Technical Journal, University of Engineering and Technology (UET) Taxila, Pakistan Vol. 25 No. 2-2020
ISSN:1813-1786 (Print) 2313-7770 (Online)

One Dimensional Convolution Neural Network Model for ECG Arrhythmia Classification

A. Ullah[1], S. Anwar[2]

[1,2] *University of Engineering and Technology, Taxila, Pakistan.*

17F-PhD-SE-16@uettaxila.edu.pk

Abstract- Electrocardiograms (ECG) are one of the most effective and significant tools to diagnose and predict cardiovascular diseases (CVDs) such as arrhythmia. An ECG provides essential information related to the cardiovascular system and the primary functions of the human heart. It is a frequently used tool for non-invasively observing different CVDs. Accurate identification of arrhythmias is critical to patient well-being in clinical settings, as both acute and chronic heart conditions are typically reflected in these readings. We propose a deep one-dimensional convolutional neural network (1D-CNN) that can accurately classify five types of ECG waves, namely: normal, ventricular premature contraction, left bundle branch block, atrial premature contraction, and right bundle branch block. Optimization of the proposed CNN classifier results in three convolutional layers, three down sampling layers and two fully connected layers, which extract best features from the given data and automatically classify these based on the extracted features. Labeled ECG recordings from the publicly available MIT-BIH arrhythmia database were used for the classification. Results have shown that our CNN classifier attained 97.8% classification accuracy, which is better than other recently reported ECG signal classification algorithms.

Keywords- ECG signal, Arrhythmia, 1D CNN, MIT-BIH arrhythmia database

I. Introduction

An electrocardiogram (ECG) is one of the vital procedures and diagnostic means to diagnose and predict cardiovascular diseases (CVDs) [1]. When the human heart beats, it records potential bioelectric variations with time, which is called an ECG. An ECG provides crucial information related to the cardiovascular system and the primary functions of the human heart. It is used to non-invasively monitor patients with different CVDs. Therefore, the ECG signal has a crucial part in the discovery of heart disorders. Surface electrodes can be used on the chest or limbs of human beings for recording human heart ECG signals [2]. This process gives vital information in the diagnosis of cardiac diseases, e.g., cardiac arrhythmia [3-5]. An irregular pattern detected in the ECG signal is called an arrhythmia. Any deviation of the cardiac signal rhythm of the human heart from a normal sinus rhythm is commonly called arrhythmia. Nowadays, many people die due to CVDs as shown in Figure 1. Continuous monitoring of the cardiac signal and prediction of cardiac diseases, especially arrhythmia in the initial phase, can prevent death and improve the quality of life of human beings. Detecting these morphological variations in ECG signals is very challenging for doctors, especially when such analysis must be done quickly during an examination.

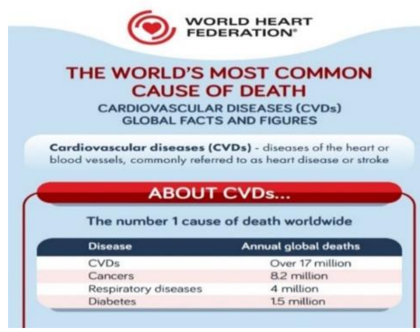

Fig. 1: Impact of different diseases

To correctly detect abnormalities in the ECG signals of patients can take several hours depending on the workload of the clinical expert. Since the quantity of data is enormous, the study and analysis of the data are challenging, and require a significant amount of time for proper diagnosis. Hence, there is a high chance of missing valuable information and vital features of the data. Therefore, now to study and analyze a large amount of data with less time and detect early cardiac disease, a very reliable system is required called computer-aided diagnosis (CAD) [5]. An ECG signal is received by evaluating the electrical potential among different points of the human body. The typical pattern that will be seen in the ECG wave is categorized by three primary waves (Figure 2) [6]:

- The P signal denotes the spread of the wave impulse from node SA across the atria (often called atrial depolarization).

- The QRS complex is the spread of the wave impulse to the ventricular chambers from the beginning to the end of the Purkinje fibers (ventricular chamber depolarization). In the ECG wave, the most significant deviation is generated by the QRS complex due to the enormous mass of ventricular myocardium, which strengthens the pumping of the blood flow throughout the entire body. Purkinje fibers are situated in the inner layer of the endocardium. Therefore, the impulse wave begins from the endocardium and ends at the outer layer of the epicardium [7, 8].
- The T signal denotes the ventricular recovery, which is often called repolarization.

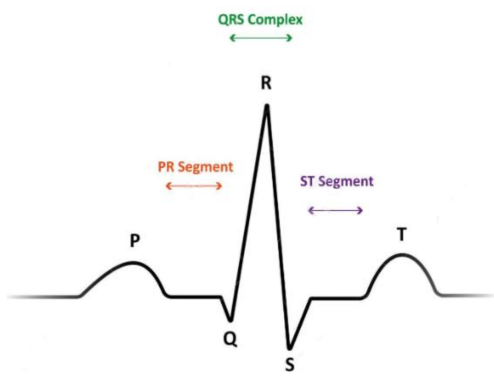

Fig. 2: External structure of ECG signals

Whenever the ECG wave is in a regular pattern, then the time between P signal waves is essentially constant, and the QRS complex follows each P signal wave at a constant interval, which is referred as a sinus rhythm [9]. When the pattern or rhythm is not periodic, then the time between two R peaks are sometimes too large or too small. Sometimes the general ECG external structure is lost, which is known as an arrhythmia.

II.LITERATURE REVIEW

Many approaches have been used to study the arrangement of ECG signals such as k-nearest neighbors (KNN), support vector machines (SVM), neural networks (NN), decision trees, linear discriminant analysis (LDA), Bayesian classifiers, etc. SVM is one of the best machine learning techniques (supervised classifier) [9, 10], which is used in the taxonomy of the ECG wave in the discovery of arrhythmia disease. The combination of SVM and LDA for the classification of six types of arrhythmia is presented in [11]. An efficient classification model, which is based on the NN and Machine Language Program (MLP), gives better performance as compared to other feature extraction methods [12]. Artificial Neural Network (ANN) method can also be used for the taxonomy of ECG images, which provides us with a new research idea about signals and pictures [13]. The processing of the wave, feature extraction, and grouping of ECG signals based on the extracted features are explained in detail in [14], which gives us information on recent approaches and their effectiveness. The evaluation of weighted conditional random fields (WCRF) and the previous algorithm of patient classification is proposed in [15] in which WCRF classifiers have better results. In the last few years, different pattern recognition techniques have been used in the prediction and classification of arrhythmia disease [16-22]. Normally, these methods have three main steps; (i) Preprocessing (ii) Feature extraction (iii) Classification. Initially, the ECG wave is cleaned by eliminating the different types of noise and outliers such as muscle contraction, baseline wanders, power line interference using different algorithms [23-27]. After completing this step, the ECG wave, which is also called PQRST, mainly contains three waves; (i) P wave (ii) QRS complex wave, and (iii) T wave, each of which can be extracted with the help of segmentation process [28-30]. From these different types of waveforms, a few handcrafted characteristics or features are computed. The existing feature representation techniques are, but are not limited to, temporal information [31,32], morphology [33,34], Hermite basis function [35], wavelet transform [36,37], hidden Markov modeling (HMM) [38], and high-order statistics (HOS) [39]. After the completion of this step, different decline approaches are implemented to reduce the features representation dimension, such as independent component analysis (ICA), LDA, and PCA [40-42]. The final step is the learning of the decision function of the classifier from the extracted features such as Gaussian processes (GPs) [43,44], path forest [40], SVMs [43,45], probabilistic neural network (PNN) [46], least-square SVM [47], recurrent NN [48] and neural networks (NN) [49]. For the detection and diagnosis of cardiac vascular disease (CAD) and myocardial infarction (MI), automatic ECG signals [50] and heart rate [51] classification have been developed. Many different signal processing procedures and algorithms have been established and used for the extraction of features accurately from ECG signals and heart rate such as Discrete Wavelet Transform (DWT) [52,53,54,55], nonlinear methods [56,57,58,59,60], linear (time and frequency domain) [61,62] and Tunable Q Wavelet Transform (TQWT) [63] for the taxonomy of ECG signal. For the discovery and classification of ECG arrhythmia previously, most of the traditional methods for pattern recognition have been successful. However, presently deep learning, particularly CNNs, have obtained better performance and popularity in the field of medical imaging [64, 65], which encourages researchers to apply these methods [66]. The application of deep learning techniques in a complex medical situation has shown favorable results [67]. Generally, manual extraction of best features from the given dataset has a better influence on the computerized organization systems performance. Unfortunately, this manual feature extraction process is very time-consuming for which expert knowledge is needed and, yet, these extracted features concerning the changes in the data often fail to be robust. In contrast, this manual feature extraction process of conventional classification methods can now be eliminated using state-of-the-art CNNs that automatically extract characteristic features directly from the given data itself.

In a recent study, a deep learning technique is projected for the recognition of PVC beats from the ECG signal [68]. To classify between normal and PVC beats, a six hidden layers deep learning architecture was trained by giving input of various six extracted features from the ECG signal. In [69] the authors revealed that a deep CNN was used for the automatic extraction of features from raw ECG data for the classification of two cardiac situations, paroxysmal atrial fibrillation (PAF) and regular beats. One of the main disadvantages of training a CNN from scratch is the requirement for a vast dataset to obtain good results from the given data. Additionally, making the CNN deeper increases the number of convolutional layers in the network model, thereby increasing the computational cost during the training phase. Now, to train such deep networks, a powerful Graphical Processing Unit (GPU) computer is needed.

In transfer learning [70], a pre-trained CNN algorithm is manually imported for the desired task of automatically extracting features from the given data. An example of a pre-trained CNN algorithm is to introduce a general image dataset for the job of medical imaging. For pathology classification, a pre-trained algorithm is used for the extraction of features automatically from the given data, which is an input to the classifier where final classification is carried out. Moreover, one or more layers can be re-trained (fine-tuned) of the pre-trained network manually for any given data task.

In this research paper, a 2-D CNN was transformed into a 1-D CNN model. The suggested 1-D CNN algorithm diagnoses and classifies the following five different types of arrhythmia, i.e., N, VPC, LBB, APC, and RBB. The contributions of the proposed model are as follows.

- The suggested technique does not demand post-processing of the ECG signals.
- The process does not require hand-crafted feature extraction.
- The proposed model has lower computational complexity than the previous models used for the classification of arrhythmia types.
- The results have better performance accuracy than current state-of-the-art algorithms for the arrhythmia classification.

III. METHODOLOGY

This part of the paper mainly explains the techniques of data processing, its principles, and its applications. From Figure 3, there are four crucial steps in the whole process, i.e., signal processing, partitioning of the signal, extraction of features from the data, and categorization based on the extracted features. Firstly, we can apply the method of wavelet threshold and reconstruction algorithm of wavelet decomposition together to remove noise from the original ECG wave. The technique of wavelet threshold can reduce electromyographic noise in addition to power line noise interference.

In contrast, the reconstruction algorithm of wavelet decomposition reduces the baseline drift noise from the noisy ECG wave. These two basic methods are initially intended to eliminate noise from the ECG wave, which is used for further processing. Finally, the heartbeat signal is put forward directly to the CNN model so that the best features are extracted, and ECG signals can be classified.

A. Preprocessing of Data

Noise has three primary forms, which are power line interference, baseline drift, and electromyographic noise in the ECG signal [71]. The noise from the source ECG wave must be removed so that we can get a denoised ECG signal for further processing. Therefore, we can apply the method of wavelet threshold and reconstruction algorithm of wavelet decomposition together for noise elimination from the original ECG wave. The technique of wavelet threshold can reduce electromyographic noise along with power line noise interference. In contrast, the reconstruction algorithm of wavelet decomposition reduces the baseline drift noise from the noisy ECG wave. These two basic methods are initially intended to eliminate noise from the ECG signal so that we can get a denoised ECG signal for further processing. After this step, the method of wavelet inverse transform is applied so that we can get the denoised ECG signal. The wavelet reconstruction algorithm is used to resolve the source ECG signals into different regions, and every part is further divided into different frequencies. At last, the ECG signal is restructured by finding the diverse range of frequencies of the useful signals.

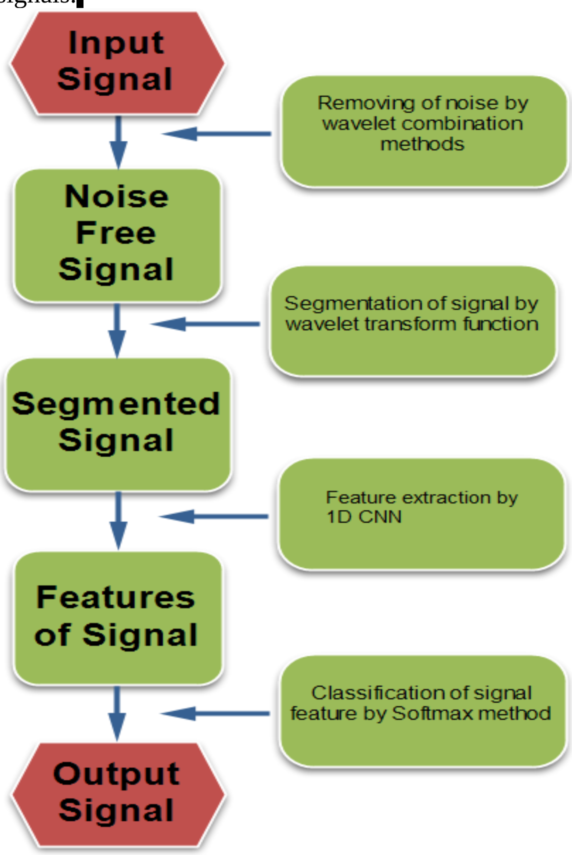

Fig. 3: Complete process flow of ECG signal classification

B. CNN (Convolution Neural Network)

There are two main parts of CNN, extraction of features and classification of features. The features extraction part of CNN is responsible for automatically extraction of best features from the ECG wave. These extracted features are used for the accurate classification of the ECG signal. In other words, these two parts of CNN accomplish the primary function of a CNN [72]. The features extraction part of the CNN consists of convolution layer and sampling layer. The fuzzy filter of the convolution layer is used to diminish the noise from the original ECG wave; then features of the ECG signal can be enhanced. The convolution process is done between the upper layer feature vector and the current layer convolution kernel layer. The activation function of the CNN finally completes the convolution process calculations. Equation 1 gives the convolution layer output.

$$y_i^l = f\left(\sum_{j\in N_i} y_i^{l-1} * W_{ji}^1 + b_i^l\right) \qquad (1)$$

Where
y_i^l is a feature vector which corresponds to 1^{th} layer of i^{th} convolution filter or kernel.
N_i is the present neuron of responsive field.
W_{ji}^1 denotes the weight or bias coefficient assign to the 1^{th} layer of j^{th} convolution filter. f is a nonlinear function.

The downsampling layer of CNN reduces the size and dimension of the ECG signal data but also maintains the vital information of the ECG data. The downsampling layer further extracts the best features from the ECG data, and spatial resolution is decreasing between two hidden layers of the CNN. The following formula represents it:

$$y_i^1 = f\left(\beta_i^l \; down\; (y_i^{l-1}) + b_i^l\right) \qquad (2)$$

Where
$down(\,)$ denotes the function of downsampling
β_i^l represents the weight coefficient
b_i^l denotes the bias coefficient

Besides the convolution layer and downsampling layer of the CNN, there are also an input layer, fully-connected layers, and an output layer. The CNN algorithm is first to assign before to train the model. Then ECG data is separated, and input as data, and specifies the target vector as output. Equation 3 calculates the error compared with determine target vector output.

$$Er = \frac{1}{2}\sum_{p=0}^{m-1}\left(g_p - x_p\right)^2 \le \varepsilon \qquad (3)$$

Where
Er is the total error function
x_p denotes the result vector
g_p is the target vector
The CNN algorithm initially was developed for a two-dimensional signal, but now we are using it for one-dimensional data. Therefore, according to one-dimensional data, we are modifying the CNN model architecture. The suggested CNN algorithm for the categorization of the 1-D ECG signal is presented in Figure 4. The proposed CNN model consists of input and output layers, three convolutional layers, three downsampling layers, and two fully-connected layers, which separate best features from the given data and spontaneously classify the given data based on the extracted attributes. In the convolution layer 1, a total

of eighteen convolution filters with a size of 7 sampling points (SP) are used, which is an input of the ECG wave with 130 SP. Its output is 18 attribute vectors with 124 SP. The downsampling layer one is applied to pool the feature vectors from the convolution layer one; then, the feature vectors are reduced into 62 SP. The convolution layer two also consists of 18 convolution filters with a size of 7 SP, and its output is 324 attribute vectors with 56 SP. The size of the attribute vectors is reduced into 28 SP when they are passed through downsampling layer 2. The convolution layer three also consists of 18 convolution filters with a size of 7 SP and 22 sampling points. In downsampling layer three, the size of the attributes is reduced into 11 SP. Then the extracted best features of the given data are passed to the fully-connected layers, which automatically classify these features into its desired output results.

C. Convolution Filter Optimization

The dimension and number of the convolution filter have an excellent effect on the behavior of the model. Different convolution filters dimensions have been tested in this research, which give a different rate of change of error. Finally, we have chosen the optimal convolution filter size, i.e., 7*7 dimension and an optimal number of convolution filters, which have a minimum error rate.

D. Learning Rate Optimization

The number of convolution filters and the learning rate also have a very significant effect on the behavior of the model and the error rate. When we choose the value of the learning rate minimal, i.e., less than 0.1, then the convergence speed of the model is prolonged. When we select the value of learning rate large, i.e., greater than 0.1, then the model speed for convergence is fast, but asymmetrical changes occur in the rate of change of error. Therefore, we have chosen the optimum 0.1 value for the learning rate, which has a minimum error rate of the model for this optimum value.

IV. EXPERIMENTS & RESULTS

1) Dataset

We have used in this research article, the MIT-BIH Arrhythmia Database [73] to train and test our proposed 1D CNN model. This repository is a famous database, which is used in the diagnosis and classification of arrhythmia disease. It comprises of 24-hour segments of 2-channel ambulatory ECG recordings (single lead ECG), acquired from 47 patients. All recordings of ECG signals have been analyzed by cardiologists independently. They label each beat, the kind of beat, and some other valuable information, i.e., changes of rhythm and artifact of noise. Due to these attributes, this dataset is very acceptable for arrhythmia classification using machine learning techniques.

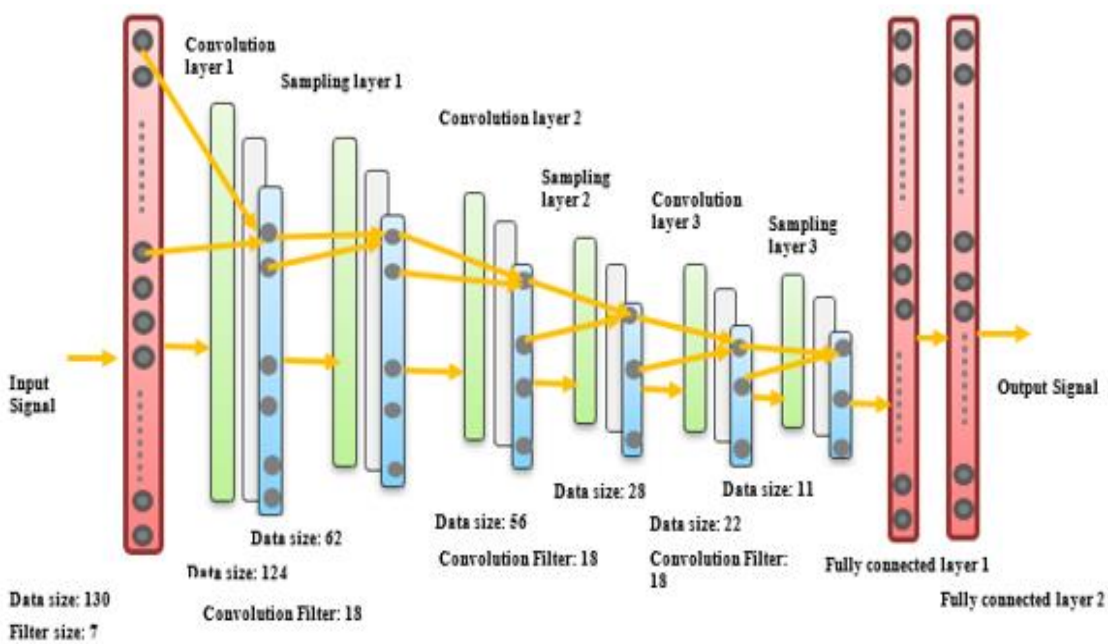

Fig. 4: Proposed CNN Model Architecture

ISSN:1813-1786 (Print) 2313-7770 (Online)

2) Performance Evaluation

The suggested 1-D CNN model diagnoses and classifies the following five different types of arrhythmia, i.e., N, VPC, LBB, APC, and RBB, with final accuracy of 97.8 %.

The accuracy is the division of rightly classified examples by the total number of examples. Mathematically it is given as,

$$A = \frac{T_p+T_N}{T_P+T_N+F_P+F_N} \tag{4}$$

where T_p denotes the number of cases correctly classified as needed, F_P represents the number of cases wrongly classified as needed,

T_N represent the number of cases correctly classified as not needed, F_N represents the number of cases wrongly classified as not needed.

3) Confusion Matrix and Accuracy

The confusion matrix and accuracy of the proposed model is shown in figure 5.

4) Comparison with other algorithms

Table 1 shows the contrast between the proposed 1-D CNN and other modern CNN algorithms. The suggested CNN model has better accuracy than the previous 1-D CNN model for the same dataset for the automatic classification of CVDs, as shown in the given Table 1

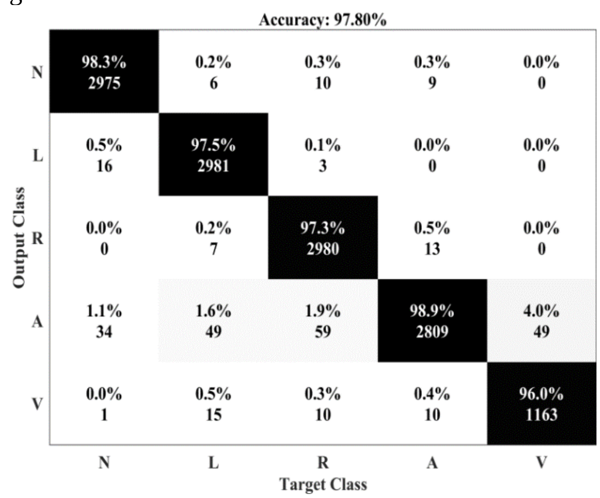

Fig. 5: Confusion Matrix of proposed 1D CNN model

Table 1: Comparison with other state-of-the-art algorithms

Reference #	Year	Types of Arrhythmia	Preprocessing Technique	Feature Extraction Method	Classification Algorithm	Accuracy Obtained
[74]	2007	N, S (superventricular ectopic), VPC, F, Q	Bandpass filter	Hermite transform	Block based NN	96.7%
[75]	2011	N, LBB, RBB, APC, VPC	Bandpass filters	CWT (Continuous Wavelet Transform)	SVM +GA (Genetic Algorithm)	97.3%
[76]	2013	N, LBB, RBB, APC, VPC	Wavelet Method	Pan Tompkins + PCA	NN+ LS-SVM	93%
[77]	2014	N, SVT (Supraventricular tachycardia), VPC, F (fusion of ventricular and normal), Q(Paced)	Wavelet Method	Wavelet+ PCA+ICA	SVM	86.4 %
[78]	2015	N, LBB, RBB, APC, VPC	Digital filter	Discrete Wavelet	NNWs	94%
[79]	2016	N, S, V, F, Q	Bandpass filter	CNN	Softmax	92.6%
[80]	2017	N, LBB, RBB, APC, VPC	Wavelet Method	Wavelet Transform	PNN (probabilistic neural network)	92.8%
[81]	2017	-	_	1-D CNN	Softmax	96.4%
[82]	2018	_	_	1-D CNN	_	90.0%
[83]	2019	N, PVC, PAB, RBB, LBB	Wavelet Method	1-D CNN	Softmax	93.6
Proposed Technique	2020	N, LBB, RBB, APC, VPC	Wavelet combination	1-D CNN	Softmax	97.8%

V. Conclusion & Future Work

Accurate classification of the ECG signal can diagnose and even prevent cardiovascular disease. Accurate classification of health-related disorders is nowadays a handy research field in the fusion of medicine and modern machine learning technology. Original ECG signal contains noise; therefore, to get a good quality ECG signals, we have applied wavelet algorithms. Then the optimized CNN model was applied to the ECG signal, which learns useful attributes from the given data. Finally, it classified the ECG signal automatically based on the extracted features. Using the 1D CNN model for the classification of the ECG signal achieved an accuracy of 97.8%, which is an improvement over over other algorithms used in previous work.

From this research, it is clear that the original 2-D CNN algorithm, which is used for two-dimensional data when optimized to a 1-D CNN algorithm, is feasible for the categorization of 1-D data. As a convolutional neural network algorithm could consume a lot of CPU (central processing unit) time in the absence of a graphical processing unit (GPU), it may present a threat to responsiveness. Hence, any change in the architecture of the CNN model needs training from the beginning, due resulting in long preprocessing times. Therefore, in the future, we can develop a more straightforward and efficient classification technique to optimize the CNN algorithm and gives better results than the present work. Besides, in this research study, we have used only a solitary lead ECG signal. In the future, we can use the proposed technique with multiple-lead ECG data so that experimental contents can be improved further.

References

[1] Haykin, S., Neural networks. Vol. 2. 1994: Prentice hall New York.

[2] De Chazal, P., M. O'Dwyer, and R.B. Reilly, Automatic classification of heartbeats using ECG morphology and heartbeat interval features. IEEE transactions on biomedical engineering, 2004. 51(7): p. 1196-1206.

[3] Ince, T., S. Kiranyaz, and M. Gabbouj, A generic and robust system for automated patient-specific classification of ECG signals. IEEE Transactions on Biomedical Engineering, 2009. 56(5): p. 1415-1426.

[4] Rangayyan, R.M. and N.P. Reddy, Biomedical signal analysis: a case-study approach. Annals of Biomedical Engineering, 2002. 30(7): p. 983-983.

[5] Acharya, U.R., et al., Classification of heart rate data using artificial neural network and fuzzy equivalence relation. Pattern recognition, 2003. 36(1): p. 61-68.

[6] Rowlands A, S.A. (2014) The ECG Workbook. 3rd revised edition, M&K Up- date Ltd.

[7] Baltazar R.F. (2009) Basic and Bedside Electrocardiography. Lippincott Williams Wilkins.

[8] Wiki How Cómocalcular lafrecuencia cardiacaapartirdeunecg. URL:https://es.wikihow.com/ calcular-la-frecuencia-cardiaca-a-partir-de-un-ECG.

[9] Maglogiannis I.G. (2007) Emerging artificial intelligence applications in computer engineering: real word ai systems with applications in ehealth, hci, information retrieval and pervasive technologies, vol. 160. Ios Press.

[10] Prusty M.R., Chakraborty J., Jayanthi T. & Velusamy K. (2014) Performance comparison of supervised machine learning algorithms for multiclass transient classification in a nuclear power plant. In: International Conference on Swarm, Evolutionary, and Memetic Computing, Springer, pp. 111–122.

[11] Song MH, Lee J, Cho SP et al (2005). Support vector machine based arrhythmia classi-fication using reduced features. International Journal of Control Automation and Systems 3(4):571.

[12] M. K. Das and S. Ari, “ECG Beats Classification Using Mixture of Features”, Int. Scholarly Research Notices, 2014.

[13] B. Mohamed, A. Issam, A. Mohamed, et al, “ECG image classification in real time based on the harr-like feature and artificial neural networks”, In procedia Computer Science, vol.73, pp.32-39, 2015.

[14] S. H. Jambukia, V. K. Dabhi, and H. B. Prajapati, “Classification of ECG signals using machine learning techniques: A survey”. In Computer Engineering and Applications (ICACEA), pp.714-721. 2015. IEEE.

[15] L. G. De, D. Francois, J. Delbeke, et al. “Weighted conditional random fields for supervised interpatient heartbeat classification”. IEEE Transactions on Biomedical Engineering, vol. 59, no. 1, pp.241-247, 2012.

[16] N. Alajlan , Y. Bazi , F. Melgani , S. Malek , M.A. Bencherif , Detection of premature ventricular contraction arrhythmias in electrocardiogram signals with kernel methods, Signal Image Video Process. 8 (2014) 931–942.

[17] R. Alcaraz, F. Sandberg, L. So⁄rnmo, J.J. Rieta,

Classification of paroxysmal and persistent atrial fibrillation in ambulatory ECG recordings, IEEE Trans. Biomed. Eng. 58 (2011) 1441–1449.
[18] F. Alonso-Atienza, E. Morgado, L. Fernandez-Martinez, A. Garcia-Alberola, J.L. Rojo-Alvarez, Detection of life-threatening arrhythmias using feature selection and support vector machines, IEEE Trans. Biomed. Eng. 61 (2014) 832–840.
[19] A. Mustaqeem, S. M. Anwar, A. R. Khan, M. Majid, A statistical analysis-based recommender model for heart disease patients, 2017, International journal of medical informatics 108, 134-145.
[20] M.R. Homaeinezhad, S.A. Atyabi, E. Tavakkoli, H.N. Toosi, A. Ghaffari, R. Ebrahimpour, ECG arrhythmia recognition via a neuro-SVM–KNN hybrid clas- sifier with virtual QRS image-based geometrical features, Expert Syst. Appl. 39 (2012) 2047–2058.
[21] M. Gul, S. M. Anwar, M. Majid, Electrocardiogram signal classification to detect arrythmia with improved features, 2018, IEEE International Conference on Imaging Systems and Techniques 2017, 1-6.
[22] S. M. Anwar, M. Gul, M. Majid, M. Alnowami, Arrhythmia Classification of ECG Signals Using Hybrid Features, 2018, Computational and mathematical methods in medicine 2018.
[23] M. Langkvist , L. Karlsson , A. Loutfi, Sleep stage classification using unsupervised feature learning, Adv. Artif. Neural Syst. (2012) e107046.
[24] R. Sameni, M.B. Shamsollahi, C. Jutten, G.D. Clifford, A nonlinear Bayesian filtering framework for ECG Denoising, IEEE Trans. Biomed. Eng. 54 (2007) 2172–2185.
[25] B.H. Tracey, E.L. Miller, Nonlocal means denoising of ECG signals, IEEE Trans. Biomed. Eng. 59 (2012) 2383–2386.
[26] J. Wang, Y. Ye, X. Pan, X. Gao, Parallel-type fractional zero-phase filtering for ECG signal denoising, Biomed. Signal Process. Control. 18 (2015) 36–41.
[27] S.K. Yadav, R. Sinha, P.K. Bora, Electrocardiogram signal denoising using non-local wavelet transform domain filtering, IET Signal Process. 9 (2015) 88–96.
[28] V. Bono, E.B. Mazomenos, T. Chen, J.A. Rosengarten, A. Acharyya, K. Maharatna, et al., Development of an automated updated Selvester QRS scoring system using SWT-based QRS fractionation detection and classification, IEEE J. Biomed. Health Inf. 18 (2014) 193–204.
[29] X. Ning, I.W. Selesnick, ECG enhancement and QRS detection based on sparse derivatives, Biomed. Signal Process. Control 8 (2013) 713–723.
[30] P. Phukpattaranont, QRS detection algorithm based on the quadratic filter, Expert Syst. Appl. 42 (2015) 4 867–4 877.
[31] P. De Chazal, R.B. Reilly, A patient-adapting heartbeat classifier using ECG morphology and heartbeat interval features, IEEE Trans. Biomed. Eng. 53 (2006) 2535–2543.
[32] Y. Kutlu, D. Kuntalp, Feature extraction for ECG heartbeats using higher order statistics of WPD coefficients, Comput. Methods Progr. Biomed. 105 (2012) 257–267.
[33] P. De Chazal, M. O'Dwyer, R.B. Reilly, Automatic classification of heartbeats using ECG morphology and heartbeat interval features, IEEE Trans. Biomed. Eng. 51 (2004) 1196–1206.
[34] S.-M. Dima , C. Panagiotou , E.B. Mazomenos , J.A. Rosengarten , K. Maharatna , J.V. Gialelis , et al. ,On the detection of myocadial scar based on ECG/VCG analysis, IEEE Trans. Biomed. Eng. 60 (2013) 3399–3409.
[35] G. de Lannoy, D. Francois, J. Delbeke, M. Verleysen, Weighted conditional random fields for supervised interpatient heartbeat classification, IEEE Trans. Biomed. Eng. 59 (2012) 241–247.
[36] H. Yang, C. Kan, G. Liu, Y. Chen, Spatiotemporal differentiation of myocardial infarctions, IEEE Trans. Autom. Sci. Eng. 10 (2013) 938–947.
[37] S.N. Yu, K.T. Chou, Integration of independent component analysis and neural networks for ECG beat classification, Expert Syst. Appl. 34 (2008) 2841–2846.
[38] P.-C. Chang, J.-J. Lin, J.-C. Hsieh, J. Weng, Myocardial infarction classification with multi-lead ECG using hidden Markov models and Gaussian mixture models, Appl. Soft Comput. 12 (2012) 3165–3175.
[39] Y. Kutlu, D. Kuntalp, Feature extraction for ECG heartbeats using higher order statistics of WPD coefficients, Comput. Methods Progr. Biomed. 105 (2012) 257–267.
[40] R.J. Martis , U.R. Acharya , L.C. Min , ECG beat classification using PCA, LDA, ICA and discrete wavelet transform, Biomed. Signal Process. Control 8 (2013) 437–448.
[41] C. Ye, B.V.K.V. Kumar, M.T. Coimbra, Heartbeat classification using morphological and dynamic features of ECG signals, IEEE Trans. Biomed. Eng. 59 (2012) 2930–2941.
[42] S.N. Yu, K.T. Chou, Integration of independent

component analysis and neural networks for ECG beat classification, Expert Syst. Appl. 34 (2008) 2841–2846.

[43] A. Mustaqeem, S. M. Anwar, M. Majid, Multiclass classification of cardiac arrhythmia using improved feature selection and SVM invariants, Computational and mathematical methods in medicine, Computational and mathematical methods in medicine 2018.

[44] F. Melgani, Y. Bazi, Detecting premature ventricular contractions in ECG signals with Gaussian processes, Comput. Cardiol. (2008) 237–240.

[45] T. A. Almohamad, M. F. M. Salleh, M. N. Mahmud, A. H. Y. Sa'd, and S. A. Al-Gailani, "Automatic Modulation Recognition in Wireless Communication Systems Using Feature-Based Approach," Singapore, 2019, pp. 403-409: Springer Singapore.

[46] J.-S. Wang, W.-C. Chiang, Y.-L. Hsu, Y.-T.C. Yang, ECG arrhythmia classification using a probabilistic neural network with a feature reduction method, Neurocomputing 116 (2013) 38–45

[47] S. Dutta, A. Chatterjee, S. Munshi, Correlation technique and least square support vector machine combine for frequency domain-based ECG beat classification, Med. Eng. Phys. 32 (2010) 1161–1169.

[48] E. Derya Übeyli, Recurrent neural networks employing Lyapunov exponents for analysis of ECG signals, Expert Syst. Appl. 37 (2010) 1192–1199.

[49] W. Jiang, S.G. Kong, Block-based neural networks for personalized ECG signal classification, IEEE Trans. Neural Netw. 18 (2007) 1750–1761.

[50] U.R. Acharya, M. Sankaranarayanan, J. Nayak, C. Xiang, T. Tamura, Automatic identification of cardiac health using modeling techniques: a comparative study, Inf. Sci. 178 (2008) 4571–4582.

[51] M.M. Rahhal, Y. Bazi, H. AlHichri, N. Alajlan, F. Melgani, R.R. Yager, Deep learning approach for active classification of electrocardiogram signals, Inf. Sci. 345 (2016) 340–354.

[52] S. Banerjee, M. Mitra, A classification approach for myocardial infarction using voltage features extracted from four standard ECG leads, IEEE, Information Systems, 2011.

[53] D. Giri, U.R. Acharya, R.J. Martis, S.V. Sree, T.C. Lim, T.V.I. Ahamed, J.S. Suri, Automated diagnosis of coronary artery disease affected patients using LDA, PCA, ICA and discrete wavelet transform, Knowl-Based Syst. 37 (2013) 274–282.

[54] E.S. Jayachandran, K.P. Joseph, U.R. Acharya, Analysis of myocardial infarction using discrete wavelet transform, J. Med. Syst. 34 (2010) 985–992.

[55] A. Kaveh, W. Chung, Automated classification of coronary atherosclersis using single lead ECG, IEEE Conference on Wireless Sensors, 2013.

[56] U.R. Acharya, H. Fujita, V.K. Sudarshan, S.L. Oh , M. Adam , J.E.W. Koh , J.H. Tan , D.N. Ghista , R.J. Martis , C.K. Chua , C.K. Poo , R.S. Tan , Automated detection and localization of myocardial infarction using electrocardiogram: a comparative study of different leads, Knowl.-Based Syst. 99 (2016) 146–156.

[57] W.S. Kim, S.H. Jin, Y.K. Park , H.M. Choi , A study on development pf multi-parameter measure of heart rate variability diagnosing cardiovascular disease, IFMBE Proc. 14 (2007) 3480–3483.

[58] H.G. Lee, K.Y. Noh, K.H. Ryu, in: Mining Biosignal Data: Coronary Artery Disease Diagnosis Using Linear and Nonlinear Features of HRV, Springer-Verlag, Berlin Heidelberg, 2007, pp. 218–228.

[59] H.G. Lee , K.Y. Noh , K.H. Ryu , A data mining approach for coronary heart disease prediction using HRV features and carotid arterial wall thickness, IEEE, International Conference on Biomedical Engineering and Informatics, 2008.

[60] H.L. Lu, K. Ong, P. Chia, an automated ECG classification system based on a neuro-fuzzy system, IEEE Comput. Cardiol. 27 (20 0 0) 387–390.

[61] S.G. Al-Kindi, F. Ali, A. Farghaly, Towards real-time detection of myocardial infarction by digital analysis of electrocardiograms, IEEE, 1st Middle East Conference on Biomedical Engineering, 2011.

[62] M. Arif, I.A. Malagore, F.A. Afsar, Detection and localization of myocardial infarction using k-nearest neighbor classifier, J. Med. Syst. 36 (2012) 279–289.

[63] S. Patidar, R.B. Pachori, U.R. Acharya, Automated diagnosis of coronary artery disease using Tunable-Q wavelet transform applied on heart rate signals, Knowl-Based Syst. 82 (2015) 1–10.

[64] S. M. Anwar, M. Majid, A. Qayyum, M. Awais, M. Alnowami, M. K. Khan, Medical Image Analysis using Convolutional Neural Networks: A Review, 2018, Journal of medical systems 42 (11), 226.

[65] A. Qayyum, S. M. Anwar, M. Awais, M. Majid,

Medical Image Retrieval using Deep Convolutional Neural Network, 2017, Neurocomputing 266, 8-20.

[66] Krizhevsky, A., Sutskever, I., Hinton, G. E., 2012. Imagenet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems, 1097–1105.

[67] Işin, A., Direkoğlu, C., Şah, M., 2016. Review of MRI-based Brain Tumor Image Segmentation Using Deep Learning Methods. Procedia Computer Science 102, 317-324.

[68] Jun, T. J. et al., 2016. Premature ventricular contraction beat detection with deep neural networks. 15th IEEE International Conference on Machine Learning and Applications, 859-864.

[69] Pourbabaee, B., Roshtkhari, M. J., Khorasani, K., 2016. Feature Learning with Deep Convolutional Neural Networks for Screening Patients with Paraoxysmal Atrial Fibrillation. IEEE International Joint Conference on Neural Networks, 5057-5064.

[70] Tajbakhsh, N. et al., 2016. Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine Tuning? IEEE Trans. Med. Imaging 35, 1299-1312.

[71] D. Zhang, "Wavelet approach for ECG baseline wander correction and noise reduction", in Proc. IEEE Int. Eng. Med. Biol. Soc, pp. 1212-1215. 2005.

[72] S. Kiranyaz, T. Ince, and R. Hamila, et al. "Convolutional Neural Networks for patient-specific ECG classification". In Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE, pp. 2608-2611. 2015.IEEE.

[73] https://www.physionet.org/physiobank/database/mitdb/.

[74] W. Jiang and S. G. Kong, "Block-based neural networks for personalized ECG signal classification," IEEE Transactions on Neural Networks, vol. 18, no. 6, pp. 1750–1761, 2007.

[75] Zadeh A E, Khazaee A. "High Efficient System for Automatic Classification of the Electrocardiogram Beats". Annals of Biomedical Engineering, vol. 39, no. 3, pp. 996-1011. 2011.

[76] R. J. Martis, U. R. Acharya, K. M. Mandana, et al, "Cardiac decision making using higher order spectra". Biomedical Signal Processing and Control, vol. 8, no. 2, pp.193-203, 2013.

[77] Zadeh A E, Khazaee A. "High Efficient System for Automatic Classification of the Electrocardiogram Beats". Annals of Biomedical Engineering, vol. 39, no. 3, pp. 996-1011. 2011.

[78]. Ismaiel, Fatima Osman Mohamed. "Classification of Cardiac Arrhythmias Based on Wavelet Transform and Neural Networks." Sudan University of Science & Technology. 2015. IEEE.

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

[80] J. A. Gutiérrez-Gnecchi, R. Morfin-Magaña, D. Lorias-Espinoza, et al. "DSP-based arrhythmia classification using wavelet transform and probabilistic neural network". Biomedical Signal Processing and Control, vol. 32, pp. 44-56, 2017.

[81] Ince, T., Kiranyaz, S., Eren, L., Askar, M., & Gabbouj, M. (2016). Real-time motor fault detection by 1-D convolutional neural networks. IEEE Transactions on Industrial Electronics, 63(11), 7067-7075.

[82] Jorge Torres Ruiz Email author Julio David Buldain PérezJosé Ramón Beltrán Blázquez, Arrhythmia Detection Using Convolutional Neural Models, International Symposium on Distributed Computing and Artificial Intelligence DCAI 2018.

[83] Rajkumar, A., Ganesan, M., & Lavanya, R. (2019, March). Arrhythmia classification on ECG using Deep Learning. In 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS) (pp. 365-369). IEEE.