of s (scale) and ω (position). ECG signal x(t) can be recovered by performing an inverse CWT, as shown in (3).

$$x(t) = \frac{1}{c} \int CWT(w, s)\Psi w, \frac{s(t)}{|s|^{3/2}} ds.\ dw \tag{3}$$

where C represents the normalization constant that entirely depends upon the wavelet selected.

CWT, with a smooth wavelet, has the capability of extracting or representing the dynamic frequency properties of any signal applied upon and we will be using this property of CWT to obtain information from ECG signals. Here we will use Morlet wavelet by applying various scales and translations on top of Morlet. Morlet wavelet has been obtained or derived from a Gaussian function and is represented by (4). Parameter σ plays a pivotal role in shaping the mother wavelet.

$$\Psi Morl(t) = e^{2\pi it}e^{-\frac{t^2}{2\sigma^2}} = (cos2\pi t + isin2\pi t)e^{-\frac{t^2}{2\sigma^2}} \tag{4}$$

At this stage of preprocessing all the one-dimensional (1 D) signals are converted into images using continuous wavelet transform (CWT) so that these images could later be fed to a deep CNN-AlexNet. The coefficients of a CWT of each 1D signal are arranged to form a CWT Scalogram and each Scalogram is represented as a colormap of type "jet" of 128 colors. Conversion of Scalogram into images is stored in their respective folders (ARR, NSR, and CHF). Each Image is resized to 227*227 as these images are fed to a deep CNN model AlexNet that can only accept images of the mentioned size. By the end of this activity, a total of 1800 Scalogram images are produced for corresponding 1800 ECG signals-600 from each category in their respective folders.

CWT methodology applied for the conversion of signals to images by virtue of a carefully chosen wavelet analytical morlet (amor) due to its equal variance in time and frequency. These wavelets make a good choice for obtaining a time-frequency analysis using CWT.12 wavelet bandpass filters are used for CWT that allows only a certain range of frequencies to pass through while blocking extremely high and extremely low frequencies. The result of conversion procedures on one of the three different categories for a single signal has been shown in Figure 2. This conversion was done for all those 1800 signals present in our database.
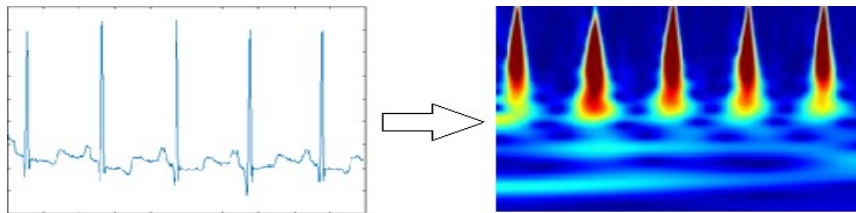

Figure 2. Conversion of 1D ECG signal into its corresponding 2D scalogram image [227*227]

3.3. Apply transfer learning mechanism

A pre-trained deep neural network-AlexNet has been used. AlexNet has been trained on over a million images and can classify images into 1000 different object categories. So basically, we will be fine tuning a pre-trained CNN to perform the classification on a new collection of images. This method of transfer learning is quicker than training a CNN from scratch which requires a lot of training time and thousands of input images. AlexNet architecture is shown in Figure 3 which consists of 8 layers out of which 5 are convolutional layers and we have 3 fully connected layers. The input size which AlexNet accepts is 227*227*3 where 3 refers to a color image. So, the input to the first convolutional is 227*227*3 which then applies 96 filters of size 11*11 with a stride of 4 pixels followed by pooling layer of window size 3*3 that applies a stride of 2. The output of first convolutional layer becomes the input of second convolutional layer and so on till convolutional layer 5. The output tensor at the convolutional layer 5 is (13*13*256) after going through a max pooling layer performed zero padded sampling operation with a stride of 2 and a window region of (3*3) and this sub sampling operation produced a tensor output of size (6*6*256). First Fully Connected layer of the architecture shown in Figure 3 is represented as FC6 which accepts (6*6*256) tensor from the previous layer and performed weighted sum operation resulting in (4096*1) tensor output. FC7 is yet another fully connected layer that accepts the 4091*1 tensor as an input and after passing through the rectified linear activation function (ReLu) produces the output with the same dimensions (4091*1) and this layer simply results in the greater number of trainable parameters when compared with the previous layer (FC6). FC8 is the last layer represents the output class that uses the SoftMax activation function for classification and performs the same function as that of FC6 and FC7 and has been modified to 3 for the model as we are trying to classify on three different classes such as ARR, CHF and NSR. As far as the mathematics for each layer of AlexNet is concerned there are two distinct cases, one for without padding which is represented by (5) and one with padding has been put in (6). The size of the image (ImS) is calculated after passing through each layer as

shown by (5) and (6), where n represents the number of sizes of the image, f refers to the filter size and s stands for the stride. For Padding we have an extra term P as shown in (6).
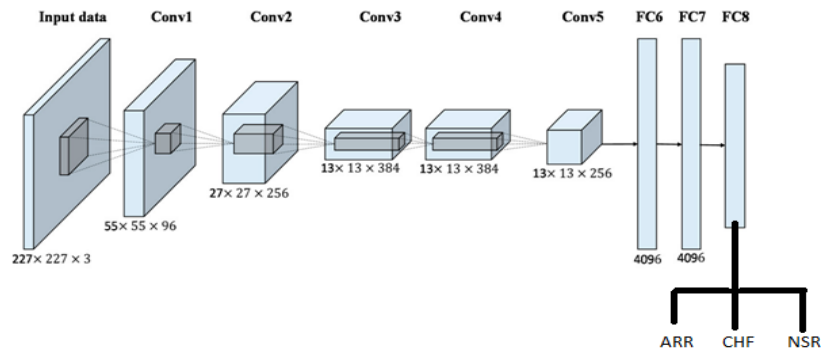

Figure 3. AlexNet architecture

$$Image\ Size\ (ImS) = \frac{n-f}{s} * \frac{n-f}{s} + 1 \qquad (5)$$

$$Image\ Size\ (ImS) = \frac{n+2P-f}{s} * \frac{n+2P-f}{s} + 1 \qquad (6)$$

We changed the last layer because AlexNet is trained for 1000 different objects but for our current problem, the total classification objects or classes are only three. That means only three types of signals must be distinguished from one another. After this step, the deep neural network is trained by feeding the system with the new set of Scalogram images. In our experiment we have chosen 1500 images of training purpose and rest 300 images to test the system for its accuracy and efficiency. That means each category of 600 images will be supplying 500 images for training and 100 images for testing. These layers are fine-tuned as per steps mentioned below and thus the use of appropriate optimization parameters in the CNN model for the classification of signals into three different categories-ARR, CHF, and NSR. Stepwise procedure for applying the deep CNN network AlexNet is summarized as shown in: i) Read images from database folder using a MATLAB function imageDatastore; ii) Split images into testing and training sets; iii) Load pretrained network-AlexNet; iv) Preserve all layers of AlexNet except last 3-since we will be using 3 classes only; v) Define the three layers; vi) Set the training option such as BatchSize, MaxEpochs, LearningRate, and ValidationRate; vii) Train the CNN followed by classification of images and plot the confusion matrix.

A careful selection of the two optimization parameters such as batch size and learning rate plays a key role in the classification accuracies. Different values of these parameters were set, and it was observed that a learning rate parameter had a direct impact on the speed of convergence and the learning rate of 0.001 proved to be ideal for classification. After testing the various batch size parameters at a fixed learning of 0.001, a batch size of 20 along with the validation frequency of 10 produced the high classification accuracy.

4.   RESULTS AND DISCUSSION

Figure 4 (a) represents the accuracy plot based on the number of iterations. Here, accuracy basically represents the number of successful predictions classified by CNN. As evident from the graph the accuracy starts with the modest value of about 38 % at the start of the iterations and reaches a value shows an increasing trend with more and more iterations and reaches a promising value of 98.7% at the end of 600 iterations during 8th epoch. This trend in increase of the accuracy value is because the CNN model is getting trained with a greater number of scalogram images and thereby the classification becomes easier and accurate during the course of time or iterations. Loss plot shown in Figure 4 (b) as expected, shows exactly the opposite trend when compared with the accuracy plot. Initially rate is much higher and gradually decreases with the increase in the number of iterations (training).

Figure 5 represents the confusion matrix that we have achieved through this research. Here we can see the three classes such as arr, chf and nsr. For ARR class, 98 out of 100 are successfully classified as arr which makes an accuracy percentage of 98% whereas the two cases of arr were misinterpreted by the classifier as nsr. For the nsr class, 98 out 100 cases were successfully classified by the CNN model which contributes to the success percentage of 98%. Results obtained for nsr were promising and the classifier could identify all the 100 cases as arr which makes a success percentage of 100%. Overall average success percentage of the model used thus stands at 98.7%. Table 1 shows the comparison our proposed strategy of classifying the ECG signals with the work done by other

researchers and the accuracy result of 98.7% testifies the fact that conversion of 1D signals to 2D scalogram images using convolutional wavelet transform (CWT) plays a pivotal role in further extracting the features and classifying the images accurately using transfer learning model.
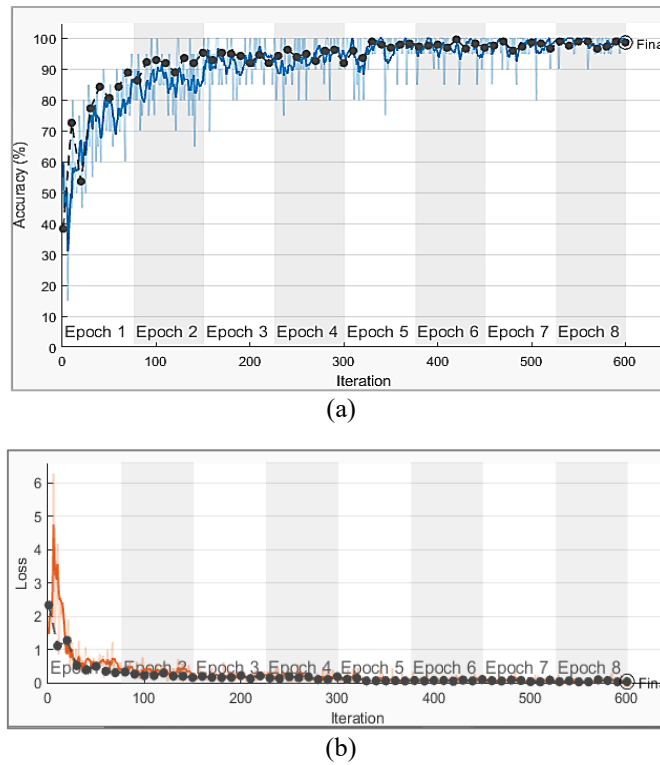

(a)

(b)

Figure 4. These figures are: (a) accuracy (%) Vs. number of iterations plot and
(b) loss plot based on the number of iterations

Figure 5. Confusion matrix of the CNN network representing success and failure rates

Table 1. Comparison with other existing approaches

Literature	Preprocessing	Feature Extraction	Classification	Accuracy
Joshi *et al*. [28]	Wavelet	PCA + Wavelet	SVM	86.4 %
Zhu *et al*. [16]	Morphological Filter	PCA	SVM	87.5 %
Ying *et al* [29]	Moving average method with predetermined window	Gibbs Sampling Algorithm	Hidden Markov Model	88.33%
Jose *et al*. [30]	Wavelet	Wavelet	PNN	92.7 %
Zubair *et al*. [31]	Bandpass Filter	CNN	SoftMax	92.7%
Acharya *et al*. [32]	Daubechies wavelet	Pan Tompkins	9-Layer CNN	93.47%
Ismaiel *et al*. [33]	Digital Filters	Discrete Wavelet	NNWs	94%
Özal *et al*. [34]	Constant Component Reduction	Rescaled Raw Data	1-D CNN	95.20%
Elif, *et al*. [24]	1D to 2D Transformation	Convolution	CNN Model	97.24%
Proposed	Analytical Morlet (amor)	CWT	CNN-AlexNet	98.7%

5. CONCLUSION

In this work, we proposed a classification model based on continuous wavelet transform and deep learning network that could classify ECG signals into three distinct classes such as NSR, CHF and ARR. ECG signals were obtained from MIT-BIH and BMDMC databases available online and preprocessed using Analytical Morlet filter followed by conversion of all 900 one dimensional recordings into 2D RGB scalograms. These resultant images were passed through a series of convolutional layers of a deep neural network followed by testing and training the dataset. Results show that the detection of heart conditions from an ECG signals by virtue of CWT followed by deep neural networks model can reach an average accuracy of 98.7% at a learning rate of 0.001. We have also compared our results with other researchers and the comparison table signifies that the fact that conversion of 1D images into 2D scalograms during the preprocessing stage yields better results than the conventional way of extracting the morphological features from ECG signals. The overall 2-D CNN deep learning models have high classification accuracies thereby can be safely used for diagnosis of arrhythmia and automatic classification in the medical applications in general.

REFERENCES

[1] S. P. Rajamhoana, C. A. Devi, K. Umamaheswari, R. Kiruba, K. Karunya, and R. Deepika, "Analysis of Neural Networks Based Heart Disease Prediction System," *2018 11th International Conference on Human System Interaction (HSI)*, 2018, pp. 233-239, doi: 10.1109/HSI.2018.8431153.

[2] S. Roostaee and H. R. Ghaffary, "Diagnosis of heart disease based on meta heuristic algorithms and clustering methods," *Journal of Electrical and Computer Engineering Innovations (JECEI)*, vol. 4, no. 2, pp. 105-110, 2016, doi: 10.22061/JECEI.2016.570.

[3] U. R. Acharya, H. Fujita, S. L. Oh, Y. Hagiwara, J. H. Tan, M. Adam, and R. S. Tan, "Deep convolutional neural network for the automated diagnosis of congestive heart failure using ECG signals," *Applied Intelligence*, vol. 49, no. 1, pp. 16-27, 2019, doi: 10.1007/s10489-018-1179-1.

[4] D. Pandit, Z. Li, L. Chengyu, S. Chattopadhyay, N. Aslam, and L. C. Peng, "A lightweight QRS detector for single lead ECG signals using a max-min difference algorithm," *Computer methods and programs in biomedicine*, vol. 144, pp. 61-75, 2017, doi: 10.1016/j.cmpb.2017.02.028.

[5] S. Nahak and G. Saha, "A Fusion Based Classification of Normal, Arrhythmia and Congestive Heart Failure in ECG," *2020 National Conference on Communications (NCC)*, 2020, pp. 1-6, doi: 10.1109/NCC48643.2020.9056095.

[6] V. Gupta and M. Mittal, "QRS complex detection using STFT, chaos analysis, and PCA in standard and real-time ECG databases," *Journal of the Institution of Engineers (India): Series B*, vol. 100, no. 5, pp. 489-497, 2019, doi: 10.1007/s40031-019-00398-9.

[7] J. M. Johnson and T. M. Khoshgoftaar, "Survey on deep learning with class imbalance," *Journal of Big Data*, vol. 6, no. 1, pp. 1-54, 2019, doi: 10.1186/s40537-019-0192-5.

[8] U. R. Acharya, H. Fujita, S. L. Oha, Y. Hagiwara, J. H. Tan, and M. Adam, "Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals," *Information Sciences* 415-416, 190-198, November 2017, doi: 10.1016/j.ins.2017.06.027.

[9] H. Liu, D. Chen, and G. Sun, "Detection of Fetal ECG R Wave from Single-Lead Abdominal ECG Using a Combination of RR Time-Series Smoothing and Template-Matching Approach," *IEEE Access*, vol. 7, pp. 66633-66643, 2019, doi: 10.1109/ACCESS.2019.2917826.

[10] T. Tuncer, S. Dogan, P. Pławiak, and U. R. Acharya, "Automated arrhythmia detection using novel hexadecimal local pattern and multilevel wavelet transform with ECG signals," *Knowledge-Based Systems*, vol. 186, p. 104923, Dec. 2019, doi: 10.1016/j.knosys.2019.104923.

[11] J. P. V. Madeiro, E. M. B. Santos, P. C. Cortez, J. H. S. Felix, and F. S. Schlindwein, "Evaluating Gaussian and Rayleigh-Based Mathematical Models for T and P-waves in ECG," in *IEEE Latin America Transactions*, vol. 15, no. 5, pp. 843-853, May 2017, doi: 10.1109/TLA.2017.7910197.

[12] A. Kennedy, D. D. Finlay, D. Guldenring, R. R. Bond, K. Moran, and J. McLaughlin, "Automated detection of atrial fibrillation using RR intervals and multivariate-based classification," *Journal of electrocardiology*, vol. 49, no. 6, pp. 871-876, Dec. 2016, doi: 10.1016/j.jelectrocard.2016.07.033.

[13] H. Alquraan, A. M. Alqudah, Abu-Qasmieh, A. Al-Badarneh, and S. Almashaqbeh, "ECG classification using higher order spectral estimation and deep learning techniques," *Neural Network World*, vol. 29, no. 4, pp. 207-219, 2019, doi: 10.14311/NNW.2019.29.014.

[14] R. G. Kumar and Y. S. Kumaraswamy, "Investigating cardiac arrhythmia in ECG using random forest classification," *International Journal of Computer* Applications, vol. 37, no. 4, pp. 31-34, Jan. 2012.

[15] M. Thomas, M. Kr. Das, and S. Ari, "Automatic ECG arrhythmia classification using dual tree complex wavelet-based features," *AEU-International Journal of Electronics and Communications*, vol. 69, no. 4, pp. 715-721, Apr. 2015, doi: 10.1016/j.aeue.2014.12.013.

[16] W. Zhu, X. Chen, Y. Wang, and L. Wang, "Arrhythmia Recognition and Classification Using ECG Morphology and Segment Feature Analysis," *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 16, no. 1, pp. 131-138, 1 Jan.-Feb. 2019, doi: 10.1109/TCBB.2018.2846611.

[17] R. Saini, N. Bindal, and P. Bansal, "Classification of heart diseases from ECG signals using wavelet transform and kNN classifier," *International Conference on Computing, Communication & Automation*, 2015, pp. 1208-1215, doi: 10.1109/CCAA.2015.7148561.

[18] Xin-Cheng Cao, Bin-Qiang Chen, B. Yao, and Wang-Peng He, "Combining translation-invariant wavelet frames and convolutional neural network for intelligent tool wear state identification," *Computers in Industry*, vol. 106, pp. 71-84, April 2019, doi: 10.1016/j.compind.2018.12.018.

[19] R. Salloum and C. J. Kuo, "ECG-based biometrics using recurrent neural networks," *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2017, pp. 2062-2066, doi: 10.1109/ICASSP.2017.7952519.

[20] A. Mostayed, J. Luo, X. Shu, and W. Wee, "Classification of 12-lead ECG signals with Bi-directional LSTM network," *arXiv preprint arXiv:1811.02090*, Nov. 2018.

[21] S. Kiranyaz, T. Ince, and M. Gabbouj, "Real-Time Patient-Specific ECG Classification by 1-D Convolutional Neural Networks," *IEEE Transactions on Biomedical Engineering*, vol. 63, no. 3, pp. 664-675, Mar. 2016, doi: 10.1109/TBME.2015.2468589.

[22] D. Li, J. Zhang, Q. Zhang, and X. Wei, "Classification of ECG signals based on 1D convolution neural network," *2017 IEEE 19th International Conference on e-Health Networking, Applications and Services (Healthcom)*, 2017, pp. 1-6, doi: 10.1109/HealthCom.2017.8210784.

[23] W. Yin, X. Yang, L. Zhang, and E. Oki, "ECG Monitoring System Integrated with IR-UWB Radar Based on CNN," *IEEE Access*, vol. 4, pp. 6344-6351, 2016, doi: 10.1109/ACCESS.2016.2608777.

[24] E. Izci, M. A. Ozdemir, M. Degirmenci, and A. Akan, "Cardiac Arrhythmia Detection from 2D ECG Images by Using Deep Learning Technique," *2019 TIPTEKNO*, 2019, pp. 1-4, doi: 10.1109/TIPTEKNO.2019.8895011.

[25] A. Ullah, S. M. Anwar, M. Bilal, and R. M. Mehmood, "Classification of arrhythmia by using deep learning with 2-D ECG spectral image representation," *Remote Sensing*, vol. 12, no. 10, p. 1685, 2020, doi: 10.3390/rs12101685.

[26] C. Mateo and J. A. Talavera, "Short-time Fourier transform with the window size fixed in the frequency domain," *Digital Signal Processing*, vol. 77, pp. 13-21, Jun. 2018, doi: 10.1016/j.dsp.2017.11.003.

[27] L. Zhao, Q. Li, Y. Zhang, H. Wang, and X. Du, "Integrating the Continuous Wavelet Transform and a Convolutional Neural Network to Identify Vineyard Using Time Series Satellite Images," *Remote Sensing*, vol. 11, no. 22, p. 2641, 2019, doi: 10.3390/rs11222641.

[28] N. P. Joshi and P. S. Topannavar, "Support vector machine-based heartbeat classification," *Proc. of 4th IRF Int. Conf*, 2014, pp. 140-144.

[29] Y. Liao, Y. Xiang, and D. Du, "Automatic Classification of Heartbeats Using ECG Signals via Higher Order Hidden Markov Model," *2020 IEEE 16th International Conference on Automation Science and Engineering (CASE)*, 2020, pp. 69-74, doi: 10.1109/CASE48305.2020.9216956.

[30] J. A. Gutiérrez-Gnecchi, *et al.* "DSP-based arrhythmia classification using wavelet transform and probabilistic neural network," *Biomedical Signal Processing and* Control, vol. 32, pp. 44-56, February 2017, doi: 10.1016/j.bspc.2016.10.005.

[31] M. Zubair, J. Kim, and C. Yoon, "An Automated ECG Beat Classification System Using Convolutional Neural Networks," *2016 6th International Conference on IT Convergence and Security (ICITCS)*, 2016, pp. 1-5, doi: 10.1109/ICITCS.2016.7740310.

[32] U. R. Acharya, *et al.*, "A deep convolutional neural network model to classify heartbeats," *Computers in biology and medicine*, vol. 89, pp. 389-396, Oct. 2017, doi: 10.1016/j.compbiomed.2017.08.022.

[33] F. O. M. Ismaiel, "Classification of Cardiac Arrhythmias Based on Wavelet Transform and Neural Networks," PhD Thesis, Sudan University of Science and Technology, 2015.

[34] Ö. Yıldırım, P. Pławiak, Ru-San Tan, and U. R. Acharya, "Arrhythmia detection using deep convolutional neural network with long duration ECG signals," *Computers in biology and* medicine, vol. 102, pp. 411-420, Nov. 2018, doi: 10.1016/j.compbiomed.2018.09.009.