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Hybrid Feature Extraction and Infinite Feature Selection based Diagnosis for Cardiovascular Disease Related to Smoking Habit

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***Abstract*—Electrocardiography (ECG) is a growing study in the realm of patient monitoring systems to detect cardiovascular disease (CVD) by smoking habits. This study investigated the categorization and analysis of CVD related to smoking habits using the ECG dataset from the Physikalisch-Technische Bundesanstalt (PTB). After acquiring ECG data, the feature vectors were extracted using hybrid feature extraction (a mix of statistical, energy, and entropy characteristics). To extract features from obtained ECG signals, nineteen characteristics were merged. Artifacts in the signal are being reduced by using a zero phase butterworth filter, and the peak identification of ECG signal is attained by using the Pom-Tompkins method. Then, infinite feature selection was used to delete unnecessary characteristics or choose the best feature subsets. After choosing the best characteristics, the ECG signals of smokers and non-smokers are classified using a supervised classifier (K-Nearest Neighbor (KNN)). KNN classifier has the advantage of balancing the data for the classification of smoker and non-smokers. This discovery has several benefits, including earlier detection of cardiovascular disorders and great assistance to physicians during surgery. The results of the experiment are evaluated using classification Accuracy, F-Score, Specificity, Sensitivity, and Mathews Correlation coefficient (MCC) for the proposed technique, and the process efficiently discriminated the ECG signals of smokers from non-smokers in comparison to the previous methods; the suggested strategy improved accuracy by 3-40%.**

***Keywords*— Electrocardiography; hybrid feature extraction; infinite feature selection; k-nearest neighbor.**

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I. INTRODUCTION

Currently, over two billion people are habituated to tobacco ingestion, and every year three million people die from smoking-related causes. Smoking is the main risk factor for cardiovascular diseases, which almost affects smokers 2.6 times more than non-smokers [1]. Cardiovascular disease affects the circulatory and heart system, leading to obesity, hypercholesterolemia, diabetes mellitus, familial growth hormone deficiency, renal failure, stroke, etc. [2]-[7]. In the present decades, several computer-aided diagnostic techniques are available that deliver valuable information about human organs' activities. Especially techniques like ECG signals, Heart Rate Variability (HRV) signals, photo-plethysmography, cardiac catheterization, etc. are available to analyze heart functions [8]. Among these techniques, the ECG signal is useful to characterize the electrical activity of the heart that records the signal by employing electrodes on the human body [9]-[13]. The original ECG signals should be within the millivolt range, and the filtered signals have lower amplitudes within the microvolt range [13]-[16]. Previously, cardiovascular disease recognition was accomplished by a physician based on visual observation of ECG signals, which is an ineffective and time-consuming task [17]. So, an automatic cardiovascular disease detection system has been developed that includes more benefits over human visual inspection, such as fast diagnosis, less time consumption to find cardiovascular disease from ECG records and helps to handle large ECG datasets [18], [19].

Various examination has been completed to enhance further the accuracy of the classification of ECG data of smokers and non-smokers, yet at the same time, the traditional techniques did not accomplish a good outcome. In this exploratory review, a capable framework is carried out to perform classification further to enhance the grouping precision of smokers and non-smokers and diagnose cardiovascular-related diseases. Initially, the ECG signals are obtained from the PTB ECG dataset, where artifacts in the ECG signals are decreased by utilizing standardization and 6th order Butterworth filter with zero phases. After pre-processing of the information, Pan-Tomkin's calculation and windowing method are utilized for peak identification. The hybridized feature selection method is used to get the features extracted from the pre-processed signals of ECG. The feature extraction technique is one of the most often used ways to extract the information subset as features. The infinite feature selection technique is used to pick the ideal feature subsets after receiving the features from the feature extraction technique. The infinite feature selection method has the advantage of removing noises with high sensitivity and avoiding the redundant data present in signals. The selected features from the infinite feature selection method are given as input to the KNN classifier. While working with uneven or non-uniform information, KNN is a decent decision for data classification since it settles the concern of imbalanced data.

Chen et al. [20] created a deep learning-based automated arrhythmia classification technique that has long short-term memory cells integrated with a convolutional neural network to recognize six types of ECG signals. The collected data has been categorized into sinus bradycardia, pacing rhythm, atrial flutter, atrial fibrillation, and ventricular bigeminy. Using a multiple-input structure, the presented approach processed 10 ECG signal segments and accompanying RR intervals from the MIT-BIH arrhythmia database. The accuracy of the developed arrhythmia classification system has improved. On the other hand, the detection of typical sinus rhythm and atrial fibrillation was not correctly done.

Using a convolutional neural network, Huang et al. [21] developed a computer-aided diagnostic approach for categorizing atrial fibrillation and normal sinus rhythm based on ECG data. The created approach pre-processes the waveform, creates pictures, and predicts if it contains an atrial fibrillation pattern. A heartbeat data series was processed into a single heartbeat, and the series of single heartbeats was turned into a picture without feature selection using the created approach. The devised approach was straightforward to use, and the categorization results were accurate. However, the created method's output does not maintain the original ECG signal information.

Wang et al. [22] developed a high-precision classification algorithm named dual fully connected convolutional neural network arrhythmia classification algorithm for arrhythmia. The difficulty in diagnosing arrhythmia in various persons was a problem with prior approaches. The current study considered a convolutional neural network that was fully connected in dual nature for accurate classification to conduct automated detection of arrhythmia. The MIT Supra Ventricular Arrhythmia Database (SVDB) and MIT arrhythmia database (MITDB) were employed in the created model. The generated model was used to automatically detect arrhythmia from an ECG, and the ECG data was insufficient for training the complicated network structure.

Atal and Singh [23] utilized a convolutional neural network with an optimization approach, which confronts a difficult challenge for accuracy and automated monitoring for classifying arrhythmia types using ECG information. Using the approach of optimization-based deep convolution, the model achieves automated arrhythmia categorization. The Rider Optimization algorithm (ROA) integrated with the multi-objective bat optimization algorithm, which creates a new technique of Bat-Rider optimization to address the characteristics and experimentation of a large dataset, proved problematic to it.

There are some previous studies related to this issue. Malleswari et al. [24] proposed the Hybrid Empirical Mode Decomposition-Discrete Wavelet Transform (EMD-DWT) based algorithm for detecting QRS complex in electrocardiogram signals which detect cardiac abnormalities. This algorithm improved the accuracy of QRS detection compared to state-of-art techniques. Here, the DWT with the appropriate thresholding method is applied to a partially denoised signal to remove the noise efficiently and detects QRS peaks. This method also gives a better estimation of the original signal than DWT. Furthermore, the PLI noise was eliminated. For that reason, the developed EMD-DWT method produced an improved accuracy value.

Gárate-Escamila et al. [25] proposed the Classification models for heart disease prediction using feature selection and PCA. Here, the dimensionality reduction methods were used to enhance the raw data results. This method focused on discovering the finest dimensionality reduction technique for predicting heart disease by using CHI-PCA method. However, this method was very complex to extend these findings on heart disease because of the small sample size.

Mandal et al. [26] proposed the tri-Stage Wrapper-Filter Feature Selection Framework for medical report-based disease detection. Here, the achieved feature subset of a meta-heuristic algorithm was deployed to reduce the feature set and to achieve higher accuracy. Moreover, in this algorithm, computational complexity was required to compute the accuracy of all the datasets based on each individual feature and to perform the WOA algorithm even though the wrapper-filter techniques do not use different classification algorithms for medical datasets.

ANCA-associated vasculitis (AAV) was newly identified in individuals with venous thromboembolism which has possessed the risk of CVD. Each patient-selected random set from the same amount of population has three non-AAV comparators with age and sex-matched, and its corresponding AAV occurrence date gives the index date [27]. The cardiac events, including CVD, are examined by comparing the comparators and patient's medical records. The participants matched with comparators higher than 8-fold possess risk higher and greater than 3-fold possess risk medium as per CVD risk factor baseline according to similar incidents that occurred.

Various CVDs and their mortality are linked with Swedish oral moist consumption by Titova [28]. However, the cigarette smoking habit has a well-known risk of CVD, and it is more unknown facts on smokeless tobacco, such as snuff on the risk of CVD. Usage of snuff was not directly related to myocardial infarction, atrial fibrillation, heart failure, abdominal aortic aneurysm, aortic valve stenosis, or stroke based on adjusting for other factors or smoking. Snuff usage was also statistically linked with a significant risk of ischemic stroke or total stroke among the people who did not smoke earlier.

Atal et al. [29] proposed the dictionary matrix generation-based compression and bitwise embedding mechanisms for

ECG signal classification. Here, the developed new embedding system was used to improve patient health information security. The signal's spectral and peak values are removed to enhance classification efficiency. Furthermore, the developed system decreased data loss during memory storage, time complexity, and transmission. However, the ECG databases were not utilized with various classification methods.

Smigel et. Al [30] proposed a deep neural network based on the PTB-XL database investigation for the automated classification of ECG signals. At first, the convolution network was taken as the base, and then SincNEt and Convolutional Neural Network (CNN) with extra entropy-based features were included over it. The expansion of network design associated with subnetworks of heterogeneous Inception model containing numerous kernels and pooling performance can be improved with tolerable cost. The experimental study on this investigation is further not yet developed.

II. Material And Method

Cigarette smoking is currently the most significant risk factor for human cardiovascular disease. As a result, the creation of an automated system for cardiovascular disease diagnostics is required. The following figure 1 is a quick description of the proposed work.

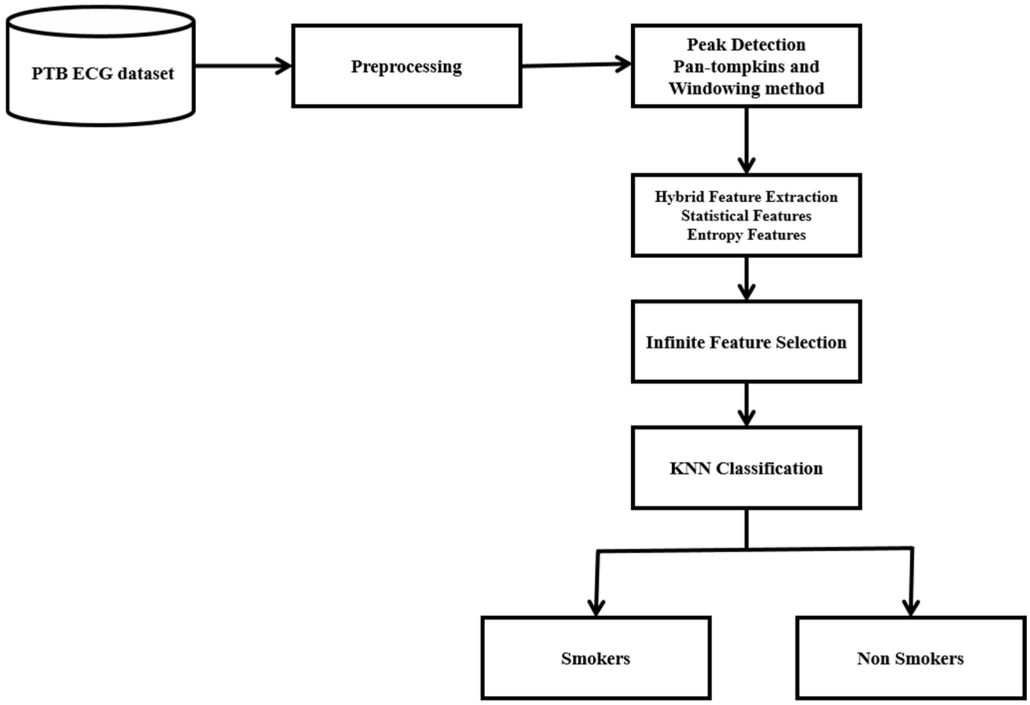

Fig. 1 Proposed Architecture

A. Data Acquisition

PTB ECG dataset has been used to render the ECG signals for CVD detection at the initial stage of the proposed method. This dataset comprises 294 subjects with 549 records. Each record is sampled at 1000 Hz with a resolution of $0.5\mu v$ at variable duration. In 294 subjects, 20 subjects belong to smokers and non-smokers (10 smoker persons and 10 non-smoker persons).

B. Signal Pre-processing

The acquired signals from the PTB ECG database have been processed with normalization to quantify their amplitude from -1 to 1. Normalization is a statistical operation performed over heterogeneous values of data to scale it into a defined uniform magnitude where the baseline is set as 0. The sixth order of the Butterworth filter is used to remove noise in the ECG signal and enhance its quality. Impulse or machinery noise is the two major categories of noises imparted into ECG signals due to the measuring apparatus. The Butterworth filter of sixth order can remove such noises effectively and eliminates the interference noise, which ranges over 0.5Hz of frequency for the CVD detection. The equation of Butterworth filter with 6th order is given in equation (1).

$$G^2(W) = |H(jw)|^2 = \frac{G_O^2}{1+(\frac{jw}{jw_c})^{2n}}, n = 6 \quad (1)$$

Where filter order is termed as n, cut-off frequency asw_c and DC gain as G_o. The peak detection for the corresponding pre-processed signals is taken by utilizing windowing and Pan-Tompkin's method.

C. Pan-Tompkin's Algorithm and Windowing Technique for Peak Detection

To produce faster results on automated signal processing, it is very essential to identify the peaks of the input signal. In the proposed method, with a low spectral frequency, ECG signals are moderated to particular bands which are taken to have better quality and frequency range than the raw data. By utilizing the filtering techniques, peak detection is conducted in the proposed methodology, and it includes four stages: filtering, derivatives, squaring of signals, and R-Peak detection.

1) Filtering: Interference occurred over the frequency of 60Hz and on T-waves, the influence of the baseline wanders in the signal, and muscle noise is eliminated with the help of a bandpass filter. The frequency range passed by the filter is 4Hz to 15Hz which also increases the energy of the QRS complex. The combination of low and high passbands is used to create the bandpass filter in which both the low and high-frequency range interference is eliminated.

2) Derivative: Noise-less signal of the QRS complex slope can be obtained using the smoothing approach on the derivative section. Moreover, the specific time interval of each peak position, width, and amplitude are also explained in this section.

3) Squaring: Sequential squaring of derivative output is done, and then the squared signals are non-linearly amplified, and the emphasis of QRS complex is given in equation (2).

$$y(nT) = [x(nT)]^2 \quad (2)$$

Where, the input signal is being denoted as $x(nT)$, and the squared output signal is being denoted as $y(nT)$

4) Peak Detection: By using the following steps, the peak detection is done using the Pan and Tompkins algorithm as mentioned follows:

Step 1: A variable with the name temp local max is randomly declared from the input signal

Step 2: A particular value is chosen randomly from the input signal. If the newly chosen value is higher than temp local max it replaces the old value

Step 3: Else if the newly chosen value is lesser than the previous one it determines the old value as a peak. And then repeats from step 2 until all the values in a signal cycle are chosen.

5) Windowing: The windowing technique is applied to the Pan and Tompkins algorithm output for the enhancement of accuracy in peak detection. This method extracts the R Peak location and its features by shifting the samples from left to right and right to left of the signal. In accomplishing this technique, hybrid feature extraction is applied to get the features from the ECG signal.

D. Feature Extraction Using Hybrid Features

The reduced transformation of data from the large redundant data feature space is done by mapping the data from one data space to another, defined as feature extraction. This process aids in reducing system complexity and is useful based on entropy and statistical features. Statistical features are standard deviation, mean, minimum value, maximum value, skewness, kurtosis, and moments. Entropy features considered are renyi, Shanon, higher-order spectra, permutation, cumset 1, 2 and 3, burg's operator, teager's energy operator, Yule-walker, and ratio of peak-magnitude to the root mean square value is also extracted as features from ECG signal. Despite several occlusion and significant clutters, data recognition is possible through several features. These six features are chosen by infinite feature selection from nineteen features in total.

E. Infinite feature selection

Based upon a particular condition, the feature selection algorithm identifies the active feature subset of ECG signals. In the proposed feature selection method, the mutual information between the features is taken as the condition for identifying the most active features and can help reduce the computational complexity. The proposed method selects the optimal subset of features by utilizing the infinite feature selection methodology. As given in equation 3, the mathematical calculation for each feature vector that has appropriate length l and energy scores $s_l(i)$ are taken as the initial condition for calculation.

$$s_l(i) = \sum_{j\in V}\sum_{p\in p_{i,j}^l}\prod_{k=0}^{l-1} a_{vk,vk+1} = \sum_{j\in v} A^l\,(i,j) \quad (3)$$

Where, representation of all paths set is given as $p_{i,j}^l$ with length l calculated within the nodes of $j$and node i , power iteration of a matrix A is denoted as A^l and feature vectors of all the vertices are given as V. Based upon the extension of the length of the path to an infinite value, normalization of the feature vector's probability is done, and its energy score for each feature f with all path lengths as infinity is computed by equation (4).

$$s(i) = [(\textstyle\sum_{l=0}^{\infty} A^l) - I]\bar{1} \quad (4)$$

Where, the identity matrix is denoted as I and the vector column of 1s is denoted as $\bar{1}$. XMatrix has the geometric series of algebra matrix as $\sum_{k=0}^{\infty} X^l$and convergence of this series happens upto $(I - X)^{-1}$ if the condition of $p(X) < 1$ met and maximum value of the X's Eigen value is denoted as $p(X)$. By equation (5) the feature vector for each feature with score fore regularized energy as per the above property.

$$s'(i) = [((\textstyle\sum_{l=0}^{\infty} r^l A^l) - I)\bar{1}]_i = [((I - rA)^{-1} - I)\bar{1}]_i \quad (5)$$

By computation of $((I - rA)^{-1} - I)$ is reduced through the equation of power iteration computation in equation (3)

F. Classification Using K-nearest Neighbors

KNN classifier is applied to the active feature subset of ECG signals after the processing feature selection. To classify the presence of smoking habit or not in the patient records of ECG signal data with CVD diagnosis, the KNN classification approach is used. To avoid the probability density of issues completely, the pattern classification of the non-parametric approach is taken via a supervised algorithm of KNN. The decision to label data x is based on the labels of nearest samples k for the data x, which has to be classified. Basically, for a new test record, it will compare the similar record in training records and give a result decision based on the nearest determination using the measure of Euclidean distance, which is defined in equation (6).

$$X_1 = (X_{11}, X_{12}, \ldots\ldots, X_{1n}), X_2 = (X_{21}, X_{22}, \ldots\ldots, X_{2n})$$
$$distance(X_1, X_2) = \sqrt{\sum_{i=1}^{n}(X_{1i} - X_{2i})^2} \quad (6)$$

Where X_1 and X_2 are the two records with attributes n. As equation (6) states, the distance between the data samples of X_1 and X_2 is determined based on matching several values of the attributes in the records of data X_1 and X_2.

III. Result and Discussion

In this article, the proposed work was simulated by using MATLAB (2017a). Here, the performance evaluation of the proposed classification work was compared with the existing methodologies of classification of CVD about the smoking habit of patients (Radial basis function neural weights using deterministic learning) on the PTB ECG dataset for estimating the proficiency of the proposed work. The infinite feature selection and hybrid feature extraction based on the proposed KNN classification work performance was evaluated using f-score, accuracy, sensitivity, specificity, and MCC.

A. Quantitative Analysis Using PTB ECG Dataset

In this segment, PTB ECG dataset is used for comparing the proposed classification approach's (KNN) evaluation performance with respect to other existing ECG classification methodologies like Random Forest (RF), SVM and NN.

TABLE I
Performance Evaluation Using Sensitivity, Specificity, F-Score and MCC

Classes	Classifiers	Sensitivity (%)	Specificity (%)	F-score (%)	MCC (%)
Smokers	RF	90	70	77.78	61.24
	SVM	70	90	81.82	61.24
	NN	40	70	60.87	10.48
	KNN	90	100	95.24	90.45
Non-smokers	RF	70	90	81.82	61.24
	SVM	90	70	77.78	61.24
	NN	70	40	47.06	10.48
	KNN	100	90	94.74	90.45

In Table 1, the performance of the proposed technique is evaluated in light of sensitivity, f-score, MCC, and specificity for a random iteration. Here, the performance evaluation is validated for 20 random ECG signals (10 smokers and 10 non-smokers ECG signals) with 20% testing and 80% data training. The simulation result showed that the proposed work outperformed the existing classifiers in light of sensitivity, f-score, MCC, and specificity, which is shown in Figure 2.

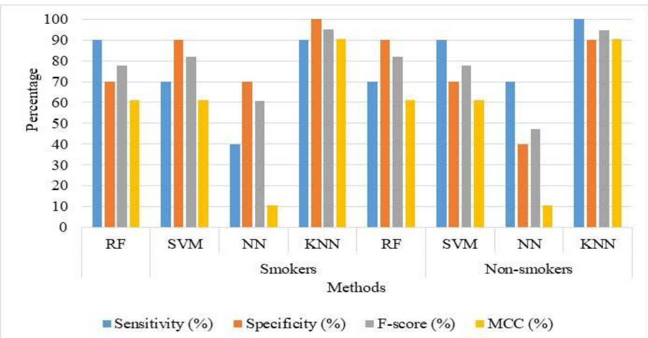

Fig. 2 Quantitative analysis

Table 2 represents the performance of various classifiers on hybrid feature extraction with infinite feature selection and without infinite feature selection. Tables 1 and 2 show that the KNN classification scheme improved the accuracy of smokers' and non-smokers' classification by up to 3-40% compared to the existing classification approaches. In this work, the hybrid features determine the non-linear and linear properties of ECG signal, and also it preserves the quantitative relationships between the low- and high-level features. The performance metrics confirm that the proposed technique performs significantly in smokers and non-smokers classification compared to previous methods for diagnosing cardiovascular diseases. The feature selection comparison is given in Figure 3.

TABLE II
Accuracy Comparison of the Proposed Technique Using With and Without Feature Selection

Feature selection	Classifiers	Feature extraction	Signal pre-processing	Accuracy (%)
Without infinite feature selection	RF	Hybrid features	Normalization and sixth order zero phase Butterworth filter	85.6
	SVM			71.4
	NN			49.5
	KNN			93.4
With infinite feature selection	RF	Hybrid features	Normalization and sixth order zero phase Butterworth filter	88.6
	SVM			69.2
	NN			51.2
	KNN			95.6

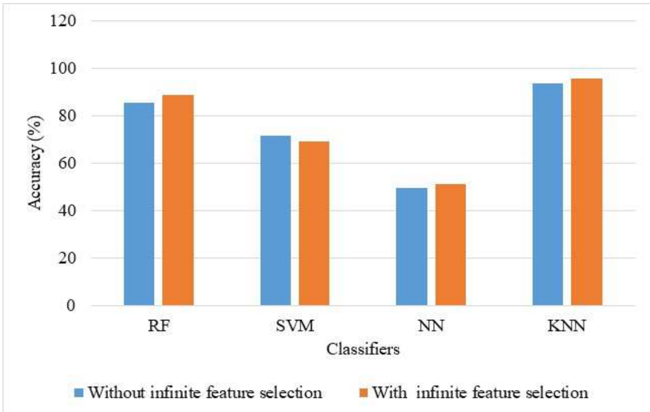

Fig. 3 Feature Selection Comparison

B. Comparative Study

Table 3 represents the comparative analysis of proposed and existing works. Ardan et al. [22] presented a dynamic system for generating synthetic ECG signals. The dynamic system comprises two phases: testing or recognition and training or identification. In the training phase, the dynamics of ECG patterns were precisely modeled and denoted as a constant radial basis function. The modeled results were used for ECG pattern recognition in a testing phase. The developed work was tested on PTB ECG dataset for validating the result in light of classification accuracy. The developed approach almost attained 89.5% of accuracy in ECG signal classification.

Additionally, Śmigiel et al. [23] developed a new measure to quantify the diagnostic information from the ECG signal. The developed measure depends on the Principal Component of Multivariate Multiscale Sample Entropy (PMMSE). In this research, the developed measure almost achieved 90.34% accuracy in ECG signal classification. Compared to the existing works, the proposed work attained 95.6% accuracy, which was superior to the existing methods of ECG classification.

TABLE III
COMPARATIVE ANALYSIS BETWEEN PROPOSED AND EXISTING METHOD

References	Database	Method	Accuracy (%)
Ardan et al. [22]	PTB ECG database	Fuzzy inference system	73%
Śmigiel et al. [23]		SincNet	89.2%
Proposed approach		Hybrid features with infinite feature selection	95.6%

IV. CONCLUSION

ECG signal-based cardiovascular diagnosis for smokers and non-smokers is the most dynamic research region in the patient health monitoring framework. This research paper aims to propose an effective feature selection calculation for grouping the smokers' and non-smokers' ECG signals to analyze cardiovascular disease utilizing the PTB ECG database. In this work, hybrid feature extraction removes the features from gathered ECG signals. Then, at that point, a proficient feature selection approach (infinite feature selection) is used for picking the dynamic feature subsets or rejecting the insignificant feature vectors. This optimal feature data is given as the input to the KNN classifier for categorizing the ECG signals of smokers and non-smokers. This activity assists doctors with diagnosing a cardiovascular disease without any problems. In association with the current strategies, the proposed method conveyed a proficient execution considering accuracy and showed a 3-40% improvement in classification accuracy. In the future, another feature selection can be executed with descriptor-level features to improve the classification accuracy of smokers' and non-smokers' ECG signals.

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