Multiclass ECG Signal Analysis Using Global Average-Based 2-D Convolutional Neural Network Modeling

Muhammad Wasimuddin, Khaled Elleithy, Abdelshakour Abuzneid, Miad Faezipour and Omar Abuzaghleh

Department of Computer Science and Engineering

University of Bridgeport, Bridgeport, CT

Abstract

Cardiovascular diseases accounted for approximately 836,546 deaths in the United States in 2018. Nearly 2,300 Americans die of cardiovascular disease each day, an average of one death every 38 seconds. To this end, research has been reported in the literature on Electrocardiogram (ECG) signal analysis to determine arrhythmia and other cardiac conditions. This work introduces a classifier that will detect abnormalities of the ECG signal with its analysis as a 2-D image fed to a Convolutional Neural Network (CNN) classifier. The proposed method classifies the ECG signal as normal or ST-change, V-change by transforming the single-lead ECG signal into images and then applying CNN classification. Images are taken from the European ST-T dataset on PhysioNet databank. Our method yields an accuracy of 99.26%.

Problem Definition and Dataset

Identifying acute myocardial infarctions early-on, and treating them promptly, increases the clinical outcomes significantly. In general, the analysis of the ECG-ST-segment, is one of the methods for identifying myocardial ischemia, involves ST-Segment Detection, ST Deviation measurement, and ST-Episode Detection. Neural Network (NN) based machine learning can be used to detect such ST episodes but requires feature extraction engineering. It is both tedious and also increases the complexity of the system. We propose a method to detect abnormalities of the heart signal that can later be used in a real-time heart attack alert system. This method uses deep learning techniques developed as a 2-D CNN-based image classifier that is trained on images of the ECG signal recorded by the single lead L3. This advanced monitoring system will lead to the determination of arrhythmia and early onset of myocardial infarction (mainly heart attack), a disease that is gaining widespread attention.

- The European ST-T Database is used (www.PhysioNet.org). Each record of a patient has two ECG signals recorded, one from Lead 3 (L3) and the other from Lead 5 (L5) (Figure 1).
- Our proposed transformed 2-D ECG image is a screenshot of the ECG signal's waveform in different ECG cycles.
- The ECG signal's waveform for every two consecutive R peaks in a two-dimensional (2-D) image of size 28×28 pixels. In order to derive a 2-D image of the ECG signal between an R-R interval, a conversion from the 1-D signal to a 2-D image is required. This is achieved by a Python code that plots the ECG signal between the R-R interval and saves it as a 2-D image. The R peaks and R-R intervals themselves are detected by a derivative-based approach in real-time.

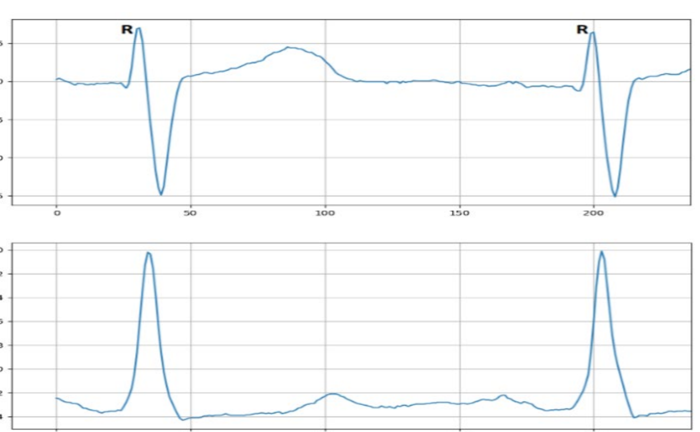

Figure 1

Methodology

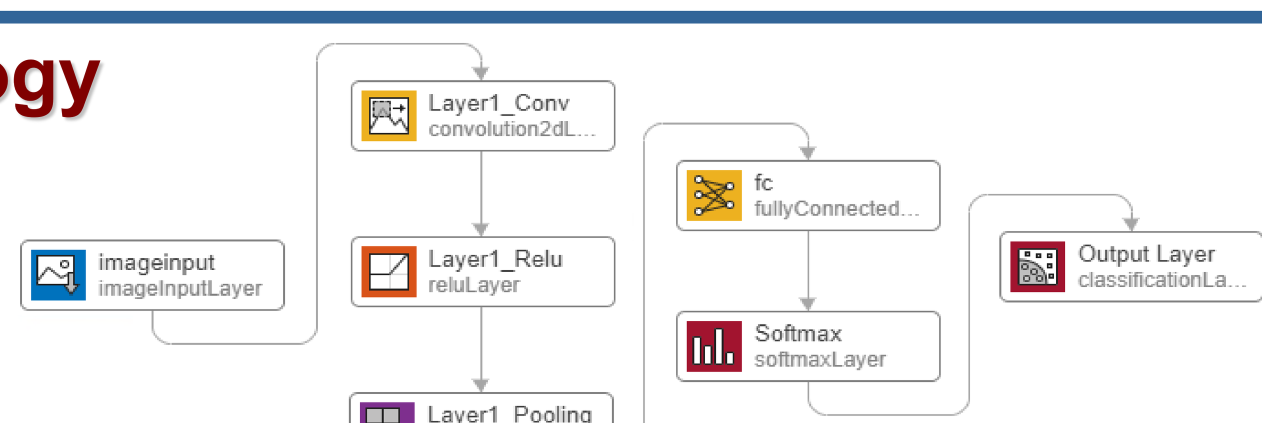

Figure 2

Our proposed CNN model consists of 7 layers, including convolutional layer. The architecture is illustrated in Figure 2. Furthermore, the data has been split into 70/30 for training and testing. Table I summarizes the options and parameters used in each layer. In the model architecture, the input image size is 28×28, which is fed to the input layer and then followed by the CNN layer with a kernel size of 5×5 and six feature maps. This is followed by the Relu activation function and then followed by a global average pooling layer, as illustrated in Table I. The output of the pooling layer is fed to the fully connected neural network. Cross entropy is the loss function deployed in our model. The output is a 3-class layer with labels of Normal, ST-change and V-change. Table II depicts a comparison of the proposed work with prior related work in the literature. Related work have not reported all the metrics. We have outperformed the work in the literature by achieving a higher accuracy of 99.26%. This is an improvement being done in this field.

Table I

Name	Layer Type	Size	Learnables
Imageinput	Image input	28×28	-
Layer1_Conv	Convolution	5×5	Weights 5×5×3×4, Bias 1×1×4, Total (304)
Layer1_Relu	Activation Function	-	-
Layer1_Pooling	Global Average	1×1	-
FullyConnected	Neural Network	1×1×3	Weights 3×4, Bias 3×1, Total (15)
Softmax	Activation Function	-	-
Output Layer	Classification Output	-	-

Approach	Class, Year	Detection Method	Performance Metrics	Dataset
Machine Learning	Ischemic , 2002	ANN+PCA	90%sen, 90%spe	ESCDB
	Ischemic , 2004	MDA-based GA	91%sen, 91%spe	
	Normal, Ischemic , 2007	DT+Fuzzy Model	91.7%acc, 91.2%sen, 92.2%spe	
	QRS-Complex delineation , 2008	DWT	90.75%sen, 89.2%ppv	
	ST-Segment changes, Multiclass , 2011	SVM	[93.33%acc]ST, [96.35%acc]Multiclass	
	Normal, Abnormal , 2014	ANN	98.73%acc	
	N, V, S, F, 2015	MSVM+CSVM	[86%acc]MSVM, [94%acc]CSVM	
	ST-Segment and T-Wave anomalies , 2016	DT and RUSBoost	86%sen, 94.85%ppv, 77%acc, 0.6f1	
	Control, AF, VF, ST , 2018	CNN	97.23%acc, 97.02%sen, 97.76%ppv, 97.35%f1	
	Normal, ST-Changes , 2018	RF	86.9%acc, 85.18%sen[ST-Normal], 87.35%sen[ST-depressed], 88.06%sen[ST-elevated]	
	S, V , 2019	ANN+MMNNS	98.8%acc, 91%sen, 99.3%spe, 90%ppv	
	Normal, ST-Change, V-Change, 2021	Proposed (2-D CNN)	99.26%acc, [100%sen,100%spe]N, [97.8%sen,100%spe]ST, [100%sen,97.8%spe]V	

Results and Evaluation

We have conducted multiple simulation experiments and the best accuracy of 97.47% was obtained, as shown in Figure 3. The loss function can be observed in Figure 4, where the error has converged within fifty epochs. The initial learning rate is 0.001, and the input images are being shuffled after every epoch to improve the validation. The Validation Frequency is calculated from Equation 2.

$$ValidationFreq = \frac{\sum TrainSet}{miniBatchSize} \quad (2)$$

The miniBatchSize in Equation 2 is selected as 10, and the training set is 70% of the entire training set of images. The Backpropagation algorithm used in this work is ADAM. Figure 5 shows the test results of ECG images with labels. These are two randomly selected images from the testing dataset and tested against the trained network by performing forward pass to classify as normal or abnormal. Though both the ECG signal images in Figure 5 look very similar; our method is capable of classifying them as normal and abnormal, successfully.

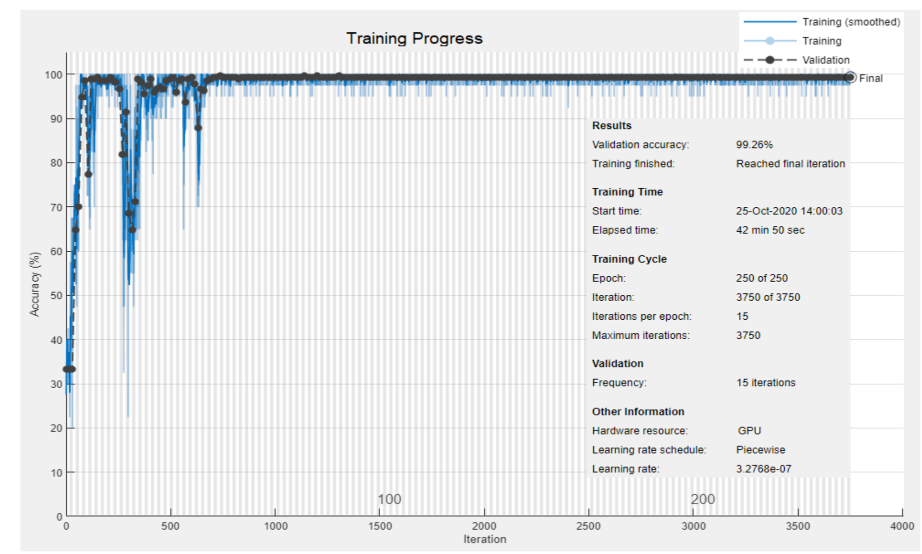

Figure 3

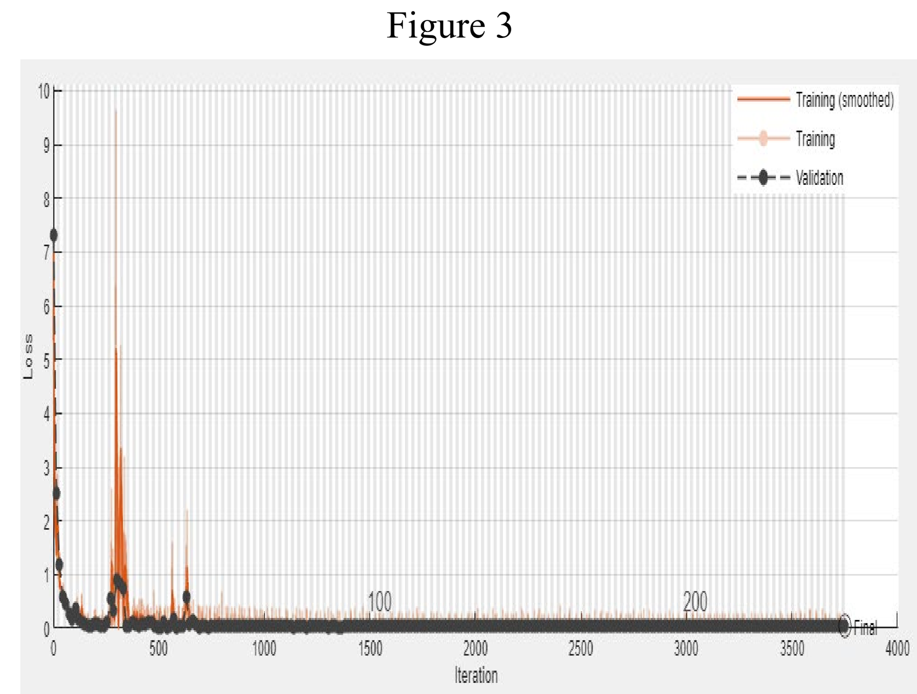

Figure 4

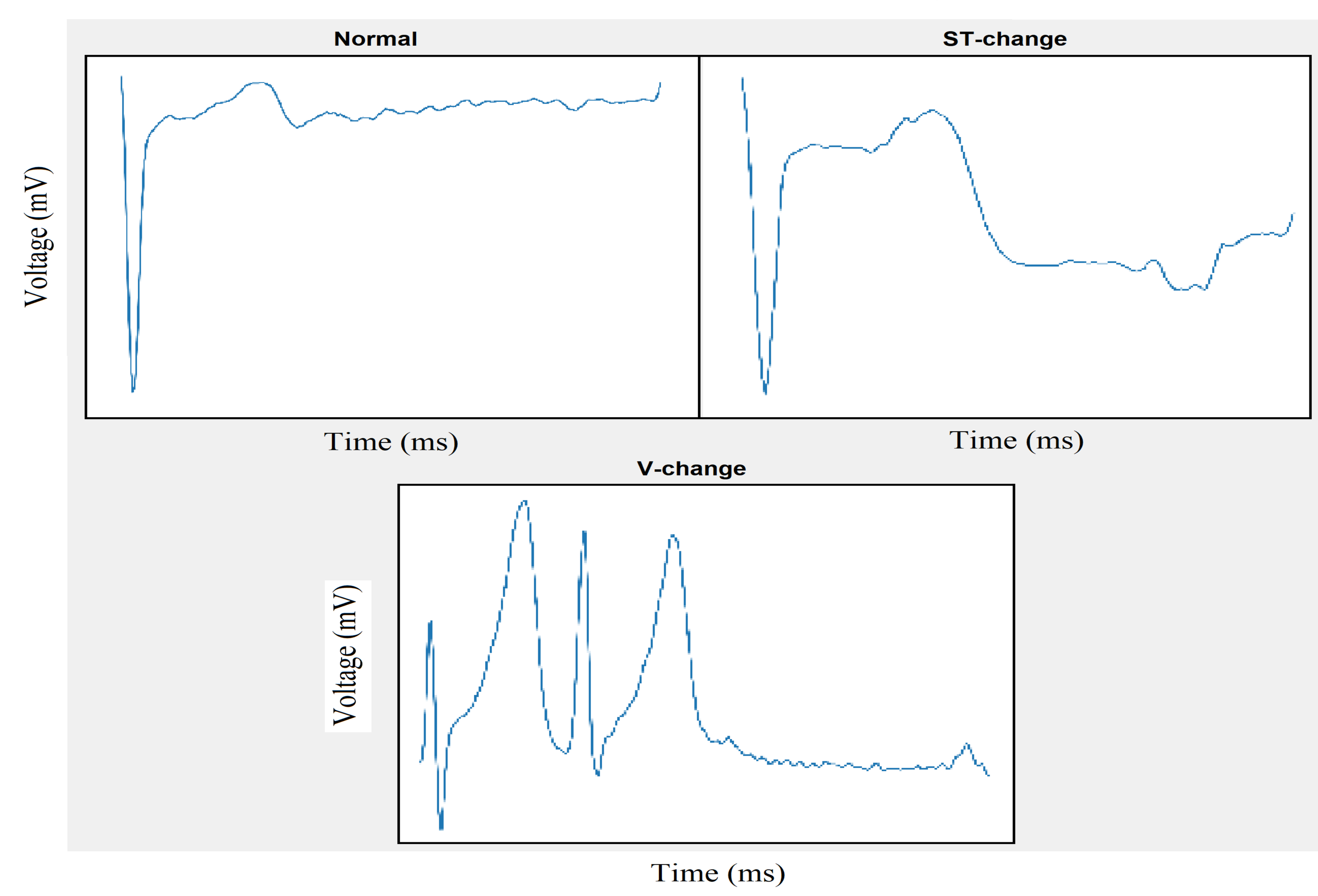

Figure 5

Besides complexity, SVM and other Neural Networks (NN) require features to be identified prior to training, as these networks strictly depend upon these features when optimizing weights during backpropagation. This is while CNN does not require features for training, but rather learns the features by itself with proper parameters selection.

Conclusion and Future Work

This proposed research used deep learning CNN as a computer vision tool to detect abnormality in the ECG signal and mainly the ST changes for myocardial infarction. The ECG signal recorded from a single lead was transformed into a 2-D image representation and then classified using CNN. It achieved better accuracy for the ECG recorded with single lead rather than the 12-lead ECG signals reported in prior work in the literature. This approach reduces the requirement of a multiple-lead signal and can work on a single-lead ECG signal record. Our method provides 99.26% accuracy, as observed in Figures 3. This proposed research can serve as an early detection tool for cardiovascular diseases and can provide early warning alerts for users who might be susceptible to heart attack.

We will further improve the classifier to further detect different types of abnormalities for both intra and inter-patient scheme. The application of this research will be implemented with the an app on a smart-phone with a two-wire attachment and can instead be connected to the Smart Watch. ECG signal can be captured and then analyzed via the proposed method and will be classified using the trained network. Building the ECG framework application using Smart Watch as input data is our future development plan.

[1] M. Wasimuddin, K. Elleithy, A. Abuzneid, M. Faezipour and O. Abuzaghleh, "Multiclass ECG Signal Analysis Using Global Average-Based 2-D Convolutional Neural Network Modeling," *MDPI Electronics*, 14 Jan 2021, 10, no. 2: 170.
[2] M. Wasimuddin, K. Elleithy, A. Abuzneid, M. Faezipour and O. Abuzaghleh, "Stages-Based ECG Signal Analysis from Traditional Signal Processing to Machine Learning Approaches: A Survey," *IEEE Access*, pp. 1-22 Sep 2020.
[3] M. Wasimuddin, K. Elleithy, A. Abuzneid, M. Faezipour and O. Abuzaghleh, "ECG Signal Analysis Using 2-D Image Classification with Convolutional Neural Network," *IEEE International Conference on Computational Science and Computational Intelligence(CSCI), At Las Vegas, NV*, 05-07 December 2019.