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Detection of Heart Dysrhythmia Using EMD

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ABSTRACT:One of the major causes of unexpected death is heart disease. Advanced detection and action for treatment of cardiac arrhythmias saves you from having to deal with unexpected deaths. According to World Health Organization (WHO) report, coronary heart disorder is spreading for the duration of the sector very unexpectedly and the scenario is turning into alarming in human beings' elderly forty or above. Different techniques and approaches are followed to hit upon and diagnose coronary heart abnormalities. For the immediate detection and prevention of cardiovascular problems, automatic dysrhythmia recognition is essential. The aim of this study is to determine how to enhance an empirical mode decomposition-based dysrhythmia detection system (EMD). The four steps in this system of rules are pre-processing, usage of empirical mode decomposition algorithm, extraction of necessary features, and finally classifying ECG signals as normal and six different arrhythmic signals received from the MIT-BIH database. Premature ventricular contractions (PVCs), paced beat, atrial premature beats, normal (N), left package deal department block (LBBB), appropriate package deal department block (RBBB), and package deal department blocks are some of these (APB). ECG signals have been classified using three distinct classifiers. Using a linear discriminant analysis (LDA) classifier for the detection of normal and dysrhythmic signals, the method gets better results with an accuracy of 87%.
KEYWORDS:EMD, Dysrhythmia, heart disease, MIT-BIH, LDA.

I. INTRODUCTION

Heart disease is the foremost reason for death worldwide. The most crucial area of clinical data analysis is prediction of heart disorders. Dysrhythmia can be innocuous and feels like a speeding or fluttering heart. The primary cause of unexpected deaths, however, is some types of heart dysrhythmia. For the control or eradication of fast, slow, or irregular heartbeats, such heart disease is treated with medicines, catheter treatments, implanted devices, or surgery. Dysrhythmia can be classified into different types depending on their position, speed, or rhythm in the heart. Detecting and treating such diseases at the earliest would reduce the death rate. With the emerging technologies many new engineering methods and models have been discoveredthat can help us detect diseases. Our goal is to make a platform to detect dysrhythmia in humans to identify the type of disease using empirical model decomposition. That helps doctors to save their time from manually analysing and accurately find the disease to provide a proper diagnosis. Empirical model decomposition is a technique to decompose a signal into physically meaningful components.

II. LITERATURE SURVEY

Larissa Montenegro et al. [1] compared the assessment metrics using dataset comprised of the combined public ECG signals datasets TNMG and CINC17, 1D-CNN and SVM were used. The accuracy of the 1D-CNN algorithm's evaluation criterion is 93.07 percent. With an accuracy of 92.00%, the SVM classifier produced the best classification metrics. SVM and one-dimensional

CNN algorithms performed best when the databases were combined. Even while both sets of results are encouraging, it should be highlighted that feature selection in the SVM needs a sleepy process of experimentation, whereas CNN approaches can significantly lessen the burden.

In Wusat Ullah et.al [2], they used two different types of datasets. Initially, MIT-BIH arrhythmia database, which has 1,09,446 ECG beats. This dataset contains five classes. The final database is the PTB Diagnostic ECG Database, where there are two classes. The various classification methods are used with these two datasets. The 20% of the data is used for testing and the remaining 80% for training. The accuracy of the results obtained by combining the classification methods is 99.12%.

In Sahil Dalal et.al [3], The author has put forth a reliable method that largely concentrates on features taken from ECG data. The DWT is used to removes noise. Multi-cumulants are used to obtain features. Three processes make up this system: feature extraction, pre-processing, and classification. Resampling approaches are applied on the imbalanced datasets that are used throughout experiments. With 99.57% accuracy on the dataset, excellent classification is achieved. This system's technique for balancing the database slows down processing as the database grows in size, which is a drawback.

In Sayak Banerjee et.al [4], The goal of this paper is to develop a complete practical application using signal preprocessing and a DL Model . This quick and precise method employs a device that can detect an arrhythmia early on. This system will continuously monitor the user's cardiac health, alerting them to growing cardiac ailments and allowing them to avoid fatal diseases. As a result, the authors developed a wearable, lightweight prototype of an arrhythmia detector that can classify real-time ECG signals. The use of CNN and LSTM improves the accuracy and precision of this work, and the mobile application makes it easier to use. Because of its precise and low-noise output, the proposed model's accuracy can be improved further by adding more effective components for recording ECG signals. This project is being carried out using mobile applications in a variety of linguistic versions.

In Mohamed Hammad et.al [5], In this study, arrhythmia is classified into five types using the three-tier deep learning model. The model has three sub-divisional units that are used in order to extract the necessary features. A genetic algorithm to optimise the features that are extracted. Additionally, classification is done, where the KNN algorithm involves the point classification, SVM is used for regression and classification problems is done using multi-layer perceptron yielding an accuracy of 98%.

In M. Chowdhury et.al [6], the author developed a model that can distinguish between typical and abnormal ECG heartbeats. They developed a technique using the discrete wavelet transform method to compress and eliminate noise from ECG readings. A convolutional neural network is used to classify ECG signals into five different arrhythmias. Each ECG signal in the database was categorised using a onedimensional CNN model with four hidden layers and filters of 32, 64, 128, and 256. Performance of the method used to develop system was compared with other algorithms and found to be efficient. An autonomous wearable gadget was created for continuous based on the results of their recommended compression and classification techniques, they monitor ECG signals.

In Ullah et.al [7], the author has divided ECG signals into eight categories using convolutional neural network (CNN) model: NB, PVCB, PB, RBBBB, LBBBB, APCB, VFWB, and VEB. With average sensitivity, specificity, and accuracy, this model successfully divided ECG signals into eight classifications (precision). Here, the proposed approach is tested using a publicly available MIT-BIH arrhythmia. Professionals can be helped with diagnosis of heart diseases by automatic classification of ECG signals employed in the suggested approach. The ECG data used in this study is a single-lead signal.

In Mohammad Mahmudur Rahman Khan et.al [8], This paper particularly specializes the five classes of heart disease from PhysioNet's Dataset. This version is used to come across asymmetry in the ECG signal. The ECG signal has undergone a number of preprocessing steps before being classified. In this paper, a complete of 109446 beats at one hundred twentyfive Hz sampling frequency from forty-four statistics are tested to educate and take a look at styles for assessing the one-dimensional convolutional neural community model's overall performance. One-dimensional CNN is used as the new classifier for the ECG heartbeat signal. The CNN model suggested in this study is applied to a dataset containing five different types of ECG alarms. These made the dataset unbalanced by bringing to light some of its pattern sizes in a significant quantity.

In HUI YANG et.al [9], In this paper, a novel strategy combined with a single morphological trait is suggested for the proper prevalence and classification of heart dysrhythmia. First, ECG signal events are discovered. Then, from the selected ECG regions, the parametric capabilities of the ECG morphology are extracted. The function vectors are then supplied into the neural network, SVM, and KNN classifiers, three well-known classifiers for automated diagnosis. Individual sources can be extracted from a mixing signal using the ICA approach. Additionally, features from ECG signals have been extracted using a deep learning technique. This stage makes use of the Pan-Tompkins algorithm for heartbeat identification and pre-processing. The algorithm consists of five steps: threshold adjustment, moving window integration, differentiation, squaring, and band-pass filtering.

In G.Latif et.al [10], In this paper MIT-BIH database is used for classifying arrhythmia. Multiple classifiers are used as individual models and checked for the best classifier that gives the highest accuracy among all. Some of the classifiers utilized include naive Bayes trees, logistical model trees, neural networks model, radial basis function algorithm, multi-layer perceptron, and random forest trees. Among these random forest algorithms has given the highest accuracy of 92%.

In Li Yin et.al [11], In this study, multi-domain electrocardiogram feature extraction is put forward to classify arrhythmia. The RR intervals, approximation co-efficient of 5-layer wavelet decomposition in the frequency domain and sample entropy of each wavelet coefficient for the nonlinear feature were used as the multi-domain features. These features constitute time-domain, frequency and non-linear features. These features are fed to the classifier for further processing of extracted features. The method of classification is done using a Support Vector Machine (SVM) algorithm. This classifies the signals into eight classes of frequently occurring arrhythmia and yields an average accuracy of 99.70%.

In Anita Patil et.al [12], This approach is validated on 48 ECG signals from the MITBIH arrhythmia classification database. Extracted features are powerful features, and can allow for quick non-invasive diagnosis of the arrhythmia. These features are effective features in classifying normal and abnormal signals and can be classified with either neural network or support vector machines. Moreover, the accuracy of the SVM-based classifier for diagnosing arrhythmia is as high as 79.48%. A two-class KNN and SVM classifier is used to categorize abnormal and normal ECG patterns. In the detection of occurrence of normal and abnormal ECG patterns, the KNN classifier is able to detect 28 of 48 normal patterns, whereas SVM detects only 18 of 48 abnormal patterns. Both classifiers' performance evaluations are also computed. The KNN classifier demonstrates an accuracy of 76.92%, while SVM has an overall accuracy of 79.48%. KNN has a sensitivity of 82.35%, with 1, 2, and even 25% overlap, while SVM has a sensitivity of 71.42% at 10% overlap. KNN is not as specific as SVM.

Figure: Table Analysis

Author & Year	**Dataset Used**	**Methodology**	**Drawback**
Larissa Montenegro et.al, 2021[1]	Telehealth Network of Minas Gerais and PhysioNet Computing in Cardiology Challenge 2017.	Convolutional Neural Networks (1D-CNN) and Support Vector Machines (SVM).	SVM- feature selection is time-consuming CNN- higher computational processing cost.
Wusat Ullah et.al, 2021 [2]	PTB Diagnostic ECG Database and MIT-BIH arrhythmia database.	CNN model, CNN+LSTM and CNN+LSTM+Attention Model	The proposed model includes ten residual blocks, there is a possibility of overfitting the data.
Sahil Dalal et.al, 2021 [3]	MLII, UCI repository arrhythmia and PTBDB databases	Random under sampling technique (RUST) and Optimization algorithm.	The technique used to balance the dataset make the processing slower.
Sayak Banerjee	Physionet Challenge 2017	Convolution Neural	The cost

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et.al, 2020 [4]	Cinc.	Networks and Long Short-term Memory.	required for this system is significantly high.
Mohamed Hammad et.al, 2020 [5]	MIT-BIH arrhythmia database.	Genetic algorithm (GA), k-NN algorithm, SVM, Multi-layer perceptron (MLP) algorithm.	The CPU time required to execute each phase is large.
M. Chowdhury et.al, 2020 [6]	PhysioNet MIT-BIH database	Discrete Wavelet Transform (DWT), Convolutional Neural Networks (CNN)	The compression method used did not provide maximum accuracy.
Ullah Yu et.al, 2020 [7]	MIT-BIH arrhythmia dataset consisting 48 records.	Convolution Neural Network	It uses only a single-lead ECG signal. The effect of multiple lead ECG data is not mentioned
Mohammad Mahmudur Rahman Khan et.al, 2020 [8]	Physionet MIT-BIH Arrhythmia Dataset.	Convolution Neural Network	The signals varied in their sample sizes to a great extent which made the dataset imbalanced.
HUI YANG et.al, 2020 [9]	MIT-BIH arrhythmia database.	Visual patterns as well as a new clustering-based feature extraction algorithm is proposed.	Cost is much higher than other methods.
G. Latif et.al, 2020 [10]	MITBIH arrhythmia and ECG database.	MLP, RBF NN, Logistic Model Tree, NB Tree and Random Forest Trees.	Uneven distribution of data will cause accuracy as a measure to be skewed and inaccurate
Li Yin et.al, 2019 [11]	MIT-BIH arrhythmia database.	RR interval, approximation co-efficient, sample entropy	Degradation of accuracy for large data sets.
Anita Patil et. al, 2018 [12]	MITBIH arrhythmia database.	Discrete Wavelet Transform (DWT), K Nearest Neighbor (KNN), Support Vector Machine (SVM)	Classification of disease is limited to certain range.

III. PROPOSED SYSTEM

The proposed system is used to detect the irregularity in human heart on ECG and classify the type of arrhythmia. In this system we will send the raw ECG signals as input and perform signal processing using EMD algorithm. We use the EMD algorithm rather than the DWT technique for signal processing since raw ECG signals have greater noise. DWT performance deteriorates more in noisy environments than EMD. The collected signal will then be classified using the widely-used PhysioNet dataset. The different classification techniques will be used to identify the different ECG dysrhythmia. In this system we will use LDA to identify the accurate target class. Based on this classification technique, we will measure the accuracy and detect the five distinct dysrhythmias in human heart.

IV. CONCLUSION

Heart diseases have become the primary reasons for increasing death rate across the world. In order to prevent more damage to human lives early diagnosis for prevention and treatment for cardiac diseases is necessary. ECG is done to determine heart rhythm (dysrhythmias) and if there are any blocked or narrowed arteries in your heart. By processing the signal of ECG, we can detect the abnormality and classify the type of arrhythmia. Our system mainly focuses to help people with early diagnosis of heart diseases and save their lives on time. literature is also presented in a conciseprocessing the signal of ECG, we can detect the abnormality and classify the type of arrhythmia. Our system mainly focuses to help people with early diagnosis of heart diseases and save their lives on time.

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