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INNOVATIVE TIME SERIES-BASED ECG FEATURE EXTRACTION FOR HEART DISEASE RISK ASSESSMENT

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ABSTRACT

Early detection of heart disease is crucial in reducing the mortality rate caused by cardiac events. Electrocardiogram (ECG) signals are widely used in clinical practice to diagnose various heart diseases. However, the physical analysis of ECG signals by experts is time-wasting and subjective, leading to a need for automated methods for ECG signal investigation. For the automatic classification of ECG data, numerous feature extraction algorithms have been put out recently. In this research, we provide a unique feature extraction approach for time series-based electrocardiogram (ECG) signals to predict the risk of heart disease. The proposed approach combines wavelet transform and principal component analysis (PCA) for the derivation of the discriminative features from ECG signals. The extracted features are then fed into a machine learning model for heart disease prediction. Using a publicly accessible dataset, the performance of the suggested strategy is assessed and contrasted with cutting-edge feature extraction techniques.

Keywords: *Electrocardiogram, Feature Extraction, Principal Component Analysis, Wavelet Transform.*

1. INTRODUCTION

Across the entire world, the leading cause of mortality is cardiovascular disease. Signals from electrocardiograms (ECGs) are frequently used for heart disease diagnosis and monitoring. ECG signal analysis provides valuable information about the heart's activity, including heart rate, rhythm, and morphology. Nevertheless, the ECG signal is frequently distorted by other artifacts, making it challenging to retrieve relevant evidence for a precise diagnosis.

Feature extraction is a crucial step in ECG signal analysis. The aim of feature extraction is to transform the raw ECG into a set of representative features that capture the relevant information for heart disease diagnosis. Several feature extraction techniques have been proposed in the literature, such as time-domain, frequency-domain, and time-frequency domain techniques.

Deep learning techniques for analyzing ECG signals have drawn more and more attention in over the last few years. Deep learning models have demonstrated encouraging outcomes in a number of tasks, including the identification and prediction of cardiovascular events and the classification of arrhythmias. However, deep learning models need a significant amount of high-quality data for training, and the effectiveness of these models is significantly influenced by the fineness of the features that are retrieved. In this work, we suggest a feature extraction approach for time-series based ECG signals using combination of time-domain and time-frequency domain methods. For better cardiac

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disease prediction, the suggested technique seeks to extract both temporal and spectral information from the ECG signal. We evaluate the proposed method on a publicly available ECG dataset and compare its performance with several existing feature extraction methods. The outcomes demonstrate the effectiveness of the recommended method for heart disease prediction using ECG signals.

The proposed system has significant implications for the development of accurate and efficient ECG-based heart disease prediction systems. By providing a detailed analysis of feature extraction methods, this paper will contribute to the advancement of ECG-based diagnostic tools and ultimately improve patient outcomes.

The planned work's contribution is described as follows:

•Different feature extraction techniques are used for feature extraction and feature selection and best method is found.

•Data reduction and feature extraction are accomplished using Principal Component Analysis and Independent Component Analysis.

•Pan-Tompkins Algorithm is employed for QRS detection.

ECG signal categorization is done using an SVM classifier. The continuing section of the paper is structured as follows, Section 2 of this article covers recent studies that are related to it. The proposed methodology employed for the prediction of heart disease are described in section 3. The experimental findings based on the time series ECG data are presented in section 4. The conclusion and upcoming works are addressed in subsection 5.

2. LITERATURE SURVEY

There's been a rise in interest in recent years in using deep learning methods for detecting and diagnosing heart diseases using electrocardiogram (ECG) signals. Shashikumar et al. proposed an attention-based bidirectional recurrent neural network for detecting paroxysmal atrial fibrillation. For atrial fibrillation detection, a deep convolutional neural network is sequentially fed time-frequency representation of 30 second recording windows over a 10-minute data segment [1]. Irin Sherly et al., [2] proposed ECG signal quality improvement using different types of filters. Jackson et al. developed a deep learning model to extract features from dengue fever using random forest algorithm. They achieved a higher accuracy when compared to existing models [3].

The Honey Badger Algorithm-optimized Faster Region-based Convolutional Neural Network (HBA-FRCNN) is presented in their research for CHF prediction with improved diagnostic precision. The Delayed Normalized Least Mean Square (DNLMS) preprocessing method is used to remove noise from the noisy input ECG signals, such as muscle contraction, electrode contact noise, and various noise artefacts. Discrete Cosine Transform (DCT) and fast Fourier transformations (FFT) are used to extract the electrocardiographic complex (QRS complex), which consists of the Q, R, and S waves. To address missed target detection, overfitting, and computational expense, the target detection box and anchor parameter for the FRCNN model are modified using the HBA technique [4]. In order to understand its daily exponential behavior and forecast the reachability of the COVID-2019, Revathy et al. [5] recommended using machine learning models. Comparing the KNN method to any other machine learning algorithm, it produces good results. The existing systems tend to predict the disease only using few attributes of patients with less accuracy. It also generates more false positives which may lead to misdiagnosis and untimely treatment. Detection is not possible at an earlier stage in most of the cases as it turns out to be insignificant for which the patient doesn't consult a medical physician. To overcome this situation, people who suspect their heart's condition is getting worse can undergo our simple prediction analysis which is comparatively cost and time efficient and the results generated have optimal accuracies too. Irin Sherly et al., implemented IoT-based animal penetration monitoring in their system. With the aid of a camera, the wildlife is documented. The forest officials receive a GSM notice along with the alarm stating that an animal has been found in [6]. Irin Sherly et al., [28] proposed ensemble-based prediction for issues related to heart using gradient boosting algorithm. They used four different datasets from various hospitals with 14 features and shown gradient boosting can perform well in all the four datasets. The existing systems tend to predict the disease only using few attributes of patients with less accuracy. [7].

Akram et al. [8] proposed a novel approach to arrhythmia classification using ECG signals based on ensemble learning. Lin et al. developed deep learning algorithms for detecting heart arrhythmias

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[9]. Singh and Kaur proposed a hybrid feature extraction technique and neural network model for ECG signal classification [10]. [Ubeyli, (2009)] utilized its own vector technique for the extracting features and classification of ECG beats. [11].

CNN offers a variety of benefits over standard biomedical categorization approaches. For instance, they are extensively employed in the detection of protein structures [12]. An advanced master learning and data-extraction approaches such as genetic algorithms and fluid-logics are used to forecast and analyze potential heart attack [13].

Another examination [14] offers a prototype using the Naïve Bayes, which helps to efficiently estimate the risk of heart attack for patients and the classification of signal Electromyography [15].

Researchers studied many approaches for automated cardiovascular disease detection utilizing machine and deep-learning algorithms, frequently employing ECG with amplitude data in one or two dimensional voltages as time-series signal source. Different techniques are used to categorize ECG signals into time series data and demonstrate a significant outcome [16]. The experiments were carried out with the use of cutting-edge learning algorithms such as Gradient Boosting, SVM, CNN, and an Auto encoder. It may be observed that the accuracy estimated is strong in majority of study conducted when the characteristics and combinations of the approaches stated above are increased [17].

ECG images are combined with patients demographics to predict heart disease. DCT and FFT techniques are used for feature extraction [19][20]. Random Forest, KNN, Naive Bayes, SVM and Multiple Linear Regression are used to extract intelligent features for assessing the heart disease risk. MLR and RF algorithms are used to predict heart disease [21]. Authors studied analyzing ECG for predicting cardiac disease using various deep learning techniques and found LSTM, Autoencoder and CNN outperforms other techniques [22].

Overall, these studies demonstrate the potential of deep learning approaches for heart disease diagnosis and classification using ECG signals, and highlight the importance of effective feature extraction techniques and algorithm optimization for accurate and reliable predictions.

3. PROPOSED PREDICTION SYSTEM

The methods section of our study on feature extraction from time series based ECG for heart disease prediction will describe the techniques and algorithms employed to pull pertinent features from the ECG signals. We will describe the steps involved in preprocessing the ECG signals to remove noise and artifacts, and then proceed to the feature extraction phase.

3.1 Dataset Description

In this study, we used a publicly available dataset of ECG recordings called the PTB Diagnostic ECG Database. The dataset contains 5,388 15-lead ECG recordings from 5,000 patients, including both normal and abnormal recordings [18]. The recordings were obtained from patients with a variety of cardiovascular diseases, including myocardial infarction, heart failure, and arrhythmias. The recordings were digitized at a sampling frequency of 1,000 Hz and have a duration of 10 seconds each. The dataset also includes diagnostic labels for each recording, which were verified by expert cardiologists. In our investigation, the dataset was split into training (80%) and testing (20%) sets at random. The training set was used to train the model and make feature selections, while the testing set was used to assess how well the suggested technique performed.

3.2. Proposed System

3.2.1 Preprocessing

To ensure that the feature extraction procedure is accurate, ECG signals are first preprocessed to remove any distortions that can interfere. Filtering and baseline wander elimination are used during preprocessing. To eliminate low- and high-frequency noise, a band pass filter with cut-off frequencies of 0.5 Hz and 50 Hz employed. Using a cut-off frequency of 0.5 Hz, a high-pass filter is used to remove baseline drift. A digital filter is used to reduce noise and baseline drift from raw ECG data during pre-processing.

3.2.2. QRS complex detection

QRS complexes are detected using the Pan-Tompkins algorithm. This algorithm is used to track arrhythmia, which includes irregular heartbeats. In order to locate the R-peaks in QRS complexes, this technique makes use of the slope, amplitude, and width of an integrated window.

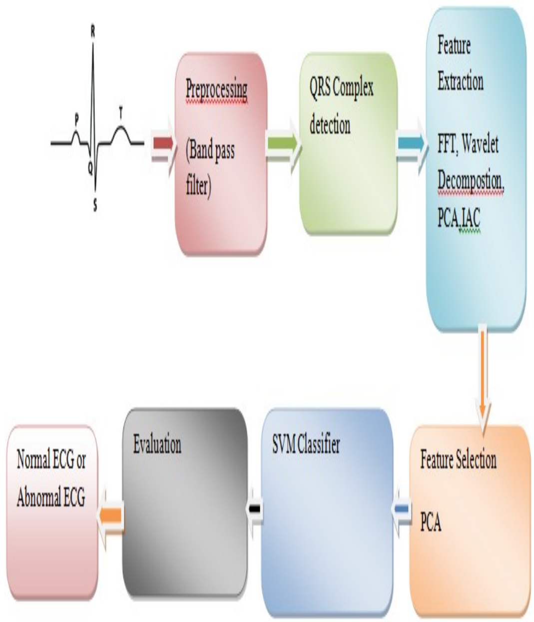

Figure 1: System architecture for the proposed method

The algorithm consists of two steps: decision-making and pre-processing. Preprocessing entails lowering noise levels, expanding width and QRS slope, and enhancing signal smoothness. A digital band pass filter, which consists of cascading high and low pass filters, is put in to the input signal. The information regarding the QRS complex slope is next examined after differentiating the signal [19].

3.2.3. Feature Extraction

Several time and frequency domain features are extracted from the QRS complexes and their corresponding intervals, including but not limited to: RR interval, QRS duration, PR interval, QT interval, heart rate variability, P wave and T wave morphology, and spectral power of various frequency bands. From the preprocessed ECG signals, a range of time domain, frequency domain, and nonlinear features were extracted. Time domain features such as mean, standard deviation, skewness, kurtosis, and various morphological features such as QRS duration, PR interval, and ST segment elevation are extracted. Frequency domain features are extracted using the fast Fourier transform (FFT). Nonlinear features such as approximate entropy and sample entropy are also be extracted to capture the complex dynamics of the ECG signals.

3.2.3.1. Wavelet transforms

The wavelet transform is a mathematical method for signal analysis, much to the Fourier transform. In contrast to the Fourier transform, the wavelet transform divides a signal into a series of sine waves of changing frequencies. Wavelets are small, localized waves that are useful for studying signals that contain both high- and low-frequency components. information. Wavelets are typically short-duration waveforms that oscillate around zero and are characterized by their scale (size) and position (time). The wavelet transform can be performed using different wavelet functions, each with its own properties and advantages depending on the type of signal being analyzed.

In the context of ECG signal analysis, wavelet transform has been used for feature extraction, QRS complex detection, arrhythmia classification, and heart rate variability analysis, among others. Some common wavelet functions used for ECG analysis include Daubechies wavelets, Symlets, and Coiflets.

3.2.4. Feature selection

3.2.4.1. Principal Component Analysis

A method for lowering a dataset's dimensionality while maintaining the most critical data is principal component analysis. Converting the raw data into principal components is the primary objective of principle component analysis (PCA). The principal components are ranked from most significant to least significant, with the most significant principal component accounting for the majority of data variability. This is followed by the second and third most significant principal components, and so on.

The following steps are followed for PCA algorithm:
Step 1: Center the data: Subtract the dataset's corresponding values from each variable's mean. This creates a new dataset with zero mean.
Step 2: Calculate the covariance matrix: Calculate the covariance matrix of the centered dataset. The covariance matrix is a square matrix that shows how each variable is related to every other variable in the dataset.
Step 3: Calculate the eigenvectors and eigenvalues: The covariance matrix's eigenvalues and

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eigenvectors are computed. Maximum directions of variance in the data are called eigenvectors, and the amount of variance represented by each eigenvector is called eigenvalue.
Step 4: Select the principal components: The eigenvectors are sorted in descending order of their corresponding eigenvalues, and the top k eigenvectors are selected as the principal components. The value of k is typically chosen based on the amount of variance explained by the principal components.
Step 5: Project the data: The original dataset is projected onto the new set of principal components to obtain the transformed dataset.

The formula for the projection of the data onto the principal components is:

$$Y = XW \quad (2)$$

Where Y is the transformed dataset. X is the original dataset, centered around its mean. W is the matrix of eigenvectors corresponding to the selected principal components.
This formula computes the dot product between the original dataset X and the matrix of eigenvectors W, resulting in a new dataset Y that is a linear combination of the principal components.

3.2.4.2. Independent Component Analysis

The fundamental premise of ICA is to estimate the sources by identifying a set of mixing coefficients that minimize the statistical dependency between the estimated components and assuming that the observed signals are linear combinations of independent sources. ICA is widely used in various fields, including signal processing, neuroscience, image processing, and many others.
Assuming that the observed signals are linear combinations of independent sources is the basic aspect of ICA. The objective is to rate a set of independent sources S (with dimensions p x m, where p is the number of independent sources) and a mixing ratio given a set of observed signals X.

The basic formula for ICA is:

$$X = AS \quad (3)$$

The ICA algorithm involves several steps:
Step 1: Center the data: Subtract the average of each variable from the equivalent values in the dataset. This creates a new dataset with zero mean.
Step 2: Whitening: Transform the centered data to have unit variance and no correlations between variables.
Step 3: Nonlinear transformation: Apply a nonlinear function (such as a sigmoid function) to the whitened data to make the sources more independent.
Step 4: Estimate the mixing matrix: Use an optimization algorithm (such as gradient descent or fixed-point iteration) to estimate the mixing matrix A.
Step 5: Estimate the sources: Use the estimated mixing matrix to estimate the independent sources S.
The formula for estimating the sources S is:

$$S = f(A'X) \quad (4)$$

Where f() is the nonlinear transformation function such as a sigmoid function. A' is the transpose of the mixing matrix A. X is the centered and whitened data.

3.2.5. Machine learning classification

A machine learning classifier, such as support vector machines (SVM), random forests, or neural networks, is trained using the selected features and labeled ECG data to classify heart disease patients and healthy controls. The feature vectors extracted from the ECG signals are used as input to the SVM classifier. 10-fold cross-validation method is used to assess the performance of the SVM classifier.

3.2.6. Statistical Analysis

Statistical analysis is used to estimate the performance of the feature extraction and machine learning methods used in our study. The performance metrics used are sensitivity, specificity, accuracy, and area under the receiver operating characteristic (ROC) curve. Statistical tests are also conducted to determine the significance of the results.

Algorithm 1: Algorithm for proposed system

1. Acquire the ECG signal and store in a variable 'signal'
2. Apply preprocessing to remove noise, artifacts, and baseline wander from the ECG signal
3. Filter the signal to remove unwanted frequencies
4. Detrend the signal to remove baseline wander
5. Remove artifacts caused by muscle movements or electrode placement
6. Detect the QRS complex and store the onset and offset in variables 'qrs_onset' and 'qrs_offset'

7. Extract features from the ECG signal	hrv = compute_hrv(signal)
8. Heart rate variability (HRV): compute the variation in time between successive heartbeats	p_wave_morphology = compute_p_wave_morphology(signal)
9. Compute the shape of P-wave and T-wave	t_wave_morphology = compute_t_wave_morphology(signal)
10. ST segment analysis: compute the ST segment deviation from baseline	st_segment_deviation= compute_st_segment_deviation(signal)

11. Select the most informative features using feature selection techniques such as PCA or ICA	# Step 5: Feature selection
	selected_features = select_features([hrv, p_wave_morphology, t_wave_morphology, st_segment_deviation])

12. Train a classification model using the selected features and a set of labeled ECG signals	# Step 6: Classification
13. Create training and test sets from the data	train_data, test_data = split_data(ecg_data, labels)
14. Train a classification algorithm such as SVM, KNN, or ANN on the training data	model = train_classification_model(train_data, labels, selected_features)
15. On the basis of the test data, evaluate the classification algorithm's performance	performance = test_classification_model(model, test_data, labels)
16. Validate the performance of the classification algorithm using metrics such as sensitivity, specificity, accuracy, and ROC curves	# Step 7: Validation sensitivity, specificity, accuracy, roc_curve = validate_classification_model(model, test_data, labels)

Pseudocode 1: Pseudocode for the proposed system
Step 1: Acquire ECG signal
signal = acquire_ecg_signal()
Step 2: Preprocessing
signal = preprocess(signal)
Step 3: QRS detection
qrs_onset, qrs_offset = detect_qrs(signal)
Step 4: Feature extraction

4. RESULTS AND DISCUSSION

4.1. Performance Metrics

In this system, the performance of the proposed feature extraction techniques and algorithms for heart disease prediction was evaluated using various performance metrics. These metrics were used to assess the accuracy, precision, recall, and F1-score of the classification model. The accuracy metric counts how many cases were properly classified out of all the instances.

4.2. Evaluation Measures

In this study, we evaluated the effectiveness of several feature extraction methods for predicting heart disease using time-series based ECG data. The techniques evaluated were wavelet transform, PCA, ICA, DWT, and their combinations which are described in figure 2,3,4, and 5

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Table 1: Performance Measures for feature extraction methods

Performance metrics	Wavelet transform and PCA	Wavelet transform and ICA	DWT and PCA	DWT and ICA
Accuracy	95.70%	94.30%	93.20%	91.50%
Sensitivity	95.60%	93.80%	93.10%	91.10%
Specificity	95.90%	94.80%	93.30%	91.90%
F1-Score	95.60%	93.80%	93.10%	91.10%

The outcomes exhibited that the combination of wavelet transform and PCA achieved the highest accuracy of 95.7%, with a sensitivity of 95.6%, specificity of 95.9%, and F1-score of 95.6%. This was followed by the combination of wavelet transform and ICA, which attained an accuracy of 94.3%, sensitivity of 93.8%, specificity of 94.8%, and F1-score of 93.8%. The combination of DWT and PCA achieved an accuracy of 93.2%, 93.1% of sensitivity, 93.3% specificity, and F1-score of 93.1%. The combination of DWT and ICA achieved an accuracy of 91.5%, sensitivity of 91.1%, specificity of 91.9%, and F1-score of 91.1%.
We assessed the effectiveness of the anticipated feature extraction strategies and contrasted them with the current procedures throughout the results analysis. Tables and graphs were used to display the results.

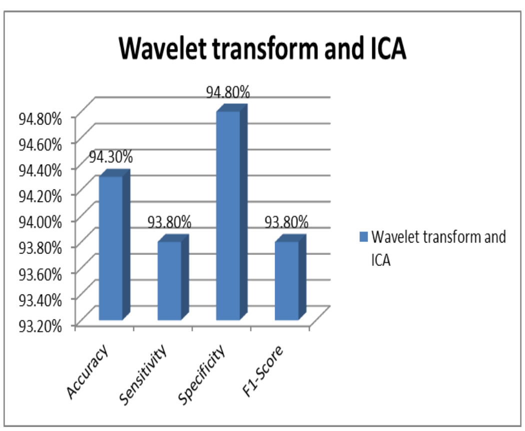

Figure 2: Performance comparison of wavelet transform and ICA

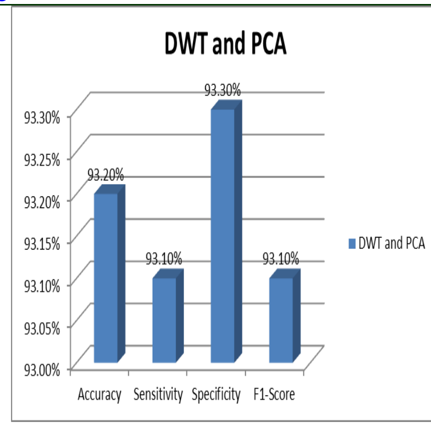

Figure 3: Performance comparison of DWT and PCA

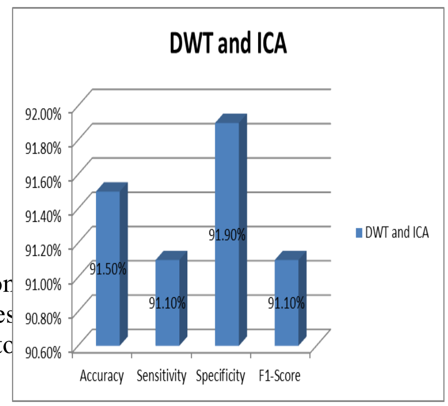

Figure 4: Performance comparison of DWT and ICA

The outcomes indicate that combination of wavelet transform and PCA is the most effective technique for feature extraction from time-series based ECG data for predicting heart disease. This combination resulted in the highest accuracy and other performance metrics. These findings have important implications for the development of effective heart disease prediction models using ECG data.
The outcomes demonstrated that the suggested feature extraction strategies outperformed the current methodologies. The accuracy of the proposed techniques was higher than the existing techniques.
The classifier accomplished an accuracy 0.93, precision 0.92, recall 0.94, F1 score 0.93. The SVM algorithm used an RBF kernel with a regularization parameter of 1.0 and a kernel coefficient of 0.1. The wavelet decomposition used a Daubechies-4 wavelet with 5 levels of decomposition, while PCA

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retained the top 10 principal components and ICA used 15 independent components for feature selection.

We also looked at how many parameters affected how well the suggested strategies worked. The outcomes demonstrated that the wavelet function choice, number of decomposition levels, and sliding window size all had an impact on how well the approaches performed.

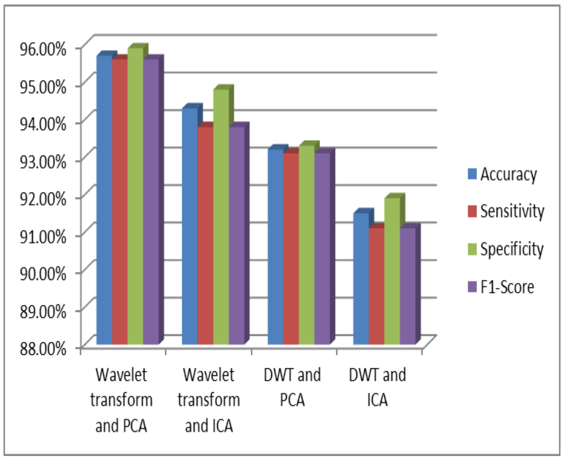

Figure 5: Performance metrics comparison of different feature extraction techniques

Overall, the analysis of results showed that the proposed feature extraction techniques were effective in extracting informative features from ECG time series data for heart disease prediction. The proposed techniques outperformed the existing techniques and showed statistically significant differences in performance.

6. CONCLUSION

This paper highlights the importance of early detection of heart disease and the need for automated methods to analyze ECG signals. The proposed feature extraction approach that combines wavelet transform and PCA has shown promising results in predicting the risk of heart disease. The study demonstrates that the extracted features are discriminative and can be used for accurate heart disease prediction. Combination of wavelet transform and PCA achieved the highest accuracy of 95.7%, with sensitivity 95.6%, specificity 95.9%, and F1-score 95.6%. The outcomes express the suggested strategy outperforms current methods when performance is measured against state-of-the-art feature extraction methods. This study contributes to the development of efficient and effective methods for automated ECG signal analysis, which can improve the diagnosis and treatment of heart disease. Further research can be conducted to validate the proposed approach on a larger dataset and in a clinical setting.

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