ECG-Based Support Vector Machine Classification for Telemedicine

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Abstract—Heart disease is a significant global health concern and early detection plays a crucial role in improving patient outcomes. This study proposes an electrocardiography (ECG) based heart disease detection using a support vector machine (SVM) machine learning model. The SVM model is trained on a comprehensive dataset consisting of ECG recordings from individuals with and without heart disease allowing it to be effectively trained to differentiate between the two. The process begins with preprocessing the ECG data to eliminate noise and artifacts followed by feature extraction to capture relevant characteristics of the heart signal. These features include time-domain and frequency-domain measures such as QRS complex duration R peak amplitude and spectral components. The SVM model is then trained using an appropriate kernel function to map the feature space enabling efficient classification. The performance of the model is evaluated using accuracy, true positive, false positive, sensitivity and specificity. The proposed SVM model achieves high accuracy in detecting heart disease demonstrating the effectiveness of ECG-based analysis and machine learning. The system shows promise in assisting healthcare professionals in identifying heart disease at an early stage which can potentially lead to timely intervention and improved patient outcomes.

Keywords—Telemedicine, Support vector machine, ECG, Classification

I. INTRODUCTION

Heart disease claims nearly one life per minute, posing a serious global problem. Early and precise detection is critical for preventing coronary artery disease and lowering cardiac-related fatalities. This work offers a machine-learning algorithm for early diagnosis of cardiac illness, with a focus on common heart attacks in India. The body's circulatory system is strongly reliant on a properly functioning heart; failure can result in serious health problems or death. Cardiovascular disease and heart disease are interchangeable terms that refer to restricted or clogged blood arteries that can cause heart failure, angina, or stroke.

Heart disease, a major cause of morbidity and mortality in humans, is difficult to anticipate due to a variety of risk factors such as diabetes, high blood pressure, and irregular pulse rhythm. Advanced approaches such as data mining and machine learning are critical in addressing this. On a heart illness dataset, this paper presents a machine-learning-based diagnostic system for heart disease prediction employing algorithms such as K Nearest Neighbor, Support Vector Machine, Decision Tree, and Random Forest.

A. Objective

The idea behind our model outlines the following goals:

1) Provide a distinctive insight into concealed data patterns.
2) Minimize human biases.
3) Utilize machine learning (ML) classifiers for illness categorization from user input.
4) Reduce the cost of medical tests.

This syndrome eventually leads to heart failure because the heart is unable to efficiently circulate blood to sustain normal body functioning [1]. In the United States, the prevalence of heart-related disorders is relatively high [2]. Breathlessness, physical weakness, swollen feet, and exhaustion are all indicators of heart illness, which may be accompanied by other symptoms such as high jugular venous pressure and peripheral edema caused by functional cardiac or non-cardiac disorders [3]. The complexity of investigative procedures used in the early phases of diagnosing cardiac disease considerably influences quality of life [4]. Identifying and treating heart illness pose substantial obstacles, particularly in developing countries, due to a lack of diagnostic devices, a paucity of medical practitioners, and a variety of other factors influencing the exact diagnosis and treatment of cardiovascular patients [5]. We can reduce the likelihood of serious cardiac difficulties and improve cardiac well-being by precisely and appropriately assessing patients' risk of heart disease [6].

According to the European Society of Cardiology (ESC), 3.6 million people worldwide suffer from heart disease, with 26 million diagnosed each year. Approximately half of patients with heart disease die within the first two years, and the expenditures of managing heart disease account for around 3% of total healthcare costs [7]. To diagnose cardiac disease using invasive procedures, healthcare professionals examine the patient's medical history, physical examination findings, and symptoms. These processes frequently result in incorrect diagnoses, causing delays in receiving results due to human error. Furthermore, the evaluation method is more expensive, computationally complex, and time-consuming [8]. Researchers developed a non-invasive medical decision support system using machine learning models such as support vector machine (SVM), k-nearest neighbor (K-NN), artificial neural network (ANN), decision tree (DT), logistic regression (LR), Ada Boost (AB), Naive Bayes (NB), fuzzy logic (FL), and rough set [9, 10]. The classifier in this investigation was a support vector machine.

B. Background details

It is observed that during the COVID-19 pandemic and post-pandemic scenarios, huge growth in heart disease patterns was observed. Detection and classification of heart disease patterns is a crucial problem in hand. This work is primarily aimed at selecting and classifying such Electro-cardio graphic (ECG) heart disease patterns. An example of a true ECG pattern is shown in Figure 1 [5]. The respective basic QPRST ECG complex pattern is shown in Figure 2.

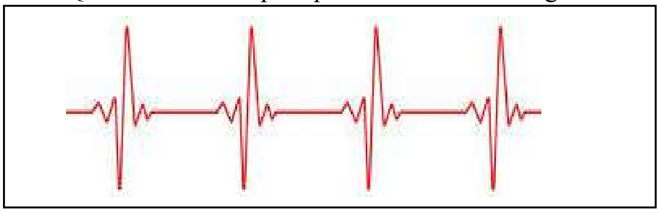


Figure 1: Normal ECG pattern waves

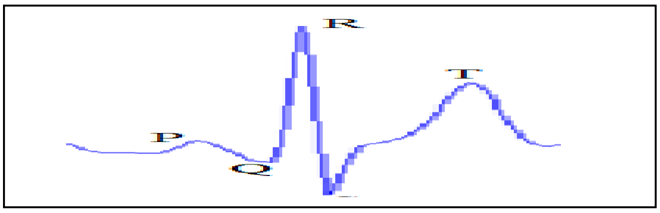


Figure 2: Representation of single PQRST ECG complex

The ECG classification has three primary stages, such as:

a) Preprocessing- This stage is required to eliminate the line interferences and noises available in the acquired ECG data at the front end of the algorithm. The Paper presents results for the filtering at the preprocessing stage using the methodology proposed by Pan and Tompkins.
b) Peak Detection- The filtered ECG database is exposed to feature detection methods. The method of ECG peak detection is proposed to be adopted for feature extraction. The PQRST peak detection is proposed in this Paper. The time domain features are extracted from the detected peaks.
c) Classification- The final stage is to apply the classifiers over the feature sets to determine the accuracy and disease patterns. The Paper proposed SVN-based classifiers to determine accuracy.

The remaining part of the paper has presented the sequential results of each of these three stages on the ECG database. The next section first describes the database used for the research in this work.

II. LITERATURE SURVEY

The processing of the ECG data provides a way to accurately identify the illness that each person has contracted. To give readers a comprehensive grasp of ECG signal processing, the survey has been done and presented here. Jeon et al. developed and implemented a wrist-worn ECG (electrocardiogram) system with smartphones for online diagnosis, self-diagnosis, and real-time monitoring before significant outbreaks of chronic heart disease. The use of cell phones for healthcare was the initial attempt of this type to deal with the issue, but it was unsuccessful because of its limited capability. Due to the recent rise in usage of smartphones with a lot more abilities, researchers and companies are conducting new research on mobile healthcare systems.

In June 2011, MTM Ltd. developed the "Smart Patient Care System (SPaCS)" with support from the Korean Government of Knowledge Economy [11]. People can use phones to manage their health via the SPaCS health care system, which comprises both apps PCS and PRM. The "Wearable Electrocardiogram module (USN Lab ver. 2.0)" was developed by Pukyong University in Korea and does not require electrodes on bare chests [12]. Once this component is transformed into t-shirts patients can rapidly put it on and take it off. Additionally, wireless transfer of these test findings to real-time equipment for analysis is possible.

By fusing mobile phones with established lab-level technologies, a medical research team at UBC (University of British Columbia) developed the Phone Oximeter, a pulse-based portable oximeter [13]. These smart oximeters monitor your heart rate, rate of breathing, and blood oxygen levels. They may also send the detected data to a distant hospital.

The authors developed and employed Android operating system-based apps in addition to a sensor-based measuring apparatus. Patients can monitor and receive a rapid diagnosis of their heart problems by using this technology with a small ECG sensor placed in a sports shirt. The application also has an automatic alarm call system, which includes preserving personal histories, and graphical data. To make the system under construction consume less energy and produce more accurate measurements, the experts also suggested conducting additional studies and making system improvements.

The author's experimental pilot study investigated the effects of pulsed electromagnetic fields (PEMF) on photo-platysma-graphic (PPG), electrocardiographic (ECG), and electroencephalographic (EEG) responses at very low frequencies. The wavelet transform (WT) was employed as a feature extraction approach to represent the electrophysiological signals. The extraction of features and selection play key roles in classification systems such as neural networks, as classification accuracy often increases when a pattern is simplified by assigning critical aspects to it. Features are the differentiating or characterizing measures that were transformations, or structural aspects extracted from any pattern's section. Characteristics are used to express trends to avoid losing important data.

The feature vector, which consists of the collection of all attributes used to characterize the pattern, reduces the amount of dimensional feature space needed to transmit it. Out of the enormous and possibly infinite collection of characteristics that might be employed for defining a specific pattern, only those aspects that are included in the feature vector can be applied. This is because little differences in certain traits can be utilized to distinguish between different aspects. The author believes that meeting technical requirements for the cost of data processing, the usefulness of pattern information compression, and the complexity of hardware and software is one goal of dimension reduction.

This research investigates the discourse about early Alzheimer's disease diagnostics within the context of aging and innovation[14]. It examines how creativity is linked to various definitions of Alzheimer's disease and coping techniques, revealing varying and sometimes contradictory interpretations. The study combines opinions on health technology assessment with those from Alzheimer's Cafés, highlighting various definitions of early diagnoses, the Alzheimer's problem, and future scenarios.

This research examines the use of Deep Learning (DL) algorithms for classifying Electrocardiogram (ECG) signals in healthcare for timely anomaly identification [15]. Based on 75 studies published between 2017 and 2018, Convolutional Neural Network (CNN) emerged as the top DL technique for feature extraction (52%). GRU/LSTM, CNN, and LSTM achieve 100% accuracy for Atrial Fibrillation (AF), 99.8% for Supraventricular Ectopic Beats (SVEB), and 99.7% for Ventricular Ectopic Beats (VEB).

The current state-of-the-art methods for automated classification of aberrant heartbeats using electrocardiogram (ECG) signals are examined in this survey. The research looks at ECG signal preprocessing, heartbeat segmentation methods, feature description methods, and learning algorithms [16]. It also describes the databases used for evaluation and the report finishes by addressing limits, identifying future challenges, and recommending a workflow for further research in this topic.

This study underlines the importance of electrocardiograms (ECGs) in the diagnosis of heart disorders, specifically arrhythmias [17]. Given the impracticality of manually examining ECG records to identify arrhythmias that could result in sudden death, various studies are focusing on developing computer-aided diagnosis (CAD) systems for the automatic detection of arrhythmias. A similar approach was created by [18] using multiple interfaces of ECG readings to automatically categorize cardiac rhythm disturbances using ANN (Artificial Neural Network) orientation.

This analysis looks at the most recent approaches for detecting abnormal heartbeats using electrocardiogram (ECG) readings. The research looks at ECG signal processing, heartbeat segmentation, feature description methods, and learning algorithms [19]. It also examines databases reviewed by the Association for the Advancement of Medical Instrumentation (AAMI) standards, identifying shortcomings, offering future challenges, and recommending an evaluation methodology workflow to guide future research in this field. This study emphasizes the growing emphasis on employing machine learning algorithms, a subset of artificial intelligence, to detect sickness in individual patients [20]. Because cardiovascular illness is the main emphasis, machine-learning techniques may be thoroughly examined in this setting [21–23]. [24] conducts a comprehensive analysis of IoT applications in the healthcare industry, emphasizing problems and possible solutions.

Automated smart homes are a rapidly emerging application of IoT that assists individuals and makes their lives easier. Remote-controlled home appliances [25], home energy management[26], security systems [27], detecting movements in the house [28], and healthcare services for the elderly, the disabled, and patients who are outdoors [29, 30] are a few examples. Agarwal et al. [31] proposed a system for health care monitoring that tracks patients' blood pressure (BP) using mobile devices. They believed that systolic and diastolic pressure information recorded might be quickly transmitted to a heart specialist or doctors via an internet interface, in which a doctor may then examine them and assist the patients online.

In their study, the authors suggest a body sensor network (BSN) based healthcare system [32]. The suggested system, also known as BSN-Care, measures physiological variables like blood pressure using a WPM device and assesses heart health using an electrocardiogram (ECG). The BSN-Care server receives the bodily data from the patient and uses it for evaluation. The system alerts the doctor and the patient's relatives in the case of an abnormality so that timely action can be taken.

Chen et al. [33] proposed an RFID-based electronic healthcare system. The technology facilitates interaction between a patient and the doctor while also evaluating the patient's state of health. Additionally, BSN can be used to collect patient data like body temperatures and pressure. Additionally, it can store medical records and profiles of patients for later use.

III. PROPOSED FRAMEWORK AND ECG PROCESSING BLOCK DIAGRAM

The identification of QRS peaks is necessary for both disease diagnosis and heart rate variability (HRV) calculation. The current suggested method for HRV peak detection is significantly influenced by the chronological recorded analysis; the MIT-BIH verified Arrhythmia ECG measurement dataset is utilized to classify the heart arrhythmias of an aberrant ECG reading. The proposed framework for feature extraction from the ECG dataset is shown in Figure 3.

The basic processes in the ECG classification of NSR data are block diagrams in Figure 4. The pre-processing step makes use of both the Pan and Tompkins filters. Peak detection is accomplished with the exact squared ECG signal option.

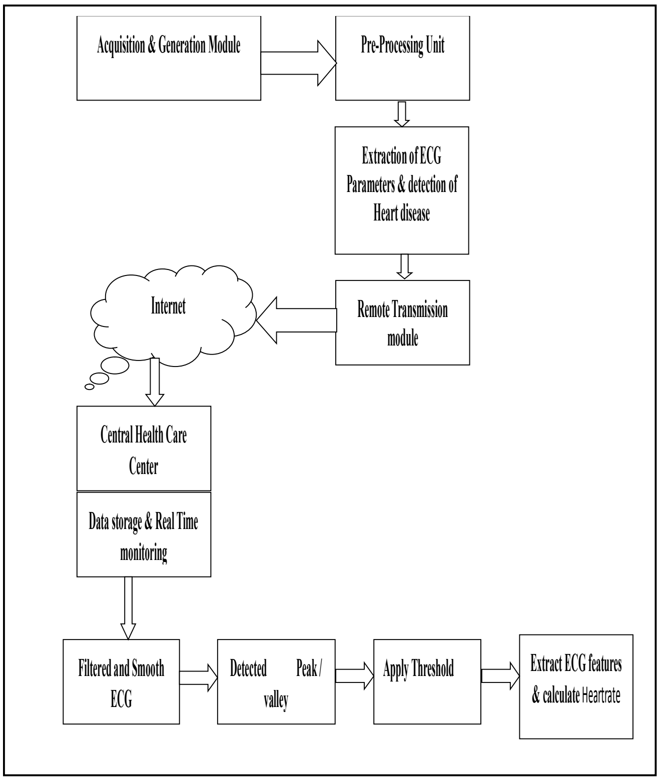


Figure 3. Proposed framework for feature extraction from ECG dataset

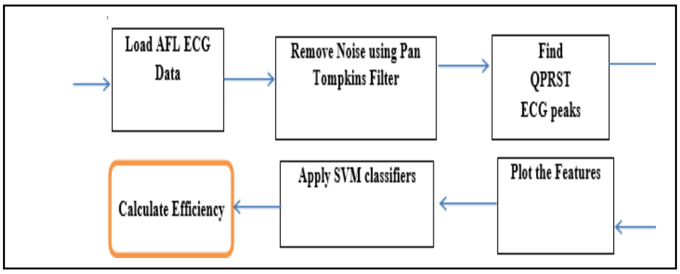


Figure 4: ECG Classification Block Diagram

TABLE I. STANDARD TIME INTERVALS USES FOR THE ECG PEAKS DETECTION AND CLASSIFICATION AS THRESHOLD

S. No.	ECG Parameters	Amplitude (mV)
1	R- wave	0.8 -0.12
2	P wave	0.25
3	T wave	0.5
4	Q Wave	1.4 of the R waves

The modified Pan and Tomokins based peak detection method is proposed for the temporal features determinations. The feature sets considered for the classification are shown in Table 1. These standard values are used for comparing and classification.

IV. PROPOSED METHOD

A. *PREPROCESSING PAN & TOMPKINS METHOD*

Over the R-R intervals, heart rates are monitored at beats per minute. This study's main objective is to demonstrate how using a Pan Tompkins filter design can enhance the ECG classifier performance. The algorithm of the Pan and Tompkins method implementation is shown in Algorithm 1.

Algorithm 1: Pan and Tompkins Processing

1. Load AFB ECG MIT data
2. Deceleration of the sampling frequency Fs,
3. Implement low pass Filter ← $[b_1 a_1,]$32 order coefficients
4. 32 Order High pass Filter.
5. Derivative Filter ← $[b_1 a_1]$
6. Apply Average filter and take threshold
7. Peak detection RR(t), R-lo

End Algorithm

B. *PROPOSED PEAK DETECTION METHOD*

Heart rate variability (HRV) computation and illness diagnosis primarily require the recognition of PQRST peaks (HRV). The proposed technique for HRV peak detection and the abnormal cardiac rhythms are significantly influenced by the chronological recorded analysis. ECG readings are categorized using the MIT-BIH certified Arrhythmia ECG measurements database.

Temporal Feature	Standard Period
P Wave Duration	0.06 to 0.11 sec
P to R Interval	0.12 to 0.2 sec
QRS complex period	< 0.12 src
S to T Interval	0.12 sec
Q to T Interval	0.36 to 0,44 Sec
R to R Interval	0.99 Sec

The flow chart of the proposed method is given in the Figure 5

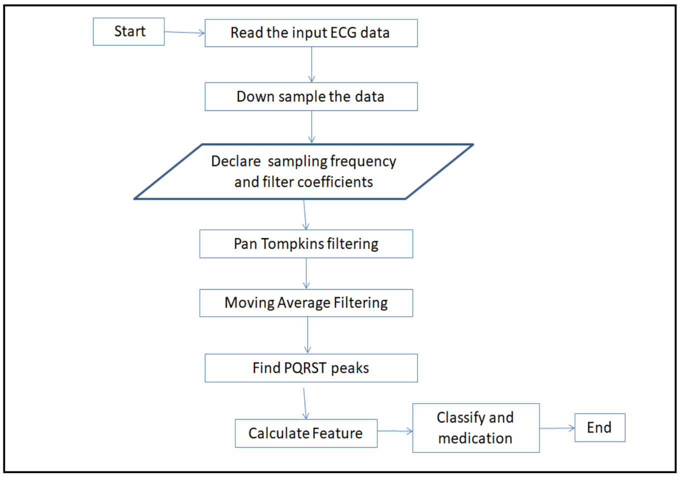


Figure 5: Proposed Flow chart of Telemedicine classification

Algorithm 2 represents the calculation of the features.

Algorithm 2: P-QRS-T Interval Calculation

1. Find the RR peaks
2. y=sigL;
3. [R_peak,R_loc] = findpeaks(y,'MinPeakHeight',.6,'MinPeakDistance',200);
   R_A= R_peak;
   R_peak
   Fs=600;
   QRS_Interval = .12;
   Look_samples = floor((Fs*QRS_Interval)/2);
4. y = [zeros(1,Look_samples) zeros(1,Look_samples) y zeros(1,Look_samples) zeros(1,Look_samples)];
   R_loc = R_loc + Look_samples;
5. Calculate the PQRST over loop
   for i=1:length(R_loc)
   [Q_A(i), Qi] = min(y(R_loc(i)-Look_samples+3:R_loc(i)));
   [S_A(i), Si] = min(y(R_loc(i):R_loc(i)+Look_samples-2));

```
Q_loc(i) = R_loc(i)-Look_samples+Qi-6;
S_loc(i) = R_loc(i)+Si+1;
x(Q_loc(i):S_loc(i)) = y(Q_loc(i):S_loc(i));
[P_A(i), Pi] = max(y(R_loc(i)-Look_samples:Q_loc(i)));
[T_A(i), Ti] = min(y(S_loc(i):R_loc(i)+Look_samples+30));
P_loc(i) = Q_loc(i)-Look_samples+Pi-1;
T_loc(i) = S_loc(i)+Ti-1+47;
x(P_loc(i):T_loc(i)) = y(P_loc(i):T_loc(i));
end
R_t = R_loc - Look_samples;
Q_t = Q_loc - Look_samples;
S_t = S_loc - Look_samples-1;
P_t = P_loc - Look_samples-30;
T_t = T_loc - Look_samples+20
```

End of Algorithm

V. RESULTS OF PEAK DETECTION & CLASSIFICATION

ECG data, which is records of the electrical activity of the heart, has recently been employed to categorize the patterns of different cardiac disorders. The objective of the study was to identify discrete ECG illness patterns using SVM-based machine learning (ML) and the chosen QRS feature set. For further classification, knowledge of the recognized QRS wave peaks is employed as a benchmark. When there is ECG HRV variability, the basic prescribed process can easily locate individual ECG signal peaks for the aforementioned Q, R, and S peaks. To classify the time domain QRS peaks, SVM classifiers are used. The graphical results demonstrate that the ECG can detect QRS even when artifacts are not present. Additionally, peak detection for this ECG APB rhythm has been confirmed.

A. ECG DATASET

Various ECG patterns exist in the literature, but in this research, the prime focus is to work on the significant and commonly found Normal Sinus rhythm (NSR) ECG pattern classification. Anomalous cardiac activity is frequently caused by a non-stimulating reserve (NSR), which originates within the atrioventricular heart valves. Since it's classified as a supraventricular condition, when it initially appears, the heart usually beats quickly. The heartbeat of an NSR patient is characterized by both an abnormally rapid and regular heartbeat. Figure 6 shows that the database contains ECG recordings for individuals in a variety of age ranges, as well as for healthy individuals, NSR Arthmiya patients, and both genders. The analysis shows a notable degree of HRV fluctuation.

B. PRE-PROCESSING PAN TOMPKINS RESULT

A total of 4 ECGs including NSR data, which are considered for persons of different age groups, have been used for implementing the classification in this research using the MATLAB environment. Figure 7 represents the AFB database. Heart rates are measured in beats per minute over three R-R intervals. The primary goal of this study is to show how utilizing a Pan and Tompkins filter design improves the ECG classification performance. The AFB ECG patterns are classified using the MIT-BIH Arrhythmia ECG bed database. The results of the pre-processing stage of the pan and Tompkins method are shown in Figure 8 for the normal ECG data ecg_60hz_200m.mat and 100m.mat file.

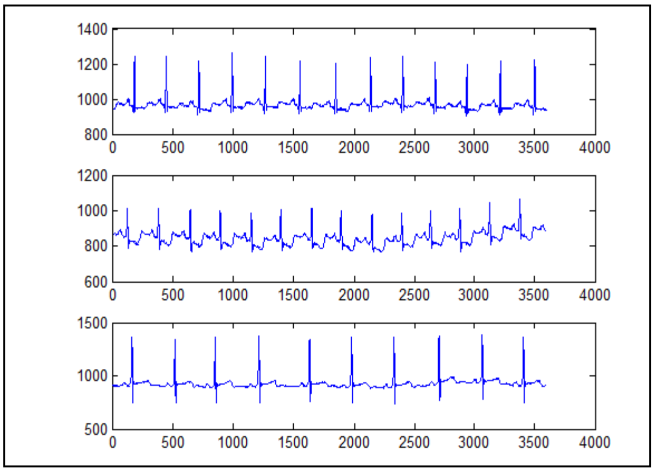


Figure 6: NSR ECG data base example of four patterns

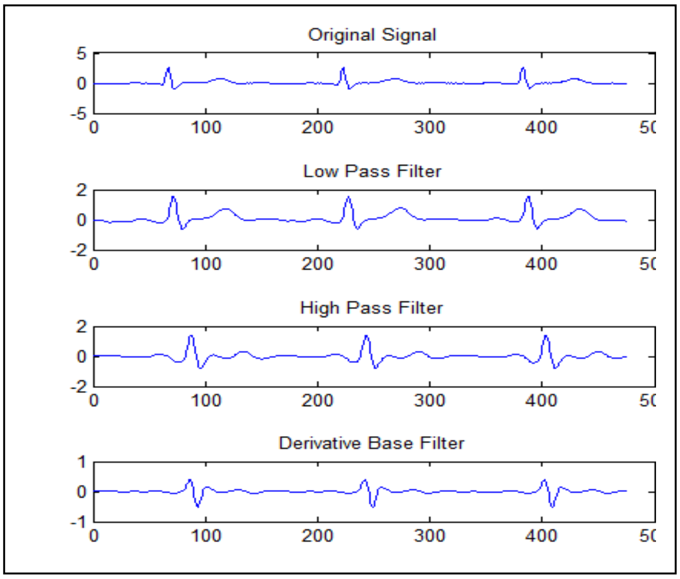


Figure 7: Pan and Tompkins methods filtering results

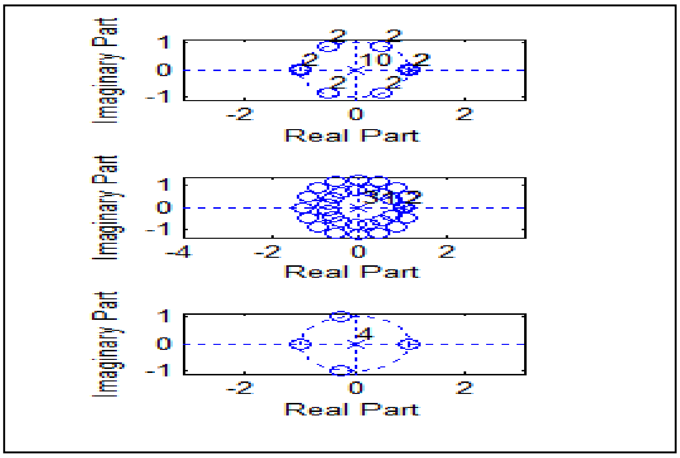


Figure 8: Respective poles zeros plot for filter tags

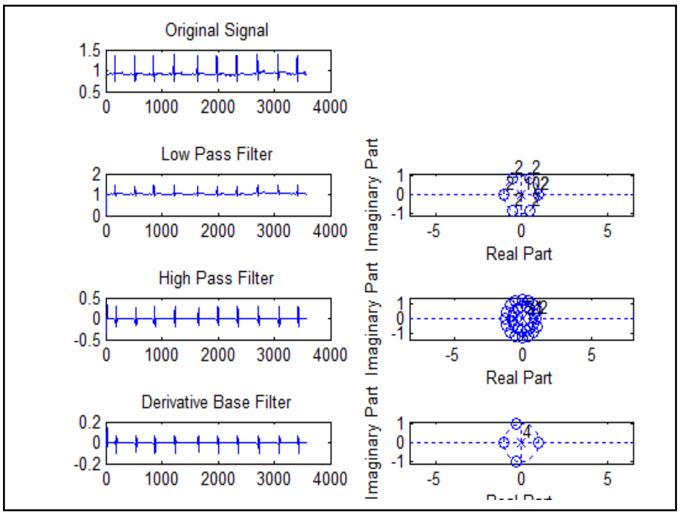


Figure 9: Results of ECG data filtering for NSR data 202m.mat

It can be observed that standard Pan and Tompkins method takes the original ECG data and then first pass it to a low pass filter followed by the high pass filter to eliminate base lime noises. The final preprocessing stage is to pass the signal to the derivative filter for detecting the sharp peaks.

The respective pole zero plot for real and imaginary parts for filters are shown in the Figure 8. Similarly the Preprocessing results for the NSR ECG data are shown in the Figure 9.

C. MOVING AVERAGE FILTER

After Pan and Tompkins method in the proposed work it is proposed to apply the moving average filter over the derivative filtered data. The results of the moving average filtering are shown in the Figure 10.

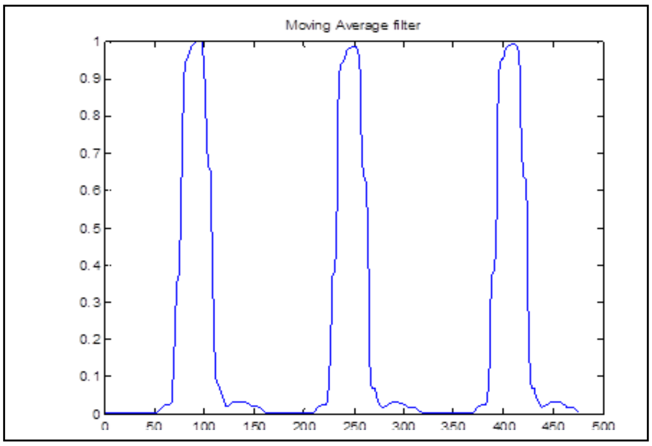


Figure 10: Results after applying the moving average filtering to the ECG signal.

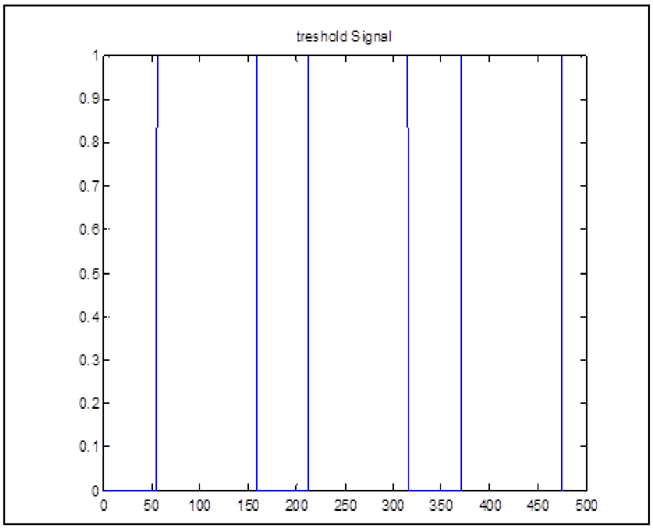


Figure 11: Threshold output for true ECG data

The process or the loop for the determination of moving average filter is given in the Algorithm 3, which is written below.

Algorithm 3: Moving average filtering

1. Declare the filter mask
h=ones(1,31)/31;
2. Convolve the filter average mask to derivative filtered signal
sigAV=conv(signorm,h);
3. Take the moving average with 15 window size
sigAV=sigAV(15+[1:N]);
sigAV=sigAV/max(abs(sigAV));
4. Plot the outcomes
figure(2);plot(sigAV)
title('Moving Average filter')

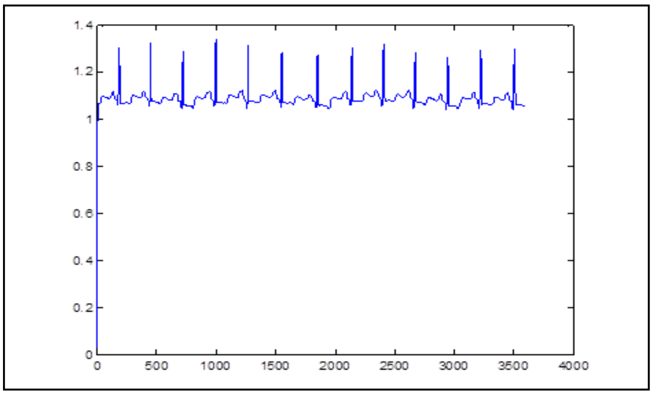
End Algorithm

D. RESULT OF PEAK DETECTION

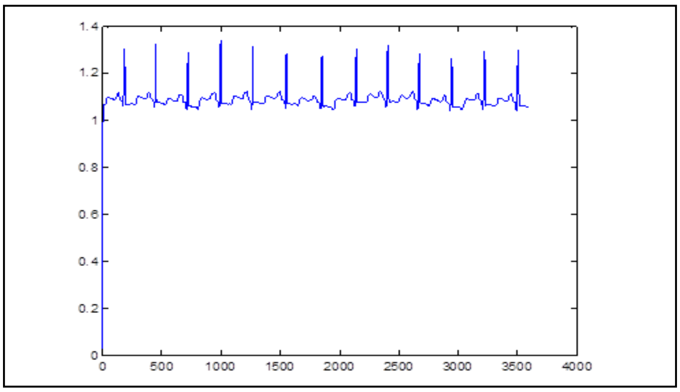
The interpretation and acquisition of the PQRST complex is one of the most important steps in the processing of ECG signals. In order to examine the outcomes of peak recognition and classification using ECG, the R wave, which is important in the diagnosis of anomalies in cardiac rhythm, as well as the assessment for heart rate variability (HRV), is presented in this paper. The ECG is a crucial instrument used by healthcare professionals in the examination and detection of heart health. ECG is commonly used by cardiologists as just a diagnostic tool to identify cardiovascular issues. The following traits apply to the ECG signals: as shown by the T wave in the QRS complex, atrial, ventricular, and ventricular repolarization have all occurred.

E. RESULTS OF PQRST PEAK DETECTION

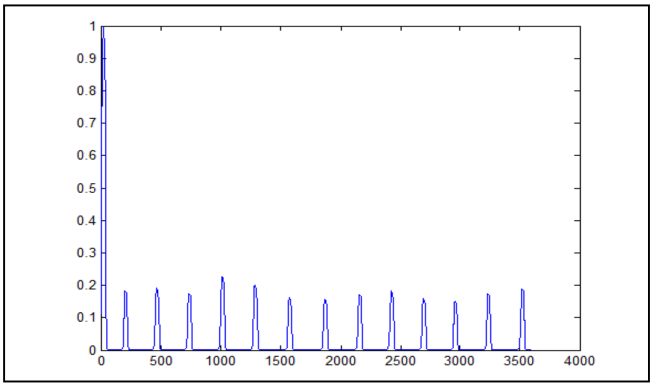
The findings of PQRST peak detection for the input ECG signals are visually presented in this section. The peaks of the ECG signal are efficiently found for the Q, R, and S peaks in all four scenarios when using the proposed technique. This can be observed from the visual results shown in figure 12. The sequential results of the PQRST complex peak detection are shown in Figure 13



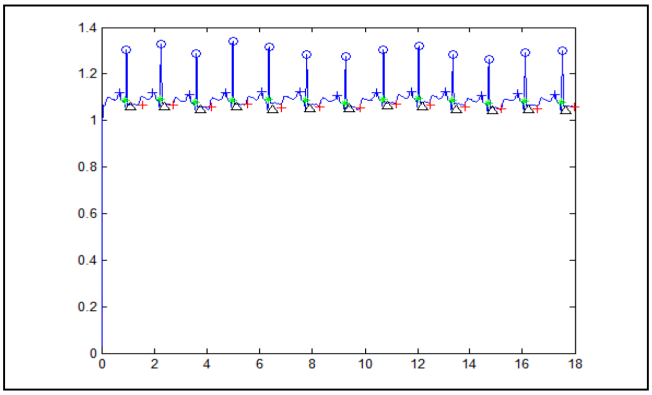
(a) Original NSR Signal



(b) Low pass Filtered ECG



(c) Moving average filtered ECG



(d) PQRST Peak detection

Figure 12: Results of peak detection methods for the 100 (0).mat NSR

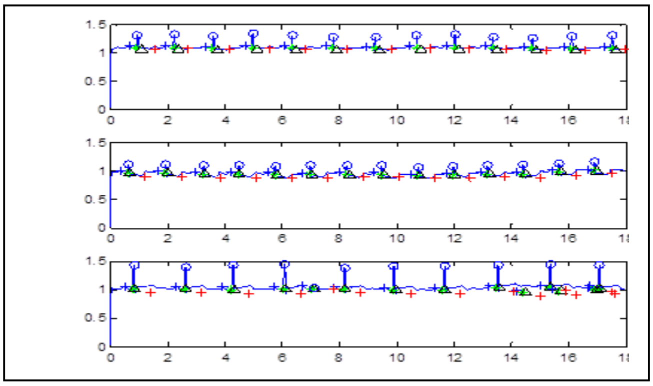


Figure 13: Peak detection of NSR signals as data

VI. Parametric Evaluation of Classification

The major objective is to demonstrate that the system's overall classification efficiency is increased by the proposed ECG peak recognition and classification technique. In order to demonstrate efficiency, this section calculates a few metrics like sensitivity, specificity, accuracy, and precision.

A. Time Domain HRV Parameter Analysis

The investigation of time domain statistical HRV features forms the basis of the proposed ECG classification and peak detection method. Different temporal domain characteristics are computed using the RR and PT intervals and the QT intervals are utilized to examine the ECG signal. The parameters employed in this study's analysis are as follows:

1) *QT interval:* The difference between Q and T time intervals is established for every pair of PQRST intervals. The QT deviation (QT) of a time interval is used to define Hypocalcemia and Hypercalcemia.

If (QT is long)
Pattern =Hypocalcaemia
Else
Pattern =Hypercalcaemia

The standard QT is obtained from the ecg_data_200.dat file sample

2) *Heart rate interval:* The HR interval is calculated using the PT time interval between the P and T peaks, where the length of the PT interval vector is used for loops over

```
for i=1:((length(P_t))-1)
HRV=P_t(i+1)-P_t(i)
End
```

TABLE III. Abnormality Analysis Parameter

S. No	Abnormal ECG Parameters	Respective Heart diseases
1	Increased Heart rates (HR)	Tachycardia
2	Decreased Heart rate (HR)	Bradycardia
3	Increased QT interval	Hypocalcemia
4	Smaller QT interval	Hypercalcemia

5	Increased PR Interval	AV is blocked

Table 3 gives the various abnormal analysis parameters for various heart diseases. By using suggested peak detection method, table 4 displays the statistical values of the observed parameters of four input ECG signals.

TABLE IV. CLASSIFICATION BASED ON STATISTICAL VALUES TIME INTERVAL MEASURED IN SAMPLES FOR THE HRV ANALYSIS

ECG signals / Parameters	ECG 100m .mat	ECG100m (0).mat	ECG 113m (0) .mat	ECG 115m (0) .mat
Mean QT	414	385	395	461
Mean ST	379	351	361	448
Mean RT	292	283	289	341
Mean PT	476	432	412	517
Mean Heart Beats	298	282	292	336
category	True	Hypercalcemia	Hypercalcemia	Hypocalcemia

B. NSR and AFL classification Results using the RR Peak Detection

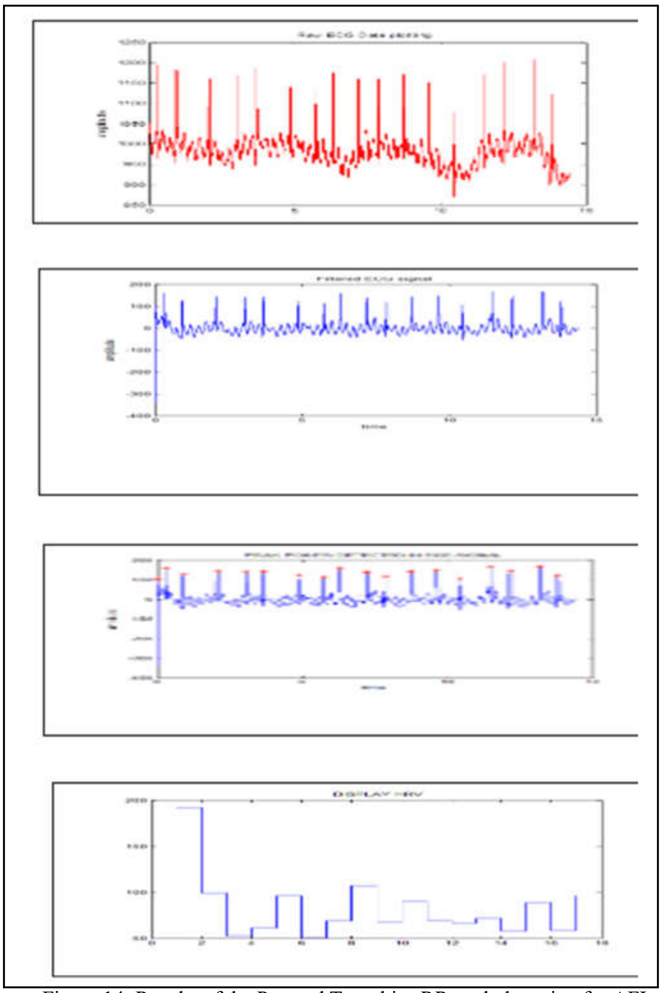


Figure 14: Results of the Pan and Tompkins RR peak detection for AFL data

It can be observed from the figure 14 that proposed Pan and Tompkins method efficiently capable of detecting all RR peaks. The statistical time domain ECG features are calculated using theses RR peak intervals.The time domain parameters are used for the ECG data classification as feature. Here we have defined few criteria such as true positive and false negative, accuracy to evaluate efficiency in order to demonstrate efficiency. A false negative (Fn) is formed when the algorithm is unable to recognize a true beat. The exact beat recognized using the suggested technique is denoted by true positive (Tp).

$$Tn = sum(Diff == 0 \,\&Actual == 0); \quad (6.1)$$

$$Tp = sum(Diff == 0 \,\&Actual == 1); \quad (6.2)$$

$$Fn = sum(Diff \sim= 0 \,\&Actual == 1); \quad (6.3)$$

$$Fp = sum(Diff \sim= 0 \,\&Actual == 0); \quad (6.4)$$

The other statistical parameters are

1) Standard Deviation of NN interval (SDNN) - For each pair of RR intervals, SDNN is defined as standard deviation (SD) of RR intervals.
2) Root Mean Square SD (RMSSD) - The RMSSD value is calculated as sum of square differences of approximation derivatives. Mathematically,

$$RMSSD = \sqrt{\frac{1}{M}(diff(RR_{Region}).^2)} \quad (6.5)$$

Where parameter M gives length of RR interval vector here which is represented as RR_{Region}.

3) NN50 Value- It is the number of R to R intervals that are higher than 50 milliseconds.

TABLE V. STATISTICAL PARAMETERS USING PAN TOMPKINS METHOD FOR RR PEAK DETECTION FOR NSR AND AFL DATABASE

ECG data	Mean HRV	SDNN	RMSSD	NN50
100	54.3433	0.038981	0.03543	1
101	52.0625	0.041545	0.029772	0
103	48.7185	0.042029	0.046111	3
105	57.9663	0.03229	0.032125	2
106	42.9932	0.115	0.13073	6
108	244.0324	0.67615	0.46946	10
112	64.6159	0.14197	0.15826	4
113	50.4792	0.31762	0.45773	8
114	37.6464	0.056343	0.062225	2
115	41.7654	0.0994	0.14672	6
202	89.7171	0.087075	0.053382	3
222(1)	240.2348	0.26488	0.22182	14
222(2)	797.646	0.37471	0.18763	17
222-4	81.4996	0.48044	0.59909	10
222-5	82.0788	0.233	0.32721	15
222-6	75.884	0.18517	0.22236	15
222-7	79.7971	0.19147	0.29101	15
222-8	77.1834	0.25577	0.25761	12

222-9	52.4206	0.37808	0.53751	10
222-10	72.3451	0.22398	0.36815	12

C. Results of the Scatter Plot for Different SVM Based Classifiers

The classification accuracy for the different SVM based classification methods are tested and presented in the Table 6.

TABLE VI. CLASSIFICATION ACCURACY AND TP AND FP

S. no.	SVM Methods	% Accuracy	TP	FP
1	Linear SVM	80	16	4
2	Gaussian SVM	86.7	17	3
3	Cubic SVM	100	20	0

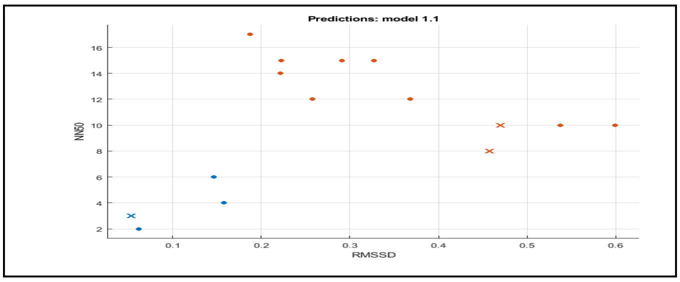
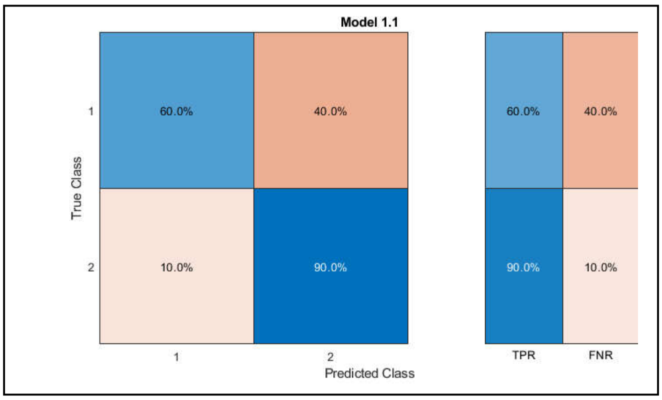


Figure 15: Scatter plot for Linear SVM case

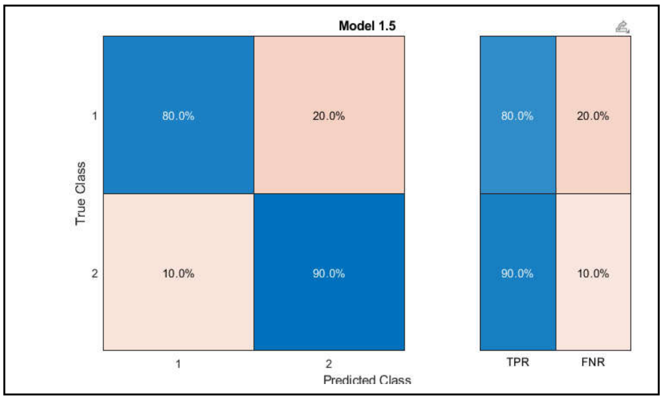
The true positives and the false negative rates determined for the three classifiers are shown in the Figure 15. It can be observed from the Figure 16 that the cubic SVM approach offers the best results and have minimum FNR to zero with 100% efficiency for ECG in our study.

VII. CONCLUSION

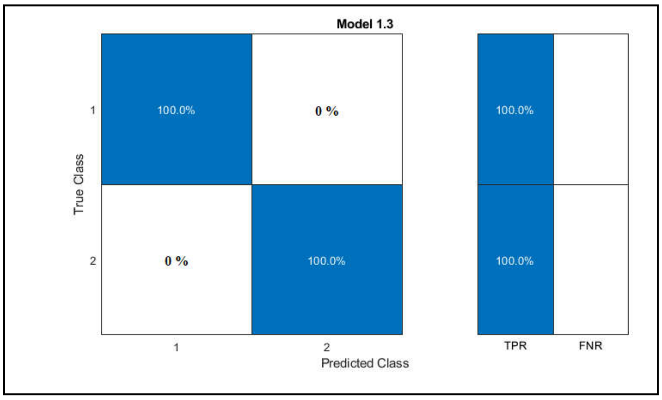
Heart disease patterns are seen to have grown significantly during the COVID 19 pandemic and post-pandemic scenarios. One of the most important issues at hand is the detection and classification of cardiac disease patterns. The main goal of this research is to identify and categorise such electrocardiographic (ECG) heart disease patterns. Heart rate variability (HRV) calculations and illness diagnosis both require the identification of QRS peaks. The MIT-BIH validated Arrhythmia ECG measurement dataset is used to characterise the heart arrhythmias of an abnormal ECG reading, and it has a substantial impact on the currently recommended approach for HRV peak detection. A machine-learning-based diagnosis method for heart disease prediction is implemented on a heart disease dataset in the proposed work. We also proposed a methodology for feature extraction from the ECG dataset in this study. In this study, a well-known machine learning technique known as support vector machine is applied to an electrocardiogram dataset and evaluated using three performance evaluation parameters: classification accuracy, specificity, and sensitivity. Our proposed system enables distinguishing between those with heart illness and those who are healthy simple.



(a) Linear SVM



(b) Gaussian SVM



(c) Cubic SVM

Figure 16: TPR and the FNR for the three SVM based classifiers

DECLARATIONS:

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Availability of data and materials: The datasets generated during and/or analyzed during the current study are not publicly available due to [security reasons] but are available from the corresponding author on reasonable request.

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[8] K. Vanisree and J. Singaraju, "Decision support system for congenital heart disease diagnosis based on signs and Table 11: Performance of best classifiers before and after features selection. Classifiers Accuracy before features selection Accuracy after features selection Logistic regression 84 89 SVM (RBF) 86 88 20 Mobile Information Systems symptoms using neural networks," International Journal of Computer Applications, vol. 19, no. 6, pp. 6–12, 2011.

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