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Original

Hybird RNN-based feature extraction for early prediction of CVDs using ECG signals for type two diabetic patients

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Abstract: Diabetes mellitus patients are at an increased risk of cardiovascular illness, and cardiovascular complications are the primary cause of morbidity. Diabetes is linked to both morbidity and mortality. Type-2 Diabetes causes a prothrombotic state that leads to acute coronary syndromes by causing endothelial damage and lowering antiaggregant factors like nitric oxide and prostacyclin, as well as increasing thrombotic substances like fibrinogen and factor VII, and suppressing fibrinolysis with factors like plasminogen activator inhibitors. The accurate identification and diagnosis of CVD (Cardiovascular Disease) is dependent on the correct detection of the ECG signal from the heart. The ECG signal is extremely important in the early detection of cardiac problems. The ECG signal for diabetic individuals offers vital information about the heart and is one of the most important diagnostic tools used by doctors to identify cardiovascular disorders. The time gap between two consecutive QRS complexes appearing contiguous in an ECG is known as heart rate. The most appealing feature is that HRV (Heart Rate Variability) measurement is non-invasive and repeatable. Several machine learning techniques have been proposed for the non-invasive automated identification of diabetes. This paper discusses innovative methods for analyzing electrocardiogram (ECG) signals in order to extract important diagnostic information. The ECG signal is first treated using a dual tree complex wavelet transform (DTCWT-SG) with threshold method. Subsequently, the features are extracted from detailed coefficients of DTCWT-SG filter, Eigen vectors by minimum normalization method and Rajan Transform. Main key features are extracted using these three methods. These features are classified and analyzed by different machine learning classifiers. The proposed approach was tested on DICARDIA, MIT-BIH and Physionet database and the performance analysis shows that the hybrid recurrent neural network (RNN) (LSTM+GRU Gated Recurrent Units) achieves better prediction of 98.8% compared to state of art techniques.

Keywords: ECG, Dual Tree Complex Wavelet Transform, Eigen Vectors, Rajan Transform,Hybrid Recurrent Neural Network, LSTM,Gated Recurrent Units, Adaboost

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1. Introduction

The heart is one of the most important organs in the human body, and heart monitoring has become a required diagnosis for human health. The ECG analysis provides the most important information regarding the health of the heart. An abnormal ECG can lead to a variety of heart related problems viz., atrial fibrillation, tachycardia, low blood pressure, and fast atrial fibrillation that lead to cardiac illness, such as prolonged ventricular tachycardia and cardiovascular diseases (CVDs). Type-2 diabetes also increases the risk of stroke and heart failure. These disorders are life-threatening and necessitate immediate treatment (Virani et.al., 2020). Manual diagnosis is difficult due to the variety of morphologies present in the ECG signal. According to the recent survey, 17.1 million people were died from CVDs in 2004, representing 29% of all global deaths. Of these deaths, an estimation of 7.2 million were due to coronary heart diseases and 5.7 million were due to stroke. 82% of deaths take place in low- and middle-income countries occur equally in men and women (Kuzu, 2018). In future the death rate due to CVDs may increase to avoid that early prediction of their symptoms need to be identified. For that ECG analysis should be done both manually and automatically.

The most significant information about the state of the heart can be observed from the ECG analysis, which can be monitored manually and automatically. Since there are various morphologies in the ECG signal, manual diagnosis is found difficult. Therefore, an automatic system of the ECG diagnosis has been interesting. Both feature extraction and classification approaches are the critical successes of any automatic ECG classification.

There are plenty of applications that ECG analysis and classification involve, such as ischemic heart disease, arrhythmia, and myocardial infarction. Since it is a time-consuming and monotonous operation, the handcrafted feature is not usually the greatest candidate feature for the ECG application (Yıldırım et al., 2018). As a result, CNN, a featureless model, was concerned in characterizing the ECG analysis. The raw data fed a model-based 1D-CNN for classifying ECG signals into some classes suggested by the Association for Advancement of Medical Instrumentation (AAMI) and the model, for example, (Zubair at el., 2016) in proposed the raw data fed a model-based 1D-CNN for classifying ECG signals into some classes suggested by the Association for Advancement of Medical Instrumentation (AAMI) and the model. (Saxena et.al., 2002) presented a feature extraction-based disease diagnosis from ECG signal. (Inan et.al., 2006) proposed a robust NN based classification using wavelet and time interval features for premature ventricular contraction. (Chandra et.al., 2018) presented a feature extraction by overlap discrete wavelet transform that achieves the sensitivity of 99.98%. Machine learning algorithms such as XGBoost is implemented to classify the diabetes using ECG signal and to predict the CVD's in early stage (Kulkarni et.al., 2022).

To identify and classify DM, (Ali et al., 2020) used various types of KNN algorithms. ML algorithms are used to construct the iridology-based or iris-based DM prediction framework. (Moreno et al., 2016) propose using a signal obtained from a pulse oximeter to screen for the emergence of type-II diabetes. (Qomariah et al., 2019) propose a method for extracting characteristics and categorizing DR using SVM. (Samant et al., 2019) conduct a comprehensive comparison of machine learning identification techniques for diagnosing type 2 diabetes using a combination of physiological parameters and iris-based characteristics. Deep learning-based methods like recurrent neural network and long short-term memory techniques are used to detect the early diagnosis of CVD's (Swapna et al., 2018). Heart diseases detection by ECG signals analysis done by Fuzzy classifiers (Mahmoodabadi et al., 2007). Wavelet based support vector machine analysis was carried to find out the abnormalities in ECG signal (Ghosh et al., 2005). A data mining-based approach was implemented to diagnose the CVD's in ECG signal (Sufi et al., 2009). A Combination of morphological feature with support vector machine classifier proposed to detect the early prediction of CVD's (Lei et al., 2007). All these research methods have the drawback of classifying the ECG signal into normal or abnormal.

The suggested study divides type-2 diabetic patients' ECG signals into three categories: normal, early stage, and abnormal. Section 3 deals with the database description and section 4 and 5 provides the detailed workflow of the proposed method. Section 6 deals with results and discussion and final section 7 concludes the proposed work.

2. Methodology

The flow diagram of feature driven hybrid RNN model for early prediction of CVDs from ECG signal is shown in Figure 1. The noise in ECG signal is removed by novel DTCWT-SG filter. The QRS complex and RR interval are analyzed and the features are extracted by Eigen vectors by minimum normalization method and Rajan Transform. Then the features are classified with hybrid RNN model. The proposed workflow is shown in Figure 1.

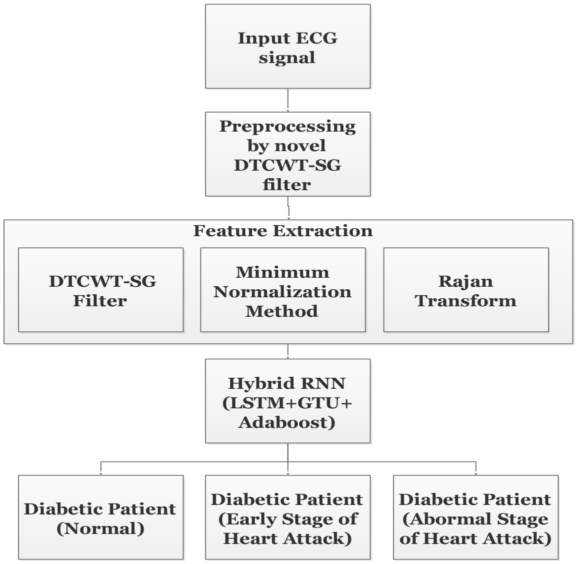

Figure 1. The workflow of the proposed method.

3. Data description

3.1. Dicardia

First database evaluated in this study is the diabetic cardiac neuropathy diagnostic and modeling database signals (DICARDIA) database (Ledezma et al., 2014). This database contains 30 incomplete and 21 complete protocol of the ECG signal taken for diabetics with cardiac complications. 3 databases are available for diabetic without cardiac complications and 11 control group ECG signals are also available in gbbanet webpage. 3 channels of 12-bit resolution with variable sample frequency of 250Hz,360Hz,500Hz,1000Hz with serial communication RS-232 are used as the main characteristics of the ECG signal recorder.

3.2. Physionet ECG database

Second database evaluated in this study is the physionet PTB Diagnostic ECG database (Bousseljot et al., 1995). It was recorded by Professor Michael Oeff, M.D., at the Department of Cardiology of University Clinic Benjamin Franklin in Berlin, Germany. The ECG signal was collected using the PTB prototype recorder. This database has 290 participants, with 209 males and 81 females of healthy and 9 abnormal heart disease classes. Males range in age from 17 to 87, while females range in age from 1 to 14. Each participant is represented by 1 to 5 records. Over a 16.384 mV range, the recordings were digitized at 1000 samples ranges with 16-bit resolution and contain 15 measured signal namely (i,ii,iii,avr,avl,avf,v1 to v6) and (vx,vy,vz) for each recording. It was downloaded through glcoud shell editor.

3.3. MIT-BIH

Third database evaluated in this study is the MIT-BIH Arrhythmia Database, which is a collection of annotated ECG recordings created by the Arrhythmia Laboratory of Boston's Beth Israel Hospital (Moody et al., 2001). This database has 47 participants, with 25 males and 22 females of healthy and different type of abnormal heart diseases. Males range in age from 32 to 89, while females range in age from 23 to 89. Over a 10-mV range, the recordings were digitized at 360 samples ranging from 0 to 2047 with 11-bit resolution and contain recordings from two leads namely ML2 and V1-V6.

4. Preprocessing

4.1. DTCWT-SG filter

One of the most important aspects signaling heart disorders by ECG signal is start with preprocessing. Since noise and artifact interference in ECG signals will influence the effective evaluation of clinical evidence and accurate diagnosis of CVD disorders. Different types of noises like baseline wander, electromyographical (EMG) noise, and electrode motion artifact noise, powerline interference, channel noise, composite and random noises are found in ECG recordings. The wavelet transform technique is well-known for removing the baseline wander noise from ECG signals. Dual tree wavelet transforms (Prashar et al., 2020) with polynomial filter is used to overcome all types of noise is shown in Figure 2. and Figure 3.

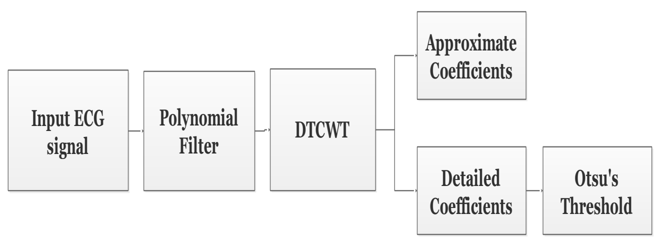

Figure 2. Forward DTCWT process.

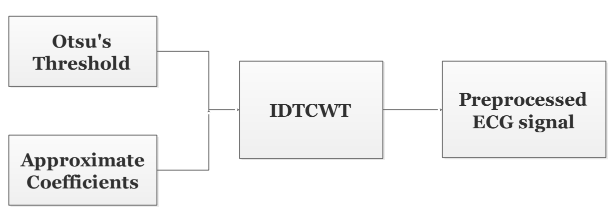

Figure 3. Inverse DTCWT process.

Initially, the Savitzky-Golay filter ($X_{sgf}(t)$) is applied to remove the noise associated with the ECG signal x(t) shown in equation (1).

$$X_{sgf}(t) = x(t) \quad (1)$$

Then the filtered signal is decomposed into detailed ($DX_{sgf}(t)$) and approximate coefficients ($AX_{sgf}(t)$) using DTCWT.

$$X_{sgf}(t) = DX_{sgf}(t) + AX_{sgf}(t) \quad (2)$$

Next stage involves applying an adaptive otsu's thresholding technique to detail coefficients by selecting a unique threshold, which resulted in changed detail at third stage of decomposition levels.

$$TDX_{sgf}(t) = Tadaptive - \alpha\sqrt{x}(t) \quad (3)$$

After that, the detailed and approximation coefficients are combined, and the reconstructed signal is obtained using inverse DTCWT.

$$DTCWTX_{sgf}(t) = TDX_{sgf}(t) + AX_{sgf}(t) \quad (4)$$

$$x(t)_{D-SG} = IDTCWTX_{sgf}(t) \quad (5)$$

5. Feature extraction

After noise removal in preprocessing stage, feature extraction by DTCWT with thresholding, eigen vectors and rajan transform. The peak value of the R signal is detected at the thresholding stage of the preprocessing signal in Figure 2. The other features are extracted by eigen vectors and key features are extracted by rajan transform.

5.1. Eigen vectors by minimum normalization method

To determine the power spectral density (PSD) of a noise-corrupted signal, the eigen vector approach uses eigen decomposition of the correlation matrix (Eldred et al.,1992) . To generate high resolution harmonic spectrum of the signal eigen vector method is performed. Minimum normalization estimation is done on the preprocessed signal maintaining the principal eigen vector components. This method distinguishes the actual and erroneous zeros through specified noise subspace vector by signal or noise eigen vectors. The PSD is calculated by equation (6)

$$PSD(x, k) = \frac{1}{|x(t)_{D-SG}|^2}(t) \quad (6)$$

k represents subspace dimension. It extracts the preprocessed signal's identical spectral properties with almost the same frequency.

5.2. Rajan transforms

To successfully recognize or classify a signal, the Rajan transform employs time –based transform with algebraic principles (Mandalapu & Rajan, 2009). This algorithm is developed based on the DIF-FFT (Decision in Time Fast Fourier Transform) and generates a transfer function with key values that is strongly integrated to the input sequence. Reverse RT is used to extract the input sequence using these key values and output sequences. It produces the output with the same length as the input signal by performing arithmetic operations like addition and subtraction. The prerequisite for RT is that the input length be a power of two. At first, the input sequence is separated into two halves with equal length as shown in equation (7) & (8). This method is repeated until there are no more divisions to be applied.

$$x_1(t)_{D-SG} = x(t)_{D-SG} + (x(t)_{D-SG} + \tfrac{D}{2}) \ ; \ 0 \le t \le \tfrac{D}{2} \quad (7)$$

$$x_2(t)_{D-SG} = \left|x(t)_{D-SG} - (x(t)_{D-SG} + \tfrac{D}{2})\right| \ ; \ 0 \le t \le \tfrac{D}{2}; \tfrac{D}{2} \le t \le D \quad (8)$$

For the input sequence, the output sequences are generated along with encryption key. The encryption keys are a combination of 1 and 0 with the binary form. The decimal value of that binary value is taken as the feature vector of the ECG signal.

5.3. Hybird RNN model

The backpropagation algorithm, which finds the network's derivatives, is used to find the variations of neural networks. The chain rule is used to find the variations of each layer by scaling the network down. This is the source of the issue. The gradient has a risk of diminishing as the number of hidden layers increases when using an activation function such as the sigmoid function. This problem can lead to disastrous results after the model has been compiled. Using Long-Short Term Memory (Abdulrazaq & Al-Ani, 2020) models with a ReLU activation function has proven a straightforward solution.

The default nature of LSTM (Long short-term memory networks), which are a type of recurrent neural network, is to learn long-term correlations by remembering information for extended periods of time. The LSTM is coupled with gated recurrent unit (Ravanelli et al., 2018) (GRU) to improve classification performance on fewer and less recurrent datasets.

Initially, the features extracted from the DTCWT, minimum normalization method and rajan transform are given as the input for the hybrid RNN model. The hidden layer h(t) with the weighted value W, as well as the bias function (b_h, b_y), make up the output layer y(t) with the gated unit (σ)shown in equation (9)

$$h(t) = \sigma(\tanh(W_{xn}\, x(t)_{DTCWT,PSD(x,k),RT} + W_{hh}h_{t-1} + b_h)) \tag{9}$$

$$y(t) = W_{hy}h(t) + b_y \tag{10}$$

The cross-entropy loss function is defined with Adaboost ensemble classifier to classify the correct class of ECG signal.

$$L = -\ln(Adaboost) \tag{11}$$

The final probability of the correct class is represented by Adaboost. (Wang, 2012).

6. Results and discussion

In the proposed work, DICARDIA, Physionet ECG and MIT-BIH database are taken for early prediction analysis of type-2 diabetic patients ECG signal. The databases are named with the numerical order with the database name. The algorithm is trained on a PC with an Intel i4 processor with 16GB of RAM and it is evaluated on MATLAB 2021a platform. The input signals are denoised by using a novel DTCWT-SG Filter, that removes different types of noise associated with the ECG signal. The Daubechies 4 (db4) wavelet has been employed as a mother wavelet in the proposed work. The different mother wavelets are compared and the db4 provides the better noise removed signal. When implementing other mother wavelets, the peak information has also been removed by considering that as the noise signal. The complete ECG waveform taken from database is shown in Figure 4.

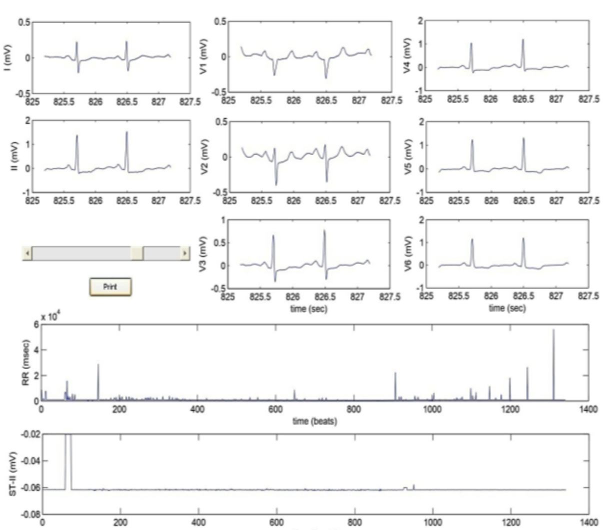

Figure 4. ECG of type – 2 diabetic patient with CVDs.

In this the study number 10385 and the ECG record number 462 shows the ECG waveform of 66-year female diabetic's mellitus 2 patient. HRmin value ranges from 79-97 and HR maximum value is 161 in resting supine and HRs maximum of 136 in resting orthostasis. After the noise removal the features are extracted from the DTCWT-SG filter atar thresholding stage. This brings out the peak value of the R- value is shown in Figure 5.

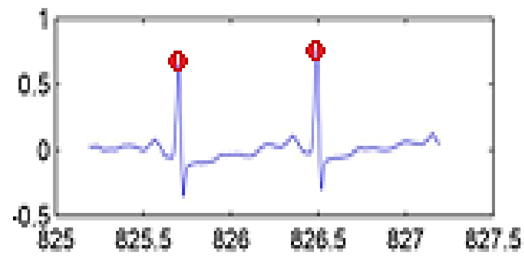

Figure 5. R-Peak detection by proposed DTCWT-SG filter.

This is considered as the first feature for the classifier. Then the eigen features and rajan key features are extracted to get the key values from R, QRS, P, T, PR, ST segment shown in Figure 6.

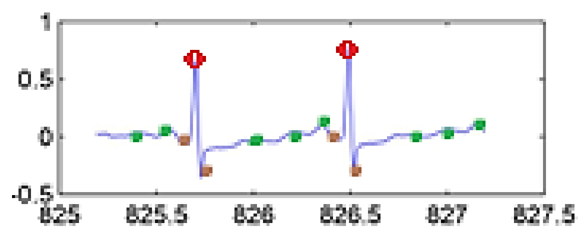

Figure 6. Feature detection by eigen and rajan key features.

Table 1 shows the feature extraction details of the datasets. Result shows the features are different for all the cases and some results are like each other. To classify these features hybrid RNN model is proposed.

This model overcomes the vanishing gradient problem and classifies the ECG signal of diabetic patients by considering the weak learners. The proposed model is validated by running more than ten times. The LSTM uses 80 hidden layers with gated recurrent model. Instead of using softmax layer as a classifier Adaboost ensemble classifier is performed and that achieves better performance compared with another recurrent model. The proposed method is also evaluated with the shortest length signal and that shows higher accuracy compared with other state of art techniques. Table 2 shows the comparative analysis of the proposed method with the state of art approaches (Abdulrazaq & Al-Ani, 2020; Acharya et al.,2017; Kachuee et al., 2018).

Table 1. Feature detection results

Data	R(peak)	R-R interval	P(Peak)	T(peak)	QRS	PR segment	ST segment
DICARDIA1	0.82	1.17	1.34	0.7	0.05	0.06	0.08
DICARDIA3	0.89	1.19	1.46	0.8	0.06	0.04	0.07
DICARDIA7	1.2	0.82	0.15	0.22	0.04	0.03	0.16
DICARDIA12	2.3	1.02	0.26	1.4	1.14	0.06	0.04
Physionet 2	1.4	0.9	0.16	0.34	0.04	0.04	0.19
Physionet 16	1.5	1.2	0.18	0.4	0.05	0.04	0.2
Physionet 18	2.26	1.48	0.47	1.6	1.19	0.06	0.06
Physionet 22	2.1	0.98	0.16	1.2	1.12	0.06	0.05
MIT-BIH2	0.8	1.12	1.14	0.6	0.04	0.06	0.09
MIT-BIH6	1.0	0.82	0.19	0.26	0.04	0.04	0.18
MIT-BIH9	2.6	1.32	0.32	1.6	1.19	0.03	0.06
MIT-BIH12	1.9	0.87	0.39	1.03	1.29	0.06	0.08

Table 2. Performance comparison of the proposed method Vs state of art methods.

Existing Methods	Accuracy	Precision	Recall
(Acharya et al., 2017)	93.2	92.75	93.45
(Kachuee et al., 2018)	95.8	95	95.2
CNN-LSTM (Abdulrazaq & Al-Ani, 2020)	98.1	96.8	98
Proposed method	98.8	97.8	98.6

Figure 7. show the comparison result of the proposed method and it reaches the accuracy of 98.8%. Furthermore, when compared to existing methodologies in the literature, the proportion of precision and recall is increased. This analysis of the proposed method shows that it achieves better accuracy compared with existing approaches and it is suited for the early diagnosis of the CVDs from the ECG signal.

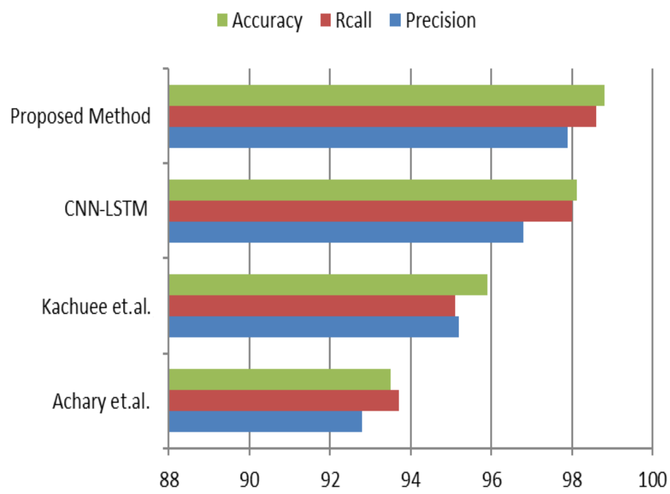

Figure 7. Proposed method - classification result.

7. Conclusion

A novel DTCWT-SG filter and feature extraction-based hybrid RNN model with Adaboost classifier technique is proposed to early prediction of CVDs in type-2 diabetic patients. Novel filtering technique is operated to remove the noise in ECG signal. Three different and novel combinations of feature extraction are proposed and that detect the important feature from the ECG signal. This method is implemented in three different databases and achieves excellent classification accuracy of 98.8%, precision of 97.8% and recall of 98.6% by Adaboost classifier. An efficient solution for detecting anomalous ECG signals enables patients to receive appropriate treatment at an early stage of disease. The early prediction of CVD's can be implemented using deep neural networks with a greater amount of data information for the faster prediction of heart diseases associated with ECG signal.

Conflict of interest

The authors have no conflict of interest to declare.

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