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Classification of ECG Signal Using Deep Convolutional Neural Network

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Abstract:

In the last ten years, the characterization and expectation of cardiac illnesses based on ECG signals have become increasingly important for doctors and patients. This paper delivers a deep learning technique that has recently been created for the order of ECG information with Normal Sinus Rhythm (NSR), Abnormal Arrhythmia (ARR), and Congestive Heart Failure (CHF). A sum of 162 ECG signals is open, including 96 arrhythmias, 30 Congestive Heart failures, and 36 Normal Sinus Rhythm signals. To exhibit the classification performance of deep learning architectures, this paper studied ECG using the two CNN models GoogleNet and DenseNet201. The proposed study's classification accuracy is 91% and 100% respectively. The outcomes uncover that the proposed profound learning architecture is more precise than traditional machine learning classifiers at classifying ECG signals.

Keywords: Electrocardiogram (ECG), Deep learning, convolutional neural network (CNN).

1. Introduction:

Society's major preoccupation has always been health issues. In 2017, cardiovascular diseases are according to the World Health Organization (WHO), the major cause of mortality worldwide [1]. In 2016, 17.9 million people kicked the bucket from cardiovascular sicknesses, representing 31 percent of all mortality around the world. The majority of Cardiovascular events result in lowered-pay nations. Individuals in these nations are habitually not protected by the general medical care framework, and clinics lack the necessary healthcare centers to provide appropriate medical care to patients.

The ECG examination, which can be checked manually or automatically, provides essential information regarding the status of the heart. Manual diagnosis is difficult due to the wide variety of morphologies present in the ECG signal. As a result, an automatic ECG diagnosis method has piqued our curiosity. Any automatic ECG classification must succeed in both feature extraction and classification. Ischemic heart disease, irregular heartbeat, heart failure, and heart attack are just some of the applications for ECG processing and analysis [2].

Machine learning models have advanced quickly, allowing them to be used for speech and facial recognition, image identification, ailment detection, and other applications [3]. In this research, researchers create a two-layered independent convolutional brain organization arrhythmia characterization framework which may assist clinicians in detecting irregular heartbeats more quickly, thereby enhancing the rate of early diagnosis and reducing CVD-related fatalities.

On ECG signals, CNN has done reasonably well. Deep learning models also do not necessitate the extraction of hand-crafted features and are quite simple to deploy.

1.1 Electrocardiography:

Electrocardiography (ECG or EKG) is a method of determining the heart's electrical action. It’s usually a non-invasive way to detect heart abnormalities.

ECG is mostly used to detect cardiac abnormalities. A commonplace ECG signal contains three significant waves: P wave, QRS complex, and T wave, as seen in Figure 1. An aberrant heart causes an arrhythmia heartbeat, this is typically brought about by broken motivation data or transmission. A clinician can diagnose a number of arrhythmia heartbeats by reading ECG data. Clinicians make decisions based on an ECG signal's interval and morphological information, like the state of the three introductory waves and the cadence of the heartbeat [1].

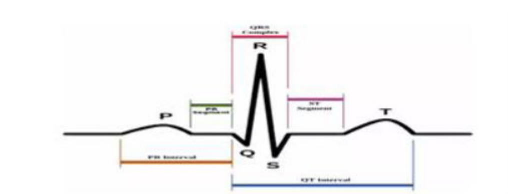

Figure 1: A heart in normal sinus rhythm with a single ECG wave [4

1.2 Deep learning algorithms:

The most recent area of machine learning approaches is deep learning algorithms., limited Boltzmann machines, Recurrent neural networks, autoencoders, beliefs networks, and CNNs are some of the architectures they possess. Each one is used for a particular type of information. CNNs are the most commonly used deep learning architecture for image recognition. CNNs are a popular design in health informatics, especially for classification and diagnosis from medical images [5] To classify ECG, four CNNs of various architectures were used in this work.

2. Related works:

The presentation of ECG arrhythmia order on ECG signals defragmented after misfortune pressure with a high-pressure proportion was explored by a group of writers. They suggested a basic however powerful methodology for deteriorating ECG signals utilizing singular value decomposition, then applying the defragmented information to a convolutional brain organization and a supporting vector machine for order. Using an optimization strategy with an objective function of precision and compression ratio [1].

For the real-time segmentation of heartbeats, Peimankar and Puthusserypady suggest a method of machine learning. The DENS-ECG technique joins a convolutional brain organization and a long momentary memory model to recognize the beginning, pinnacle, as well as offsetting of other heartbeat waves, including the P-wave, QRS complex, T-wave, and No wave (NW). The empirical results suggest that the consolidated CNN-LSTM model for ECG signal depiction is flexible and accurate [4].

The authors of [6] offer a new deep learning approach for detecting VA. The ECG impulses are first converted into visuals that have never been seen. These photographs are then standardized and used to prepare the profound learning models AlexNet, VGG-16, and Inception-v3. To prepare a model and recover profound information from unmistakable result layers, move learning is utilized. The elements are then intertwined utilizing a connection strategy, and the best highlights are picked utilizing a heuristic entropy computation technique. At long last, administered learning classifiers are used to

classify the features.

3. Methodology :

3.1 The MIT-BIH Database :

This study, Uses CNN Models in the classification of ECG signals with the MIT-BIH arrhythmia database, and the training and test datasets were generated.

In this paper, three ECG signals, Arrhythmias, NS, and CHF. A sum of 162 ECG signals has been investigated, 96 of them are utilized for arrhythmias, 30 for NS, and 36 for CHF. For arrhythmias data, the MIT-BIH Arrhythmias Database from Physio.Net is used. The MIT-BIH Arrhythmia Database has 48 half-hour extracts recording two-channel ambulatory ECGs from 47 people examined by the BIH Arrhythmia Laboratory. A sum of 96 of these signs is delegated Arrhythmia in the framework. The usual sinus rhythm wave is represented by the database below. The collection contains 18 long-term ECG recordings of individuals who were referred to Beth Israel Hospital in Boston Arrhythmia Laboratory (Beth Israel Deaconess Medical Center is now located in Boston, Massachusetts). There were no major arrhythmias in the subjects in this database, which included 5 boys between the ages of 26 and 45 and thirteen girls between the ages of 20 and 50. A sum of 30 signs is handled. The following database provides 36 CHF signals for the CHF signal. This information base contains long-haul ECG accounts from 15 patients with an extreme congestive cardiovascular breakdown (NYHA class 3–4) (11 males, ages 22-71-years, and four females, ages 54-63-years) [7]. Three of these signals are grouped together and classified. Figure 2 shows an example of ECG impulses indicating arrhythmias, CHF, and NSR rate.

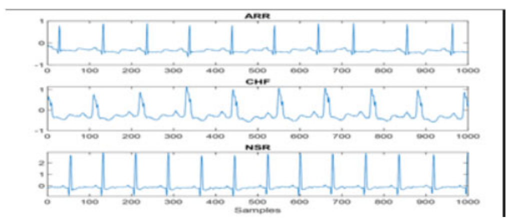

Figure 2: ECG signs from arrhythmias, CHF, and NSR rate

3.2 Convolution Neural Network [CNN]:

Include extraction and grouping are the two main components of a convolution neural network. The feature extraction component is in duty of obtaining useful characteristics from ECG signals autonomously, whereas the classification section is in charge of accurately classifying signals using the extracted features [8].

A convolution neural network (CNN) is composed of several layers [9]. Layers that are convolution, pooled, and completely linked are all included. Convolutional mathematical 9 operations are performed by the bulk of layers. Understanding the basics of CNN is required to comprehend this neural network

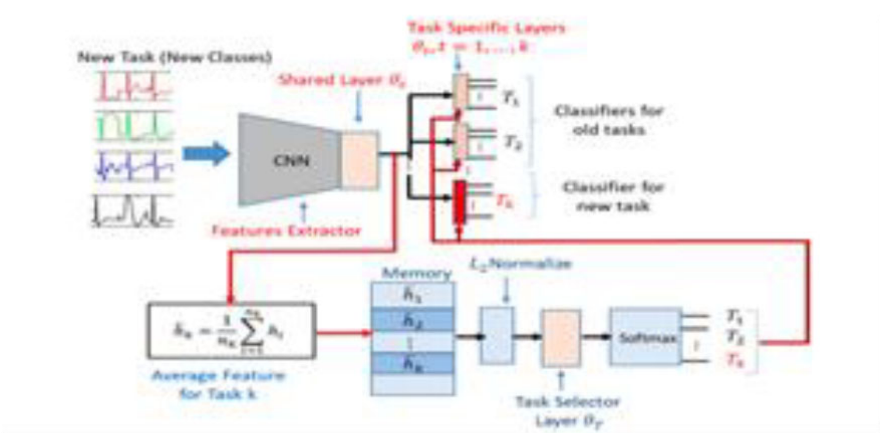

Figure 3: An outline of the fully convolutional CNN architecture for ECG classification learning without forgetting applications [6

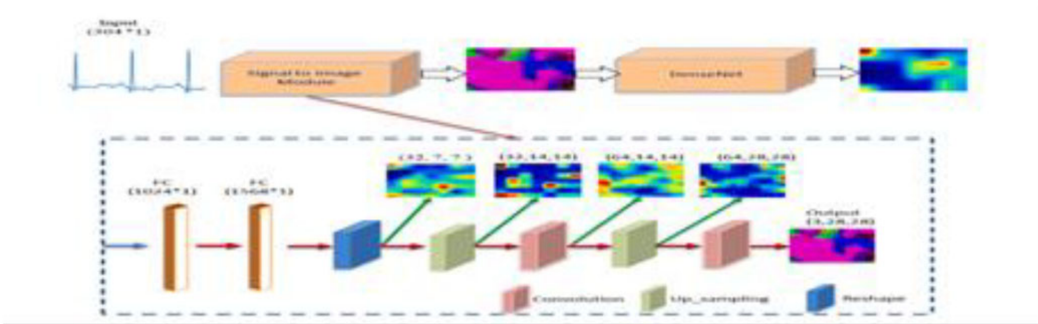

Figure 4: The CNN modules are used to transform an ECG cardiac signal into a picture [6]

3.3 Convolutional Neural Network algorithms

1. GoogLeNet

GoogleNet is famed as (Inception-V1) [7],[8]. The GoogleNet architecture introduced in 2014 (ILSVRC14) developed by researchers at Google, solved computer vision tasks such as image classification and object detection. It accomplished a top-5 error rate of 6.67%, This was very close to human-level performance [7]. where the major aim of this architecture was to reduce computational cost and obtain high accuracy [9].

2. DenseNet201

This structure was developed by Gao Huang, Zhuang Liu, Laurens van der Maaten, and Kilian Q. Weinberger in 2016, and DenseNet has won the CVPR 2017 Best Paper Award. DenseNet was reported to achieve the best performance with the least complexity, compared to ResNet. A DenseNet is a type of CNN that utilizes dense connections between layers, through Dense Blocks[10],[11], DenseNet needs lesser numbers of parameters than a conventional CNN because it does not learn redundant feature maps [12] DenseNet was created explicitly to address the vanishing gradient's impact on high-level neural networks' accuracy. Simply put, the information vanishes before it reaches its destination due to the longer path between the input and output layers [10].

DenseNets have many compelling advantages: they alleviate the vanishing gradient problem, strengthen feature propagation, encourage feature reuse, substantially decrease the number of variables, and it requires substantially fewer parameters and less computation to attain state-of-the-art performances [12].

3.4 Data Preprocessing

Because the suggested CNN model requires 2D data, designers must first convert (csv) data to 2D signal(images) by use Continuous wavelet transform (cwt) and the filter bank to plot the scalogram of the signal. The cwt function sets the time and frequency axes in the scalogram and creates a vector representing the sample times.

The first time use a filter bank to take the CWT of a signal, the wavelet filters are constructed to have the same data type as the signal.

which is performed using a design function that reads data, plot the appropriate image, resize it to be used as input to the appropriate model, and saves the image. Because the original signal is difficult to supplement, a two-dimensional signal is particularly significant in data augmentation.

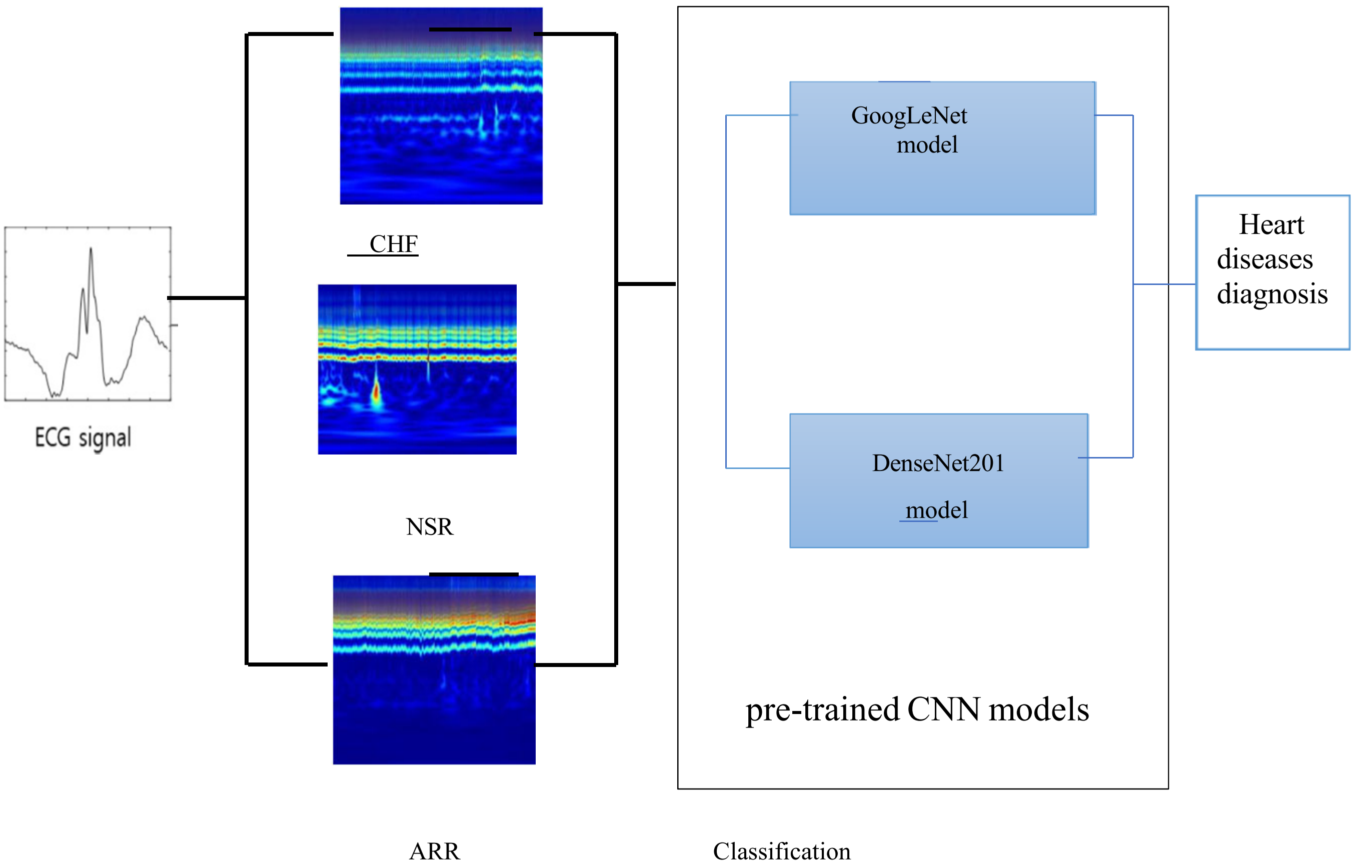

Figure 5: The Proposed methodology

3.5 Classification

ECG signal classification is split into 2 parts: feature extraction and classification. The signal's main critical characteristics are extracted in the feature extraction section. The categorization section aims to classify signals algorithm to extract features. The features are extracted to characterize the signals during feature extraction. These characteristics are a shorter set of values that describe the signal's attributes. Depending on the categorization needs, various aspects might be derived from the signals. The extracted signal characteristics are supplied into a decoder in order to make a judgment, i.e. to determine what category every signal belongs to.

The MIT-BIH ECG dataset, which is separated into train and test sets, is used to train and test the suggested models. Matlab R2020a is used to run the experiments on a core i7 2.9 GHz CPU with 16 GB RAM. The proposed approaches' performance is assessed using several measures including as accuracy, precession, sensitivity, and specificity

4. Result discussions

1. GoogLeNet : The most accurate performance for each class was obtained for the ARR class with 100% sensitivity, CHF with 50 %, and NSR with 100%.
Figure

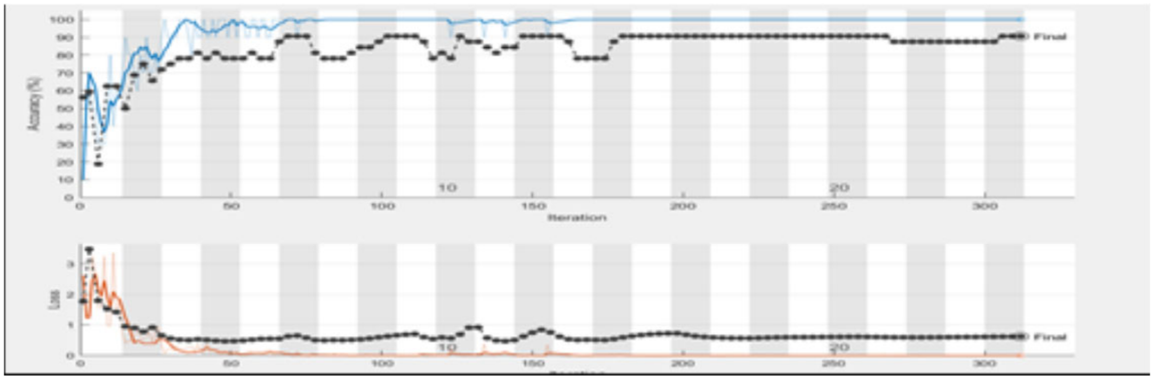

Figure 6: The relations between training and validation accuracy and loss of GoogLeNet

Table 1: Confusion matrix of GoogLeNet

	ARR	CHF	NSR
TP	19.00	3.00	7.00
FP	3.00	0.00	0.00
FN	0.00	3.00	0.00
TN	10.00	26.00	25.00

Table 2: result of GoogLeNet

Class	ARR	CHF	NSR
precision	0.86	1.00	1.00
sensitivity	1.00	0.50	1.00
specificity	0.77	1.00	1.00

GoogLeNet Accuracy is 91%

2. DenseNet201:

This approach has been compared with other reported ECG classification solutions. Experiment results show that our proposed classifier achieves outstanding classification accuracy: 100% classification accuracy. The proposed model's performance is better than most of the models in ARR, CHF, and NSR classification based on the same database. The proposed model has a significant performance improvement over the other networks in the same testing environment

Table 3: confusion matrix of DenseNet201

	ARR	CHF	NSR
TP	19.00	6.00	7.00
FP	0.00	0.00	0.00
FN	0.00	0.00	0.00
TN	13.00	26.00	25.00

Table 4: The main classification criteria for DenseNet201

	ARR	CHF	NSR
Precision	1.00	1.00	1.00
Sensitivity	1.00	1.00	1.00
Specificity	1.00	1.00	1.00

DenseNet201Accuracy is 100%

5. Comparison between CNN Approaches:

It is evident that DesneNet201 exhibits the highest accuracy of all the recent works to the best of our knowledge, which could be useful in developing a prototype that can automatically classify results into ARR, CHF, and NSR.

Table 5: The main classification Accuracy for CNN models.

CNN Model	Accuracy
GoogleNet	91%
DesneNet201	100%

From the above table and after a number of actual practical experiments, it was found that Densenet201 is better than the rest of the models and more accurate in the classification of ECG signals.

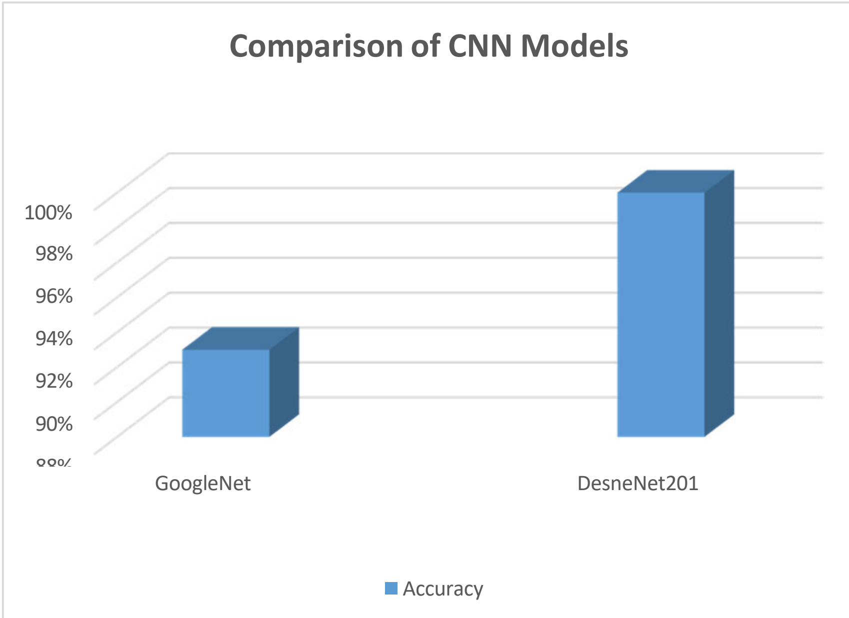

Figure 7: accuracy of all CNN Models

5. Conclusions:

To improve heart disease prediction and classification accuracy, this research offers a deep neural network-based categorization and prediction system and designed convolutional neural networks.

The key contribution of this study is that we use a two-dimensional convolutional neural network to increase classification accuracy, arrhythmias, NSR, and Congestive Heart Failure type waveforms in ECG signals were classified using these methods. The findings were evaluated using a confusion matrix and precision values. Then, divide the ECGs are included in both the training and testing sets. This allows us to precisely assess the model's performance when additional patients' ECG data is provided. The model structure's hyper-parameters are established through numerous experiments. The results of the experiments suggest that there two models GoogleNet and DenseNet201 have a classification accuracy of 91% and 100% respectively percent.

The suggested model is compared to other arrhythmia classifiers. The majority of the models that were compared used the same database perform worse than our proposed models.

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