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ECG signal analysis using continuous wavelet transformation and deep neural network

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Abstract - The objective of this research is to develop an algorithm that can identify and classify various electrocardiogram (ECG) data beat kinds. Using the Deep The neural network and the Continuous Wavelet Transform (CWT). The goal is to teach a CNN how to distinguish between ARR, CHF, and NSR. Identification and treatment of arrhythmias can reduce the risk of mortality from cardiovascular disease (CVD). The electrocardiogram (ECG) is examined beat by beat in clinical practise to make the diagnosis, but this is frequently time-consuming and challenging. In this study, we describe an automated method for classifying ECGs based on Continuous Wavelet Transform (CWT) and Convolutional Neural Network (CNN) (CNN). While CNN is used to extract features from the 2D-scalogram created from the time-frequency components stated above, CWT is used to break down ECG signals into discrete time-frequency components. Four RR interval characteristics are collected, combined with CNN features, and then input into a fully connected layer for ECG classification because the surrounding R peak interval, also known as the RR interval, is crucial for identifying arrhythmia. In the MITBIH arrhythmia database, our method achieves an overall performance of 70.75%, 67.47%, 68.76%, and 98.74% for positive predictive value, sensitivity, F1-score, and accuracy, respectively. In comparison to earlier methods, our technique raises the overall F1- score by 4.7516.85%.

Key Words: Cardiovascular disease; Deep neural network; ECG signal classification; ARR; CHF; NSR

1. INTRODUCTION

An irregular heartbeat known as an arrhythmia is one of the main reasons why people die from cardiovascular disease (CVD). While the majority of arrhythmias are benign, some can be deadly. For instance, atrial fibrillation can cause cardiac arrest and strokes. It needs to be treated right away because it is so dangerous. The World Health Organization (WHO) estimates that 17.5 million deaths worldwide were attributable to CVD in 2012. By 2030, 23 million fatalities from CVD are expected to have occurred. Additionally, treatments for CVD, including medical care, are prohibitively expensive. Over US $3.8 trillion is expected to be spent in low- and middle-income countries between 2011 and 2025. For this goal, researchers have developed a system that automatically categorises heartbeats in ECG measurements. Most methods involve categorization and feature extraction. RR interval characteristics and heartbeat morphology are frequently used. For categorization, a variety of methods were used, including continuous wavelet transformation, deep neural networks, and artificial neural networks (ANNs). Even though these methods have a high level of effectiveness, different people have ECG waves with very diverse morphologies, and even the same patient can have different ECG waves at different times. The fixed features of these methods are insufficient for consistently differentiating arrhythmia in different individuals. The rapid advancement of deep neural networks has led to a recent rise in popularity for methods based on deep learning. Deep learning can automatically derive discriminant properties from training data as a representation learning strategy. Numerous studies indicate that deep learning-based methods for classifying ECGs may be able to extract more abstract traits and eliminate patient-specific discrepancies. Because the ECG signal contains so many different types of frequencies, it will be challenging to categorise the different signals of the ECG, which will be made even more challenging if we utilise straightforward deep neural networking for the extraction. Shifting the ECG signal to time-frequency domain is one easily imaginable way to lessen the effects of aliasing of different frequency components. Two well-liked time frequency methods are Wavelet Transform (WT) and Short-Temporal Fourier Transform (STFT). Although STFT served as inspiration for WT, WT has the ability to provide both high frequency resolution and low time resolution at low frequencies, as well as high time resolution and low frequency resolution at high frequencies. WT typically performs better in time-frequency domain analysis than STFT. Using the Continuous Wavelet Transform (CWT), which is a WT with a continuous wavelet function, and the Convolutional Neural Network (CNN), we develop an automatic ECG categorization method. CNN is a deep learning tool that has been used for categorising images and successfully mimics the human visual system. The ECG heartbeat signal is converted to the time-frequency domain using the CWT, and features are extracted from the 2D scalogram created from the time-frequency components using CNN. The method combines CNN's visual feature extraction capabilities with CWT's expertise in multidimensional signal processing. To fully utilise all of the data for ECG classification, the RR interval characteristics are also obtained and fused into our CNN.

2. LITERATURE REVIEW

Over the past 20 years, numerous automatic ECG categorization techniques have been put out. I therefore opt for the journal that uses the CNN neural network to distinguish between the various types of ECG readings.

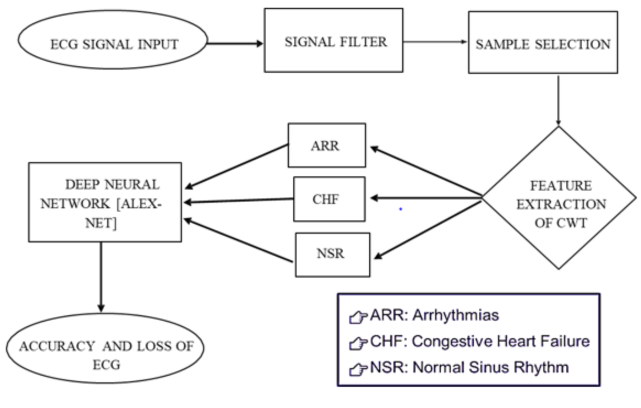


Figure 1: ECG classification flow diagram

2.1 ECG-SIGNAL CLASSIFICATION

Arrhythmia There are several forms of ECG signals, and in this study, we have mostly used the following ECG signals for categorization.

ARR stands for arrhythmias.

CHF stands for Congestive Heart Failure.

NSR stands for Normal Sinus Rhythm.

2.1.1 Arrhythmias

A problem with the rate or rhythm of the heartbeat is known as an arrhythmia. The heart will beat irregularly, too rapidly, or too slowly as a result of arrhythmias. The disease known as tachycardia causes the heart to beat too fast.

2.1.2 Congestive heart failure

Bradycardia is a condition where the heart beats too slowly. Congestive heart failure can result in heart failure. The heart cannot efficiently fill or pump blood (systolic) (diastolic). Symptoms include shortness of breath, fatigue, and swollen legs. having a rapid heartbeat Less salt may be consumed as a treatment.

2.1.3 Normal sinus rhythm

using prescription medication and limiting fluid intake In In some circumstances, a pacemaker or defibrillator may be placed. The term "normal sinus rhythm" (NSR) refers to this beat. rhythm characterising the average heartbeat of a healthy human being that comes from the sinus node. The NSR % is typically constant, but it can change depending on the autonomic inputs that the sinus node receives. Therefore, we previously used all three ECG signal kinds. We previously utilised CWT to classify them and determine their correctness. using a deep neural network as a tool.

Using an electrocardiogram (ECG), arrhythmias can be identified (ARR). It involves checking the pulse and the attitude. The clinical illness known as congestive heart failure (CHF) occurs when the heart is unable to pump blood at the rate required by the body's using tissues or when the heart can only do so with a height in filling weight. When referring to a specific type of sinus rhythm, NSR used to mean that all other ECG readings fell within the typical range of the breaking point, as depicted in the diagram.

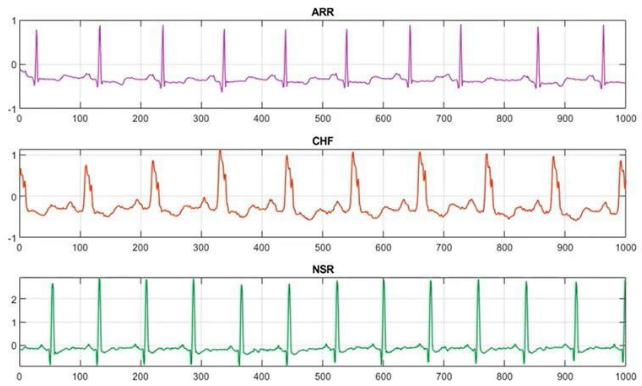


Figure 2: Arrhythmia, CHF, normal ECG signals

2.2 CONTINUOUS WAVELET TRANSFORM

The continuous wavelet transform is a signal processing and mathematics technique that is frequently used for image compression, denoising, and other similar tasks. It is also used in many other fields, such as solving partial differential equations, financial time series analysis, and biomedical signal processing, which includes ECG and EEG analysis. The input layer of the convolutional neural network receives coefficients right away as a "image," creating a "Transfer learning" scenario. For this task, we only used Mortlet Wavelet.

2.3 DEEP NEURAL NETWORK

Many different applications have made use of deep neural networks. Natural language processing and pattern recognition are two examples. processing and computer-based learning Machine learning has provided enormous benefits for decades prior to now. examples of how this has an impact on our daily lives include effective web search, self-driving automobiles, computer vision, and others Understanding optical characteristics Particularly deep neural networks have developed into effective machine learning tools. both machine learning and artificial intelligence A multi-layer artificial neural network is referred to as a large neural network (DNN) (ANN). between the input and output layers are further layers.

The success of deep neural networks has led to significant advances, such as a 30% reduction in word error rates in speech recognition over conventional methods (the largest gain in 20 years) or a radically lower error rate in an image recognition competition since 2011 (from 26% to 3.5%, compared to 5% for humans). In order to analyse photos of varied signals, we therefore use the "ALEX" neural network in this research.

2.4 ALEXA NEURLA NETWORK

One of the large-scale image net visual recognition networks, the Alex neural network, was utilised to recognise every distinct picture with a range of frequencies. There are eight layers of parameters in the Alexnet that can be taught. Five layers make up the model; the first is a max pooling layer, followed by three fully connected layers. All of these layers, with the exception of the output layer, use Relu activation. They found that the training process was roughly six times faster when the relu was used as an activation function. To prevent overfitting, they also used dropout layers in their model. The Image Net dataset is used to train the model as well. About 14 million images from a thousand distinct classifications are included in the Image Net dataset. As a result, we chose this variant of the Alex neural network to analyse the various types of ECG data because it had all the characteristics of the Alex neural network.

There are three types of neural networks that are often employed in all of them:

A. Multi-Layer Perceptrons (MLP);

B. Convolutional Neural Networks (CNN)

C. Recurrent Neural Networks (RNN)

A. Multiple-Neural network

A A feed forward artificial neural network is called a multilayer perceptron (MLP) (ANN). An MLP has an input layer, a hidden layer, and an output layer as its minimum number of node layers. All nodes—aside from the input nodes—are neurons with nonlinear activation functions. The bulk of developers utilise this neural network because it is one of the best ones.

B. Convolutional neural network

An artificial neural network called a convolutional neural network (CNN) is designed specifically to analyse pixel input during image recognition and processing. CNNs are powerful artificial intelligence (AI) systems that recognise images and videos using deep learning in addition to recommender systems and natural language processing (NLP). A multilayer perceptron-like technique used by CNNs has been tuned for reduced processing requirements.

Input, output, and a hidden layer with several convolutional, pooling, fully connected, and normalising layers make up a CNN's three layers. A significantly more efficient system is produced by removing restrictions and increasing image processing efficiency.

C. Recurrent Neural Networks

Recurrent neural networks (RNN) are the most advanced technique for sequential data and are used by Google voice search and Apple's Siri. It is the first algorithm that, because of its internal memory, remembers its input, making it perfect for sequential data machine learning applications. One of the algorithms responsible for the phenomenal advancements in deep learning over the past few years is this one. In this article, we'll discuss the principles of recurrent neural networks' operation as well as their main drawbacks and solutions.

3. METHODOLOGY

This project's primary objective was to categorise the various ECG signal types using continuous wavelet transformation [CWT]. To do this, we first used to generate the final waveform of all the different ECG signal types, which was primarily used to indicate the "efficiency" and "accuracy" of the various ECG signals.

ECG Signals to Image conversion using CWT

We transfer the ECG signal to the timefrequency domain to facilitate feature extraction because it consists of discrete frequency components. The most popular time-frequency analysis tool is CWT, which employs a set of wavelet functions to deconstruct a signal in the time-frequency domain. Therefore, we used the CWT to get the 2D-scalogram waveform made up of various ECG signals. Therefore, in this instance, the CWT is primarily utilised to generate the following characteristics, which are then used to categorise the various kinds of ECG signals. The Wavelet "Analytic Morlet (amor)" is what we primarily use. Wavelets having one-sided spectra and complex time values are known as analytical wavelets. When creating a timefrequency-analysis with the CWT, these wavelets are a great option. 12 wavelet band-pass filters are used by CWT for each octave (12 voices per octave).

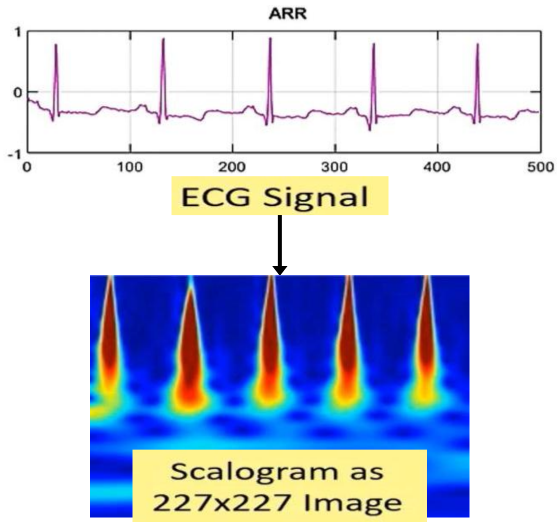


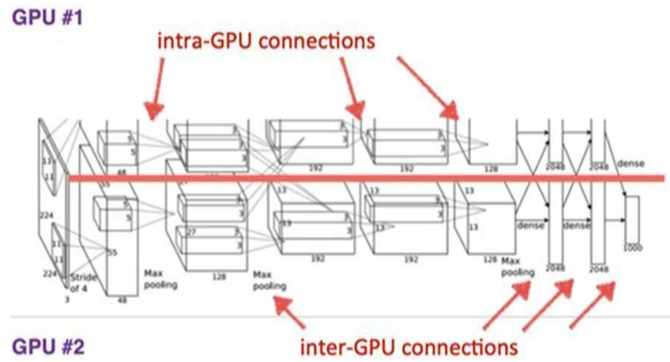
Figure 3: CWT of ECG signal

Then, utilising all of the CWT's properties, we created scologram images of each ECG signal stored in the database. As a result, each 1D signal from the ECG signals is converted into a CWT scalogram using the CWT, and each scalogram is represented by a color-map of a jet of 128 colours. After conversion, we received 900 separate 2d-scalogram images of various ECG signals, such as ARR, CHF, and NSR, which we used to identify them by creating various folders for each type of ECG signal.

a. ECG signal classification using neural network

A neural network having more than two layers and a certain level of complexity is referred to as a deep neural network. Deep neural networks use sophisticated mathematical models to handle data in complex ways. As a result, we were able to evaluate the accuracy of all the various neural network types that were present in the ECG database using the "ALEX" neural network. Alex Krizhevsky developed the deep neural network known as Alex Net. It was developed to classify images for the ImageNet LSVRC2010 competition, and it produced ground-breaking outcomes. Additionally, it worked with a variety of GPUs.

Compared to earlier CNNs used for computer vision tasks, Alex Net was significantly larger. It has 650,000 neurons and 60 million parameters, and training on two GTX 580 3GB GPUs requires five to six days. Today's faster GPUs can execute even more complex CNNs extremely well, even on very large datasets. Interesting visual properties are extracted using multiple convolutional kernels. A single convolutional layer often has many kernels of the same size.



Following the first two Convolutional layers, the next Overlapping Max Pooling layers are added. Direct coupling exists between the third, fourth, and fifth convolutional layers. The Overlapping Max Pooling layer, whose output is routed through a series of two fully connected layers, follows the fifth convolutional layer. The 1000 class label Softmax classifier receives input from the second fully connected layer.

As a result, every operation that has been explained has been carried out using an Alex neural network. We used this form of Alex net for ECG signals to determine the correctness of the various types of ECG signals images that are included in the database. In order to produce what is the certain accuracy of all ECG signals present, the alex net is used to receive photographs as input. As a result, it requires 900 photographs of various ECG signals. This helps people determine whether or not the ECG signals are good.

4. RESULTS

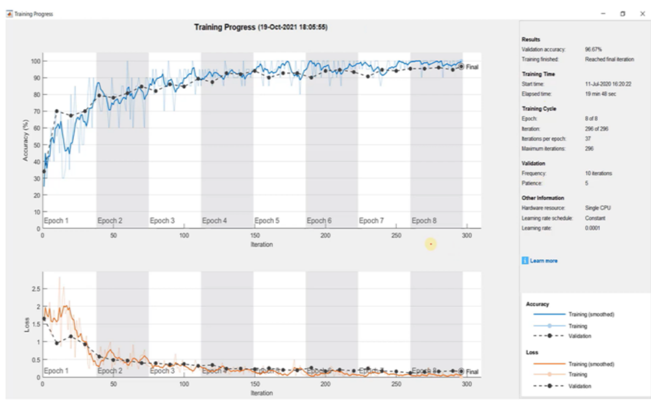


FIGURE 4 .Accuracy and loss of the ECG signal

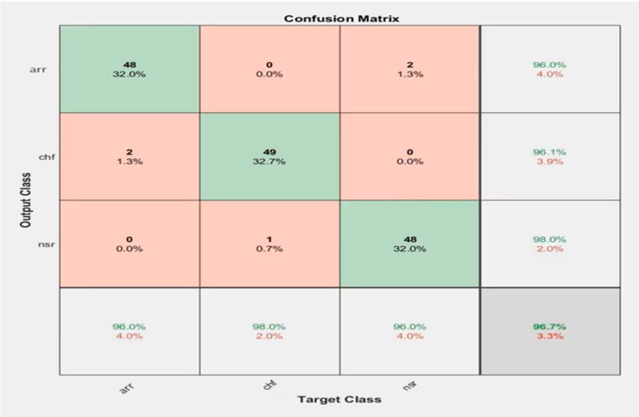


FIGURE.5 Confusion Matrix

4.1 ACCURACY MEASUREMENT

Using an electrocardiogram (ECG), arrhythmias can be identified (ARR). It involves checking the pulse and the attitude. The clinical illness known as congestive heart failure (CHF) occurs when the heart is unable to pump blood at the rate required by the body's using tissues or when the heart can only do so with a height in filling weight. A specific type of sinus rhythm known as NSR is one in which all other ECG readings remain within predetermined typical breaking limits.

4.2 TRAINING PROGRESS OF THE SIGNAL

Therefore, we used to predict them using the 900 different types of ECG images that are used to provide this much accuracy. In this, 750 images are primarily taken into account for training and 150 images are taken into account for testing. We also used to have a confusion matrix in which we used to have a separate accuracy value for the various ECG signals and we used to calculate the error.

5. CONCLUSION

We developed a special ECG classification technique based on CWT and a deep neural network. The ECG heartbeat signal is first converted into the timefrequency domain using CWT to prevent the effects of aliasing of separate frequency components. Then, features are recovered from a decomposed time-frequency scalogram using Alexnet. The strategy completely takes advantage of CWT's advantages in multidimensional signal processing and alexnet's advantages in image recognition. It was put to the test on the MITBIH arrhythmia database using the inter-patient paradigm. Due to its extremely accurate ECG categorization, our method has the potential to be used as a clinical additional diagnostic tool. In general, early detection of ARR, CHF, and NSR is essential because they are key contributors to cardiovascular disease. After a thorough early diagnosis, effective therapy, such as vagal stimulation or medications, can reduce arrhythmia and avoid cardiovascular disease.

However, there are some other neural networks that provide greater efficiency, so we may enhance with the help of the other neural networks to provide even higher accuracy. Despite the fact that our technique achieves high overall performance, in this case, we have been using deep neural networks like Alexnet to provide the most accuracy. In general, this can be made better with more annotated ECG data. But classifying ECG heartbeats is expensive and time-consuming. Nowadays, there are many freely accessible unlabeled ECG databases, and the use of unsupervised learning techniques like auto encoder may help to further improve the performance of the F class in a practical way. We'll give it another shot later.

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