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A Novel Deep Learning-based Model for the Efficient Classification of Electrocardiogram Signals

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Abstract

To manage healthcare, an electrocardiogram, often known as an "EKG" or "ECG", is a measurement of the electrical activity of the organ "heart". Deep Learning (DL) or Deep Neural Networks have recently attracted the attention of researchers in many other sectors, including healthcare and medicine. There has been a frequent rise in the number of researchers developing the model to classify and detect several diseases, out of which cardiac complications are the keen focus due to the mortality associated with it. Therefore, the objective of the present research is to develop a classification model for efficient and accurate classification of signals received from ECG. The present study uses a "deep neural network" for the classification of the ECG signal into a total of five criteria including Normal ECG, QRS Widening, ST Elevation, ST Depression, and Sinus Rhythm. The developed classification method is tested and evaluated with the "MIT-BIH arrhythmia database" which revealed significant matrices for all parameters such as "precision", "accuracy", "recall", and "F-1 score". In addition to that, the proposed model demonstrated competent results which further highlights the practical applicability of the model to implementation and adoption in the healthcare sector.

Keywords

Arrhythmia, Congestive Heart Failure (CHF), Deep Learning, Deep Neural Network, Electrocardiogram (ECG), Convolution neural network (CNN)

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INTRODUCTION

Everyone should prioritize their health since it affects their quality of life. The heart is one of the organs that have to be maintained in good condition since it is a crucial organ that pumps blood throughout the body. The worst thing that may happen to a person is dead if their heart cannot perform its functions normally. The "World Health Organization (WHO)" reports that 17.9 million people globally, or about 31% of the population, died from heart disease in 2016, with around 17 million of those deaths occurring in persons under the age of 70 [1]-[3].

In 2030, it is predicted that 23.4 million people would die from cardiac abnormalities worldwide, contributing to 35% of all mortality (WHO, 2018) [4]. Figure 1 below demonstrates the projected number of different diseases by 2030. The current foundation for heart diagnosis is the examination of electrocardiogram (ECG) patterns, clinical symptoms, and testing of significant cardiac biomarkers. A hematological analyzer with biochemical reagents and skilled clinical staff for checking blood and conducting tests are among the specialized equipment, costs, and infrastructural facilities needed for this type of diagnosis, which relies on an invasive laboratory test. Due to this, developing countries or remote healthcare monitoring find it challenging to apply such assessments.

Artificial intelligence (AI) will be used more frequently in the health industry because of the volume and growth of data in that industry. Payers, healthcare professionals, and biological sciences corporations are already using a variety of types of AI [5]–[7]. Implementations are divided into three main categories administrative duties, patient involvement and adherence, and suggestions for diagnosis and treatment. Even though there are various situations where AI can execute healthcare activities just as well as or superior to humans. As cardiovascular health and its take care are becoming important day by day to reduce the mor-

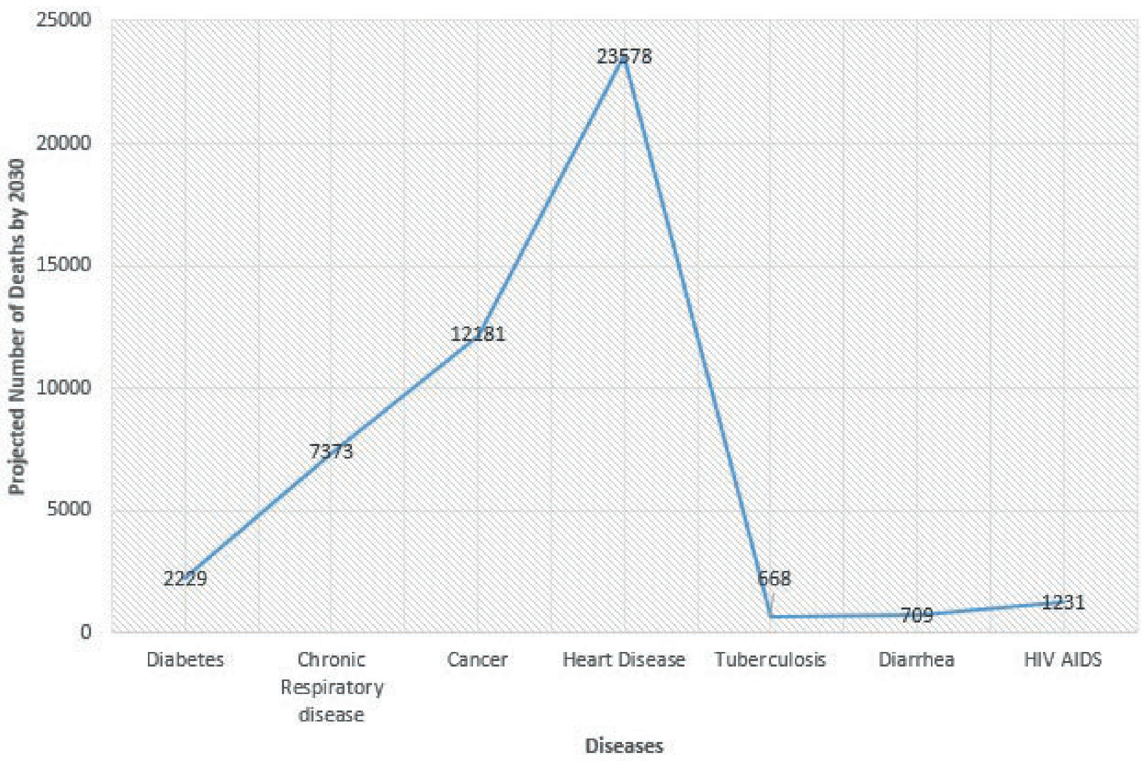

Figure 1: Illustrating the Projected Number of Deaths from Different Diseases by 2030.

tality rates due to heart diseases, AI is now taking a majority of part in various tasks employed in the detection diagnosis of heart diseases as well as the management of the heart patients [8]–[10]. The report and the growth of AI in healthcare in the U.S. Market are illustrated in Figure 2 below, where the significant increase can be seen in hardware, software, and services of the healthcare sector.

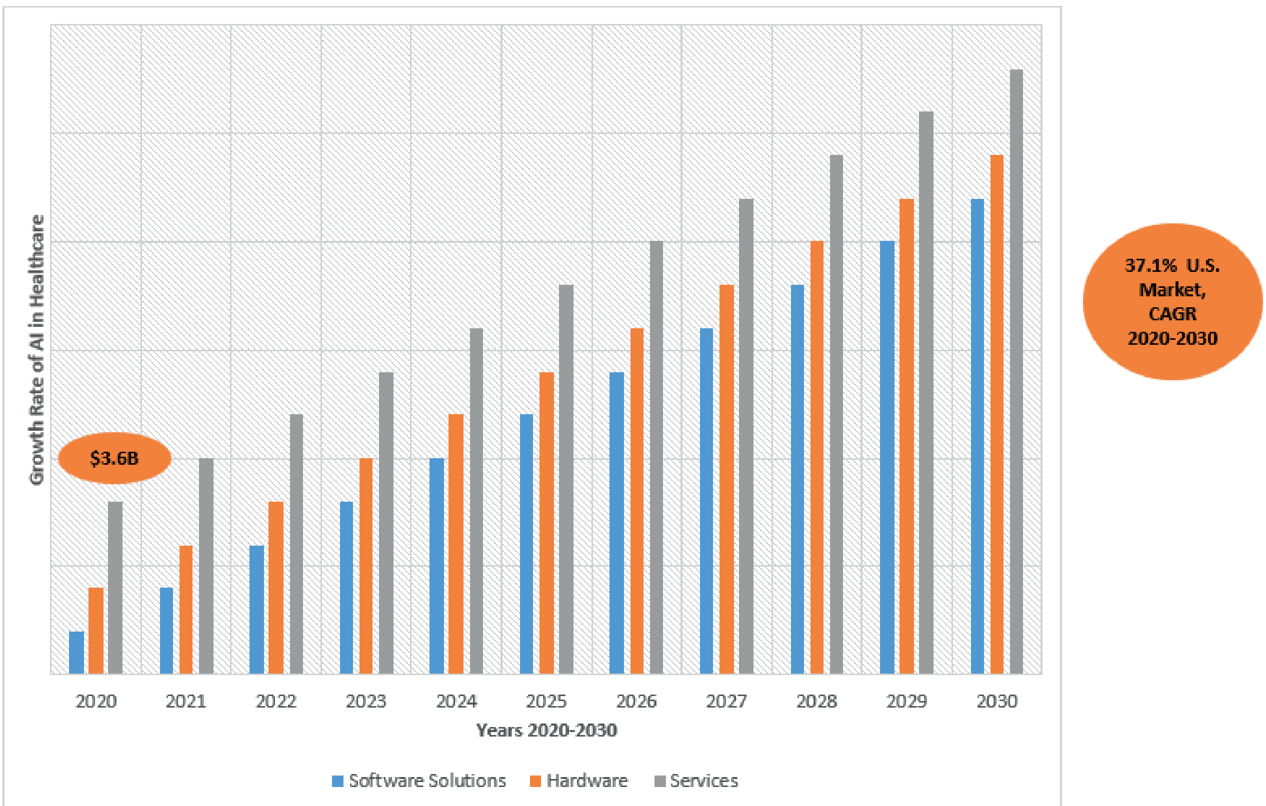

Figure 2: Illustrating the growth of Artificial Intelligence in the Healthcare Market; U.S. CAGR Report.

It is critical to detect and characterizes aberrations in the heart as well as its suggested ECG signal. The deep learning methodology is ideally suited to the challenge and integrating several neuronal layers in a neural network to find the methods for detecting the signals of ECG in less time with reliable findings. "Deep learning" has already been used to perform a range of tasks in patterns and recognition of images, which has prompted medical researchers to study this cutting-edge technology.

A division of machine learning called deep learning can autonomously extract features. Deep learning-based solutions have lately been recognized as a key element in healthcare providers for automatically extracting high-level abstract features, removing the need for time-consuming human feature design. DNN which is elaborated as a DNN is constructed in the same manner as the brain of humans. Depending on the logic shared by the various components, a single neuron comprehends and identifies a pattern. The present paper provides a novel classification method employing deep learning to classify the raw signals of ECG.

The present paper is divided into a total of five sections. The first section discusses the fundamentals and significance of carrying out the study while the second section provides the literature review on the existing and already developed approaches and classification model. The third section provides and discusses the design utilized to carry out the study followed by the fourth section providing the result and the fifth section of concluding remarks.

LITERATURE REVIEW

Madan et al. carried out the development of a hybrid "deep learning method" to classify arrhythmias based on ECG. In their study, they used 2D scalogram images for the automation of feature extraction and noise filtering and then developed a model with CNN and the "Long Short-term Memory (LSTM)" network. In their study, the experimental analysis was performed with the help of the MIT-BIH database. The results of their study revealed 99% accuracy for "Congestive Heart Failure (CHF)", "Normal Sinus Rhythm (NSR)", and an accuracy percentage of 98.7% for Cardiac Arrhythmias (ARR) [11].

Another study by Yao et al. developed a DNN model, the "attention-based time-incremental convolutional neural network (ATI-CNN)", that achieves temporal as well as a spatial fusion of data using signals of ECG by combining recurrent cells, an attention module, and CNN. The results of their study demonstrated that the developed model of classification attained a classification accuracy of 81.2% [12].

Arief Kurniawan et al. presented a "Deep Learning method", "Convolutional Neural Network (CNN)", that is employed to categorize a total of five different types of irregular heartbeats on signals of ECG: "Right Bundle Branch Block (RBBB)", "Normal Beat (NOR)", "Premature Ventricular Contraction (PVC)", "Fusion of Ventricular and Normal (FVN)" and "Left Bundle Branch Block (LBBB)". They examined the CNN architecture's ability to differentiate heartbeats in the "MIT-BIH Arrhythmia database". The recommended performance results have also demonstrated an accuracy of approximately 98% [13].

Liang et al. introduced a novel deep learning approach and performed a comprehensive comparison of various methodologies and databases. Databases I and II containing single-lead ECGs and 12-lead ECGs were utilized to investigate a realistic and feasible categorization algorithm for heartbeat events. In processing heartbeat event categorization, a "neural system technique" referred to as "Method I" and a "deep learning approach" referred to as "Method II" that integrates "CNN" with the "BiLSTM" network were assessed and compared. It has been revealed that Method I performed marginally better than Method II. The results of their study revealed the better performance of Method I in comparison to that of other state of art algorithms [14].

Li et al. developed an autonomous-detection method that can extract valid and important features from a 12-lead ECG to categorize various sorts of cardiac conditions. The created system was trained and evaluated on ECG information from nine different types of cardiac conditions, completing a multi-label classification assignment. The results of their study revealed an average F1 score of 0.908 and an area under the curve of 0.974 thus demonstrating the potential of classifying and auto-detecting the different types of cardiac complications [15].

The intriguing approach for categorizing ECG signals in "Machine Learning" is used to examine time data. Deep Learning delivers the greatest results, which is a new trend in the medical profession investigating which issues require extra attention in biological signal processing. The current technique necessitates preprocessing (Denoising, Feature Extraction) and classification (classify signal)

METHODOLOGY

3.1. Design

The present research develops a classification model for carrying out the classification of ECG signals obtained from patients. The cut signals were first converted into JPG images and then the classification model depending on a "deep neural network" was used for classification. ECG input signals were used from the "MIT Arrhythmia database", which was then followed by the identification of each peak, estimation of RR interval peaks, segmentation into single peak signals followed the formation of 2 D images. The 2-D images were then labeled into particular 4 categories and then the model was trained by the "deep neural network". The methodology for the developed system is illustrated in Figure 3 below.

Sample and Data Collection

For model training, ECG data were obtained from publicly available sources in an open database «(MIT-BIH Arrhythmia Database)" to create a strong classification model. The database comprises 48 recordings, each lasting 30 minutes and including two leads. The MIT-BIH arrhythmia database is a freely accessible set of data that offers common research materials for the identification of cardiac arrhythmia. It has been utilized since 1980 for the development of medical devices and basic research on cardiac rhythm and associated diseases. The goal of the database construction is to produce automated arrhythmia detectors that can diagnose the heart automatically based on the variety of the signal.

Instrumentation

Deep neural networks are a potent class of machine learning algorithms that are constructed by stacking multiple neural network layers along the width and depth of smaller structures. Deep networks have lately exhibited discriminatory and representational learning skills across a wide range of applications in recent years. Deep learning researchers are broadening their horizons by looking for potential applications in other fields.

Input image features are extracted by a neural network called CNN, and the image features are then classified by another neural network. The input image is utilized by the feature extraction network. The neural network classification process subsequently creates the output according to the features of the input image. The neural network utilized for feature extraction includes convolution layer stacking and groups of pooling layers.

The Study utilized pre-trained VGG-16, ResNet50, and Inceptionv3. VGG-16 is a 16-layers deep neural network whereas Inceptionv3 is 48 layers and ResNet50 is 50 layers deep neural network.

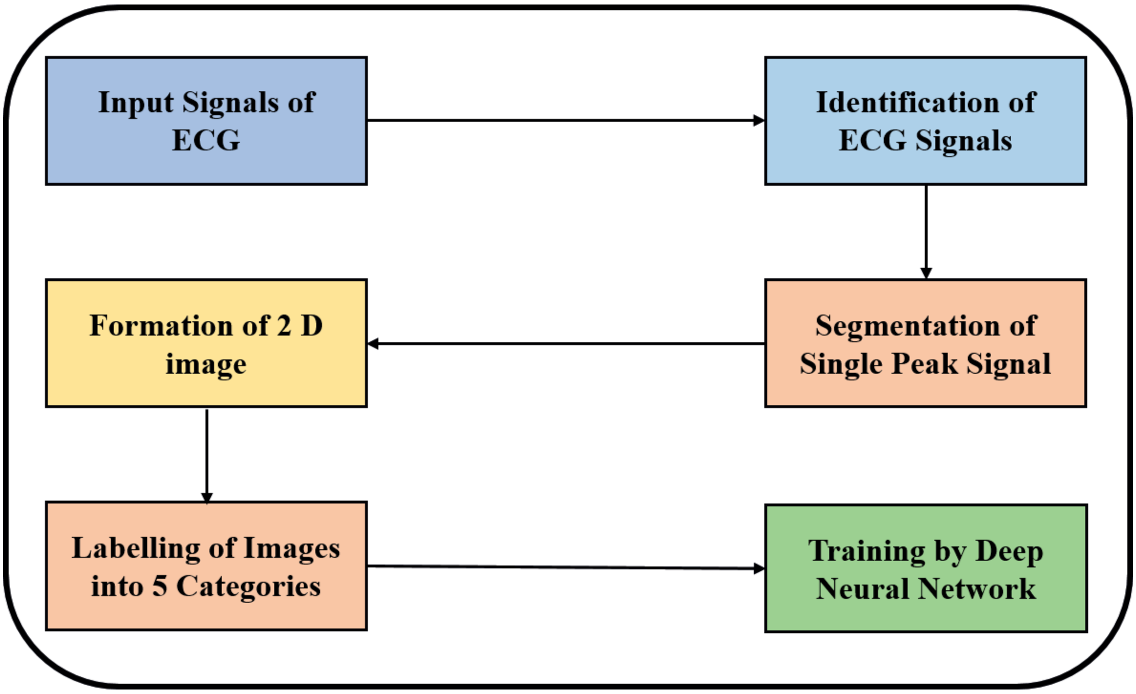

Figure 3: Illustrating the Methodology used to Carry out the Development of the Classification model.

Data Analysis

The four ECG signal patterns used in this investigation, as listed in the "MIT-BIH Arrhythmia Database", are "normal ECG", "sinus rhythm", "QRS widening", "ST depression", and "ST elevation". Convolution neural network (CNN) models were created using the four ECG patterns that were converted into 2D images. The testing and training datasets for the classifier were split equally at 60% and 40%. The dataset is employed to train the classification model (training set), while the testing dataset is employed to evaluate and assess it. Table 1 illustrates the different labels and the number of 2-D images taken in the analysis and testing of the model (Table 2).

Table 1
Illustrating the Number of Two-Dimensional Images Employed for Each of Five Labels.

Label	Number of 2D images
Normal ECG	20,488
QRS Widening	19,755
ST Elevation	8899
ST Depression	6163
Sinus Rhythm	5777

RESULTS AND DISCUSSION

As per the results of different matrices of classification mode, it has been revealed the proposed classification model using deep learning can classify the ECG signals with great accuracy, recall, precision, and F-1 score as illustrated in Table 3 demonstrating the three different matrices and Table 4 demonstrating the results of transfer learning.

4.1. Recall

The parameter called "recall" is calculated as the percentage of positive samples accurately labeled as positive to all samples that are positive. This parameter measures how effectively the model can distinguish between positive sample. The bigger the recall, the more positive samples that are found.

4.2. Accuracy

Accuracy is one of the criteria used to evaluate models of classification. Accuracy is the percentage of predictions that the developed classification model predicted correctly. According to formal definitions, accuracy is:

Table 2
Illustrating the Confusion Table for the Five Categories with "True positives", "True negatives", "False Positives", and "False Negatives".

Label	VGG-16/ResNet50/Inceptionv3				
	Normal ECG	QRS Widening	ST Elevation	ST Depression	Sinus Rhythm
Normal ECG	2701/2644/2087	44/87/289	31/46/127	46/94/266	59/43/349
QRS Widening	38/63/568	2803/2752/2021	2803/2752/22222	2/25/99	3/6/212
ST Elevation	58/54/767	77/34/235	3/87/99	4/23/155	2098/1098/1088
ST Depression	66/43/312	52/64/88	60/43/188	2672/2847/2014	6/4/320
Sinus Rhythm	28/66/196	5/5/74	4/20/122	4/20/125	2808/2744/2661

Table 3
Illustrating Different Matrices Received for Different 5 labels by VGG-16/ResNet50/Inceptionv3.

Categories	VGG-16/ResNet50/Inceptionv3		
	Precision	Recall	F-Score
Normal ECG	0.932/0.943/0.753	0.967/0.941/0.648	0.944/0.924/0.681
QRS Widening	0.955/0.956/0.734	0.988/0.954/0.823	0.966/0.933/0.059
ST Elevation	0.945/0.945/0.750	0.971/0.976/0.877	0.934/0.964/0.734
ST Depression	0.967/0.955/0.834	0.965/0.967/0.745	0.970/0.965/0.775
Sinus Rhythm	0.986/0.955/0.834	0.967/0.967/0.756	0.956/0.945/0.745

Table 4
Illustrating the Transfer Learning Results for VGG-16/ResNet50/Inceptionv3.

Index	VGG-16	ResNet50	Inceptionv3
Image Size	224 x 224	224 x 224	224×224
Accuracy	0.96001	0.94698	0.75021
Recall	0.96007	0.94687	0.71253
Precision	0.98012	0.94538	0.78235
F-1 Score	0.96008	0.98542	0.65486

$$\text{Accuracy}(A) = \frac{\text{No. of Correct Prediction}}{\text{No. of Total Prediction}}$$

$$A = \frac{TP + TN}{FP + TP + TP + FN}$$

4.3. Precision

"Precision" is determined by dividing the total number of positively identified samples (True Positive) by the proportion of accurately classified positive samples (either incorrectly or correctly). Therefore, precision enables users to see if the machine learning models are reliable in categorizing the model as positive.

4.4. F-1 Score

The "F-score", sometimes referred to as the F1-score, evaluates the accuracy of a model on a dataset. This parameter is used to evaluate binary classification systems that categorize instances as either «negative» or «positive.» It is feasible to modify the F-score so that recall is evaluated more highly than accuracy or vice versa. The F0.5-score and the F2 score are two popular modified F-scores in addition to the regular F1 score.

The developed classification method is also compared with existing classification models. A study carried out by Pourbabaee et al., developed a method for effective classification of electrocardiograms. In their study, they used CNN for classification. In their study, they demonstrated that the proposed method will increase the Classification performance by 91% in comparison to the others [16]. Khan et al. suggested a technique for detecting heart disorders using 12-lead ECG images. To diagnose cardiovascular illness, a Deep Neural Network architecture based on Single Shoot Detection (SSD) MobileNet v2 was deployed. The study demonstrated great accuracy in distinguishing and detecting four main heart anomalies. Several cardiology experts manually validated the accuracy results of the developed approach and advised that it be used to screen for heart conditions [17]myocardial infarction, abnormal heartbeat, previous history of MI, and normal class.

CONCLUSION

The electrical signal from the heart is measured during an electrocardiogram (ECG or EKG), a test used to identify different predisposing factors. Automation of signal detection can help advance identification and detection because it is one of the pillars of heart health. In this study, a classification system for ECG data is developed using deep neural networks to provide better and much more effective diagnoses. Instead of focusing on whether the techniques will be capable enough to be useful, the biggest challenge for AI throughout many healthcare domains is securing their acceptance in daily clinical practice. Though it will take far longer than the development of the technology themselves, these issues will eventually be addressed.

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