

A Review on Performance Evaluation using Convolutional Neural Network to Predict Cardiac Event

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Abstract— Cardiovascular diseases (CVD) may cause fatal medical conditions such as brain damage or stroke or even sudden cardiac death. These days, artificial intelligence based on machine learning and deep learning models are being commonly utilized to analyze and classify cardiac disease. Deep learning models have shown a promising performance in the healthcare field. These models have the potential to select high level features from the input data with the help of several hidden layers. Among the deep learning models, Convolutional neural networks (CNNs) are commonly used to process clinical images. This review is concentrated on exploring recent works for analyzing ECGs using CNN. The aim of this research is to investigate whether utilizing CNN provides better results and if patients can be diagnosed earlier before getting cardiac events.

Index Terms— Cardiovascular diseases, Artificial intelligence, Convolutional Neural Network, CNN, ECG

I. INTRODUCTION

Cardiac disease is caused by the change in heartbeat rate, regularity, origin of electrical impulses, and its symptoms range from little palpitation to the pain in the person's chest which may result in death also [1]. Abnormal intervals of heartbeats are caused by cardiac disease which can be detected and classified. There are many types of cardiovascular diseases like heart failure and coronary heart disease. Few of them cannot be healed completely but they can be regulated by monitoring the heart condition and accordingly implementing preventive measures [2]. Different methods like blood tests for troponin levels, electrocardiogram (ECG), chest X-ray, angiogram, and stress tests are present to access the heart of an individual [2]. Among all of them, ECG is preferred mostly for continuous heart tracking because it is highly accurate, non-invasive and it does not require any sophisticated machines [2]. The heart of a normal individual rhythms at a specific trend, hence any deviation in the ECG signal shows a cardiac issue [2]. The anomaly in ECG is the prime important factor that aids the detection of cardiovascular diseases in the individual [1]. The abnormality in ECG is an irregular indicator since the abnormal heartbeats arise in a small time, hence limiting its diagnosis in the hospitals. Also, the conventional monitoring of ECGs at hospitals is done by linking the person to the instrument with direct wiring while wireless sensors are utilized for wearable devices which monitor the cardiac activities without any influence on the daily life of the individual [1]. The ECG signals collected from internet of things (IoT) wearable devices like smart vest and chest strap should be investigated accurately to detect the cardiovascular diseases [2]. The wearable devices collect a huge amount of data which needs to be inspected by the clinician or cardiologists to detect any abnormality in the ECGs based on the rhythm of heart, rate of heart beats, and the variations in the heartbeat pattern. But investigating

everyone's heartbeat increases the complexity of the inspection and limits the accuracy of the clinician [2]. Hence, heartbeat classification using ECGs at an early stage is necessary and it should be automated with continuous accuracy [1]. These days, artificial intelligence based on machine learning and deep learning models are being commonly utilized to analyze and classify heart disease [2]. Deep learning models have shown a promising performance in the healthcare field. These models have the potential to select high level features from the input data with the help of several hidden layers. Among the deep learning models, CNNs are commonly used to process the clinical images [2].

II. LITERATURE SURVEY

This work has reviewed the recent relevant research from 2019 to 2023. The reports from WHO show that non-disease deaths in the world are mainly caused by cardiovascular disease corresponding to 17.9 million people which accounts for 44% of all non-communicable disease fatalities in the world [3]. Hence, identifying heart condition earlier is important to save people from cardiac events. The ECG is a popular technique for evaluating a patient's heart activity [3]. ECG, stands for electrocardiograph, is a method commonly used by medical practitioners to diagnose cardiovascular diseases [4]. It is a simple non-invasive technique to utilize and provides a good understanding of cardiovascular health of the patient [4]. The prime symptoms of heart issues are abnormal heart rhythms also known as cardiac arrhythmias [4]. A normal ECG cycle (known as normal sinus rhythm NSR) consists of many parts (P wave, Q wave, R wave, S wave and T wave) as shown in Figure 1 [5]. Figure 1 demonstrates that ECG is shown using time domain features like duration, amplitude, interval, and segment [4]. The waveform of ECG consists of five peaks, P, Q, R, S, and T that indicate each feature (heartbeat) [5]. It is possible to detect the activity of heart effectively by evaluating each peak of ECG [3]. The ECG signal shows the information of the cardiac functions of any patient [3]. The main phase in ECG classification is the feature extraction which identifies the important characteristics in the images to obtain the best performance (accuracy) [3]. The classification of ECG wave is important to identify the normal and abnormal heartbeats [3].

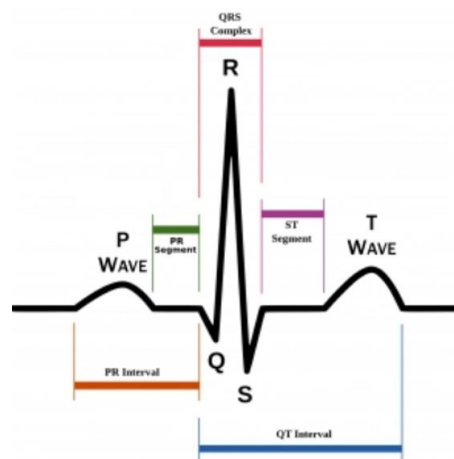


Figure.1 Normal sinus rhythm of heart or normal ECG cycle [5]

The analysis of heartbeat by a specialist requires a long-time examination consuming more time and exposed to low accuracy because of fatigue [1]. Hence, there is a necessity of the automated technique for classification of the heartbeats to diagnose the individual with cardiac issues [1]. There are different approaches utilized for automatic ECG classification like support vector machine (SVMs), k-nearest neighbor clustering, classification and regression trees, hidden Markov models, convolutional neural network (CNN) and artificial neural networks [1]. Classifying heartbeats using these techniques saves time and provides better results helping in early diagnosis of the cardiac event. Improving the accuracy for the classification of ECG signals is a tough task to solve which has stimulated for the research to be carried out for development of different techniques [3].

Deep neural networks which learn from examples are utilized for ECG classification in this work [6]. Neural networks have attained success in increasing the accuracy for classifying ECG. This study [6] has utilized Telehealth network of Minas Gerais dataset and CNN has given a better performance for it compared to other machine learning algorithms with specificity around 99% and F1-score of 80%.

The leading cause of death in the world is cardiovascular diseases and ECG is the main mechanism to diagnose it which is very popular to access heart condition in medical diagnosis [6]. Till now, almost all the applications were

utilizing supervised learning techniques to automate ECG classification as it learns from mapping input to output from examples providing better performance than a medical specialist. However, it requires a huge quantity of labelled data for medical application which introduces many challenges because of security and confidentiality issues for health information. Hence, recently, CNN has gained success in tasks like image classification and speech recognition, and it has a lot of expectations to improve health care. Convolutional neural network, CNN, is one of the deep learning algorithms developed by K. Fukushima from the original multi-layer network in the 1980s [4]. CNNs extract the features of the input image or video through its several hidden layers and generate the learnt output through its fully connected layer [4]. Implementation of CNN has provided better results compared to other machine learning algorithms [6].

There are different types of ECGs that doctors prescribe. The standard, short duration, resting 12-lead ECG is the commonly used examination for assessing the heart condition worldwide [7]. The exercise ECG, also known as stress ECG, evaluates the heart activity under physical conditions like exercise in controlled and monitored environment. The Holter exam type of ECG assesses the heart activities for a long period of time by wearing a device. The device records any abnormalities of the heart which may not be detected by shorter ECGs. The Holter exam provides details mainly about the heart rhythm and repolarization whereas the resting 12-lead ECG provides a complete assessment of the heart electrical activity which includes cardiac chamber hypertrophy, arrhythmias, acute coronary syndromes, conduction disturbances and the electrolyte disturbances and the effect of drugs [6]. Hence, the deep learning techniques for accurate performance of resting 12-lead ECG will have the maximum effect [6]. This resting 12-lead ECG is generally performed in primary health centers and emergency units, but many times it is not able to get analyzed and interpreted due to the lack of specialists which causes more than 75% of deaths related to cardiovascular diseases. Hence, there is the need for accurate automatic interpretation which can be performed through deep learning technique. This paper [6] demonstrates the CNNs performance for resting 12-lead ECG where CNN learnt the parameters using the training dataset and the best performance on the test dataset is obtained with F1-score above 80% and specificity about 99%. To attain the stability of the network, 10 different CNNs have been trained in this work with the same set of hyperparameters with different initializations. To compare the performance, the same dataset was assessed by many doctors and medical students for F1-score, where CNN outperformed the result obtained by medical people [6].

Electrocardiogram (ECG) signals have been used to evaluate the heartbeat using machine learning and neural network techniques which have been reviewed in this work [3]. The main parts in CNN are feature extraction along with classification [3]. The feature extraction obtains the important and useful characteristics from the images and classification precisely classifies the ECG signals utilizing the generated characteristics from the feature extraction [3]. The feature extraction method comprises of layers: convolution and downsampling that are explained in detail in the second chapter. Convolution layer improves the quality of the ECG signals by reducing the noise [3]. This work utilized the CNN model for ECG classification consisting of input, two fully connected layers, two down-sampled layers, a full connection layer, and an output layer [3]. The input for each neuron is coupled to the output of the preceding layer to extract the local characteristics [3]. This paper [3] has reviewed different works to predict the cardiac event from ECG signals using SVM and CNN. This review paper showed many works have used the MIT-BIH arrhythmia dataset consisting of 48-hour data for 47 patients and digitized at 360 samples per second per channel in a 10mV range with 11-bit resolution. The best accuracy reported in this work using CNN was 97.4% and using SVM was 96%. [3].

Another work using the same MIT BIH arrhythmia dataset has been implemented in this where beats were classified into five heartbeat types [8]. This work has proposed the ECG classification utilizing CNN which used feature extraction and classification together [8]. The experiment showed that this model obtained a superior performance of classification for the identification of cardiac events. The performance of ECG classification is measured using four metrics: accuracy, sensitivity, specificity, and positive predictivity. The best obtained accuracy from this model was 98.9% with a high sensitivity of 95.9%.

This paper [4] presented a technique to diagnose cardiac disorders by recognizing 17 different types of arrhythmias. Arrhythmia is the irregular heartbeat and the prime index of serious heart issues [9]. This work [4] included training and validating a 2D-CNN with ECGs from MIT-BIH database. The diagnosis of cardiac disorders is susceptible to human error due to the high variations in individuals at different phases of disease which can lead to loss of life also in some cases [4]. To obtain accuracy and consistency of detection, many works have been implemented in the field of machine learning to automatically detect and predict arrhythmias [4]. This work [4] developed a machine learning technique which helped diagnosis of cardiac arrhythmias rapidly with high accuracy. This work has achieved an accuracy of 96.67% with reduced processing time. It has proposed as future work that the further step for the research in this field can be the fusion of other data with ECG images to model more robust and

thorough health diagnostic system that can help in deciding and scheduling the following stages of health plans for the patients [4].

This paper [10] has demonstrated a less complex and improved CNN model to distinguish types of cardiac events for European ST-T ECG dataset and achieved an accuracy of 99.23% better than many other works. The 2D CNN model used in this work had three layers and trained on 2D ECG images. The paper has also stated that this model can help in real time monitoring and can be integrated with wearable and portable devices like smartwatches and smartphones for collecting ECGs [10]. Then the collected images can be sent to a central place where the presented 2D CNN model will classify the ECGs, and this will encourage the users to agree on this as a support tool for improving health and quality of life. This model has presented stages in structured model as three layers: ECG signal acquisition, noise removal by preprocessing, detecting the points and waves in ECG image and distinguishing it into various types of arrhythmias. This work has utilized 2D CNN model instead of 1D model which mainly uses many different layers which makes it computational complex which increases more on increasing more layers [10]. More complex models yield relatively poor performance; hence this work has tried converting 1D ECG image to 2D image to train and evaluate 2D CNN model and to identify the arrhythmias and obtained a high accuracy of 99.23%. As a future work, this research has suggested using different datasets and integrating the ECG images with other data for monitoring the health of the individual's heart [10].

This work [11] has introduced a CNN classifier to detect the abnormalities of ECG signal by analyzing it as a 2D image. This technique has classified ECG image of European ST-T dataset as normal or abnormal by converting the single lead ECG signal to images and then implementing CNN classification and achieved an accuracy of 97.47% [11]. This work has employed the ECG signal recorded with a single lead only instead of 12-lead device and it is shown that both are equally effective in identifying arrhythmia. This work has reduced the requirement of pre-processing and feature extraction to detect cardiac issues hence reducing the complexity of the system. CNN is utilized to learn from ECG signals through enough training to improve the performance of detecting normal and abnormal ECG signal classification [11]. This CNN model consisted of 10 layers having 2 convolution layers. This work has provided a high accuracy of 97.47% with a sensitivity of 95.1%. This work helped in saving many lives because of early detection of heart attack and contributing to improvement the quality of life. This work has also proposed to integrate different datasets for further improvement as a future work [11].

1D-CNN approach has been implemented in this work [2] on MIT-BIH arrhythmia database to investigate ECG signals captured from IoT wearable devices and to predict cardiovascular disease with an accuracy of 99.46%. This 1D- CNN has data extraction and classification part where convolution, batch normalization, activation, and max pooling layers are included in extraction and Softmax layers, flatten, and fully connected are included in classification part [2]. This CNN model has 319 nodes that represent the length of heartbeat segments. This model has given an accuracy of 99.46% in 44 epochs. The future work mentioned in this paper states to add more different deep learning models to monitor the ECGs of the patients [2].

One more work [12] has been done on MIT-BIH arrhythmia dataset using CNN for implementation and analysis ECG images with an accuracy of 97%. This convolutional neural network is employed in the IoT devices to process the data. It has mentioned using Recurrent neural networks, RNN for implementation to check the performance as a future work [12]. Another work on MIT-BIH arrhythmia dataset is done in this work [12] using CNN with optimization technique. Many existing techniques for classification of arrhythmia meet with a challenge of varying classification accuracy hence there is need of automatic monitoring and classification techniques [12]. This work [12] has proposed the automatic classification of arrhythmia utilizing the optimization technique with CNN. The optimization algorithm known as Bat-Rider optimization algorithm is used with CNN. The features are extracted from ECG signals such that those features characterize the individual ECG features. And then the signals are provided to the optimization algorithm with CNN to identify the ECG signals as normal or abnormal one. This technique is analyzed on MIT-BIH arrhythmia dataset and the best performance obtained are accuracy of 93.19%, specificity of 95% and sensitivity of 93.98% [12]. In this work, classification of heartbeat is optimally done using CNN and is optimally tuned using an optimization algorithm. The next step of classification consists of feature extraction and feature classification. The proposed technique of CNN with optimization algorithm gave a better accuracy of 93.19% whereas without optimization algorithm, CNN provided accuracy of 92.26% and SVM gave an accuracy of 91.68%. The future work mentioned in this research is to use other optimization algorithms for better performance and to use more datasets to investigate the performance of models. More other research using CNN has been implemented on MIT-BIH arrhythmia dataset whose results are tabulated in Table 1.

This work [13] has implemented CNN on another publicly access database, PTB-XL dataset having 21837 clinical 12-lead ECGs of 18885 patients. Here two different neural networks were experimented with, one based on 1D CNN, and another based on 1D CNN with entropy-based features. The CNN model consists of 5 layers of 1D convolutions with LeakyReLU as activation functions and 1 fully connected layer with softmax as activation

function [13]. Here, leakyReLU is utilized instead of ReLU to maintain the gradient loss for neurons yielding negative values. The other model is an extension of the first CNN model including entropies such as Shannon entropy, approximate entropy, sample entropy and others [13]. The CNN with entropy provided an accuracy of 89% whereas the CNN model without entropy gave an accuracy of 88.2%. So, it can be noted here that adding entropies did not help in getting better accuracy for a CNN model [13].

Many papers have mentioned integrating different datasets together for more accurate performance as seen above [1][2][4][10][11][12]. On investigating and researching more, a few works integrating different datasets have been found which are discussed here.

This paper [14] has researched breast cancer patients and proposed a novel model integrating clinical information and Hematoxylin and Eosin (H&E) slide images to evaluate the risk of metastasis in breast cancer patients. After resizing the complete H&E staining images of breast cancer patients to 512x512 pixels, CNN was implemented on those images to extract image features and combined them with the clinical data. This joined dataset is used with machine learning model to predict breast cancer in patients with an area under curve of 0.72 whereas the clinical dataset only showed a ROC of 0.57. Hence it showed that H&E images with clinical information provide better results than individual dataset. This paper did not talk about any other performance metrics than ROC [14]. This paper [15] has worked on Covid-19 patients for prediction of survival using clinical data and radiomic features obtained from chest CT images. The modelling was implemented separately and in combination of both data. The area of radiomics enables one to extract important information from images using different features, according to which they are correlated to clinical data. The experiment showed the combined data of images and clinical records provided accuracy of 94% while separately accuracy of 87% is obtained. This work showed the combination of images and clinical data effectively improves the performance of model [15].

This work [16] showed the prediction of pulmonary venous obstruction implementing machine learning models by using clinical data and CT images together. CNN was used to extract features from CT images and logistic regression was implemented to clinical data. The final model was obtained by integrating the two data obtained features. It showed that joint clinical data and CT images improved the performance compared to the models built on each individual dataset. The joint dataset gave a high sensitivity of 82.8% and AUC of 0.94 [16].

A. Conclusions

Below Table 1 shows the recent work done in the cardiac field using deep learning techniques. It can be seen from the Table that many works have been carried out on MIT-BIH arrhythmia dataset and achieving a high accuracy of 99.84% using CNN. Few works have been done on other dataset also. As seen in the literature review above, many papers have mentioned integrating different datasets together for more accurate performance [1][2][4][10][11][12]. On investigating and researching more, a few works integrating different datasets have been found which are discussed here. The last three works mentioned above [14,15,16] have utilized the clinical data and images jointly to obtain the best performance but none of them have shown how the joint data was implemented using machine learning algorithm to obtain the results. These latest works are in different areas and to my knowledge, the cardiovascular field lacks research integrating both clinical and image datasets. Hence, for future work, research can be carried out for the implementation of joint data of clinical records and ECG images for cardiac patients.

TABLE 1 SUMMARY OF LITERATURE REVIEW FOR DIFFERENT DATASETS

Papers	Dataset	ML Techniques used	Best Result
[1]	MIT-BIH arrhythmia	CNN	Accuracy, specificity and sensitivity of 93.19 %, 95 %, and 93.98 %
[2]	MIT-BIH arrhythmia	1D CNN	Accuracy of 99.46%
[3]	MIT-BIH arrhythmia	CNN and SVM	accuracy of CNN: 97.4% accuracy of SVM: 96%
[4]	MIT-BIH arrhythmia	CNN	accuracy of 96.67%
[6]	Minas Gerais	CNN	specificity of 99% & F1-score of 80%
[8]	MIT-BIH arrhythmia	CNN	accuracy of 98.9% & sensitivity of 95.9%
[10]	European ST-T	2D CNN	accuracy of 99.23%
[11]	European ST-T	CNN	Accuracy of 97.47%
[12]	MIT-BIH arrhythmia	CNN	Accuracy of 97%
[13]	PTB-XL dataset	1D CNN	Accuracy of 88.2%
[14]	HER2-positive breast cancer patients	CNN	AUC of 0.72
[15]	Covid patients	CNN	accuracy of 94%

[16]	pulmonary venous patients	CNN & logistic regression for joint data	sensitivity of 82.8% & AUC of 0.94
[17]	MIT-BIH arrhythmia	CNN	Accuracy of 98.33%
[18]	MIT-BIH arrhythmia	1D CNN	Accuracy of 97.1%
[19]	MIT-BIH arrhythmia	CNN	Accuracy of 97.41%
[20]	MIT-BIH arrhythmia	CNN	Accuracy of 95%
[21]	MIT-BIH arrhythmia	CNN	Accuracy of 97%
[22]	MIT-BIH arrhythmia	1D CNN	Accuracy of 99.8%
[23]	MIT-BIH arrhythmia	CNN	Accuracy of 99.45%
[24]	MIT-BIH arrhythmia	CNN	Accuracy of 99.84%
[25]	MIT-BIH arrhythmia	CNN	Accuracy of 95.2%
[26]	MIT-BIH arrhythmia	CNN	Accuracy of 99.01%
[27]	MIT-BIH arrhythmia	CNN	Accuracy of 98%
[28]	MIT-BIH arrhythmia	CNN	Accuracy of 97.38%

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