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# Diagnosis of arrhythmia based on ECG analysis using CNN

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# ABSTRACT

Arrhythmia is the prime indicator of serious heart issues, and, hence, it is essential to be detected properly for early phase treatment. This article presents an approach for the diagnosis of cardiac disorders via the recognition of 17 types of arrhythmia. The proposed approach includes building a convolution neural network (2D-CNN) which is trained by using images of Electrocardiograph (ECG) signals collected from the MIH-BIH database. The ECGs are first converted into images. This step serves twofold: first, CNN is best suited for classifying image data and thus reduces preprocessing, and second, most ECG recordings are still being produced on thermal paper which can then be captured as image. Next, 2D-CNN is trained and validated. Test results show that the proposed method achieves classification accuracy of 96.67% and error of 0.004%. in addition to the superior accuracy achieved by this method compared to the previous literature, this approach enjoys reduced processing time and complexity apart from the training phase, also by dealing with images this method offers high degree of versatility and can be integrated as utility within other applications or wearables.

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#### 1. INTRODUCTION

Cardiovascular problems are the main challenge to healthcare providers worldwide. They are known for prevalence and related high mortality rates. It is estimated that around 17.3 person die every year as a result of heart related problems, accounting to around 37% of all deaths worldwide [1]. This also puts enormous pressure on health services in terms of hospital costs due to the recurrent nature of this illness that requires long-term care and treatment. ECG is the abbreviation of the electrocardiograph [2, 3]. It is a technique widely used by cardiologist in the diagnosis of cardiovascular diseases. It is relatively non-invasive and otherwise an easy to utilize technique. ECG provides good insight on cardiovascular health and pathology. The main clinical symptoms of heart issues are cardiac arrhythmias which is an abnormal heart rhythm. Due to the high individual variability among patients and among different stages of disease, diagnosis of cardiac issues becomes prone to human error and may contribute in some cases to life loss.

In order to achieve accuracy and consistency of diagnosis, many experiments have been conducted in the area of machine learning to predict arrhythmias automatically [4-6]. Therefore, the problem this paper is trying to tackle is the automatic diagnosis of cardiac arrhythmia; an automatic (perhaps wearable) diagnosis system can provide early warnings to rare and infrequent issues. The aim of this research is to develop a machine learning based computation mechanism that helps to diagnose cardiac arrhythmia speedily, accurately, and reliably such that proper treatment can be issued by trained doctors.

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Furthermore, this paper proposes a technique that utilizes images of the ECG recording directly by employing image processing to digitize those recordings. This has the advantage of making the proposed technique usable with older ECG devices (particularly used in developing countries) which produce their recordings on thermal paper. Figure 1 shows the structure of a general cardiac arrhythmia classification system. First, there is the data acquisition stage where images of ECG recordings are captured (this can be skipped for digital ECG devices). Next, algorithm stages are fed with data to derive and train the network until expert level knowledge is achieved. Testing is then performed to verify accuracy and measure performance.

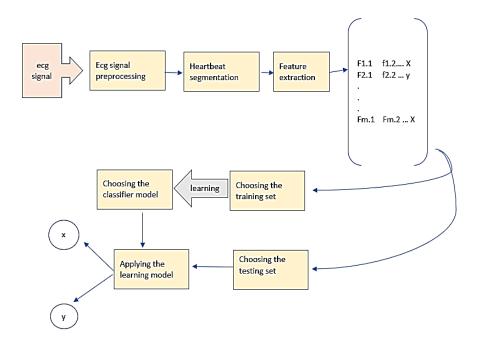


Figure 1. Detailed arrhythmia classification computing system

# 2. RESEARCH METHOD

In the proposed approach CNNs are employed to detect and classify lengthy segments of ECG recordings (10-s).in order to achieve accuracy and reduce the effects of transient fluctuations generated by acquisition equipment and other sources of noise [7]. Generally, the system of classification of heart disease using ECG signals is divided into five stages [8] (also shown in Figure 1):

- Pre-processing with normalization: The output from this stage puts data from different ECG devices and different patients in a rather standard form.
- Feature extraction: This stage isolates and strengthens signals in order to reinforce the detection of the operational disruptions (morphological changes) of the Electrocardiogram signal.
- Feature selection: The objective at this stage is to perform data reduction of features and thereby speed up the calculation
- Machine learning algorithms: The objective of the whole analysis is to classify sample-based cardiac illnesses (captured by ECG fragments), derived on the layout and choice of suitable variables as well as training models, and evaluated utilizing machine learning algorithms.
- Cross validation: the goal here is to reduce the impact of over-fitting of the algorithms in order to increase the generalization of the algorithm as well as increase the accuracy of the results achieved with new unseen data [9].

The proposed system utilizes 15-layer deep network architecture by using regular CNN layers. The input for this system framework (training/verification/testing data) consisted of images derived from the 360 sample/second raw Electrocardiogram signals of the MIT-BIH dataset. In comparison with the manual methods or even some computation methods, the Electrocardiogram signals were not detected as segmented QRS complexes but rather treated as whole signals [10-12]. This reduces the complexity of the algorithm. The training and testing of system performance are carried out on the Arrhythmia database which consists of 1000 fragments representing 17 different classes of arrhythmia. It is essential to stress here

that the proposed method, unlike previous approaches, uses 2-D image data rather than 1-D ECG signals. The experimental results show that this decision makes valuable contribution to the accuracy of the achieved results.

#### 2.1. Materials

Electrocardiogram data have been obtained from PhysioNet's MIT-BIH Arrhythmia database [13, 14]. As mentioned earlier, this Electrocardiogram data set consisted of 1000 non-overlapping frames. Each of these frames represents 10 seconds of ECG recording collected from subjects with various cardiac issues as well as healthy one totaling 45 subjects. Those subjects are distributed as 19 women 23-89 years old and 26 men 32-89 years old. The sample fragments were registered at a 360Hz sample frequency. In Table 1, a summary of the distribution of the seventeen cases included in the database is given.

Table 1. Number of ECG segments in various ECG classes

Number	Class	Fragment Numbers (Total 1000)	
1	Normal sinus rhythm(NSR)	238	
2	Atrial premature beat(APB)	66	
3	Atrial flutter(AFL)	20	
4	Atrial fibrillation(AFIB)	135	
5	Supraventricular tachyarrhythmia (SVT A)	13	
6	Pre-excitation (WPW)	21	
7	Premature ventricular Contraction(PVC)	133	
8	Ventricular bigeminy	55	
9	Ventricular trigeminy	13	
10	Ventricular tachycardia(VT)	10	
11	Idioventricular rhythm(IVR)	10	
12	Ventricular flutter(VFL)	10	
13	Fusion of ventricular and normal beat	11	
14	Left bundle branch block beat(LBBB)	103	
15	Right bundle branch block beat (RBBB)	62	
16	Second-degree heart Block(SDHB)	10	
17	Pacemaker rhythm(PR)	45	

All these cases are known cardiovascular diseases, except for the normal sinus rhythm which is the case of normal heart rhythm, i.e. healthy heart condition. The table includes the name and common abbreviation of the medical condition as classified by expert cardiologists (ground truth) as well as the number of samples per condition. Figure 2 shows plotted examples of the data included in the database. In Figure 2, it is easy even for non-experts to notice the differences among difference images, however, the exact diagnosis and the case and its severity requires skill and experience which the proposed systemaims to gather.

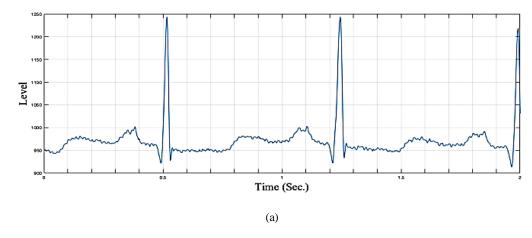


Figure 2. Actual signal samples of four different classes, (a) Normal sinus rhythm NSR

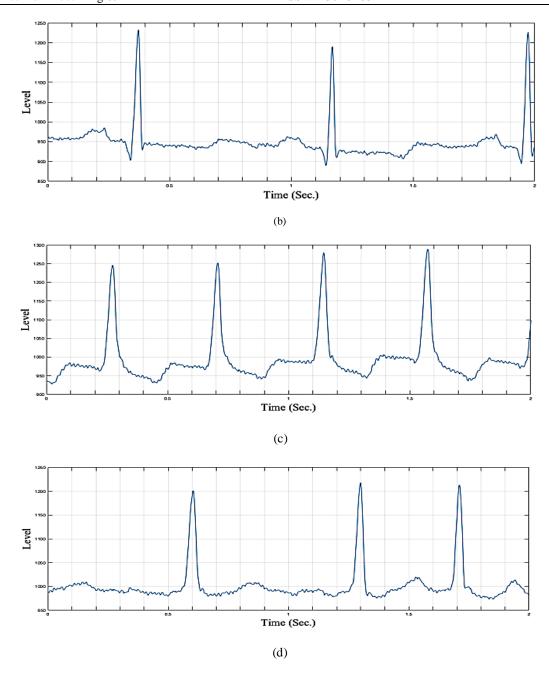


Figure 2. Actual signal samples of four different classes, (b) Atrial premature beat APB, (c) Atrial flutter AFL, (d) Atrial fibrillation AFIB (continue)

# 2.2. Convolution neural network (CNN)

Convolutional NNs or CNN is one of the types of deep learning algorithms. It was developed by K. Fukushima [14, 15] in the early 1980s from the original multi-layer network Perceptron. CNNs are widely utilized for machine learning, visual processing and computer vision [16, 17]. Through its several hidden layers the algorithm extracts features of a picture or video and through its fully connected layer it generates the appropriate learned output. It deals with two-dimensional and one-dimensional signals. In this article, we built a 2D CNN model. The main elements of this system are the Convolutional Layer, the Activation layer, the Pooling Layer, and the Fully Connected Layer. Activation function: is a nonlinear function that based on its input causes the firing of the node. Figure 3 shows various types of this function. Rectified Linear Unit (ReLU) is used in this work due to its many significant advantage, particularly: not triggering all neurons at the exact moment, that tends to minimize the number of simulations performed, removing negative values from activation map, and etc.

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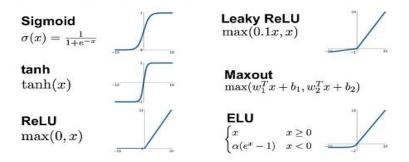


Figure 3. Various types of activation functions used in CNN

# 2.3. Operation of neural network model

- Load new image of ECG.
- Apply Conv. Layer with 30 filters (kernel size 3\*3).
- Apply activation function (ReLU).
- Submit the output of the function to the next Conv. Layer with 50 filters.
- Apply activation function (ReLU).
- Repeat steps (2-5) 60 times (epochs) and produce trainable works.
- Feed the output to the flatten layer.
- Apply fully connected layer.

The above algorithm is applied to each image during the training phase. The stages of this algorithm are also shown in details in Figure 4. In the first stage of the algorithm, 2D convolution layer is implemented on the input ECG. After that there is the pooling layer, which basically performs down sampling operation. This help to reduce processing time, as well as to identify and define the new parameters. Next layer we have dropout layer, this layer drops out random set of responses (activations) by setting them to 0, this help reduce over-fitting (training only). After that another convolution layer is used. Also, another convolution layer is applied. After that there is pooling layer preceded by dropout layer and then there is a ninth layer for flattening the dataset that can be used for fully connected layer and then a dropout layer and then a connected layer followed by another dropout layer and finally we have output layer. In this algorithm the dropout percentage rate used is 25%. The detailed specifications of these elements are given in Table 2. The suggested 15-layer CNN was built to classify segments of Electrocardiogram recordings of heart arrhythmia. The proposed network gives an auto categorization of input with no requirement for manual segmentation or annotation.

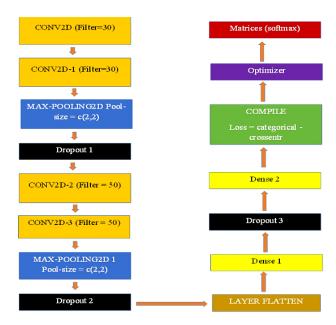


Figure 4. The layers of the proposed model for CNN

Table 2. Summary model's layers for CNN						
Layer	Layer Name	shape	Layer Parameters			
1	conv2d	(248, 48,30)	840			
2	conv2d_1	(246, 46, 30)	8130			
3	max_pooling2d	(123, 23, 30)	0			
4	dropout	(123, 23, 30)	0			
5	conv2d_2	(121, 21, 50)	13550			
6	conv2d_3	(119, 19, 50)	22550			
7	max_pooling2d_1	(59, 9, 50)	0			
8	dropout_1	(59, 9, 50)	0			
9	flatten	(None, 26550)	0			
10	dense	(None, 100)	2655100			
11	dropout_2	(None, 100)	0			
12	dense_1	(None, 17)	1717			

Table 2. Summary model's layers for CNN

# 3. RESULTS AND DISCUSSION

Throughout this research, computer vision/deep learning model is created by using the R programming platform utilizing Keras and Tensorflow libraries to develop the proposed model. The dataset consists of 1000 fragments of ECG signals. It is divided into three groups, the training set accounting for 70% of the dataset, the validation set with 15%, the testing set with 15%. The input samples were converted into images. After training the 2D CNN, the model obtained overall accuracy of 96.67% for all class. Verification and training sets were chosen on a random basis. Figure 5 shows average the convergence of the proposed model in learning all 17 categories of cardiac arrhythmia during the training phase. The figure shows that the algorithm settles very quickly. It is shown here that at around 30 epochs the algorithm reaches the vicinity of its maximum accuracy of 96%. The complexity of the algorithm in terms of time and space is reasonable with (14m and 29 sec) training time at 6 GB maximum memory usage. As for classification, with (4m and 38 sec.) time at 2 GB maximum memory usage the algorithm is considered light-weight given the fact that it deals with 2D image data.

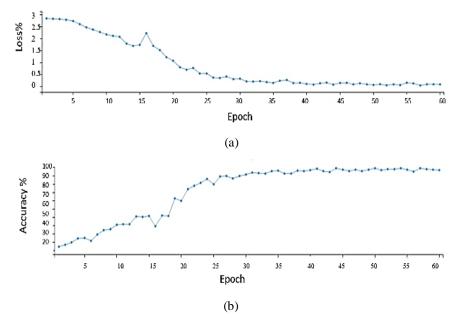


Figure 5. The convergence of the proposed model, (a) Loss function for training data, (b) Accuracy for training data

Table 3 gives detailed comparison of the performance of the proposed method with other related research. In this table, it is seen that only three researchers consider all 17 classes with full length signals. Among those three, the proposed method produces the highest accuracy by high margin. The proposed algorithm also proves superior compared to the other approaches which consider less categories and shorter signals, albeit with lower margin. The table also shows clear lead for the deep learning methods and SVM over other machine learning approaches. It is obvious that the layout adopted here, as well as the decision to utilize 2-D images rather than 1-D signals gave clear advantage to this implementation as compared to other settings and choices made previously. Table 4 summarizes the performance metrics of the algorithm.

Table 3. Comparison with other results in the literature

Work	Year	Length of signal	No. of classes	Type of classifier	Accuracy
Lin and Yang [18]	2014	120 samples (0.33 s)	5	Weighted LD	93%
Huang et al. [19]	2014	200 samples (0.56 s)	5	Ensemble of SVM (Support Vector Machines)	94%
Acharya et al. [20]	2017	360 samples (1 s)	5	Convolutional NN	94.03%
Ye, Kumar, and Coimbra [21]	2012	300 samples (0.83 s)	5	SVM	86%
Bazi, et al [22]	2013	300 samples (0.83 s)	5	SVM, IWKLR, DT SVM	92%
Zhang and Luo [23]	2014	227 samples (0.63 s)	5	Combined SVM	87%
Pławiak [24]	2018 3600 samples (10 s)	15 Encamble of constitution	93.04%		
riawiak [24]	2018	2018 3600 samples (10 s)	17	Ensemble of genetic SVM	91.40%
			13		95.20%
Yıldırım, et al [25]	2018	3600 samples (10 s)	15	1D-CNN	92.51%
		•	17		91.33%
Proposed method	2019	3600 samples (10 s)	17	2D-CNN	96.673%

Table 4. Performance metrics of the proposed algorithm sensitivity specificity precision recall F score Overall AC 84.52% 99.28% 90.02% 84.16% 86.62% 96.67%

# 4. CONCLUSIONS

This study's objective was to develop a 2D CNN deep learning model capable of successfully detecting a cardiovascular issue among 17 annotated categories of heart arrhythmia in long-term (10-s) Electrocardiograms. The proposed approach is shown to be: effective, quick (real-time ranking), comprehensive and can be integrated within other possibly wearable applications/devices. This 2D-CNN system obtained a general ranking precision of 96,673% averaged for the 17 arrhythmia categories. An important finding here is that this algorithm is the best to date compared to its contemporaries. The results show that despite the use of big numbers of variables (up to 17 portions of cardiovascular illnesses) the algorithm managed to find discriminatory features and avoided local optima and overfitting. The results of the proposed algorithm states a strong case for adopting deep learning based automatic diagnosis techniques on larger scales in the healthcare systems. It also shows that these approaches can save lives by providing continuous and momentarily update about patients' states, this is of particular importance for vulnerable groups and in countries with weak presence of hospitals and healthcare institutions. It is also important in places where cardiologists are overloaded as it creates a framework for tracking and monitoring patients remotely without the need to book specialist clinic visits. The next step for this research can be the fusion of other data from sources other than ECG recordings to build more robust and comprehensive health diagnostic system. Such system can add the feature of case management which helps decide and schedule the subsequent stages of the health plans for patients.

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