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DEEP NEURAL NETWORK CLASSIFICATION OF ECG SIGNALS USING WAVELET TRANSFORM

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ABSTRACT

In this project, we propose a transfer learning approach for Arrhythmia Detection and Classification in Cross ECG Databases. This approach relies on a deep convolutional neural network (CNN) pretrained on an auxiliary domain (called ImageNet) with very large labelled images coupled with an additional network composed of fully connected layers. As the pretrained CNN accepts only RGB images as the input, we apply discrete wavelet transform (DWT) to the ECG signals. Then, we feed the resulting image-like representations as inputs into the pretrained CNN to generate the CNN features. Next, we train the additional fully connected network on the ECG labelled data represented by the CNN features in a supervised way by minimizing cross-entropy error with dropout regularization. The experiments reported in the MIT-BIH arrhythmia, the INCART and the SVDB databases show that the proposed method can achieve better results for the detection of ventricular ectopic beats (VEB) and supraventricular ectopic beats (SVEB) compared to state-of-the-art methods.

1. Introduction

The most common manifestation of heart disease in the clinic is persistent arrhythmia, and atrial fibrillation (AF) occurs more frequently in heart disease. The main hazard of atrial fibrillation is the increased risk of vascular embolism, which is one of the main causes of ischemic stroke. Atrial fibrillation is manifested in the disappearance of the sinus P wave in each lead, the shape and amplitude of the QRS wave are basically the same as sinus rhythm, and the R-R interval is absolutely unbalanced. The automatic analysis and classification system of electrocardiograms can greatly help doctors diagnose heart disease and is of great significance in improving medical efficiency, reducing medical costs and preventing heart disease.so for classification we use DWT (Discrete Wavelet Transform) in order to calculate the accuracy and compare the accuracy between them. For this classification we use pretrained networks in order to feed the CNN (Convolution Neural Network). Discrete Wavelet Transform

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(DWT) is used to decompose a signal into wavelets. The DWT is used to construct a time-frequency representation of a signal that offers very good time and frequency localization. The DWT is an excellent tool for mapping the changing properties of non-stationary signals. The DWT is also an ideal tool for determining whether or not a signal is stationary in a global sense. When a signal is judged non-stationary, the DWT can be used to identify stationary sections of the data stream. Discrete Wavelet Transform (DWT) is a technique to transform image pixels into wavelets, which are then used for wavelet-based compression and coding. A Convolution Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics.

LITERATURE SURVEY

Bioelectric signal of a cardiac nature registered in the Electrocardiogram (ECG), contains mostly noise originated by the electrocardiograph or by network interference, which can hardly be eliminated or reduced completely by using filters. One of the primary advantages of this procedure is its ease of implementation in a computer program. In fact, the networks of artificial neurons will be exploited in this memory for the recognition of certain cardiac pathologies (precisely cardiac arrhythmias) and their classifications. In our case, the neural networks are chosen as a model and their performances are reinforced by a multi-agent system. In this project, we have to work on a transfer learning approach for Arrhythmia Detection and Classification in cross ECG databases. This approach relies on a deep convolutional neural network (CNN) pretrained on an auxiliary domain with very large labelled images coupled with an additional network composed of fully connected layers. As the pretrained CNN accepts only RGB images as the input, we apply Discrete wavelet transform (DWT) to the ECG signals under analysis to generate an overcomplete time–frequency representation. Then, we feed the resulting imagelike representations as inputs into the pretrained CNN to generate the CNN features. Next, we train the neural network by the CNN features in a supervised way by minimizing cross-entropy error with dropout regularization and can be implemented by using Discrete Wavelet Transform (DWT). The experiments reported in the MIT-BIH arrhythmia, the INCART and the SVDB databases show that the proposed method can achieve better results for the detection of ventricular ectopic beats (VEB) and supraventricular ectopic beats (SVEB) compared to state-of-the-art methods. All the simulations can be done through MATLAB.

Mohamad M. Alrahhal et.al [1] proposed separation of ECG signals using the Continuous Wavelet Technique this method has the following attractive content: (1) transmits data from CNN built in a different domain from a computer view with large labeled images; (2) uses CWT to enable the ECG to sign the appropriate input into the network; and (3) also uses an effective AL strategy to configure an additional network placed above CNN by minimizing the intrusion error. Experiments performed outside of the nonGPU unit and in the three-dimensional ECG data (obtained under different acquisition conditions) include its ingenuity and ability to provide differentiated results compared to many other methods. Serkan Kiranyaz et.al [2] proposed a fast and accurate patientcentered (ECG) and monitoring system. “The flexible use of 1D Convolutional Neural Networks (CNNs). in this way. CNN is trained for a specific patient with specific training details, so the ability to extract a specific patient-specific feature can improve the functioning of the isolation. The fastest and most accurate signal of an ECG signal can be determined by a trained CNN. Once a dedicated CNN is trained for a particular patient, it can only be used to differentiate long-term ECG data distribution. Besides, the speed and efficiency of the computer is achieved, as long as CNN is dedicated to training each patient, it can only be used to separate his long ECG records. UMR Homaeinezhad et.al [3] proposed a supervised method with the desired speed of calculation and an acceptable accuracy of classification. The SVM algorithm is used as a method for arranging arrhythmias. ECG arrhythmia detection was performed using hybrid neuro-SVM-KNN separation with visual QRS signals for the image. In the proposed method, for the first time, ECG signal events were detected using a powerful wavebased algorithm. After that, each QRS circuit and its corresponding DWT were supposed to be visual images and each of them was divided into eight polar regions. Next, the curve length of each extracted section is calculated and used as part of the feature space.

Zhancheng Zhang et.al [4] proposed that a new diagnostic specialization method for cardiac separation and ECG data be introduced by the OvO integration method using a series of SVM binary classifiers. (MITBIH-AR) used to evaluate the selection of the proposed feature. Accepted ECG features include inter-beat and intra-beat intervals, amplitude morphology, spatial morphology and morphological distance. The test results show that the average accuracy of the proposed feature selection method is 86.66% . Wei Jiang et.al [5] proposed e-based neural networks (BbNNs) for custom separation of ECG cardiac pattern. Network structure and connectivity tools are developed using EA using evolution-based search operators and gradients. The flexibility adjustment scheme that demonstrates the operator's efficiency in building the right people produces higher durability compared to pre-determined standards. Performance tests using the MIT-BIH arrhythmia database show a sensitivity of 86.6% and a complete accuracy of 98.1% of VEB detection. With the SVEB acquisition, sensitivity was 50.6% and total accuracy was 96.6%. K. Devi Priya et.al [6] proposed various capture techniques tested on the sound ECG signal. The ECG signal was not removed using a variety of limitations such as hard, soft, SUFFERING, hybrid shrinkage and compared to a wilt based wiener filter. The path on the hard edge slides the signal, but false blips are visible on the output. A soft way to get rid of this problem. Reliable mitigation methods and hybrid methods for better signal reduction but do not provide MSE reduction. It is evident that when two wavelet operations have a slightly different filtering bank a better performance is obtained, as it emits all the lower SNR coefficients. When two wavelet functions have different filter banks with greater variability when the signal is diffused and does not provide better performance. Maxime Yochum et.al [7] proposed a new method based on the continuous modification of the defined wavelet to detect QRS, P and T waves. The results show the localization of the QRS, T and P waves into the ECG signal calculated with various indicators such as sensitivity and accuracy. It is a matter of sound signals, basic issues and magnitude and distractions. To improve this algorithm, a descriptive step that allows boundary areas (osets and offsets) for P, QRS, and T waves is proposed. Using 12 guidelines the ECG allows for good determination of complex areas in those cases. In this validation step, the calculation of quality indicators is based on the determination of the total and offsets of each complex on the ECG from the physician. Manu Thomas et.al [8] proposed a two-dimensional complex drug wavelet transform (DTCWT) procedure to exclude the automatic differentiation of cardiac arrhythmias. The feature set consists of complex wavelet coefficients extracted from the fourth and fifth scales DTCWT complex QRS signal decomposition in combination with four other factors (AC power, kurtosis, skewness and time information) extracted from a complex QRS signal. Experimental results show that the DTCWT-extracting process separates ECG beats with a total sensitivity of 94.64%, respectively when tested on more than five ECG beats of the MIT-BIH Arrhythmia database. Yakup Kutlua et.al [9] proposed feature extraction methods using high-order (HOS) statistics of wavelet pack (WPD) coefficients for the purpose of detecting automatic heartbeat.

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The proposed approach consists of three stages. First, wavelet package coefficients (WPC) are calculated for each type of ECG beat. After that, high WPC statistics are obtained. Finally, a set of acquired feature is used as an input separator, based on the k-NN algorithm. The proposed method uses WPD coefficients with high frequency resolution. The MIT-BIH arrhythmia database is used. The accuracy of the proposed system phase is measured with an average sensitivity of 90%, an average selection of 92% and an average specificity of 98%. Yingthawornsuk et.al [10] proposed Separation of ECG Signals using Modified Hjorth Descriptors. In signal processing, feature extraction, and feature classification of three standard ECG signals obtained from NSR, AF and CHF studies. Depending on the study results, the optimal segmentation scores can reach 95% with LS, RBF, ML and SVM dividers. The main advantages of using Hjorth's modified definitions are ease of feature detection and lower cost of use in algorithm usage. It can be concluded that the modified Hjorth definitions work in terms of the class-class discriminators and achieve high segmentation performance.

3 METHODOLOGY

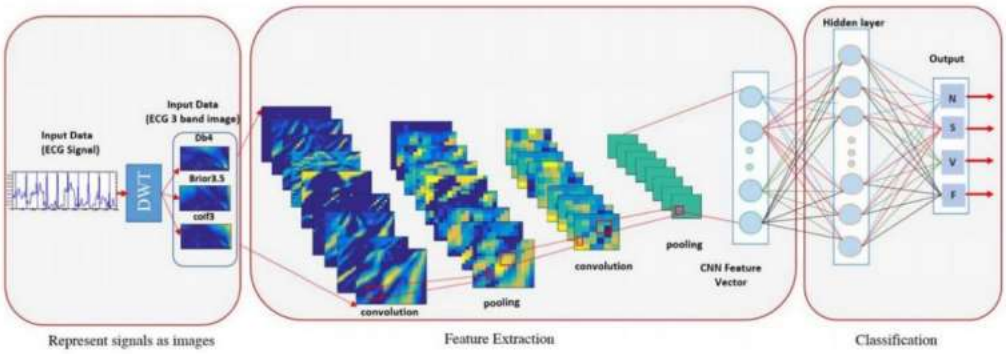

Fig 1 Block Diagram

ECG signals are taken as input Database as shown in fig 3.1. Input is given to Discrete Wavelet Transform (DWT). This DWT will convert the input data (1D signals) into corresponding 2D images.

4 FEATURE EXTRACTION:

A dataset can be viewed as a collection of data objects, which are often also called as records, points, vectors, patterns, events, cases, samples, observations, or entities. Data objects are described by a number of features that capture the basic characteristics of an object. such as the mass of a physical object or the time at which an event occurred, etc. Features are often called as variables, characteristics, fields, attributes or dimensions. Feature is an individual measurable property or characteristics of a phenomenon being observed. For instance, color, mileage and power can be considered as features of a car. There are different types of features that we can come across when we deal with data Images are given to pooling layer in order to extract the features like edges, contours etc. The layers we see in feature extraction are Convolution layer and Pooling layer.

CONVOLUTION LAYER:

The convolutional layers are capable of extracting different features from an image such as edges, textures, objects, and scenes. As pointed above, forgery is better captured around the boundary of forgery regions. Thus, the low-level features are critical to identify manipulated regions. The filters in convolutional layer will create feature maps that are connected to the local region of the previous layer.

POOLING LAYER:

The pooling layer is used for a down sampling operation after obtaining feature maps through convolution process. In classical CNN, convolution layers are followed by a subsampling layer. The size of effective maps is reduced by pooling layer, and some invariance features are introduced. The output of a max-pooling layer is given by the maximum activation over nonoverlapping regions, instead of averaging the inputs as in a classical subsampling layer. A bias is added to the resulting pooling and the output map is passed through the squashing function. In our network, a max-pooling layer with filter of size 2×2 is used to decrease the size of feature maps to 30×30 after C1 layer. Following the pooling layer (P2) is another pair of convolution and pooling layer with 64 kernels of size 3×3 and a filter of size 2×2. After the feature extraction the images are classified. The accuracy of the classified images can be calculated and observed. A confusion matrix will be displayed giving the information about how accurately the signals were classified.

5 Algorithm:

Step-1: Start

Step-2: collection of the ECG dataset.

Step-3: Data is given to Wavelet Transforms.

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Step-4: DWT will convert the dataset into image.

Step-5: Image is given to CNN for further classification.

Step-6: Further given to pretrained networks like ALEXNET and GOOGLENET.

Step-7: Accuracy is obtained using the formula.

$$Accuracy(\%) = \frac{TP + TN}{TP + TN + FP + FN} \times 100\%$$

Where

$T\ P$ indicates the number of true positive values, F

N indicates the number of true negative values

$T\ N$ indicates the number of true negative values and

$F\ P$ indicates the number of false positive values

Step-8: Results are compared.

Step-9: Analyzing the comparison results.

In the above algorithm step by step procedure of ECG signal classification is shown, obtained results are analyzed and compared. Comparison between ALEXNET and GOOGLENET is done according to the Accuracy obtained.

6 Flow Chart:

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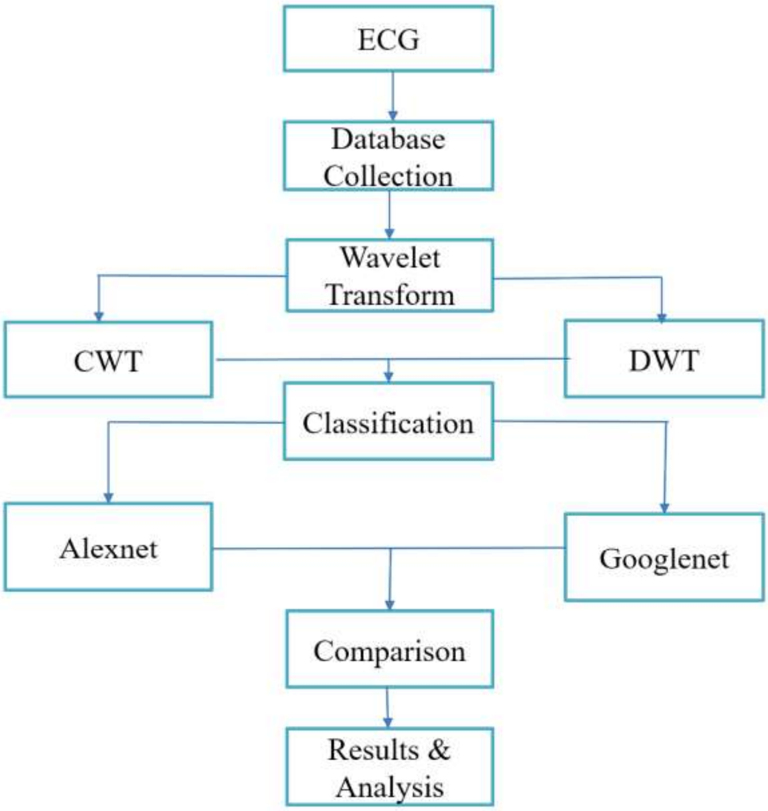

Fig 2 Flow Chart

Results

We have taken all raw data files from the PhysioBank ATM website. We have each recording of 65,536 samples. It can be broken into small signals of length 500 samples to increase the size of data base to make it appropriate to train a CNN. We just took 30 recordings of each type from 3 to have equal distribution. Each recording is broke to 10 pieces of length 500 samples. So, each category provide 300 (30x10) of size 500 samples & in total we have (900) (300+300+300) recordings. Out of 900, 750 signals are used for training and 150 will be used for testing.

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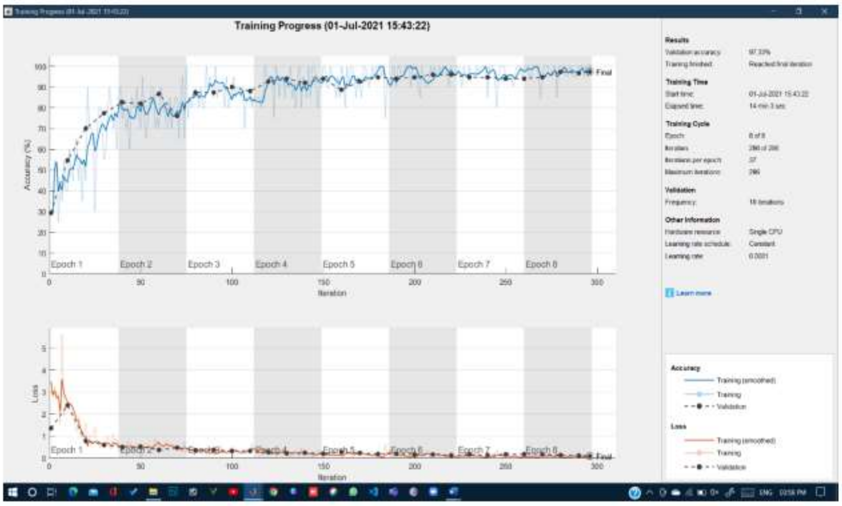

Fig 3 DWT Using ALEXNET

Fig 4 Confusion Matrix

Fig 5 DWT Using GOOGLENET

CONCLUSION:

we presented a method based on a CNN for the classification of ECG signals. Compared to the existing solutions, this method has the following attractive proprieties: (1) it transfers knowledge from a CNN pretrained on a different domain from computer vision (called ImageNet) with large labelled images; (2) it exploits the DWT to make the ECG signals suitable inputs for this network; and (3) it uses an efficient AL strategy to fine-tune the extra network placed on top of the CNN by minimizing the cross-entropy error with dropout regularization. Experiments carried out on a non-GPU unit and on three ECG cross-databases (obtained under different acquisition conditions) confirmed its efficiency and ability to provide improved classification results versus several other methods.

FUTURE SCOPE:

In ECG signal classification for determining the Accuracy of Diseases like ARR (Arrhythmia), CHF (Congestive Heart Failure) and NSR (Normal Sinus Rhythm) using DWT will give the more Accuracy of the Diseases.

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