Atrial Fibrillation (A-Fib), Atrial Flutter (AFL) and Ventricular Fibrillation (V-Fib) are fatal cardiac abnormalities commonly affecting people in advanced age and have indication of life-threatening condition. To detect these abnormal rhythms, Electrocardiogram (ECG) signal is most commonly visualized as a significant clinical tool. Concealed non-linearities in the ECG signal can be clearly unraveled using Recurrence Quantification Analysis (RQA) technique. In this paper, RQA features are applied for classifying four classes of ECG beats namely Normal Sinus Rhythm (NSR), A-Fib, AFL and V-Fib using ensemble classifiers. The clinically significant ($p < 0.05$) features are ranked and fed independently to three classifiers viz. Decision Tree (DT), Random Forest (RAF) and Rotation Forest (ROF) ensemble methods to select the best classifier. The training and testing of the feature set is accomplished using 10-fold cross-validation strategy. The RQA coefficients using ROF provided an overall accuracy of 98.37%
against 96.29% and 94.14% for the RAF and DT, respectively. The results achieved evidently ratify the superiority of ROF ensemble classifier in the diagnosis of A-Fib, AFL and V-Fib. Precision of four classes is measured using class-specific accuracy (%) and reliability of the performance is assessed using Cohen's kappa statistic (κ). The developed approach can be used in therapeutic devices and help the physicians in automatic monitoring of fatal tachycardia rhythms.

Keywords: ANOVA; decision tree; ensemble classifiers; feature ranking; recurrence plot; tachycardia.

1. Introduction

Atrial Fibrillation (A-Fib), Atrial Flutter (AFL) and Ventricular Fibrillation (V-Fib) are the serious atrial and ventricular tachycardia, typically encountered in elderly people (age ≥ 75 years).\(^1,2\) A-Fib is a completely irregular ventricular rhythm with the absence of P-wave and AFL is a fast regular atrial rhythm due to an atrial macro-reentrant path. V-Fib is characterized by uncoordinated vibration of the ventricle with improper contractions.\(^3\) Further these fatal arrhythmias may cause acute stroke, cardiac arrest or lead to sudden cardiac death. The most common sources for the cause of dangerous arrhythmia beats are ischemic or non-ischemic cardiomyopathy, hypertension, mitral or tricuspid valvular disorders, hyperthyroidism and excessive alcohol consumption.\(^4\)

Among the tachycardia, A-Fib is the most common condition and a serious global health problem.\(^5\) Recently, AHA estimates approximately 33.5 million people (12.6 million women and 20.9 million men) worldwide have condition of A-Fib.\(^6\) Around the globe, about 1% of patients with A-Fib are < 60 years of age, while up to 12% of patients with A-Fib are 75–84 years of age.\(^7\) For European origin subjects, the lifespan risk of rising A-Fib after 40 years of age is 26% for men and 23% for women.\(^8\) In United States, more than 467,000 patients yearly hospitalize with A-Fib as the major diagnosis, and A-Fib is estimated to contribute for greater than 99,000 deaths per year. The annual threat of cardiac stroke subject able to A-Fib is 1.5% for individuals of 50–59 years of age and 23.5% for individuals with 80–89 years of age.\(^9\) Accordingly, A-Fib is a common cardiac rhythmic disorder that increases its predominance with age but AFL and V-Fib are less common.\(^10\)

AFL is a complex and continuous wave on Electrocardiogram (ECG) leads similar to the edge of a wood saw with a rate exceeding 240 beats per minute (bpm). Subjects with AFL can have hypertension or certain form of structural heart disease.\(^11\) In acute myocardial infarction stage, about 90% of the deaths globally are due to V-Fib beats and for 70% of the cardiac arrest patients, V-Fib rhythm is commonly present.\(^12\)

The incidences of tachycardia is rising rapidly with the age in men and also, in women after the menopause. In elderly people, cardiac arrhythmias and their conduction disturbances are described by high frequency, diagnostic complications, low tolerance and very delicate treatments.\(^12\) ECG is very simple, non-invasive and low cost tool to capture any cardiac abnormalities. However, during the critical care
conditions discriminating A-Fib, AFL and V-Fib rhythms is highly challenging for the medical experts because of their complex nature, clinical interrelations and unknown morphological variations. The Computer-Aided Cardiac Diagnosis (CACD) systems can perceptively classify fatal cardiac abnormalities from normal rhythm and help clinicians in choosing the appropriate therapeutic approach, hence save life in critical situations.\textsuperscript{13,14}

Numerous algorithms have been proposed for the tachycardia diagnosis based on the temporal, spectral and non-linear features extracted from the ECG. Christov \textit{et al.}\textsuperscript{15} classified three classes Normal Sinus Rhythm (NSR), A-Fib and AFL using absence of P-wave and obtained an accuracy of 98.8\% using sequential analysis. Übeyli\textsuperscript{16} detected four classes (NSR, Congestive Heart Failure (CHF), Ventricular Tachycardia (VT) and A-Fib) using Eigen vector method and achieved an accuracy of 98.33\% with Artificial Neural Network (ANN). However, in these systems time-domain features are considered, in which minute deviations in the amplitude may affect the classification performance.

Martis \textit{et al.}\textsuperscript{17} detected three classes of beats (NSR, A-Fib and AFL) using Discrete Cosine Transform (DCT)\textsuperscript{65,66} and achieved 99.45\% of accuracy using $k$-Nearest Neighbor ($k$-NN). Ríeta \textit{et al.}\textsuperscript{18} identified same three classes with 100\% of accuracy using features extracted from spectral parameters and logistic regression. Fahim and Khalil\textsuperscript{19} classified four classes (V-Fib, Ventricular Flutter (VFL), Premature Ventricular Contraction (PVC) and A-Fib) with 97\% accuracy using frequency domain compression and data mining technique.

Lee \textit{et al.}\textsuperscript{20} discriminated three classes of atrial arrhythmia beats (AFL, \textit{Atrial Tachycardia} (AT) and A-Fib) using time-frequency spectrum and Bayesian approach and achieved an overall accuracy of 88\%. Tsipouras \textit{et al.}\textsuperscript{21} diagnosed three classes (NSR, A-Fib and AFL) using Wigner–Ville Distribution (WVD) and ANN and reported 94.2\% of accuracy. Martis \textit{et al.}\textsuperscript{22,23} classified atrial tachycardia beats (NSR, A-Fib and AFL) with 97.65\% and 99.5\% of accuracy using Higher Order Spectra (HOS) bispectrum and cumulants methods, respectively with $k$-NN classifier. Güler and Übeyli\textsuperscript{24} using Discrete Wavelet Transform (DWT) and ANN classified four classes (NSR, CHF, VT and A-Fib) and obtained 97.78\% of accuracy. The non-linear techniques\textsuperscript{60–64} deliver information about the temporal and frequency content of the ECG, but fail to convey clear visualization of the unseen periodicities. Hence, recurrence systems are the powerful tools in quantification of short-duration linear as well as non-linear time sequences.\textsuperscript{55}

ECG is a highly non-linear and non-stationary physiological signal whose periodicity is hidden by the chaotic nature.\textsuperscript{58} Recurrence Quantification Analysis (RQA) evidently captures invisible rhythmicity of the ECG classes without transformation. RQA is applied in automated diagnosis of different physiological signals such as Electroencephalogram (EEG)\textsuperscript{25,26} Heart Rate Variability (HRV)\textsuperscript{27–30} and cardiorespiratory.\textsuperscript{31}

In this paper, four classes of tachycardia (NSR, A-Fib, AFL and V-Fib) are clearly discriminated using Recurrence Plot (RP) and diagnosed by applying RQA
parameters. The clinically significant \((p < 0.05)\) features are ranked based on \(F\)-value index and fed to the single tree (DT) and ensemble classifiers (RAF and ROF) to choose the best classifier. Classifiers performance is measured using: (i) Overall accuracy (%), (ii) Class-specific accuracy (%) and (iii) Cohen’s \(kappa\) statistic (\(\kappa\)).

The paper is further organized as follows: Section 2 describes the dataset used in this work, Sec. 3 briefly presents the extracted features and classifiers that are used, and defines the performance measures used to evaluate the classifiers. Section 4 presents the results obtained. A full review of the literature connected to the automatic detection of tachycardia beats using ECG signals is listed in Sec. 5, which also converses the results achieved in this work. Finally, conclusion is given in Sec. 6.

2. Dataset Used

In this work, in total 3858 ECG beats are taken from three database viz. MIT-BIH Arrhythmia Database,\(^{32,33}\) MIT-BIH Atrial Fibrillation Database\(^{34}\) and Creighton University Ventricular Tachyarrhythmia Database.\(^{35}\) Utilizing these databases 1008, 887, 855 and 1108 ECG beats of four classes NSR, A-Fib, AFL and V-Fib, respectively are carefully chosen considering reference beat and cardiac rhythm remarks and also these rhythms are verified by a medical professional. Table 1 summarizes the dataset used, in which beats of NSR taken from MIT-BIH arrhythmia database, A-Fib and AFL beats from MIT-BIH Arrhythmia Database and MIT-BIH Atrial Fibrillation Database and V-Fib beats from Creighton University Ventricular Tachyarrhythmia Database are considered in our study.

3. Methodology

The block diagram of proposed methodology is presented using Fig. 1. Following are techniques used in this strategy: Preprocessing, RPs and feature extraction using RQA, Feature ranking, Cross-validation and Classification.

3.1. ECG preprocessing

ECG signals in MIT-BIH Arrhythmia Database are sampled for 360 Hz, while in MIT-BIH Atrial Fibrillation Database and Creighton University Ventricular Tachyarrhythmia Database are sampled at 250 Hz. Hence, the ECG from MIT-BIH

<table>
<thead>
<tr>
<th>ECG class</th>
<th>Number of beats</th>
</tr>
</thead>
<tbody>
<tr>
<td>NSR</td>
<td>1008</td>
</tr>
<tr>
<td>A-Fib</td>
<td>887</td>
</tr>
<tr>
<td>AFL</td>
<td>855</td>
</tr>
<tr>
<td>V-Fib</td>
<td>1108</td>
</tr>
<tr>
<td>Total beats</td>
<td>3858</td>
</tr>
</tbody>
</table>
Arrhythmia Database resampled for a common sampler frequency of 250 Hz and resultant ECG signals are denoised using DWT technique. Steps are as follows:

(i) ECG of 250 Hz is exposed to sub-band decomposition applying Daubechies-4 (Db4) mother wave into eight stages.
(ii) 1st stage detail coefficients (62.5–125 Hz) corresponding to high-frequency noise and 8th stage approximation coefficients (0–0.488 Hz) related to baseline wander are set to zero.
(iii) Finally, for the remaining sub-bands 2nd, 3rd, 4th, 5th, 6th, 7th and 8th stage detail coefficients inverse DWT is computed.

Ultimately, noise removed ECG signal is subjected to Pan–Tompkin’s QRS detection algorithm and segmented into beats. At this point, the entire window starting from 74 samples to the left of R-peak till 75 samples to the right of R-peak as a segment of 150 samples is selected as a beat for the following study.

### 3.2. RP and RQA features

Recurrence Plots (RPs) published by Eckmann et al. is the graphical picturing of greater dimensional phase space paths, specifically suited to identify hidden dynamical patterns and non-linearities in the time series. The recurrence proceeds when the gap between two states $i$ and $j$ falls less than a predefined fixed value $\varepsilon$. Let $x_i$ and $x_j$ be two points on the trajectory in a $m$-dimensional space. After $x_j$ is very near to $x_i$ in distance, a recurrence is said to be followed and a spot is located at $(i, j)$ position. In the diagonal $(i = j)$ path, the plot is symmetric because if $x_j$ is near to $x_i$ then, $x_i$ is equally near to $x_j$. Hence, this RP is a patch of dots on a square of $N \times N$ dimension. It can also be visualized as a gray and dark dot image in a time delay space with dark dot represents the incidence of recurrence.

Webber and Zbilut and Marwan et al. introduced advanced tools to capture hidden information in RPs of the time series. These numeric quantities of RP are acquired from RQA. The RQA parameters measure the non-linearity and complexity.
present in the ECG. In this work, for the classification of ECG beats 15 features of RQA are extracted using cross recurrence toolbox.\textsuperscript{42} They are briefly explained below.

(i) **Recurrence Rate (RR)**: It indicates the percentage with recurrence spots \((N)\) or the correlation sum, and counts the dark dots in the recurrence plot.\textsuperscript{43}

\[
RR = \frac{1}{N^2} \sum_{i,j=1}^{N} R_{i,j}
\] (1)

(ii) **Determinism (DET)**: Proportion of recurrence spots which form crosswise lines,\textsuperscript{43} and is given by

\[
DET = \frac{\sum_{l=d_{\text{min}}}^{N} lH_D(l)}{\sum_{i,j=1}^{N} R_{i,j}},
\] (2)

where, \(H_D(l) = \sum_{i,j=1}^{N} (1 - R_{i-1,j-1})(1 - R_{i+l,j+l}) \prod_{k=0}^{l-1} R_{i+k,j+k}\) is the histogram of the intervals, \(l\) of the crosswise lines and the \(d_{\text{min}}\) parameter sets the lower bounds on the definition of lines in the recurrence plot. In this work, \(d_{\text{min}}\) is set to 2.

(iii) **Ratio (RATIO)**: It is proportion concerning DET and RR computed based on the number \(H_D(l)\) of crosswise lines of length \(l\) as follows:

\[
\text{RATIO} = N^2 \frac{\sum_{l=d_{\text{min}}}^{N} lH_D(l)}{(\sum_{i,j=1}^{N} H_D(l))^2}.
\] (3)

This ratio reveals the transitions in the dynamics.\textsuperscript{43}

(iv) **Trend (TND)**: It quantifies the recurrence rate in a diagonal line parallel with Line of Identity (LOI).\textsuperscript{43}

\[
TND = \frac{\sum_{i=1}^{\tilde{N}} (i - \tilde{N}/2)(RR_i - \langle RR_i \rangle)}{\sum_{i=1}^{\tilde{N}} (i - \tilde{N}/2)^2},
\] (4)

where \(\tilde{N}\) is the maximal number of diagonals parallel to the LOI and the operator \(\langle \rangle\) specifies average value.

(v) **Maximal Diagonal Line Length \((D_{\text{max}})\)**: Represents the length of the single elongated diagonal, inside the complete recurrence plot. These lines give an indication about the deviation of the trajectory sectors.\textsuperscript{43}

\[
D_{\text{max}} = \arg \max_l H_D(l),
\] (5)

where, smaller \(D_{\text{max}}\) indicates more deviation in the trajectories.

**Divergence (DIV)**: It is connected with the length of the diagonal lines and gives information about the separation moments of the paths. This RQA parameter is an approximation of the positive maximal Lyapunov exponents\textsuperscript{43} expressed as,

\[
\text{DIV} = \frac{1}{D_{\text{max}}},
\] (6)
(vi) **Mean Diagonal Line Length** (\(\langle D \rangle\)): This parameter given as,

\[
\langle D \rangle = \frac{\sum_{l=d_{\min}}^{N} lH_D(l)}{\sum_{l=d_{\min}}^{N} H_D(l)}.
\]  

While the average time between two segments of the trajectory are close to each other, \(\langle D \rangle\) can be interpreted as the mean prediction time.\(^{43}\)

(vii) **Entropy of the Diagonal Line Lengths (ENT)**: This parameter reflects the complexity of the deterministic structure in the system.\(^{43}\) Higher ENT value represents the complexity of the dynamical system.

\[
\text{ENT} = -\sum_{l=d_{\min}}^{N} p(l) \ln p(l) \quad \text{with} \quad p(l) = \frac{H_D(l)}{\sum_{l=d_{\min}}^{N} H_D(l)}.
\]  

(viii) **Laminarity (LAM)**: It quantifies the relative amount of vertical structuring over the entire RP. It also represents the frequency of occurrence of laminar states within the system.\(^{43}\)

\[
\text{LAM} = \frac{\sum_{l=v_{\min}}^{N} lH_v(l)}{N},
\]  

where \(H_v(l) = \sum_{i,j=1}^{N} (1 - R_{i,j-1})(1 - R_{i,j+l}) \prod_{k=0}^{l-1} R_{i,j+k}\) is the histogram of lengths of vertical lines.

(ix) **Trapping Time (TT)**: It is average length of vertical structures

\[
\text{TT} = \frac{\sum_{l=v_{\min}}^{N} vH_v(l)}{\sum_{l=v_{\min}}^{N} H_v(l)}.
\]  

TT contains information about quantity and interval of the perpendicular structures in the RP by reporting that the mean time system will take at a specific state.\(^{43}\)

(x) **Maximal Vertical Line Length** (\(V_{\text{max}}\)): Measures the longest vertical line in RP

\[
V_{\text{max}} = \arg \max_l H_v(l),
\]  

\(V_{\text{max}}\), can be related to singular states in which the system is fixed in a holding pattern inscribing rectangles in the RP.\(^{43}\)

(xi) **Transitivity (\(\Gamma\))**: In a complex network, the transitivity gives probability of three nodes connection:

\[
\Gamma = \frac{\sum_{i,j,k} A_{i,j} A_{j,k} A_{k,i}}{\sum_{i,j,k} A_{i,k} A_{k,j}},
\]  

where \(A\) is adjacent node. Regular dynamics like periodic orbits are related with a higher transitivity, while disordered structures show relatively low transitivity.\(^{43}\) Transitivity symbolizes the definite total dimensionality of the system.
**Recurrence Time:** Recurrence times are the events of complexity. These events make use of the probability dispersal of the recurrence periods and permit to distinguish between different types of dynamics or the onset of dynamical changeovers.\(^{(43)}\)

(xii) **Recurrence Time of 1st Type** \((T_1(i))\):

\[
T_1(i) = t_{i+1} - t_i, \quad t = 1, 2, \ldots k.
\]  

(xiii) **Recurrence Time of 2nd Type** \((T_2(i))\):

\[
T_2(i) = t_{i+1} - t_i, \quad t = 1, 2, \ldots k.
\]

(xiv) **Recurrence Time Entropy** \((H_{RTE})\): Determines the periodicity, or repetitiveness of a signal.\(^{(43)}\)

\[
H_{RTE} = -(\ln T_{\text{max}})^{-1} \sum_{t=1}^{T_{\text{max}}} P(t) \ln P(t),
\]

where \(T_{\text{max}}\) is the largest recurrence value and \(P(t)\) is the histogram recurrence of the periodic function. For purely periodic signals, \(H_{RTE} = 0\).

### 3.3. Statistical test (ANOVA) and feature ranking

In this work, statistical significance of the 15 RQA features verified by subjecting to one-way Analysis-of-Variance (ANOVA) test. Subsequently, the discrimination among multiclass labels is computed using \(F\)-value (proportion of between class variance to the within class variance) and \(p\)-value measures (\(p < 0.05\) is clinically preferred). The larger \(F\)-value indicates that the between group variation is greater than within group variation.\(^{(44)}\) Feature ranking technique helps to rank the medically significant features according to their discriminating criteria.\(^{(45)}\) In this work, the significant features are ranked using \(F\)-values and fed to the classifier for ECG pattern classification.

### 3.4. 10-fold cross-validation

The 10-fold cross-validation method is applied to obtain robust automated diagnosis system. In this method, total heartbeats are divided into 10 equal parts, 1 part for testing and remaining 9 parts for training. This process is repeated for 10 stretches, so that each division is used for testing just once.\(^{(46)}\) In this work, each fold performance of the four classes of beats is evaluated and average of the 10 folds is computed to get the overall accuracy (%) and class-specific accuracy (%).

### 3.5. Classification

In this work, tachycardia beats are classified into four classes using DT and ensemble classifiers. The ensemble classifiers offer superior performance compared to single classification approach. Classifiers used in this study are developed using WEKA machine-learning tool.\(^{(47)}\)
3.5.1. Decision Tree-single tree classifier

A Decision Tree (DT) is a supervised if-then rule-based classifier which is a recursive divider of the instance space which consists of nodes that form a deep-rooted tree. A node with outgoing edges is called as test node. All other nodes are called leaves or decision nodes. The parent node is split into youngster nodes based on the data gain. Method of splitting the parental node into youngster nodes ends when there is no further data increase. The node has a characteristic, $T$ to select a limited data from the set so that it is as “pure” as likely.\(^{46}\) In the present work, entropy impurity is used and DT classifier is implemented applying Classification and Regression Tree (CART) algorithm.\(^{48}\)

3.5.2. Random forest

Random Forest (RAF) is a new ensemble classification method proposed by Breiman.\(^{49}\) RAF contains DT as a collection of randomized base classifiers $\{R_n(x, \theta_p, d_n), p \geq 1\}$, where $\theta_1, \theta_2, \ldots$ are outputs of a randomizing variable $\theta$. These random trees ensemble to form the aggregated classification estimate

$$\bar{R}_n(x, d_n) = E_{\theta}[R_n(x, \theta, d_n)], \quad (16)$$

where $E_{\theta}$ denotes expectation with respect to the random parameter, conditionally on $x$ and dataset $d_n$. Expectation in (16) is estimated by creating $M$ random trees, and taking the average of the individual outcomes. The randomizing variable $\theta$ is used to determine how the successive cuts are performed when building the individual trees.\(^{50–52}\) In this work, the tree is grown using CART\(^{48}\) without pruning and number of trees arbitrarily chosen are 100 to get the highest performance.

3.5.3. Rotation forest

Rotation Forest (ROF), a modern method for constructing an ensemble of classifiers\(^{53}\) in which base classifiers are individually built DTs and every tree is expert on the complete dataset with a revolved feature set. Training data for a base classifier is generated by arbitrarily splitting feature set into $K$ divisions ($K$ is a constraint of system) and Principal Component Analysis (PCA) is subjected on each division. All major components are considered in order to maintain the variability in the features. Finally, $K$ axis rotations take place to form the diverse features for a base classifier.\(^{52,53}\)

3.6. Performance measures of classification

The performance of multiclass tachycardia diagnosis using RQA feature sets is individually evaluated using three classifiers on succeeding measures:

(i) **Overall accuracy (%)**: Indicates the total accuracy, which is given by proportion of amount of detected (classifier output) heartbeats of all the classes to total amount of beats used in this study.
(ii) **Class-specific accuracy (%)**: Indicates accuracy of a particular class (NSR, A-Fib, AFL and V-Fib). This is given by proportion of classified beats of particular class to the total amount of heartbeats of that class.

(iii) **Cohen’s kappa statistic (κ)**: This is a new technique published by Cohen, using which the reliability of diagnosis is measured.

These performance measures for the 10-fold cross-validation are evaluated in each fold and graphically represented using error bar plots. Also, the confusion matrix can be used for the validation of class-specific accuracy (%) and overall accuracy (%).

4. Results

In this work, ECG signals taken from three different databases are preprocessed and in total 3858 heartbeats considered. Individual beat of 150 samples, belonging to four classes (summary of beats used given in Table 1) are considered. These beats are independently transformed to higher dimensional plots which depict the non-linear dynamical patterns of time series. Figures 2–5 represent typical RP of 150 × 150 dimensions for four classes of beats viz. NSR, A-Fib, AFL and V-Fib beats, respectively. Using these plots, 15 RQA features are extracted. Table 2 summarizes mean and standard deviation for four classes of beats. F-value and corresponding p-value measures are computed using ANOVA test. Clinically significant (p < 0.05) features are ranked based on F-value index (first rank with highest F-value and so on) as shown in Table 3. As a result, *Recurrence Time of 1st Type* (\(T_1(i)\)) is ranked first with highest F-value 4499.45 and *Recurrence Time Entropy* (\(H_{RTE}\)) ranked at the end with least F-value 965.01. These feature sets are fed independently to three classifiers viz. DT, RAF and ROF according to the F-value ranking (\(R_1, R_1+R_2, R_1+R_2+R_3, \text{ and so on}\)). Thus, \(T_1(i)\) feature set is applied first for classification, then \(T_1(i) + \text{TND}, T_1(i) + \text{TND} + \text{RATIO} \text{ and so on as displayed in Table 3. It is}

![Fig. 2. Typical RP of NSR beat.](1640005-10)
perceived that overall accuracy (%) progressively rises as the number of feature set increases. Using the 15th feature set (containing $R_1$–$R_{15}$ ranks) overall accuracy (%) achieved is 94.14%, 96.29% and 98.37% for DT, RAF and ROF classifiers, respectively. These classifiers are developed using 10-fold cross-validation to avoid bias in the selection of training and testing sets. The performance of classifiers in the 10-fold cross-validation is quantified using confusion matrix as given in Tables 4–6 for DT, RAF and ROF, respectively. In these tables, rows represent gold standard and columns indicate classified outputs. Table 7 defines the summary of class-specific accuracy (%), overall accuracy (%) and equivalent Cohen’s kappa statistic ($\kappa$) using three different classifiers. It can be noted that, the ROF provides the highest overall accuracy with 98.37% and its kappa value ($\kappa$) is 0.9821. The kappa

Diagnosis of Multiclass Tachycardia Beats

![Fig. 3. Typical RP of A-Fib beat.](image)

![Fig. 4. Typical RP of AFL beat.](image)
statistic ($\kappa$) indicates constancy in accuracy ($\%$). A kappa value ($\kappa$) close to one indicates, 10 classification accuracies ($\%$) of the 10-fold cross-validation do not have much variation and hence the results are consistent. Figures 6–8 indicate the error bar plot of class-specific accuracy ($\%$) for NSR, A-Fib, AFL and V-Fib and overall accuracy ($\%$) over the 10 folds (fold 1, fold 2 . . . fold 10) using DT, RAF and ROF, respectively. Cross mark on the error bar specifies mean value and two extremities of line stretch the standard deviation. The deviation in the plot for overall accuracy ($\%$) using ROF is less than the other two methods. Hence, the ROF ensemble method diagnoses four classes consistently with highest accuracy compared to RAF.

<table>
<thead>
<tr>
<th>RQA features</th>
<th>NSR</th>
<th>A-Fib</th>
<th>AFL</th>
<th>V-Fib</th>
</tr>
</thead>
<tbody>
<tr>
<td>RR</td>
<td>$0.28 \pm 76.09 \times 10^{-3}$</td>
<td>$0.31 \pm 61.13 \times 10^{-3}$</td>
<td>$0.31 \pm 54.01 \times 10^{-3}$</td>
<td>$0.28 \pm 79.21 \times 10^{-3}$</td>
</tr>
<tr>
<td>DET</td>
<td>$0.95 \pm 35.81 \times 10^{-3}$</td>
<td>$0.95 \pm 37.48 \times 10^{-3}$</td>
<td>$0.95 \pm 37.94 \times 10^{-3}$</td>
<td>$0.94 \pm 36.54 \times 10^{-3}$</td>
</tr>
<tr>
<td>RATIO</td>
<td>$3.58 \pm 1.25$</td>
<td>$3.24 \pm 0.84$</td>
<td>$3.13 \pm 0.59$</td>
<td>$3.73 \pm 1.33$</td>
</tr>
<tr>
<td>TND</td>
<td>$3.57 \pm 0.52$</td>
<td>$3.73 \pm 0.32$</td>
<td>$3.77 \pm 0.21$</td>
<td>$3.44 \pm 0.65$</td>
</tr>
<tr>
<td>$D_{\text{max}}$</td>
<td>$7.21 \pm 1.53$</td>
<td>$7.11 \pm 1.54$</td>
<td>$7.09 \pm 1.55$</td>
<td>$7.13 \pm 1.53$</td>
</tr>
<tr>
<td>DIV</td>
<td>$16.15 \pm 2.99$</td>
<td>$17.01 \pm 1.94$</td>
<td>$17.27 \pm 1.38$</td>
<td>$15.31 \pm 3.97$</td>
</tr>
<tr>
<td>$\langle D \rangle$</td>
<td>$65.11 \pm 11.52$</td>
<td>$64.63 \pm 12.19$</td>
<td>$64.49 \pm 12.39$</td>
<td>$64.13 \pm 12.03$</td>
</tr>
<tr>
<td>ENT</td>
<td>$2.57 \pm 0.28$</td>
<td>$2.69 \pm 0.26$</td>
<td>$3.07 \pm 0.39$</td>
<td>$2.56 \pm 0.25$</td>
</tr>
<tr>
<td>LAM</td>
<td>$0.97 \pm 20.62 \times 10^{-3}$</td>
<td>$0.97 \pm 21.55 \times 10^{-3}$</td>
<td>$0.99 \pm 21.81 \times 10^{-3}$</td>
<td>$0.96 \pm 21.53 \times 10^{-3}$</td>
</tr>
<tr>
<td>TT</td>
<td>$8.62 \pm 1.81$</td>
<td>$8.71 \pm 1.86$</td>
<td>$8.73 \pm 1.88$</td>
<td>$8.51 \pm 1.82$</td>
</tr>
<tr>
<td>$V_{\text{max}}$</td>
<td>$36.33 \pm 11.21$</td>
<td>$37.99 \pm 10.85$</td>
<td>$38.51 \pm 10.68$</td>
<td>$36.96 \pm 11.14$</td>
</tr>
<tr>
<td>$\Gamma$</td>
<td>$0.82 \pm 33.14 \times 10^{-3}$</td>
<td>$0.81 \pm 32.16 \times 10^{-3}$</td>
<td>$0.81 \pm 31.89 \times 10^{-3}$</td>
<td>$0.81 \pm 34.03 \times 10^{-3}$</td>
</tr>
<tr>
<td>$T_1(i)$</td>
<td>$2.41 \pm 0.51$</td>
<td>$2.29 \pm 0.41$</td>
<td>$2.25 \pm 0.35$</td>
<td>$2.49 \pm 0.66$</td>
</tr>
<tr>
<td>$T_2(i)$</td>
<td>$18.16 \pm 3.77$</td>
<td>$17.36 \pm 3.02$</td>
<td>$17.13 \pm 2.79$</td>
<td>$18.49 \pm 3.81$</td>
</tr>
<tr>
<td>$H_{\text{RTE}}$</td>
<td>$0.55 \pm 41.23 \times 10^{-3}$</td>
<td>$0.54 \pm 41.14 \times 10^{-3}$</td>
<td>$0.54 \pm 41.02 \times 10^{-3}$</td>
<td>$0.55 \pm 45.36 \times 10^{-3}$</td>
</tr>
</tbody>
</table>
Table 3. Results of ANOVA and ranked features for comparison of overall accuracy (%).

<table>
<thead>
<tr>
<th>Feature ranks (R₁–R₁₅)</th>
<th>Ranked features</th>
<th>p-value</th>
<th>F-value</th>
<th>DT</th>
<th>ROF</th>
<th>RAF</th>
</tr>
</thead>
<tbody>
<tr>
<td>R₁</td>
<td>Tᵢ(τ)</td>
<td>0.0000</td>
<td>4499.45</td>
<td>71.04</td>
<td>62.49</td>
<td>70.92</td>
</tr>
<tr>
<td>R₂</td>
<td>TND</td>
<td>0.0000</td>
<td>3624.79</td>
<td>85.64</td>
<td>84.96</td>
<td>85.33</td>
</tr>
<tr>
<td>R₃</td>
<td>RATIO</td>
<td>0.0000</td>
<td>3482.19</td>
<td>88.31</td>
<td>89.84</td>
<td>89.84</td>
</tr>
<tr>
<td>R₄</td>
<td>DIV</td>
<td>0.0000</td>
<td>3414.57</td>
<td>91.78</td>
<td>93.21</td>
<td>94.01</td>
</tr>
<tr>
<td>R₅</td>
<td>RR</td>
<td>0.0000</td>
<td>2757.34</td>
<td>91.39</td>
<td>93.31</td>
<td>93.96</td>
</tr>
<tr>
<td>R₆</td>
<td>TT</td>
<td>0.0000</td>
<td>2296.91</td>
<td>92.07</td>
<td>94.35</td>
<td>94.17</td>
</tr>
<tr>
<td>R₇</td>
<td>τ</td>
<td>0.0000</td>
<td>2243.45</td>
<td>91.92</td>
<td>93.93</td>
<td>94.40</td>
</tr>
<tr>
<td>R₈</td>
<td>LAM</td>
<td>0.0000</td>
<td>2102.34</td>
<td>92.09</td>
<td>94.24</td>
<td>94.24</td>
</tr>
<tr>
<td>R₉</td>
<td>DET</td>
<td>0.0000</td>
<td>2081.11</td>
<td>91.96</td>
<td>94.58</td>
<td>94.44</td>
</tr>
<tr>
<td>R₁₀</td>
<td>ENT</td>
<td>0.0000</td>
<td>1842.62</td>
<td>92.24</td>
<td>94.76</td>
<td>94.79</td>
</tr>
<tr>
<td>R₁₁</td>
<td>⟨D⟩</td>
<td>0.0000</td>
<td>1713.31</td>
<td>92.79</td>
<td>94.94</td>
<td>95.53</td>
</tr>
<tr>
<td>R₁₂</td>
<td>Dₘₐₓ</td>
<td>0.0000</td>
<td>1652.25</td>
<td>93.41</td>
<td>95.15</td>
<td>95.98</td>
</tr>
<tr>
<td>R₁₃</td>
<td>Vₘₐₓ</td>
<td>0.0000</td>
<td>1381.17</td>
<td>93.93</td>
<td>95.56</td>
<td>96.71</td>
</tr>
<tr>
<td>R₁₄</td>
<td>T₂(i)</td>
<td>0.0000</td>
<td>1075.08</td>
<td>94.01</td>
<td>95.86</td>
<td>97.93</td>
</tr>
<tr>
<td>R₁₅</td>
<td>Hᵣᵣₜₑ</td>
<td>0.0000</td>
<td>965.01</td>
<td>94.14</td>
<td>96.29</td>
<td>98.37</td>
</tr>
</tbody>
</table>

Table 4. Confusion matrix using DT over the 10 folds.

<table>
<thead>
<tr>
<th>Gold standard</th>
<th>Classes</th>
<th>NSR</th>
<th>A-Fib</th>
<th>AFL</th>
<th>V-Fib</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NSR</td>
<td>985</td>
<td>18</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>A-Fib</td>
<td>15</td>
<td>856</td>
<td>14</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>AFL</td>
<td>2</td>
<td>84</td>
<td>759</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>V-Fib</td>
<td>0</td>
<td>2</td>
<td>2</td>
<td>1099</td>
</tr>
</tbody>
</table>

Table 5. Confusion matrix using RAF over the 10 folds.

<table>
<thead>
<tr>
<th>Gold standard</th>
<th>Classes</th>
<th>NSR</th>
<th>A-Fib</th>
<th>AFL</th>
<th>V-Fib</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NSR</td>
<td>997</td>
<td>8</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>A-Fib</td>
<td>15</td>
<td>811</td>
<td>54</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>AFL</td>
<td>2</td>
<td>48</td>
<td>803</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>V-Fib</td>
<td>0</td>
<td>2</td>
<td>2</td>
<td>1104</td>
</tr>
</tbody>
</table>

Table 6. Confusion matrix using ROF over the 10 folds.

<table>
<thead>
<tr>
<th>Gold standard</th>
<th>Classes</th>
<th>NSR</th>
<th>A-Fib</th>
<th>AFL</th>
<th>V-Fib</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NSR</td>
<td>993</td>
<td>12</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>A-Fib</td>
<td>9</td>
<td>856</td>
<td>14</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>AFL</td>
<td>4</td>
<td>5</td>
<td>441</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>V-Fib</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>1105</td>
</tr>
</tbody>
</table>
5. Discussion

The superiority of the recurrence property of dynamical systems is that, it can deliver most appropriate information even for the short non-stationary time sequence without prior assumptions. In this paper, the recurrence behavior of the system is visualized by converting ECG samples to higher dimensional phase space paths. These structural configurations reveal hidden periodicity and dynamicity in ECG.

In our paper, chaotic nature of four classes of ECG beats NSR, A-Fib, AFL and V-Fib are captured and textures of the plots are closely inspected. Regular cardiac

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Table 7. Classifiers performance for four classes of beat detection over the 10 folds.

<table>
<thead>
<tr>
<th>Classifiers</th>
<th>NSR</th>
<th>A-Fib</th>
<th>AFL</th>
<th>V-Fib</th>
<th>Overall accuracy (%)</th>
<th>Cohen’s kappa statistic (κ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DT</td>
<td>97.72</td>
<td>88.95</td>
<td>88.77</td>
<td>99.19</td>
<td>94.14</td>
<td>0.9185</td>
</tr>
<tr>
<td>RAF</td>
<td>98.91</td>
<td>91.43</td>
<td>93.92</td>
<td>99.64</td>
<td>96.29</td>
<td>0.9504</td>
</tr>
<tr>
<td>ROF</td>
<td>98.51</td>
<td>96.5</td>
<td>98.36</td>
<td>99.73</td>
<td>98.37</td>
<td>0.9821</td>
</tr>
</tbody>
</table>

---

Fig. 6. Error bar of class-specific accuracy (%) and overall accuracy (%) for 10 folds using DT.
conduction (NSR) is usually characterized by slow change of the paths, which quantifies high percentage of recurrence points with more dark patches or dots and is presented in Fig. 2. The abnormal classes A-Fib, AFL and VFL are symbolized by irregular ventricular responses increase in ventricular rate and wide ventricular complexes, respectively. These sudden changes and hidden rhythmicity of A-Fib, AFL and VFL beats are captured in Figs. 3–5, respectively. It is marked with these plots that, activities of abrupt changes for A-Fib, AFL and VFL classes are distinguished in the phase space trajectory by few dots (or more white area), distinctive vertical, and horizontal line segments and added diagonal lines, respectively. However, the graphical interpretation requires certain skills. Hence, using quantification of recurrence plots classes can be objectively and precisely discriminated. In this study, 15 RQA features are used to develop CACD system. In order to achieve best classification accuracy the robust classifiers namely, DT as a single classifier and ensemble classifiers (RAF and ROF) are developed. ROF discriminated NSR, A-Fib, AFL and V-Fib classes with highest class-specific accuracy of 98.51%, 96.5%, 98.36% and 99.73%, respectively and with overall accuracy of 98.37%. Table 8 presents the performance of different studies carried out in automated diagnosis of multiclass tachycardia beats using ECG.

Fig. 7. Error bar of class-specific accuracy (%) and overall accuracy (%) for 10 folds using RAF.
Fig. 8. Error bar of class specific accuracy (%) and overall accuracy (%) for 10 folds using ROF.

Table 8. Comprehensive summary of works carried on computerized diagnosis of tachycardia class using ECG.

<table>
<thead>
<tr>
<th>Authors</th>
<th>Classes</th>
<th>Dataset</th>
<th>Method</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Studies that dealt with a three-class problem</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>59</td>
<td>A-Fib, V-Fib, VT</td>
<td>120 beats</td>
<td>Short-time Multifractality–Fuzzy Neural Network</td>
<td>99.4 A-Fib, 97.2 V-Fib, 97.8 VT</td>
</tr>
<tr>
<td>15</td>
<td>A-Fib, AFL, NSR</td>
<td>329 records</td>
<td>P wave absence–Sequential Analysis</td>
<td>98.8</td>
</tr>
<tr>
<td>21</td>
<td>A-Fib, AFL, NSR</td>
<td>100,000 beats</td>
<td>Time-Frequency Analysis–ANN</td>
<td>94.2</td>
</tr>
<tr>
<td>18</td>
<td>A-Fib, AFL, NSR</td>
<td>30 records</td>
<td>Independent Component Analysis (ICA)–Spectral Parameter Extraction</td>
<td>100</td>
</tr>
<tr>
<td>22</td>
<td>A-Fib, AFL, NSR</td>
<td>2383 beats</td>
<td>Bispectrum–ICA–10-fold cross-validation (TFCV–k-NN)</td>
<td>97.65</td>
</tr>
<tr>
<td>23</td>
<td>A-Fib, AFL, NSR</td>
<td>2383 beats</td>
<td>Cumulants–ICA–TFCV–k-NN</td>
<td>99.5</td>
</tr>
<tr>
<td>17</td>
<td>A-Fib, AFL, NSR</td>
<td>2383 beats</td>
<td>DCT–ICA–TFCV–k-NN</td>
<td>99.45</td>
</tr>
<tr>
<td></td>
<td>Studies that dealt with a four-class problem</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>V-Fib, VFL, PVC, A-Fib</td>
<td>52 records</td>
<td>Compressed ECG-Data Mining</td>
<td>97</td>
</tr>
<tr>
<td><strong>Our work</strong></td>
<td><strong>A-Fib, AFL, V-Fib, NSR</strong></td>
<td><strong>3858 beats</strong></td>
<td><strong>RQA–TFCV–ROF</strong></td>
<td><strong>98.37</strong></td>
</tr>
</tbody>
</table>
In this research paper, we have presented unique plots to discriminate four classes NSR, A-Fib, AFL and V-Fib, which is a novel contribution from this work. We have also obtained the highest classification accuracy of 98.37% using RQA features coupled with ROF classifier. Hence, quantification of RP provides objective method to evaluate the individuals with abnormalities. However, the classification accuracy needs to be tested with large database. In this work, we have considered only 3858 ECG beats and 15 RQA features. In future, we intend to test with more data and better features.

Salient features of this work are as follows:

(i) Unique recurrence plots are proposed for each class.
(ii) Obtained highest accuracy of 98.37% using ROF ensemble classification.
(iii) Assessed using class-specific accuracy (%) and consistency of classifiers over 10 folds is verified Cohen’s kappa statistic.
(iv) Developed system is entirely computerized, precise and non-invasive. Hence, requires less involvement of clinicians.
(v) Established method is cost efficient and can be used in mass screening of tachycardia classes, telemonitoring, and in cardiac defibrillators.

6. Conclusion

Now-a-days the magnitude of cardiac death is progressively increasing around the globe. The developed CACD systems using a new non-linear dynamical technique and new classification algorithms can significantly help the clinicians in decision making and improve the life span of old people. ECG signal is highly informative and can be used to discriminate NSR, A-Fib, AFL and V-Fib classes. In this work, the non-linearity in these classes is extracted using RQA features for diagnosis and unique recurrence plots are proposed for each class. The four classes are automatically detected with an overall accuracy of more than 98%.

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References


42. Marwan N, Cross recurrence plot Toolbox for MATLAB®, Ver. 5.18 (R29.3). Available at http://tocsy.pik-potsdam.de/CRPtoolbox/ (accessed on 31 August 2015).

