Applications of Convolutional Neural Network for Automated Detection of different diseases Using ECG

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Abstract: Our cardiovascular system weakens and is more prone to arrhythmia as we age. An arrhythmia is an abnormal heartbeat rhythm which can be life-threatening. Atrial fibrillation (A-Fib), atrial flutter (AFL), and ventricular fibrillation (V-Fib) are the recurring life-threatening arrhythmias that affect the elderly population. An electrocardiogram (ECG) is the principal diagnostic tool employed to record and interpret ECG signals. These signals contain information about the different types of arrhythmias. However, due to the complexity and non-linearity of ECG signals, it is difficult to manually analyze these signals. Moreover, the interpretation of ECG signals is subjective and might vary between the experts. Hence, a computer-aided diagnosis (CAD) system is proposed. A CAD system will ensure that the assessment of ECG signals is objective and accurate. In this work, we present a convolutional neural network (CNN) technique to automatically detect the different ECG segments. Our algorithm consists of an eleven-layer deep CNN with the output layer of four neurons, each representing the normal (NSR), A-Fib, AFL, and V-Fib ECG class. Further, no feature extraction or selection is performed in this work. Hence, our proposed algorithm can accurately detect the unknown ECG signals even with noise. So, this system can be introduced in clinical settings to aid the clinicians in the diagnosis of MI.

Keywords: *Electrocardiogram (ECG), myocardial infarction (MI), deep convolutional neural network (DCNN)*

I. INTRODUCTION

Cognitive Myocardial infarction (MI) is caused when the blood flow to a segment of the myocardium is disrupted [1-2]. Coronary arteries are the arteries that supply oxygen-rich blood to the heart muscle. However, if there is a blockage of the coronary artery due to the buildup of plaques, it reduces the blood flow to the heart muscle. That segment of the heart muscle will start to die if blood flow is not restored in time [3]. Fig. 1 illustrates the myocardial infarction due to the blockage of a coronary artery. This artery gets blocked with blood clots also known as a thrombus. These blood clots are formed due to the plaque build-up in the artery. The complete blockage of blood flow results in a heart attack as a part of the heart muscle is damaged [4].

Furthermore, MI is also often referred to as the silent heart attack. It is because patients are not aware that they are suffering from MI until a heart attack occurs. According to the American Health Association, it is estimated that 750,000 Americans have a heart attack every year. Out of these 750,000 Americans, 210,000 of them have a recurrent heart attack.

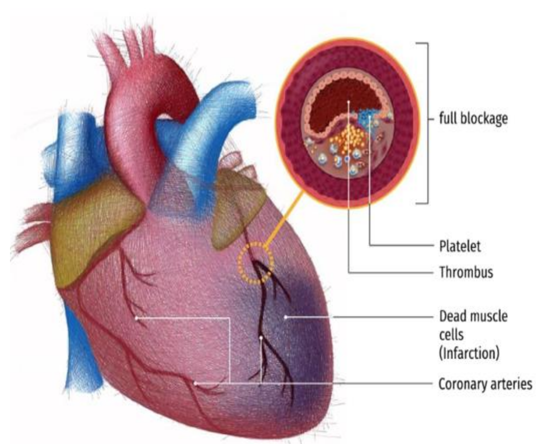

Fig. 1. An illustration of myocardial infarction.

Hence, approximately 72% of the heart attacks are silent. In other words, 72% of the patients' heart muscles are damaged but they are not aware of it. As a result, the mortality rate of MI is very high.

Therefore, an early diagnosis of MI will help patients to get timely treatment, and hence decreasing the prevalence of mortality [5]. The death of the heart muscles is irreversible hence, it is essential to get diagnosed early. The early diagnosis of MI can be conducted with an electrocardiogram (ECG). The ECG is the noninvasive economical primary tool which can be used to diagnose the cardiac abnormalities. Fig. 2 shows the samples of normal and MI ECG signals with and without the removal of noise.

However, the ECG signals are having a very small amplitude (mV) and small duration (sec). Hence, the interpretation of these long duration of signals may lead to inter and intra-observer variabilities. Moreover, it is time-consuming and strenuous to analyze the ECG signals.

The limitation of manual inspection of ECG signals can be overcome by using computer-aided diagnosis system. A computer-aided diagnosis (CAD) system is preferred due to its fast, objective, and reliable analysis. Many works have been conducted on the development of CAD for MI.

The studies presented in Table 6 have denoised their ECG signals before performing any feature extraction. Nevertheless, denoising is not required in our proposed algorithm. Our algorithm can detect MI ECG signal without filtering any noise present in the ECG signal. Various features extraction techniques have been proposed to automatically detect MI using ECG signals. However, the process of choosing a set of optimal features to classify normal and MI ECG signals is very difficult.

Therefore, deep learning technique is introduced in this work to overcome the challenges faced by conventional automated systems. Recently, deep learning techniques have been used by many companies namely Adobe, Apple, Baidu, Facebook, Google, IBM, Microsoft, NEC, Netflix, and NVIDIA. In our work, we have used an eleven layer deep CNN for the classification.

Deep learning is a representation based learning which consists of an input layer, hidden layers, and an output layer. A representation based learning is a set of systematic procedures that provides a network to be fed with raw data and automatically learns the necessary representations for classification. The term deep describes the multiple stages in the learning process of the network structure. The deep learning neural network is trained using the backpropagation algorithm. The CNN is one of the most popular neural network techniques.

CNN has been successfully utilized in computer vision since the early 21st century. It performed well in recognizing handwritten digits, detecting objects, and speech recognition. It has been used in the medical research field such as analyzing health informatics, and medical images using computed tomography (CT) images, fundus images, histopathological images, magnetic resonance (MR) images, and X-ray images as well. It is also noted that researchers in the medical analysis field are moving into CNN and obtaining desirable results. Furthermore, we applied CNN in our previous work. Our proposed system achieved the highest accuracy of 92.50% and 94.90% in the detection of arrhythmias with two- and five-seconds ECG signal. Hence, the CNN has performed well in the biomedical signal and image processing domain. So, in this work, we employed it for the automated diagnosis of MI using ECG signals with and without noise.

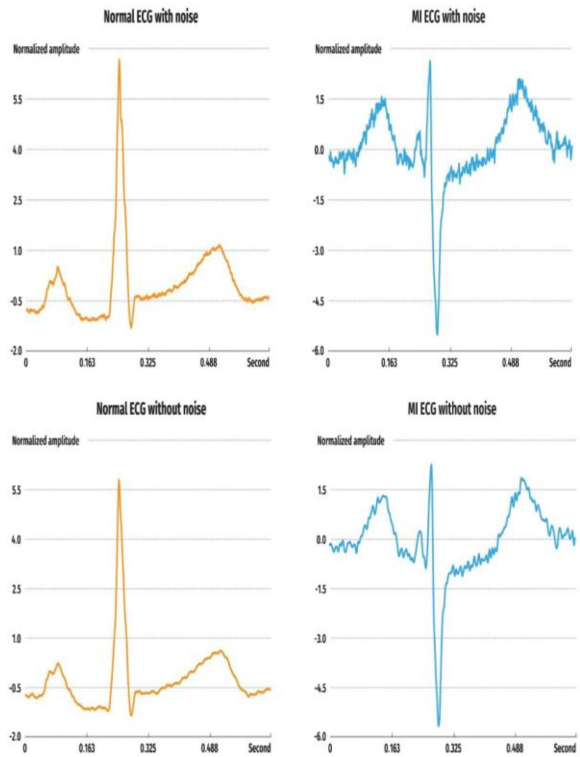

Fig. 2. Sample normal and MI ECG beat with and without noise removal.

II. LITERATURE SURVEY

Faust. O. et.al (2012) [6], in their paper used chaotic behavior of electrocardiogram (ECG) signal to differentiate myocardial and non-myocardial infarctions using neuro-GA approach, incorporating heuristically chosen phase space fractal dimension (PSFD) of ECG data. A remarkable improvement of diagnostic efficiency, sensitivity and specificity was observed in case study.

M. Roffi et.al (2017) [7]**,** in their paper present automatic detection and localization of myocardial infarction (MI) using K-nearest neighbor (KNN) classifier. Time domain features of each beat in the ECG signal such as T wave amplitude, Q wave and ST level deviation, which are indicative of MI, are extracted from 12 leads ECG. Detection of MI aims to classify normal subjects without myocardial infarction and subjects suffering from Myocardial Infarction. For further investigation, Localization of MI is done to specify the region of infarction of the heart. Total 20,160 ECG beats from PTB database available on Physio-bank is used to investigate the performance of extracted features with KNN classifier. In the case of MI detection, sensitivity and specificity of KNN is found to be 99.9% using half of the randomly selected beats as training set and rest of the beats for testing.

F. A. Masoudi, et.al, (2006) [8] stated in their paper that electrocardiogram (ECG) is a biophysical electric signal generated by the heart muscle, and is one of the major measurements of how well a heart functions. Automatic ECG analysis algorithms usually extract the geometric or frequency-domain features of the ECG signals and have already significantly facilitated automatic ECG-based cardiac disease diagnosis. Hence, they proposed a novel ECG feature by fitting a given ECG signal with a 20th order polynomial function, defined as PolyECG-S. The PolyECG-S feature is almost identical to the fitted ECG curve, measured by the Akaike information criterion (AIC), and achieved a 94.4% accuracy in detecting the Myocardial Infarction (MI) on the test dataset. Currently ST segment elongation is one of the major ways to detect MI (ST-elevation myocardial infarction, STEMI). However, many ECG signals have weak or even undetectable ST segments. Since PolyECG-S does not rely on the information of ST waves, it can be used as a complementary MI detection algorithm with the STEMI strategy. Overall, their results suggest that the PolyECG-S feature may satisfactorily reconstruct the fitted ECG curve, and is complementary to the existing ECG features for automatic cardiac function analysis.

Y. LeCun, et.al, (2015) [9] in their paper stated that Myocardial infarction (MI), is commonly known as a heart attack, occurs when the blood supply to the portion of the heart is blocked causing some heart cells to die. This information is depicted in the elevated ST wave, increased Q wave amplitude and inverted T wave of the electrocardiogram (ECG) signal. ECG signals are prone to noise during acquisition due to electrode movement, muscle tremor, power line interference and baseline wander. Hence, it becomes difficult to decipher the information about the cardiac state from the morphological changes in the ECG signal. These signals can be analyzed using different signal processing techniques. They propsed using multiresolution properties of wavelet transformation because it is suitable tool for interpretation of subtle changes in the ECG signal. They analyzed the normal and MI ECG signals. ECG signal is decomposed into various resolution levels using the discrete wavelet transform (DWT) method. The entropy in the wavelet domain is computed and the energy–entropy characteristics are compared for 2282 normal and 718 MI beats. Their proposed method is able to detect the normal and MI ECG beat with more than 95% accuracy.

A. Krizhevsky et.al, (2012) [10] in their paper stated that, the Electrocardiogram (ECG) is the P-QRS-T wave depicting the cardiac activity of the heart. The subtle changes in the electric potential patterns of repolarization and depolarization are indicative of the disease afflicting the patient. These clinical time domain features of the ECG waveform can be used in cardiac health diagnosis. Due to the presence of noise and minute morphological parameter values, it is very difficult to identify the ECG classes accurately by the naked eye. Various computer aided cardiac diagnosis (CACD) systems, analysis methods, challenges addressed and the future of cardiovascular disease screening are reviewed in this paper. Methods developed for time domain, frequency transform domain, and time-frequency domain analysis, such as the wavelet transform, cannot by themselves represent the inherent distinguishing features accurately. Hence, nonlinear methods which can capture the small variations in the ECG signal and provide improved accuracy in the presence of noise are discussed in greater detail in this review. A CACD system exploiting these nonlinear features can help clinicians to diagnose cardiovascular disease more accurately.

C. Szegedy, et.al, (2015) [11] in their paper stated that, Cardiovascular diseases (CVDs) are the main cause of cardiac death worldwide. The Coronary Artery Disease (CAD) is one of the leading causes of these CVD deaths. CAD condition progresses rapidly, if not diagnosed and treated at an early stage may eventually lead to an irreversible state of heart muscle death called Myocardial Infarction (MI). Normally, the presence of these cardiac conditions is primarily reflected on the electrocardiogram (ECG) signal. However, it is challenging and requires rich experience to manually interpret the visual subtle changes occurring in the ECG waveforms. Thus, many automated diagnostic systems are developed to overcome these limitations. In this study, the performance of an automated diagnostic system developed for detection of CAD and MI using three methods such as Discrete Wavelet Transform (DWT), Empirical Mode Decomposition (EMD) and Discrete Cosine Transform (DCT) are compared. In this study, ECG signals are subjected to DCT, DWT and EMD to obtain respective coefficients. These coefficients are reduced using Locality Preserving Projection (LPP) data reduction method. Then, the LPP features are ranked using F-value. Finally, the highly ranked coefficients are fed into the K-Nearest Neighbor (KNN) classifier to achieve the best classification performance. Our proposed system yielded highest classification results of 98.5% accuracy, 99.7% sensitivity and 98.5% specificity using only seven features obtained using DCT technique. The screening system can help the cardiologists in detecting the CAD and hence presents any possible MI by prescribing suitable medications. It can be employed in routine community screening, old age homes, polyclinics and hospitals.

III. PROPOSED METHOD

A. Pre-processing

In this work, we validate our proposed method with two sets of ECG data. Both datasets consist of the same number of ECG beats. However, in one of the dataset, we denoised and removed the baseline wander from the ECG signal using Daubechies wavelet *6* mother wavelet function. But, in the other dataset, we retained the noises present in the ECG signals. Then, we carried out the R-peak detection on both datasets (with and without noise) using Pan Tompkins algorithm. All the ECG signals are segmented using the detected R-peaks without the inclusion of the first and last beat. Each segment is normalized with Z-score normalization to address the problem of amplitude scaling and eliminate the offset effect before f eeding the ECG segments into the *1* -dimensional deep learning CNN for training and testing. Each ECG beat consists of 651 samples (250 samples before R-peaks detection and 400 samples after R-peaks detection). Typical ECG beat with and without noise used in this study is shown in Fig. 2.

B. The architecture

The standard architecture of a CNN consists of *four* stages

(i) Convolution,

(ii) Rectified linear activation function,

(iii) Pooling function, and

(iv) Fully connected layer.

Fig. 3 shows a graphical representation of the architecture of our proposed system. Table 2 summarizes the details of the CNN structure used in this work.

(i) **Convolution layer:**

The convolution layer is the main building block of a CNN. This layer does most of the computational intensive lifting. The prime objective of convolution is to extract features from the input ECG signals. The convolution layers are arranged in feature maps (11 layers of feature maps in total).

(ii) **Rectified linear activation function:**

In general, rectified linear activation serves to map nonlinearity into the data.

In this work, the leaky rectifier linear unit (LeakyRelu) is used as an activation function for layers 1, 3, 5, 7, 9, and 10. Also, the softmax function is implemented for layer 11 (last layer).

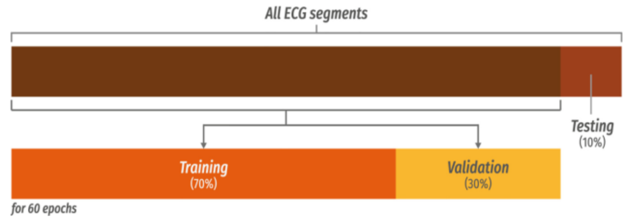

Fig. 4. The apportion of ECG beats used for training and testing the proposed algorithm.

(iii) **Pooling function:**

Pooling also referred to as down sampling which is an operation to condense features and computational complexity of the network. The max-pooling operation is employed in this work. Max-pooling outputs only the maximum number in each kernel, thus reducing the feature map size. Kernel size also refers to the size of the filter which convolves around the feature map while stride controls how the filter convolves around the feature map. The amount by which the filter slides is the stride. In this work, the stride is set at 1. Therefore, the filter convolves around the different layers of feature map by sliding one unit each time.

(iv) **Fully connected layer:**

The final layer of the fully-connected network is a softmax layer with an output of X dimensional vector where X is the number of classes that we desire to have. In this study, it is a two-class (normal and MI ECG signals) problem, hence, X is set at 2 in this work. The input layer (layer 0*)* is convolved with a kernel size of 102 to form the first layer (layer 1). After which, a max- pooling of size 2 is applied to every feature map (layer *2).* After performing the max-pooling operation, the number of neurons reduces from 550 ×3 to 275 ×3. Then the feature map from layer 2 is convolved with a kernel (filter of size 24) to form layer 3. A max-pooling is again applied to every feature map (layer 4). After that, a feature map from layer 4 is convolved with a filter of size 11 to produce layer 5. A max-pooling of size 2 is applied to every feature map to reduce the number of neurons to 58 ×10 (layer 6). Subsequently, the feature map in layer 6 is convolved with a kernel (filter of size 9) to form layer 7. A max-pooling is once again performed (layer 8). Finally, in layer 8, the neurons are fully connected to 30 neurons in layer 9. Layer 9 is connected to 10 neurons in layer 10. Layer 10 is connected to the last layer with 2 output neurons.

C. Training:

A standard backpropagation with a batch size of 10 is executed in this work. The regularization, momentum, and learning rate parameters are set to 0.2, 3 ×10 −4, and 0.7

respectively. These parameters are tuned accordingly to obtain optimum performance. The function of these parameters are as follows:

a. Regularization: To prevent overfitting of the data.

b. Momentum: To control how fast or slow the network learn during training.

c. Learning rate: To help in the convergence of the data.

D. Testing:

In this work, we ran a total of *60* epochs of training and testing rounds. At the end of every epoch, our proposed algorithm validates the CNN model. Out of the 9 10 training ECG beats, we used 7 10 to validate our proposed algorithm. Fig. 4 shows the apportioning of the total ECG beats for training and testing purposes.

E. k-fold cross-validation:

We have employed a *10* -fold cross-validation [8] strategy in this work. We separated our total ECG beats almost equally into *10* segments. 9 10 ECG beats are used in the training of CNN while the remainder (1 10) of the ECG beats are used to validate the performance of our proposed system. This approach is iterated *10* times by shifting the test data. The performances (accuracy, sensitivity, and specificity) are evaluated in each iteration. Finally, the performances recorded in all *10* iterations are averaged and considered as the overall performance of our proposed system.

Table 3
Confusion matrix of ECG beats with noise across *10*-folds.

		Predicted					
		Normal	MI	ACC (%)	PPV (%)	SEN (%)	SPEC (%)
Original	Normal	9790	756	93.53	79.48	92.83	93.71
	MI	2527	37,655	93.53	98.03	93.71	92.83

ACC = Accuracy, PPV = Positive Predictive Value, SEN = Sensitivity, SPEC = Specificity

Table 4
Confusion matrix of ECG beats without noise across *10*-folds.

		Predicted					
		Normal	MI	ACC (%)	PPV (%)	SEN (%)	SPEC (%)
Original	Normal	9933	613	95.22	84.56	94.19	95.49
	MI	1814	38,368	95.22	98.43	95.49	94.19

ACC = Accuracy, PPV = Positive Predictive Value, SEN Sensitivity, SPEC = Specificity

Table 5
The overall classification results for the classification of normal and MI classes across *10*-folds.

Beats Type	*TP*	*TN*	*FP*	*FN*	ACC (%)	PPV (%)	SEN (%)	SPEC (%)
Noise	37,655	9790	756	2527	93.53	98.03	93.71	92.83
Without Noise	38,368	9933	613	1814	95.22	98.43	95.49	94.19

TP = True Positive, *TN* = True Negative, *FP* = False Positive, *FP* = False Negative
ACC = Accuracy, PPV = Positive Predictive Value, SEN = Sensitivity, SPEC = Specificity

IV. RESULT

In this study, we trained our algorithm on a workstation with two Intel Xeon 2.40 GHz (E5620) processor and a 24GB RAM. It typically took approximately 2151.055 s to complete an epoch of training for ECG beats data with noise and 2025.178 s for ECG beats data without noise. The confusion matrix for ECG beats with noise and without noise are presented in Tables 3 and 4 respectively. It can be observed from Table 3 that, out of 10,546 normal ECG beats, approximately 7.17% of the ECG beats are wrongly classified as MI. Likewise, for MI, a total of 6.29% of ECG beats are wrongly classified as normal ECG beats. Similarly, in Table 4, 94.19% of ECG beats are correctly classified as normal ECG beats and 4.51% are wrongly classified as normal ECG beats. Furthermore, the PPV values for each class (normal and MI) are recorded in Tables 3 and 4. In Table 3, the PPV in the normal class is 79.48% whereas the PPV in the MI class is 98.03%. This shows that the probability of correctly detecting the MI ECG signals from the ECG signals is higher as compared to the correct detection of normal ECG signals. Similarly, in Table 4, the PPV in the normal and MI classes are 84.56% and 98.43% respectively. This also shows that the probability of identifying MI ECG signals is higher than the identification of normal ECG signals in the ECG signals with noise removal. The performance rate of both ECG beats with and without noise are summarized in Table 5. An average accuracy, sensitivity, and specificity of 93.53%, 93.71%, and 92.83% are achieved using ECG beats with noise introduced respectively. Fur- thermore, the highest average accuracy of 95.22% sensitivity of 95.49% and specificity of 94.19% is obtained for ECG beat without noise.

V. CONCLUSION & FUTURE WORK

The early diagnosis of MI can save life and can help to provide timely treatment. Thus, it is necessary to go for annual health checkups. The ECG is the primary tool to diagnose the electrical activity of the heart. Any abnormalities present in the heart activity is reflected in the ECG signals. However, it is challenging and time-consuming to visually assess the ECG signals. Therefore, implementing a CAD system in clinical settings will ensure an objective and fast diagnosis of MI. In this work, we proposed a novel method to automatically diagnose MI using 11 -layer deep CNN. We have used *two* different datasets (with and without noise) to evaluate the effectiveness of our proposed method. We have achieved an average ac- curacy, sensitivity, and specificity of 93.53%, 93.71%, and 92.83% respectively for ECG beats with noise. Our proposed system attained high-performance results even though there are noises present in the ECG beats. This suggests that our system can recognize the class of the ECG signals even with the presence of noise in the signal. Also, we obtained an average accuracy, sensitivity, and specificity of 95.22%, 95.49%, and 94.19% for ECG beats without noise.

This shows that the overall performance of our proposed system is good enough and hence, can be introduced in clinical settings. Our proposed system can assist doctors in their diagnosis.

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