Cardiac Arrhythmia Detection using Dual Tree Wavelet Transform and Convolutional Neural Network

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Cardiac Arrhythmia detection using dual tree wavelet transform and Convolutional Neural Network

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Abstract

The non-stationary ECG signals are used as a key tools in screening coronary diseases. ECG recording is collected from millions of cardiac cells' and depolarization and re-polarization conducted in a synchronized manner as: The P-wave occurs first, followed by the QRS-complex and the T-wave, which will repeat in each beat. The signal is altered in a cardiac beat period for different heart conditions. This change can be observed in order to diagnose the patient's heart status. There are life-threatening (critical) and non-life - threatening (noncritical) arrhythmia (abnormal Heart). Critical arrhythmia gives little time for surgery, whereas non-critical needs additional life-saving care. Simple naked eye diagnosis can mislead the detection. At that point, Computer Assisted Diagnosis (CAD) is therefore required. In this paper Dual Tree Wavelet Transform (DTWT) used as a feature extraction technique along with Convolution Neural Network (CNN) to detect abnormal Heart. The findings of this research and associated studies are without any cumbersome artificial environments. The CAD method proposed has high generalizability; it can help doctors efficiently identify diseases and decrease misdiagnosis.

May 24, 2021

Keywords: Bundle Branch Block; Dual-Tree Wavelet Transform; Convolutional Neural Network classifier; ECG; Myocardial Infarction; Atrial Fibrillation.

1. Introduction

The chaotic, low voltage, and non-invasive signal is an electrocardiogram (ECG). Due to variations, ECG is noisy and artifacts occur during their acquisition by pasting electrodes at defined locations. These deviations and artifacts occur in the current carrying cables, muscle artifacts, body motions, worst electrode consistency, etc, and also due to electromagnetic contamination. The ECG is a visual recording of the electrical potential produced by the heart's pumping action. The depolarization and repolarization of the SA node followed by the depolarization and repolarization of the AV node is nothing but a pumping operation. Today, since it reveals vital clinical knowledge, ECG is the most promising heart diagnostic method in the world. It diagnoses the ECG's rhythmic episodes, and if the patient has any heart failure, further arrhythmias are listed. Arrhythmia is caused by heart muscle injury, diabetes, tobacco use, low and high respiration, blood pressure, etc. There are life-threatening (critical) and non-life - threatening (non-critical) arrhythmias. Critical arrhythmias do not give any time for surgery, whereas noncritical requires special care to save life.

Simple diagnosis using naked eye may mislead the detection. Therefore, Computer aided diagnosis (CAD) is required at that stage. Computers in the field of ECG signal interpretation have also enhanced the diagnosis of the critical health (43), (45). The ECG displays and records electrical activity of the heart using electrodes pasted on the skin surface of the body. It is the depolarization and repolarisation of the heart tissue, which generates a potential difference to examine. This cycle begins with the activation of the SA node, the heart's pacemaker, which produces an electrical impulse that sets off a chain of electrical events in the heart. Normal phenomena are noted by the electrodes, and variations in the ECG signal's wave portion are reflected. P-wave component indicates atrial depolarization, QRS complicated wave component indicates ventricular depolarization, ST slope indicates blood flow in the body, and T wave component indicates ventricular repolarization are all common components of an ECG signal. Identification of diseases from ECG signal is done with rhythm, measure heart rate and QRS duration. The R-wave peak classification is much essential in automatic signal classification, especially in critical conditions and cardiac abnormalities. Many coronary heart diseases can be detected by analysing ECG signal. In this paper three different diseases are identified, namely AF, MI and BBB (3).

1.1. Atrial Fibrillation

Atrial fibrillation is the most severe cause of Supra-ventricular tachycardia. That occurs as unregulated 'forces' of electric signals travel across the atria from the sinus node instead of standard regulated signals. Such unregulated impulses contribute to muscle fibers in the atria contracting out of time to fibrillate. Any of this signals enter the ventricles and induce a fast and erratic heartbeat. The heart does not move normally or work as it should when it is in atria fibrilla-

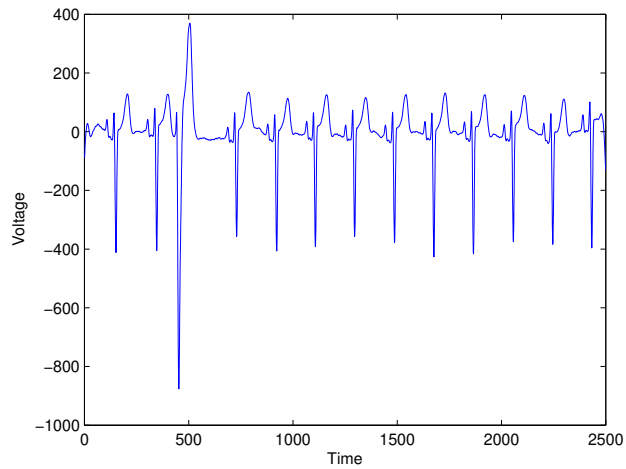

Figure 1: AF signal

tion. Atrial fibrillation may result in rhythm fluttering, erratic pulse, chest pain, or pressure, fatigue, and dizziness. The likelihood of stroke can also increase from auric fibrillation because atria-trapped blood can coagulate. Such coagulations can break loose from the heart and move into the bloodstream, triggering a stroke, into the brain. Figure 1 demonstrates following morphological shifts found in ECG, unsteady signals rather than P waves (f waves).

1.2. Myocardial Infarction

MI (5), (10) is a dangerous condition which occurs when blood flows unexpectedly to the heart muscle, causing tissue damage. A cardiac attack or myocardial infarction is a medical emergency. A blood clot usually happens where a MI prevents cardiac movement. The tissue lacks nutrients and fails without oxygen. Tension and/or stomach, throat, back and arms discomfort, and exhaustion, light-headedness, irregular pulse and anxiety are the major signs. The atypical signs in women are more common than with males. On ECG, high peaked T waves (or hyperacute T waves), then ST eye elevation may be detected, and then T waves negative and gradually Q waves pathological will evolve. The ST height (Type 1) and ST dipression

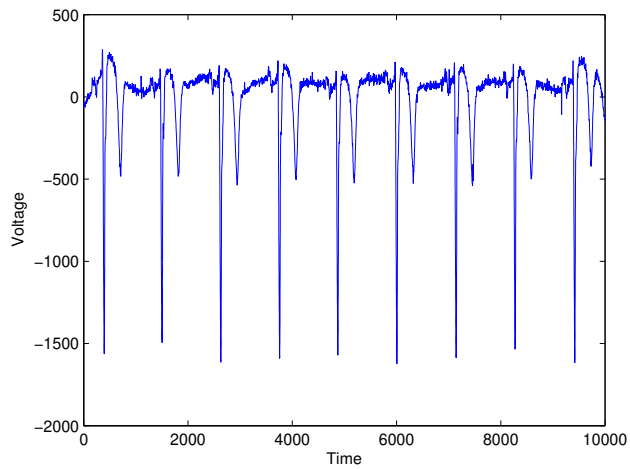

Figure 2: Myocardial Infarction signal

(Type 2) of two separate forms of MI can be detected from ECG. MI-2 signal in Figure 2 and the morphological adjustments of form 2 MI are seen.

1.3. Bundle Branch Block

The electrical motion of the heart begins at the Sino-atrial junction (the typical pacemaker of the heart), which is arranged in the upper right chamber. Next, the electrical pulse moves across the left and right atria and sums up at the atrioventricular (AV) node. The electric pulse drive goes down to

the bundle from the AV point, and partitions into the divisions of the right and left bundle. Finally, the divisions spread out into a large number of Purkinje fibres, interdigitating with individual cardiovascular myocytes thus accounting for the ventricles' rapid, synchronized, and synchronous physiological depolarization.

BBB normally allows the QRS complex to stretch and can shift the electrical axis of the heart slightly on one side. In the BBB condition of the heart, the length of the QRS complex on the ECG is greater than 120 ms. The ECG would display a terminal R wave in lead V1 and a slurred S wave in lead I. LBBB spans the entire QRS and shifts the electrical axis of the core to one side for most of the time. Reasonable T wave dipression is another normal finding for BBB. The T wave of the QRS complex would be redirected inversely to terminal avoidance. Cardiovascular dyssynchrony may be prompted by the left block. Around the same moment, the occurrence of left and right blocks adds up to AV block prompts.The variations in BBB signals are depicted in Figures 3 and 4.

The main steps in the ECG signal classification are ((i) Preprocessing; ii) feature extraction; iii) classification) as represented in Figure 5. Feature extraction step plays a main role in the classification of arrhythmia. Different feature extraction methods available in literature study due to the accessibility of information with lager number of variables (features). Using the Physionet database, recent spectral estimation-based feature extraction approaches, such as Continuous Wavelet Transform (CWT), Discrete

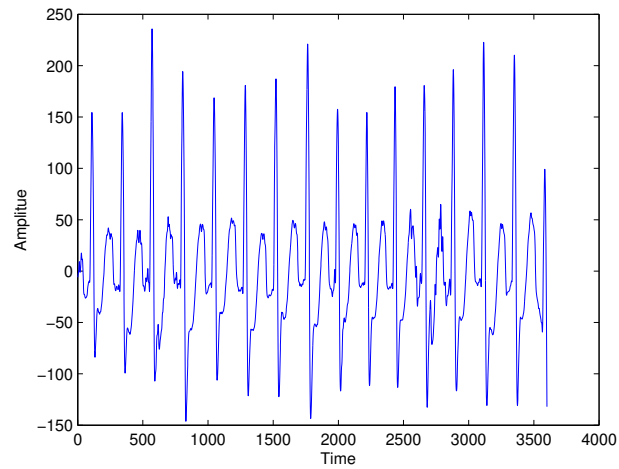

Figure 3: Left Bundle Branch Block

Wavelet Transform (DWT), Magnitude Squared Coherence (MSC), and Wavelet Coherence (WTC) (44), yielded a wide feature set. In this paper we have used DTWT as a feature extraction technique as it furnish performance over the standard wavelet transform for signal, image and video processing. The DTWT is realized using two different filter banks. To implement this transform we cannot randomly select the two filters (scaling, wavelet) in two separate trees as shown Figure 6. The scaling and wavelet (low pass (ho), high pass (h1)) of upper filter bank should generate hilbert transform of lower filters (go,g1). Hence approximately analytic complex-valued filters (scaling and wavelet) are generated from the two trees.

For signal processing, multiple transforms have been proposed: (37), (38). For such research, the option of signal transforms is typ-

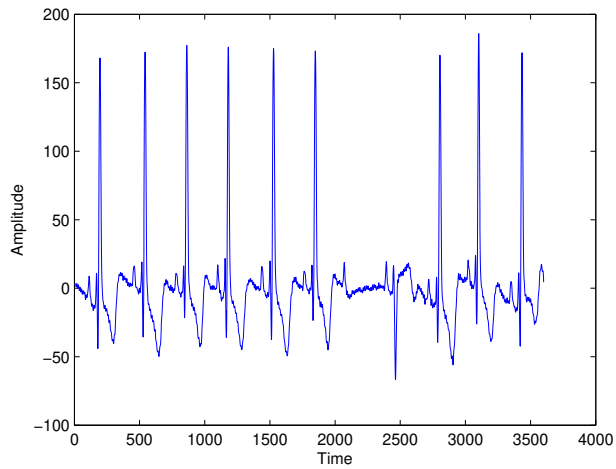

Figure 4: Right Bundle Branch Block

ically attributed to certain useful characteristics that these transforms provide, including their compact signal representation, reversibility, the availability of fast computer computer models, the capacity to independently interpret signals at each frequency, among others. Feature separation technique commonly used nowadays is the WT, has many applications such as (39), de-noising (40), feature extraction (41), (42), a time-frequency transformation.

Wavelet transforms express feature of signal in both frequency and time domain view. WT has a disadvantage, as more additional sort out is required to distinguish features that most important. Feature optimization techniques include independent component analysis, principal component analysis and linear discriminant analysis. The details to be added to the classifier to separate these characteristics from their distinct disease groups with each of these machine learning feature extraction algorithms. Bal et al (28) utilized complex dual tree wavelet transform to remove noise in optical micoscopy images. Sudarshan et al (30) extracted features using dual tree complex wavelets transform then classified these features using different classifiers. Accuracy for detection of congestive heart failure using this method was high. Thomas et al (31) demonstrated DTWT with four other features to detect five cardic arrhythmias, then classified using neural network. The performance DTWT was compared with WT. Mishu et al. (34) utilized DTWT to denoise ECG signals collected from MIT/BIH database.

2. Preprocessing of ECG signal

The information was obtained from the Physionet database. Sinus rhythm (N), AF, MI, LBBB, and RBBB are examples of ECG signals from the Physionet dtabase, and they refer to the files in Table 1.

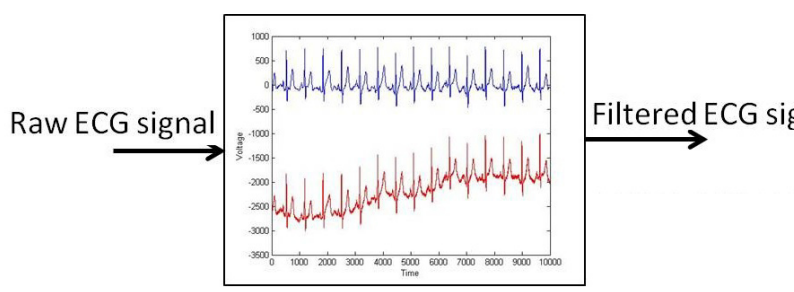

Figure 5: ECG pre-processing flow diagram

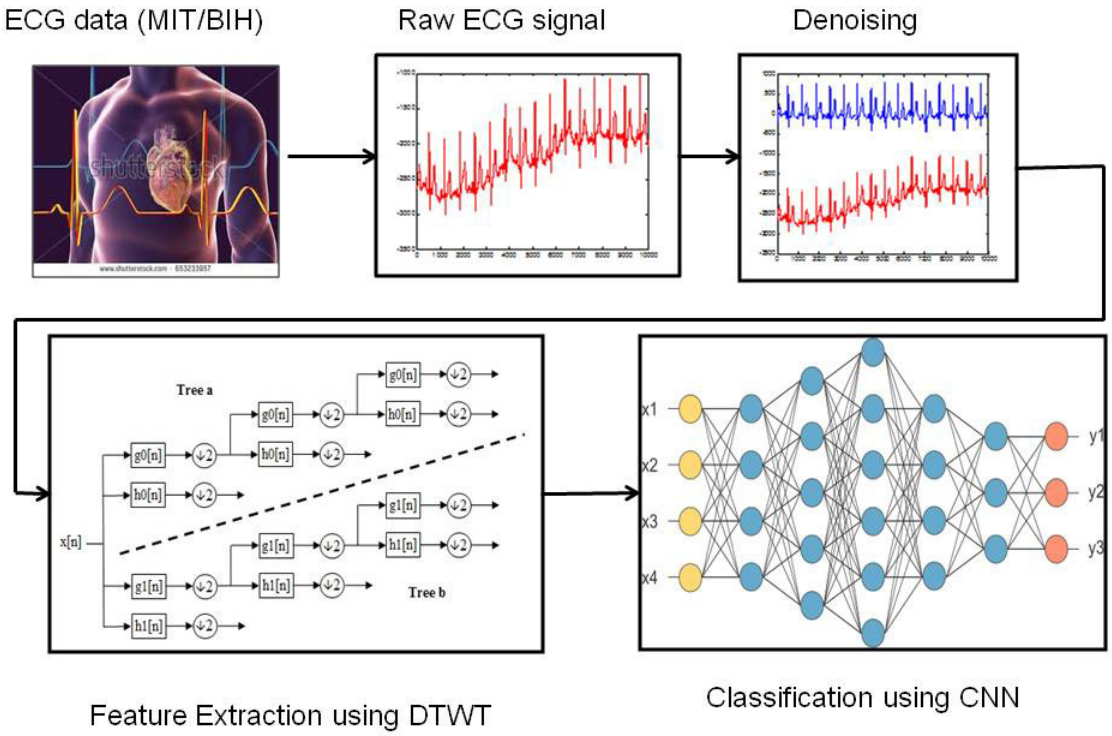

Figure 6: Classification flow diagram

Table 1: **Data-base from MIT-BIH**

Normal-Data	AF-Data	MI Data	LBBB	RBBB
16265,16272,16273,	04015,04043,04048,	s0043lre,s0088lre	109	118
16420,16483,16539,	04126,04746,04908,	s0100lre,s0235lre	111	124
16773,1676,16795,	04936,0501,05121,	s0242lre,s0386lre	207	207
17052,17453,18177,	05261,04426,0645,	s0559lre		
18184,19088,19090,	05261,04426,0645,			
19103,19140,19830.	06995,07162,07859,			
100,101,103,106	0787,07910,08215			
109,111,118,123	08219,0837,08405			
124,127, s0301lre,	08434,08455.			
s0303lre, s0306lre,				
s0311lre, s0472lre,				
s0469lre				

3. Feature Exraction

3.1. Dual Tree Wavelet Transform

Discrete Wavelet Transform (DWT) (14) was recently modified to provide additional enhancements such as :
i) Directionally selective at higher dimensions
ii) Shift invariant
iii)Rotational In-variance
The traditional Dual tree wavelet transform makes the use of two real DWTs parallel to process the input data. The upper DWT computes the real component value, whereas the lower DWT computes the imaginary part, collectively combined together to form a complex WT. The Dual tree transform gives a key way to find out the solution for shift-invariant and directional selectivity problem for signals, has proven somewhat disappointing in processing complex signals like music, speech and radar of higher dimensions. To avoid these problems, the complex wavelets was introduced to provide additional potential improvement. Dual tree wavelet transform produces real (R) and imaginary (I) parts in six sub bands directed in $\pm 15^o$, $\pm 45^o$, and $\pm 75^o$. In $h_i(n)$ and $g_i(n)$ are the fitters in stage 1. where 2 wavelets g,1(t)and h,1(t)generates an approximate Hilbert transform pair, g2(t)and h2(t) likewise. This is to say that the decomposition f(t) by utilizing the dual tree WT

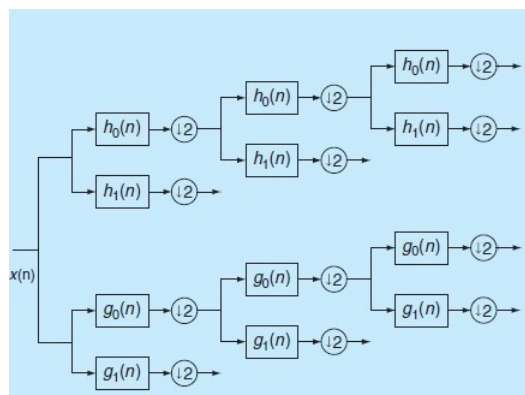

Figure 7: Dual Tree Wavelet Transform

creates six complex valued high-pass subband and six complex valued lowpass subbands at every level of decomposition as shown Figure 6.

4. Classification of ECG

4.1. Convolutional-Neural-Network

There are several layers in a Convolutional Neural Network, accompanied by neural network layers (15), (16). A CNN's structure is designed to take advantage of a 1D signal or a 2D picture anatomical structure as an input. CNN's main moves are as follows:
i) Convolution
ii)Pooling
As seen in Figure 8, convolution operations with weights are accompanied by pooling, which optimizes invariant functionality. The neural network is simpler to understand with less features, which is CNN's biggest benefit. The design of CNN and the neural network used to compute the gradient will be discussed here.

5. Results

MI data was obtained from the Physionet PTB online database containing data from 52 average persons and 148 MI patients at 1000 Hz sampling frequencies. BBB data was compiled from the same collection of 48 half-channel outpatient ECG recordings from 47 persons. 3 LBBB and 3 RBBB files with a length of 30 minutes at a 360 Hz sampling rate were used from the arrhythmia data base. Along with its informative coefficients of levels D1 to D6, a ten-second ECG waveform during AF. Although the sampling rate of the AF signal is 250Hz, 1,250 samples are used in this signal. It can be clearly seen that in the wavelet domain, especially in the comprehensive coefficients, atrial behavior can be evident as Shown in Figures 9 and 10. A ten-second MI data for all of its D1 to D6 coefficients. As the MI waveform rate is 1000 Hz, 10000 samples are included in this signal. In the WT domain, the characteristics of MI are noticeable, especially in the comprehensive coefficients as seen in the 11 and 12 Figures. Ten-second LBBB and RBBB data with their coefficients from levels D1 to D6. The BBB signal rate is 360Hz, with 3600 samples containing this info. It can be clearly seen that in the wavelet domain, especially in the detailed coefficients, the BBB operation can be evident. ECG signal, which comprises of many characteristic lines. These points describe the ECG signal's behaviour. It is especially essential for identification and diagnostic functions to reflect these points (features) with a lower number of parameters. The division of a signal into a variety of scales of each dimension reflects a basic coarseness of the signal under this analysis. These multiscale properties of the DWT. The multiresolution decomposition process of the x[n] signal is shown schematically in Figure 7. The approximation (A) coefficients are the signal's lowpass representation and the wavelet coefficients are the information (D). The approximation coefficients are again split into a coarser approximation (lowpass) and highpass (detail) segment at each subsequent step. Each step of this

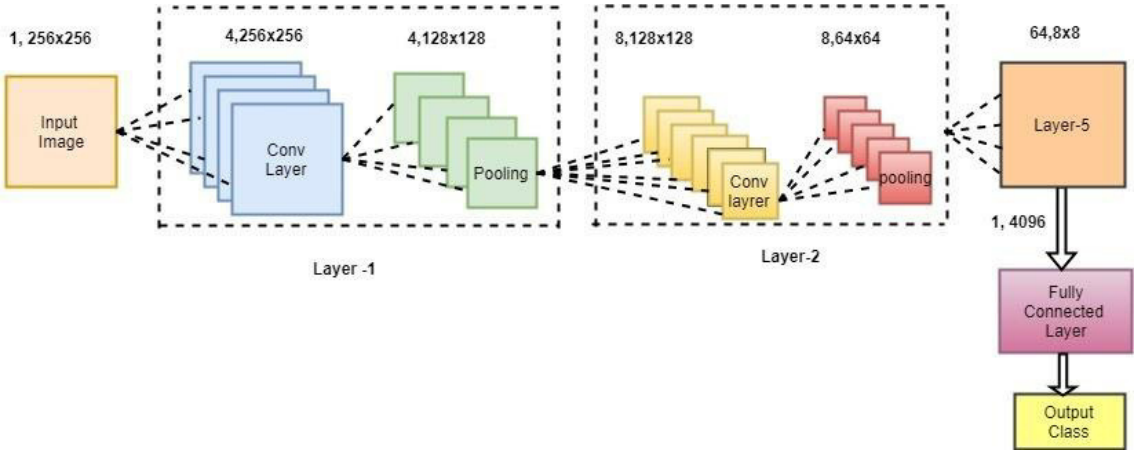

Fig 8: CNN Architecture

Table 2: **Classification of XWT, WT and DTWT features using SVM, KNN and CNN classifiers**

Classifier	AF (%)			MI (%)			BBB (%)		
	Se	Sp	Acc	Se	Sp	Ac	Se	Sp	Ac
XWT+SVM	80.3	85.1	85.5	81.3	82.5	81.4	91.6	84.3	89.9
XWT+KNN	71.9	70.5	70.3	79.4	78.4	77.5	86.2	83.4	85.5
XWT+CNN	83.2	87.3	88.1	90.5	87.3	92.2	93.3	91.3	94.5
WT+SVM	85.3	80.1	87.5	86.3	76.5	79.4	80.6	87.3	86.9
WT+KNN	60.9	60.5	60.1	69.4	68.2	67.4	85.9	83.2	85.5
WT+CNN	91.1	90.6	99.1	87.6	85.1	87.1	94.6	95.1	96.1
DTWT+SVM	80.3	85.1	87.5	90.3	89.5	90.4	89.6	87.3	89.9
DTWT+KNN	61.1	60.6	60.2	85.5	88.3	87.5	56.1	53.3	56.1
DTWT+CNN	92.2	88.3	91.1	94.5	92.3	98.9	93.3	99.2	99.3

device requires 2 digital filters and 2 down samplers. Information, D1 and approximation, A1, respectively, are supplied by the down-sampled outputs of first high pass and low-pass filters. Figures 9, 10, 11, 12, 13 ,14, 15 and 16. The first approximation, A1, is more decomposed and this phase is persisted. The parameters precision, sensitivity, and output accuracy in terms of ROC efficiency curves seen in Figures 17, 18, and 19 are used to approximate overall achievement. In terms of sensitivity, specificity, and accuracy, Table 2 compares the performance of various feature extraction techniques.

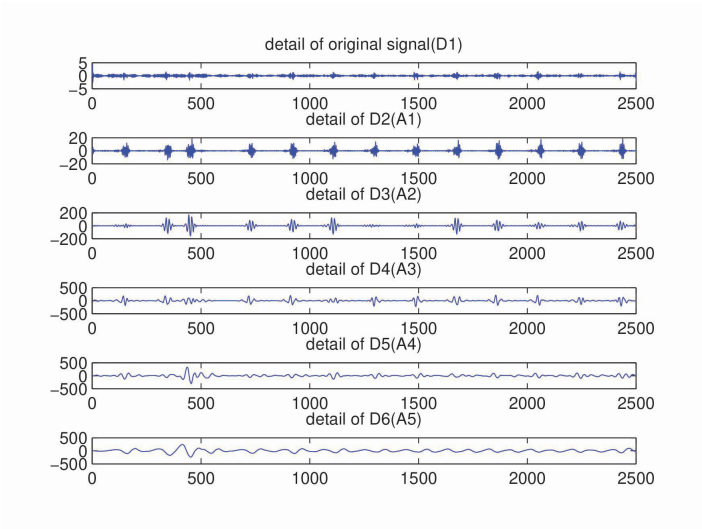

Figure 10: Detailed AF signal coefficients (D1-D6)

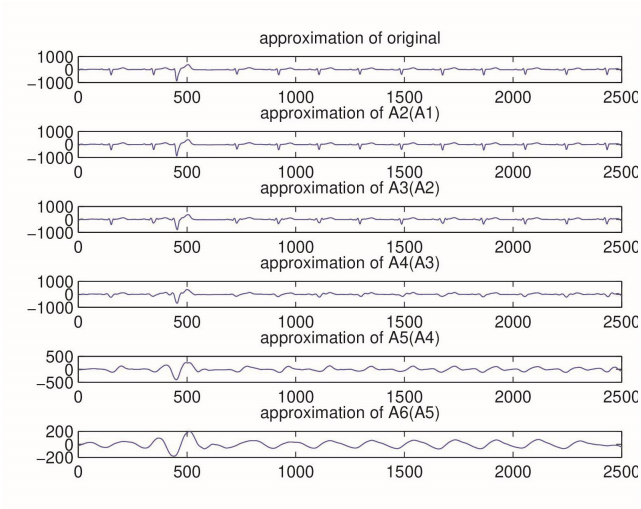

Figure 9: Estimated A1-A6 coefficients of the AF signal.

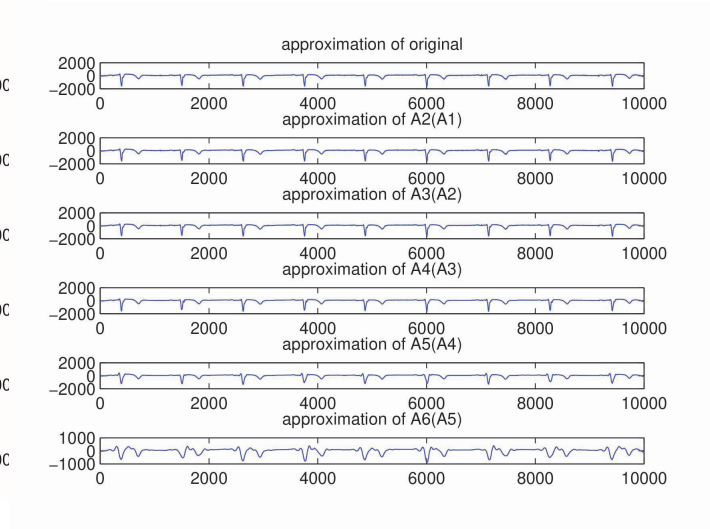

Figure 11: Estimated MI signal coefficients (A1-A6)

6. Discussion

Lee et al. derived linear and nonlinear features from (17) and categorised them utilising various forms of classifiers to detect coronary artery diseases. To differentiate three cardiac conditions, Kim et al.(18) used multiple discriminant study. Sridhar et al.(36) used SVM, DT, KNN and PNN classifiers to evalu-

Table 3: Comparison of accuracy for identifying MI

Author	Approach used	Performance
Schreck et al. (1988) (19)	Emperical Mode Decomposition	Men: Se=84.3% Sp=81.8% Women: Se= 76.2% Sp=80%
Lehtinen et al. (1998) (20)	ANN	ROC=91.5%
Babaoglu et al. (2005) (21)	PCA	Accuracy=80%
Kim et al. (2007) (18)	Linear features Nonlinear features Multiple discriminant analysis	Angina: Se=72.5% Sp=81.8% Coronary syndrome: Se=84.6% Sp=91.5%
Acharya et al. (2011) (24)	Bispectrum and cumulant	Se=94.8% SP=99.3% Ac=98.2%
Kaveh et al. (2013) (23)	DWT &PCA and SVM	Accuracy=80%
Sridhar et al. (2013) (36)	DWT, nonlinear features and Classifiers: SVM, DT, KNN and PNN	Se=95.02% Sp=99.2% Ac=98.67%
Kumar et al. (2017) (25)	Features Flexible Analytic Wavelet Transform Cross Information Potential (CIP) Classifiers KNN, DT	Se =94.8%, SP =99.3% Ac =98.2%
Proposed	DTWT & CNN	AF Ac=99.1% MI Ac=98.9% BBB Ac=99.3%

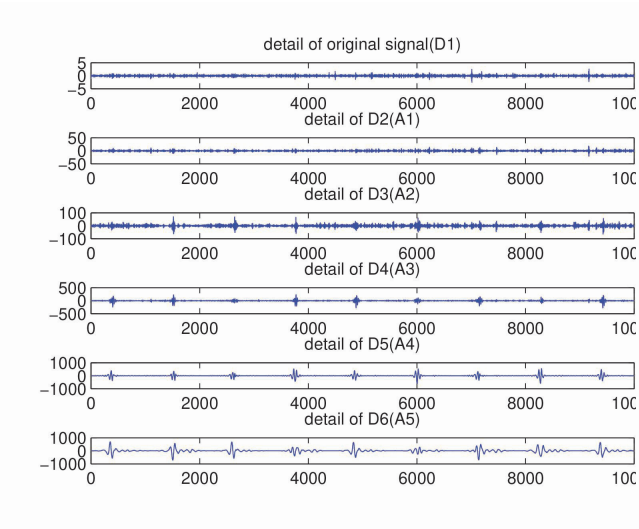

Figure 12: Estimated MI signal coefficients (D1-D6)

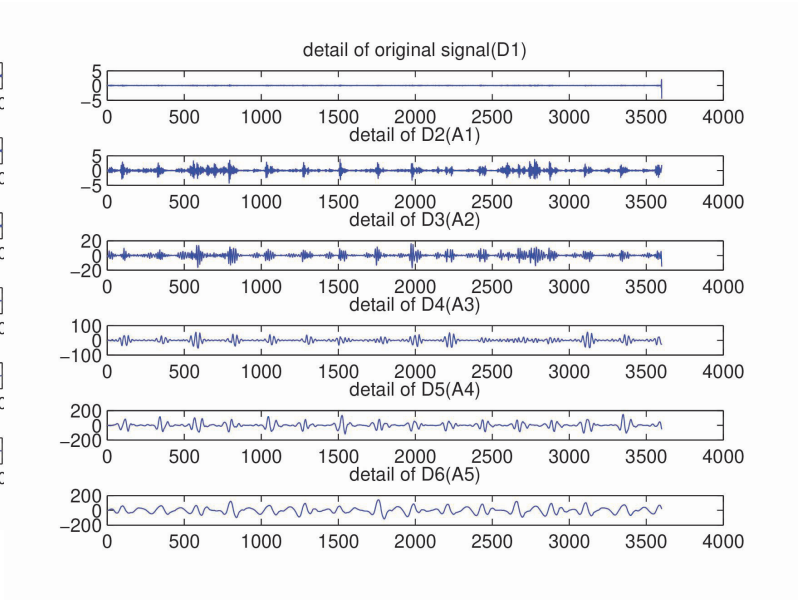

Figure 14: Estimated MI signal coefficients (D1-D6)

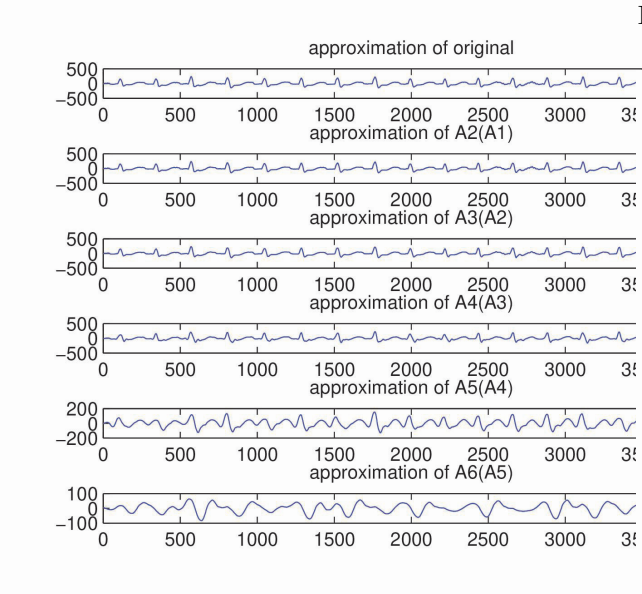

Figure 13: Estimated LBBB signal coefficients (A1-A6)

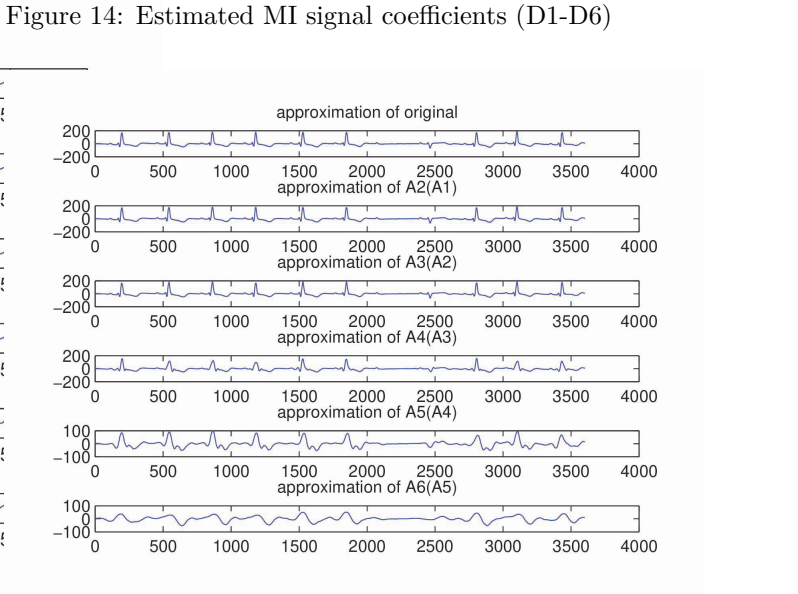

Figure 15: Estimated RBBB signal coefficients (A1-A6)

ate the efficiency of DWT and nonlinear techniques techniques for detecting normal and coronary heart diseases. In order to distinguish regular and resting ECGs, Schreck et

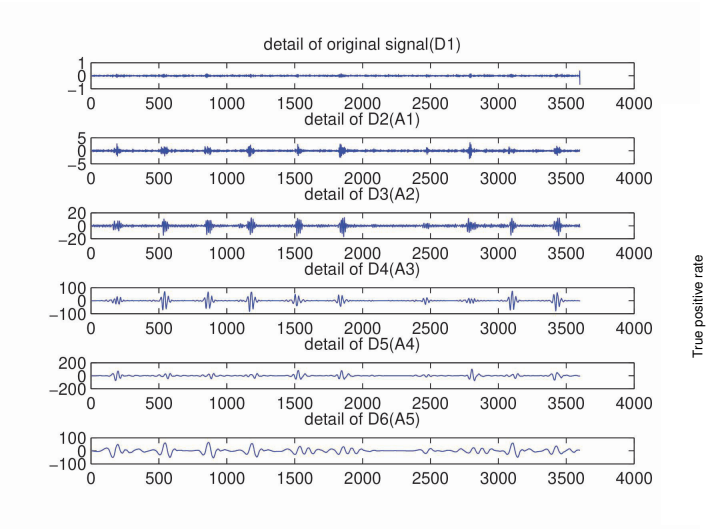

Figure 16: Estimated RBBB signal coefficients (D1-D6)

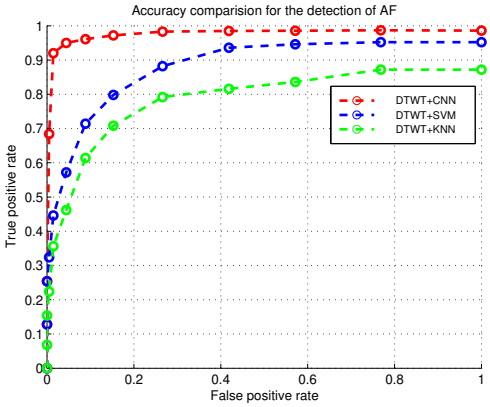

Figure 17: Detection of AF using DTWT and three classifiers

al.(19) used the technique of emperical mode decomposition. Lehtinen et al.(20) used the multilayer perceptron neural network to identify coronary artery disorders and found that the precision of identification was enhanced by computer-aided diagnosis. To diagnose coronary artery disease, Lewenstein et al.(22) analysed the efficiency of an RBF neural network to be categorised as stable and unsafe patients. Babaoglu et al.(21) utilized optimization using binary particle swarm and genetic algorithm as strategies of function optimization and SVM as a classification tool for identifying coronary heart diseases. In order to diagnose coronary artery atherosclerosis, Kaveh et al.(23) used electrocardiogram exercise stress test results acquired from the Physionet database. Using DWT and PCA, functions are collected and optimised and then listed using SVM. Higher-Order Figures and

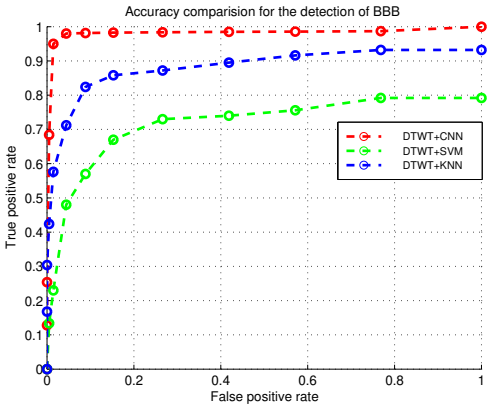

Figure 18: Detection of BBB using DTWT and three classifiers

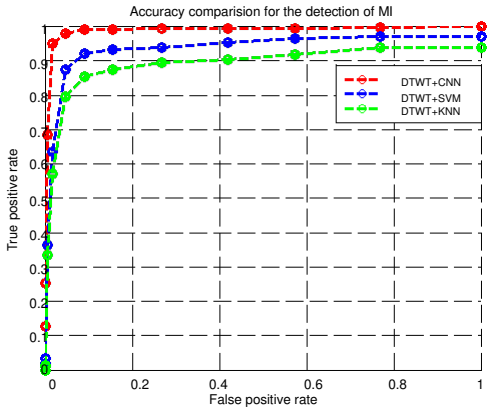

Figure 19: Detection of MI using DTWT and three classifiers

Spectra were used by Acharya et al. (24), and multiple coronary heart disorders were cate-gorised using KNN and decision tree classi-fiers. For the purpose of decomposing ECG signals, Kumar et al. (25) used the Flexi-ble Analytic Wavelet Transform and then the Least Squares support vector machine. The Morlet kernel has a classification performance of 99.6%, compared to 99.56 percent (Kernel RBF).

7. Conclusion

The classification of ECG signals is useful for preventing and diagnosing cardiovascular disease, and it is a hot topic in preventive medicine science. The Physionet database was used to achieve higher-quality ECG sig-nals, and the Dual Tree Wavelet Transform filter was used for function extraction. Then, CNN model realizes the classification of dif-ferent arrhythmia signals. Finally, a sophis-ticated CNN model will automatically recognize and acquire good functionality. In comparison to previous work, a high level of classification correctness is achieved.

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