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ECG Signal Analysis for Heart Disease Detection Based on Sensor Data Analysis with Signal Processing by Deep Learning Architectures

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Abstract

Land-use mapping and crop classification have both benefited greatly from the analysis of high-resolution remote sensing photos based on deep Heart disease (HD) is extremely lethal by nature and claims a disproportionately large number of lives worldwide. Early and reliable identification techniques are necessary to prevent fatalities from HD. This research Propose novel technique in ECG signal feature extraction and classification-based HDD utilizing DL technique. here the input data has been collected as sensor data of ECG signal which has been processed and obtained ECG fragments. Then this signal processed for noise removal, smoothening. The processed ECG signal features has been extracted using Hilbert radial function transform networks. Then the extracted ECG signal has been classified using Markov convolutional U-Net architecture. Here the experimental analysis has been carried out for various ECG signal dataset in terms of accuracy, precision, recall, F_1 score, RMSE, MAP and SNR

Keywords: ECG signal, feature extraction, classification, heart disease detection, deep learning

1. Introduction:

One of the leading causes of death in the US is heart disease. According to the American Heart Association's most recent figures, heart disease was responsible for 121.5 million deaths in the US [1]. Despite the fact that electrocardiogram (ECG) signals are frequently employed in the medical diagnosis of cardiac problems [2], it is difficult to automatically extract pertinent and trustworthy data from ECG signals using computer programmes [3]. Each heartbeat creates a unique electrical depolarization-repolarization pattern during the cardiac cycle. This characteristic might serve as an example of heart electrical activity [4]. Preprocessing, feature extraction, and classification make up the core of these techniques' typical workflows. The ECG signals are first de-noised using preprocessing techniques [5]. Three common ECG procedures are the resting ECG, the ambulatory

ECG, and the cardiac stress test. A repeating series of P, QRS, T, and a conditional U wave can be seen on an ECG graph [6].

2. Related works:

To have a deeper understanding and to be aware of current trend, this section reviews the literature on the detection of HDs. Artificial Neural Network (ANN), Naive Bayes (NB), Support Vector Machine (SVM), and Adaboost classifier were some of machine learning techniques employed in work [7]. Three categories of learning models exist in ML: reinforcement learning, unsupervised learning, and supervised learning [8]. Machine learning, however, is unable to automatically extract features. The features that are extracted manually and used in machine learning are features. [9] presents a paper that details the use of DL for heart rate modelling and prediction. AUC of 77% was achieved utilizing Logistic Regression and method selection based on Bayesian data Criterion in a heart failure prediction model that relied on machine learning approaches applied to EHR data [10]. MKL with ANFIS has been proposed in another study for the detection of heart disease and has demonstrated good specificity (99%) and sensitivity (98%) for KEGG Metabolic Reaction Network dataset [11].

3. System model:

This section discuss novel technique in ECG signal feature extraction and classification based HDD utilizing DL technique. here the input data has been collected as sensor data of ECG signal which has been processed and obtained ECG fragments. Then this signal processed for noise removal, smoothening. The processed ECG signal features has been extracted using Hilbert radial function transform networks. Then the extracted ECG signal has been classified using Markov convolutional U-Net architecture. the proposed architecture is shown in figure-1.

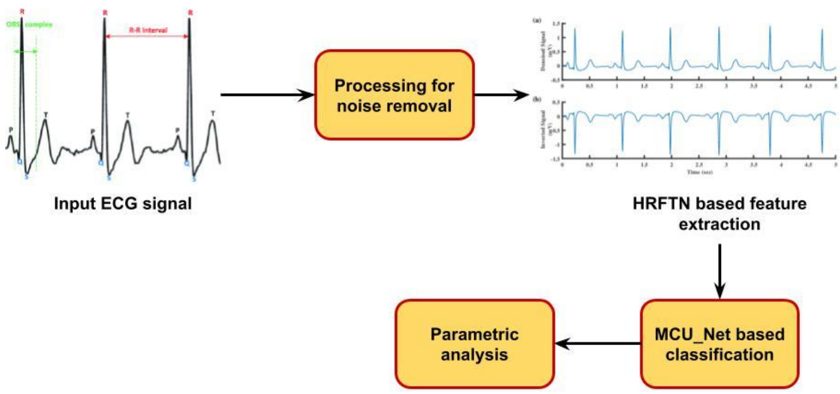

Figure 1: Overall proposed architecture

3.1 Hilbert radial function transform networks-based Feature extraction:

The Hilbert transform of a real-time function x(t) is described as eq. (1), (2)

$$\hat{x}(t) = H[x(t)] = \frac{1}{\pi}\int_{-\infty} x(\tau)\frac{1}{t-\tau}\mathrm{d}\tau. \quad (1)$$

$$\hat{x}(t) = \frac{1}{\pi t} * x(t) \quad (2)$$

Using the Fourier transform and rewriting (2), we have by eq. (3)

$$F\{\hat{x}(t)\} = \frac{1}{\pi}F\left\{\frac{1}{t}\right\}F\{x(t)\}. \quad (3)$$

Since by eq. (4), (5)

$$F\left\{\frac{1}{t}\right\} = \int_{-\infty}^{\infty}\frac{1}{x}\mathrm{e}^{-j2\pi f x \mathrm{d}x} = -j\pi \mathrm{sgn}\ f, \quad (4)$$

where

$$\operatorname{sgn} f \text{ is } +1 \text{ for } f > 0, 0 \text{ for } f = 0 \text{ and } -1 \text{ for } f < 0 \quad (5)$$

therefore (4) provides Fourier transform of the Hilbert transform of x(t) as eq. (6)

$$F\{(\hat{x})\} = -j\operatorname{sgn} f F\{x(t)\} \quad (6)$$

The index is related to the row subscript x and the column subscript y in the 2D Euclidian Domain by eq. (7).

$$d_{xy} = \left(\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}\right) - w_{xy'},$$

$$s(m,n) = \langle s, x_{mn}\rangle = \sum_{j=1}^{N}\sum_{i=1}^{N} x_{mn}(i,j) * s(i,j), (m,n = 0,1,\cdots,N-1) \quad (7)$$

$$s(i,j) = \sum_{n=0}^{N-1}\sum_{m=0}^{N-1} \hat{s}(m,n)x_{mm}(i,j), (i,j = 1,2,\cdots,N),$$

It has been expanded to include the situation of two dimensions. The ratio is thus established using the geometric and arithmetic means in both rows and columns by eq. (8).

$$SB = \frac{\sum_{i=F}^{N/2}\sum_{j=F}^{N/2} |s(i,j)|}{\sum_{i=1}^{N/2}\sum_{j=1}^{N/2} |s(i,j)|}$$

$$SR = \mathrm{m} \quad F: \sum_{j=1}^{F}\sum_{i=1}^{F} s(i,j) \geq \beta \sum_{j=1}^{N/2}\sum_{i=1}^{N/2} s(i,j) \quad (8)$$

3.2 *Markov convolutional U-Net architecture based classification:*

Each element Xi from the process is specified by a vector of indicator functions, with Xji =< Xi, gj>. Take note of the following from the definition of expectations for a simple random variable by eq. (9):

$$P(X_i = g_j) = E[< X_i, g_j >]$$

$$P(Y(k) = y_{jk}) = E[< Y(k), y_{jk}) >] \quad (9)$$

Where *Yjk* = (0,..., 0, 1, 0,..., 0)t ∈Rm(k) Describe a new matrix C(k)=(cji(k)), whereby eq. (10)

$$c_{ji}(k) = P(Y(k) = y_{jk} \mid X_i = g_i), \quad 1 \leq i \leq N, \quad 1 \leq j \leq m(k) \quad (10)$$

4. Experimental analysis:

This paper's preprocessing was put into practise using MATLAB 2021a. The suggested model was developed using Python 3.6. The operating system was Windows 64-bit, and it had an Intel(R) Core (TM) i7-5500U CPU running at 2.40 GHz and 8.00 GB of RAM.

Table-1 Comparative analysis between proposed and existing technique for EEG dataset

Parameter	ANN	SVM	EEG_SA_HDD_DLA
Accuracy	81	85	90
Precision	77	81	83
Recall	65	68	71
F1_Score	55	59	63
RMSE	45	48	51

MAP	52	53	55
SNR	61	63	65

The above table-1 shows comparative analysis between proposed and existing techniques in terms of accuracy, precision, recall, F-1 score, RMSE, MAP and SNR. Here the analysis has been carried out based on number of epochs. Accuracy calculation is done by the general prediction capability of projected DL method. For calculating F-score, number of images processed are EEG signal for both existing and proposed technique. The F-score reveals each feature ability to discriminate independently from other features. For the first feature, a score is generated, and for the second feature, a different score is obtained. However, it says nothing about how the two elements work together. Here, calculating the F-score using exploitation has determined the prediction performance. It is created by looking at the harmonic component of recall and precision. If the calculated score is 1, it is considered excellent, whereas a score of 0 indicates poor performance. The actual negative rate is not taken into consideration by F-measures. The accuracy of a class is calculated by dividing the total items classified as belonging to positive class by number of true positives. Probability that a classification function will produce a true positive rate when present. It is also known by the acronym TP amount. In this context, recall is described as ratio of total number of components that genuinely fall into a positive class to several true positives. How well a method can recognise Positive samples is calculated by recall. Recall increases as more positive samples are determined. When training regression or time series models, RMSE is one of the most widely used metrics to gauge how accurately our forecasting model predicts values compared to real or observed values. MSE squared root is used to calculate RMSE. The RMSE calculates the change in each pixel as a result of processing.

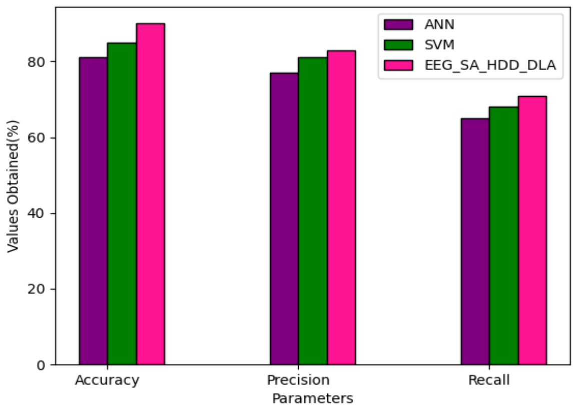

Figure-2 Comparative analysis between proposed and existing technique in terms of accuracy, Precision, Recall

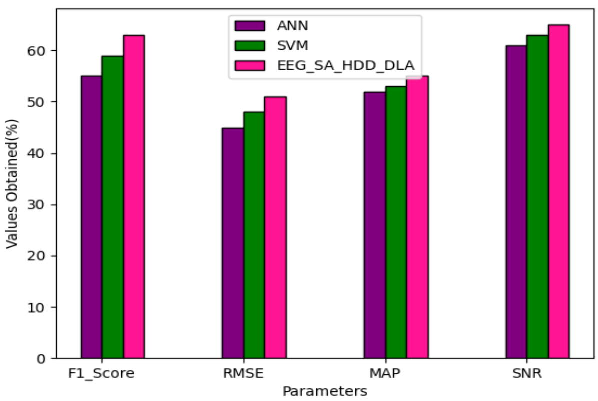

Figure-3 Comparative analysis between proposed and existing technique in terms of F-1 score, RMSE, MAP, SNR

From above figure 2 and figure3 shows comparative analysis between proposed and existing technique. the proposed technique attained accuracy of 90%, precision of 83%, recall of 71%, F-1 score of 63%, RMSE of 51%, MAP of 55% and SNR of 65%. While the existing ANN attained accuracy of 81%, precision of 77%, recall of 65%, F-1 score of 55%, RMSE of 45%, MAP of 52% and SNR of 61%; SVM attained accuracy of 85%, precision of 81%, recall of 68%, F-1 score of 59%, RMSE of 48%, MAP of 53% and SNR of 63%.

5. Conclusion:

This research Propose novel technique in ECG signal feature extraction and classification based HDD utilizing DL technique. The processed ECG signal features has been extracted using Hilbert radial function transform networks and classified using Markov convolutional U-Net architecture. here the experimental analysis has been carried out for various ECG signal dataset in terms of accuracy, precision, recall, F_1 score, RMSE, MAP and SNR. The proposed technique attained accuracy of 90%, precision of 83%, recall of 71%, F-1 score of 63%, RMSE of 51%, MAP of 55% and SNR of 65%. The future scope of this research can be extended to EEG based brain wave analysis using proposed model with improved accuracy.

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