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ORIGINAL ARTICLE

Ensemble classifier fostered detection of arrhythmia using ECG data

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Abstract

Electrocardiogram (ECG) is a non-invasive medical tool that divulges the rhythm and function of the human heart. This is broadly employed in heart disease detection including arrhythmia. Arrhythmia is a general term for abnormal heart rhythms that can be identified and classified into many categories. Automatic ECG analysis is provided by arrhythmia categorization in cardiac patient monitoring systems. It aids cardiologists to diagnose the ECG signal. In this work, an Ensemble classifier is proposed for accurate arrhythmia detection using ECG Signal. Input data are taken from the MIT-BIH arrhythmia dataset. Then the input data was pre-processed using Python in Jupyter Notebook which run the code in an isolated manner and was able to keep code, formula, comments, and images. Then, Residual Exemplars Local Binary Pattern is applied for extracting statistical features. The extracted features are given to ensemble classifiers, like Support vector machines (SVM), Naive Bayes (NB), and random forest (RF) for classifying the arrhythmia as normal (N), supraventricular ectopic beat (S), ventricular ectopic beat (V), fusion beat (F), and unknown beat (Q). The proposed AD-Ensemble SVM-NB-RF method is implemented in Python. The proposed AD-Ensemble SVM-NB-RF method is 44.57%, 52.41%, and 29.49% higher accuracy; 2.01%, 3.33%, and 3.19% higher area under the curve (AUC); and 21.52%, 23.05%, and 12.68% better F-Measure compared with existing models, like multi-model depending on the ensemble of deep learning for ECG heartbeats arrhythmia categorization (AD-Ensemble CNN-LSTM-RRHOS), ECG signal categorization utilizing VGGNet: a neural network based classification method (AD-Ensemble CNN-LSTM) and higher performance arrhythmic heartbeat categorization utilizing ensemble learning along PSD based feature extraction method (AD-Ensemble MLP-NB-RF).

Keywords Arrhythmia detection · ECG data · Support vector machines (SVM) · Naive Bayes (NB) and random forest (RF) · MIT-BIH arrhythmia database · Residual exemplars local binary pattern

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1 Introduction

In recent years, it has become quite common to use various machine learning (ML) approaches to solve problems from various sectors, especially medicine [1]. This popularity is a result of ML's capacity to handle issues that, because of the unknowable rules, are challenging to resolve in a conventional manner [2]. These techniques are effective in resolving a wide range of issues because of the characteristics of learning and knowledge generalization [3]. Computer-aided diagnosis (CAD) helps doctors to make decisions [4, 5]. This also applies to the topic of automated cardiac arrhythmia classification, which helps doctors to classify different types of arrhythmia [6]. By using CAD, problems including misdiagnosis, human error, and lack of human skill can be avoided or reduced [7]. As a consequence, CAD systems are highly recommended for long-term patient monitoring. Artificial intelligence techniques perform well in a variety of science domains [8–11]. The merits of ML (computational intelligence) share with their biological counterparts, namely learning and knowledge generalization (artificial neural networks), global optimization (evolutionary approaches), and inexact terms (fuzzy systems) [12–14, 32–44].

Any deviation from the heart's normal rhythm in which the heart beats too quickly, too early, too slowly, or irregularly is known as a heart arrhythmia [15, 16]. Symptoms of arrhythmias may include feeling lightheaded, fainting, wheezing, and palpitations [17]. However, some arrhythmias, like atrial fibrillation, premature ventricular contractions, and excessive supraventricular ectopic, are linked to a number of cardiovascular illnesses, including stroke, cardiac arrest, and heart malfunction [18, 19]. As per World Health Organization, cardiovascular illness is a major cause of worldwide mortality (around 31% in 2016) [20, 21]. Early detection of these symptoms can prevent hospitalization or even unexpected death. The electrical actions of the heart are monitored by a group of electrodes (typically 10) connected to patients' skin during electrocardiography (ECG). It is a typical non-invasive method of diagnosing heart issues, like arrhythmias [22]. There are various categories of ECG patterns. For example, a 2-lead ECG monitors the patient closely for long period with the help of a Holter monitor device [23]. ECG recording remains 24–48 h and requires to be assessed by a cardiologist to diagnose any heart illness. This is a very time-consuming and tedious process. Because these properties vary between individuals, it is imperative and challenging to develop an automatic method for diagnosing ECG waves. These factors prevent the methods currently described in the scientific literature from achieving adequate performance [25–44]. The aforementioned facts provide motivation for further investigation into novel approaches to support the early and accurate medical diagnosis of cardiac diseases.

1.1 Goals

The primary objectives of this paper are as follows:

- New and effectual ensemble (network) of classifiers is structured for automatic cardiac arrhythmias categorization on the basis of ECG signal segments.
- Universal model is designed for the general population

1.2 Novelty

In the real world, the capacity to accurately and rapidly detect and classify arrhythmia by applying classification models with high confidence is still a goal that has to be accomplished. This is due to the fact that while accuracies as high as 99.5% have been reached in theory and practice, it is unclear if these will hold true when used in practice. The general physician and specialist concepts serve as the foundation for the proposed approach. When a patient visits their general physician, also known as a general practitioner (GP), with concerns about a problem, the GP does an initial evaluation and, based on their diagnosis, either sends the patient to a specialist or simply states that there is nothing to worry about. The ensemble classifier acts as a GP and specialist, which decides what disease type they have.

The aim of this paper is to propose a method for the classification of individuals with arrhythmia utilizing the Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) arrhythmia database with enhanced performance over existing models. Here, a two-stage heart arrhythmia classification is considered and tested under MIT-BIH database utilizing Ensemble Classifier. In the first phase, the input ECG signal is pre-processed and then the statistical features are extracted with the help of Residual Exemplars of Local Binary Pattern (RELBP). In the second stage, different from single classifies applied in many researches [25–46], ensemble classifiers, like support vector machines (SVMs), Naive Bayes (NB), and random forest (RF) are employed for arrhythmia detection using ECG Data. It automatically classifies the arrhythmia as normal (N), supraventricular ectopic beat (S), ventricular ectopic beat (V), fusion beat (F), and unknown beat (Q).

The leftover manuscript is organized as follows: the literature survey is divulged in Sect. 2. Section 3 illustrates the proposed technique. The result and discussion are demonstrated in Sect. 4. Section 5 concludes this manuscript.

2 Literature survey

Among various studies related to Arrhythmia detection with different ensemble machine learning classifiers, a few recent studies are reviewed here,

Essa and Xie et al. [25] have suggested Multi-Model depending on the ensemble of deep learning for ECG heartbeats Arrhythmia categorization. Wherein, 2 dissimilar deep-learning bagging methods were presented to categorize heartbeats as various arrhythmias. Firstly, CNN-LSTM was dependent on a combined convolutional neural network with a long short-term memory network for capturing local features, and temporal dynamics. Secondly, RRHOS-LSTM incorporates few classical aspects. To deal highly uneven distribution of arrhythmia classes in ECG data, they build a packing mode from CNN-LSTM and RRHOS-LSTM in various subsample datasets. Each model was trained using a weight loss function to give underrepresented classes more weight. Such methods were merged by meta-classifier to make a robust coherent mode. The outcome of the meta-classifier was validated by other CNN-LSTM methods to lessen false positives. It attains high accuracy with a low area under the curve value.

Goswami et al. [26] have presented the ECG signal categorization under VGGNet: neural network base categorization mode. The ensemble-based classification combines CNNs and linear with bio-inspired classifiers. It attains higher precision with a high error rate. The data were gathered via the MIT-BIH dataset.

Yakut and Bolat et al. [27] have presented a higher-performance arrhythmic heartbeat classification utilizing ensemble learning model. The presented model categorizes the arrhythmic heartbeats automatically as per the patient-based estimation plan. The baseline wander was eradicated by a two-stage median filter. The developed QRS complex detection method was used to locate the fiducial points of the ECG signal. The 4 different feature extraction models were used. The feature extraction was dependent on Power Spectral Density. Hybrid sub-feature sets structured by Wrapper-base feature selection approach. Then the ensemble learning was suggested by the stacking algorithm. Multi-layer perceptron and random forest as base learners and linear regression as meta learners. It attains high sensitivity with a low F-Score.

Zeng et al. [28] have presented the Arrhythmia identification utilizing tunable Q-factor wavelet transform (TQWT), complete ensemble empirical mode decomposition (CEEMD), deep CNN-LSTM neural networks including ECG signals. To automatically identify various kinds of arrhythmias, deep learning, and one-lead ECG signals were utilized depending on TQWT and CEEMD. Firstly, TQWT distorts the ECG signal as diverse frequency bands through Q, R, and J input parameters without any segmentation that extracts the major subband and ECG signal's energy. Secondly, CEEMD distorts the major subband of ECG signals as various inherent models. It captured main subbands information, and keep significant waveform features as asymmetry. It scales the ECG signals inconsistency. The experiments were done in the MIT-BIH arrhythmia database. It attains higher specificity with low precision.

Rath et al. [29] have presented heart disease detection using deep learning methods from imbalanced ECG samples. Generative Adversarial Network was deemed to handle unbalanced data by additional fake data for the purpose of detection. Standard MIT-BIH displays that the presented method offers a greater F-Score with a lower area under the value.

Hammad et al. [30] have presented deep learning methods for arrhythmia identification at the Internet of things healthcare applications. Wherein, a convolutional neural network together with convolutional long short-term deep learning was suggested for automated arrhythmia identification. Input ECG signals were specified in 2-dimensional format, then gathered images were given to deep learning models for classification. It aids to deal with the overfitting issue. MIT-BIH, PhysioNet 2016, and PhysioNet 2018 were applied for assessment. It attains a lower error rate with low specificity.

Ramasamy et al. [31] have presented cardiac arrhythmias detection from ECG signals utilizing Fourier–Bessel series expansion (FBSE) along Jaya optimized ensemble random subspace K-nearest neighbor approach (JO-ERSKNN). Firstly, electrocardiogram signals were segmented to make a perfect image of a single heartbeat. Afterward, FBSE was applied to transfer the series of every heartbeat that differentiates the arrhythmia's structural integrity. Fourier–Bessel series expansion was trained by JO-ERSKNN to classify 5 kinds of cardiac arrhythmia beats. It attains a high area under curve value with low sensitivity.

3 Proposed methodology

In this section, accurate arrhythmia detection using an ensemble classifier (AD-Ensemble SVM-NB-RF method) is discussed. The block diagram of the proposed AD-Ensemble SVM-NB-RF methodology is given in Fig. 1. It contains four stages: data acquisition, pre-processing, feature extraction, and classification. A detailed description of each stage is given below.

3.1 Data acquisition

Initially, MIT-BIH [24, 45] is considered for addressing considerations of ANSI/AAMI standard EC57 [46] that standardizes the assessment of computation tools for cardiac arrhythmia datasets categorization. MIT-PIH Arrhythmia data set comprises signals from electrocardiography examinations that are employed to assess the presentation of task-related approaches for arrhythmia detection [46]. The data having 48 records totaling 30 min each were chosen during a 24-h period of ECG acquisition for the data, which included samples from 2 separate channels. The signals are derived through 47 patients between 1975 and 1979 at Arrhythmia Boston's Beth Israel Hospital Laboratory amidst aging 23 and 89 years; out of these, 25 were males and 22 were females. The heartbeats are manually marked and categorized by professionals into 15 classes according to the type of arrhythmia on the analogue records that have been digitalized at a sampling rate of 360 Hz. Table 1 tabulates the categories of arrhythmia.

Additionally, 4 records from pacemaker-using patients were removed in accordance with ANSI/AAMI standard EC57, which categorizes 15 classes listed in the database's annotations into 5 classes (Table 1).

3.2 Preprocessing phase

The preprocessed dataset is taken via https://physionet.org/content/mitdb/1.0.0/ to run the model created a python file in a Jupyter Notebook, which helps to run the code in an isolated manner and able to keep code, formula, comments, images and plot together which is convenient for visual data analysis also Jupyter is very extensible, upholds many programming dialects, effectively facilitated on practically any server; you must have ssh or http installed. Admittance to a server. After analysis our data is highly imbalanced so need to preprocess our data by giving equal weightage in each class. Our dataset has five classes so we gave equal weightage to all 5 classes so that the dataset gets balanced; these are a classical representation of each class heartbeat.

To run different libraries in Python which helps to assemble the proposed utilize boa constrictor bundle supervisor which is an appropriation of the Python and R programming tongues for sensible enlisting (data science, AI applications, enormous extension data taking care of, insightful examination, etc.), that used to deal with the group the leaders and deployment it has more than 1500 Python/R data science packs. It has instruments to easily assemble data from sources using AI and AI.

3.3 Feature extraction phase

In this step, Residual Exemplars Local Binary Pattern (RELBP) is employed to extract the features from pre-processed ECG signals [47]. RELBP is a real operative along a non-pretentious feature extractor. To reach a global optimum, the primary purpose of RELBP is to address discriminative structures. From this, it eradicates computation complexity. Residual with exemplars is employed in local binary pattern (LBP) to get nine statistical features of ECG signal. Initially, LBP is applied on pre-processed ECG signal and it is exhibited in Eq. (1)

$$F = LBP(ECG\ data) \tag{1}$$

where F depicts the extracted feature of pre-processed ECG signal. Then exemplars are carried out in ECG data and are divulged in Eq. (2)

$$Exemplars\ Division = ECG\ data \tag{2}$$

Afterward, LBP is employed for exemplars division to acquire feature extraction. RELBP feature extraction is exhibited in Eq. (3)

$$RELBP\ feature\ Extraction = LBP(ExemplarsDivision) \tag{3}$$

From RELBP, the extracted features are delineated below.

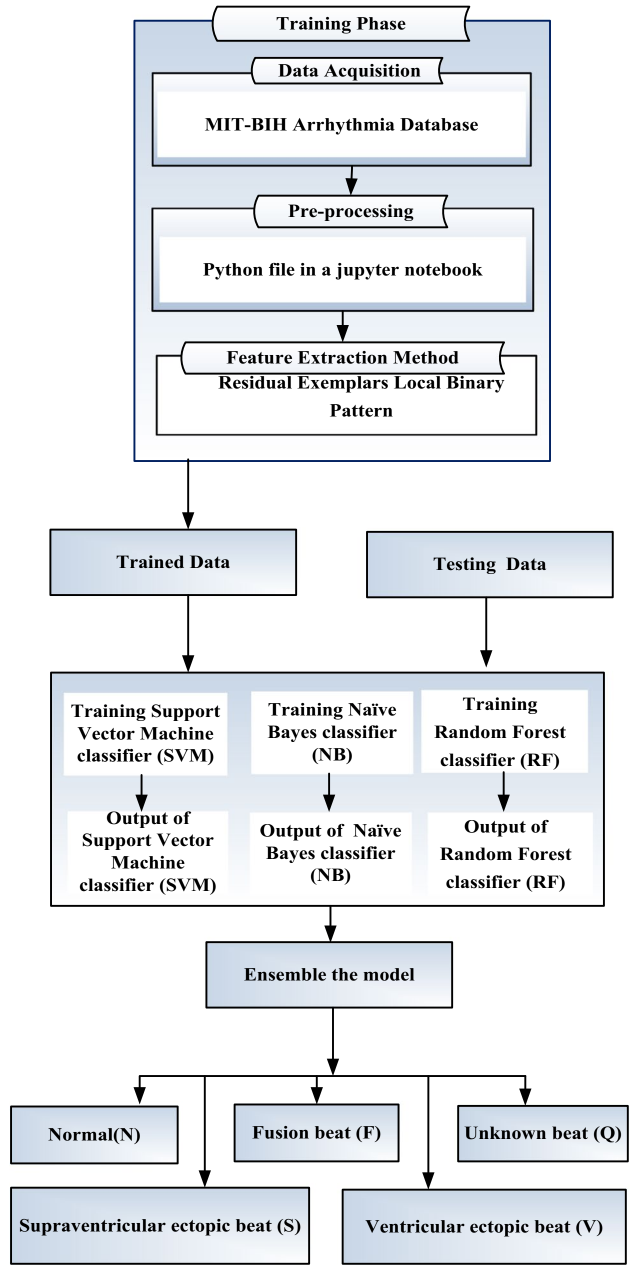


Fig. 1 Proposed AD-Ensemble SVM-NB-RF methodology

3.3.1 *Statistical features*

The nine statistical features of pre-processed ECG signal are as follows:

- Power spectrum of signal

A average absolute value of spectral means.

- Mean absolute value of signal

This is computed by adding every absolute value of coefficients as well as normalizing the sum.

- Standard deviation

This coefficients dispersal from the mean value is intentional.

- Skewness of signal

This is the frequency distribution asymmetry surrounding its mean.

- Kurtosis of signal

Measurement of curvature of deemed coefficients.

- Mean ratio

Ratios of detailed signal mean value to the approximate signal mean value.

- Peak positive value

The maximal positive amplitude of deemed coefficients.

- Peak negative value

The maximal negative amplitude of deemed coefficients.

- Second peak negative value

The second maximal negative amplitude of deemed coefficients.

3.4 Classification phase

In this work, SVM, Naïve Bayes, RF classifier is proposed as an ensemble classifier for classifying the arrhythmia detection using ECG data as normal (N), supraventricular ectopic beat (S), ventricular ectopic beat (V), fusion beat (F), and unknown beat (Q). The detailed process of the ensemble classifier is as follows.

3.4.1 Support vector *machine classifier*

SVM is a popular machine learning algorithm that is widely deployed in pattern recognition, object identification, character identification, segmentation, and classification of the image. In the aforementioned applications involving clustering, classification, and ranking, the SVM classifier uses complicated features. The decision function between the two classes performs the division of values and grouping. The weight with bias values is employed in classification issues to minimize the cost operation. MIT-BIH is considered for arrhythmic beat categorization and abnormality identification [48]. Hyper-plane segments the feature space along the maximal margin. SVM characterizations depend upon kernels that build the hyper-plane for categorization purposes. Consider the statistically extracted features from ECG data (w) are depicted as$w = \left\{w_1, w_2, \ldots\ldots\ldots\ldots, w_n\right\}$, mapping process implies ϕ by $\phi = w \rightarrow c$ here c as feature space. Arrhythmia detection L_w is expressed in Eq. (4)

Table 1 Categories of heartbeats in MIT-BIH database grouped according to AAMI standard

AAMI class	MIT-BIH original class	Category of beat	Sample size
Normal (N)	N	Normal beat	72,471
	L	Left bundle branch block beat	
	R	Right bundle branch block beat	
	e	Atrial premature beat	
	J	Nodal (junctional) escape beat	
Supraventricular ectopic beat (S)	A	Atrial premature beat	2223
	a	Aberrated atrial premature beat	
	J	Nodal (junctional) premature beat	
	S	Supraventricular premature beat	
Ventricular ectopic beat (V)	V	Premature ventricular contraction	5788
	E	Ventricular escape beat	
Fusion beat (F)	F	Fusion of ventricular with a normal beat	641
Unknown beat (Q)	/	Paced beat	6431
	f	Fusion of pace with normal beat	
	Q	Non-classifiable beat	
Total samples			109,446

$$L_w = \min\left(\frac{1}{2\|w\|^2 + \frac{1}{w\sum_{w=1}^{o}(\gamma_w - r)}}\right) \tag{4}$$

here$w.\phi \geq r - \gamma$, $W_w$indicates weight map of every statistical extracting feature from ECG data, $\gamma_w$denotes $\gamma_w \geq 0$ a slack variable, $r$implies bias with samples. SVM selects the feature extracted ECG data randomly stored on k-fold mode. The folded data is assessed under SVM then ECG data are classified as normal, supraventricular ectopic beat, ventricular ectopic beat, fusion beat, and unknown beat.

3.4.2 Naïve Bayes classifier

The naive Bayes classifiers have no inherent way of evaluating highlight significance. The restrictive and genuine probabilities related to the highlights are dictated by Nave Bayes calculations, which then, at that point, figure the class with the most elevated likelihood [49]. Accordingly, the elements you used to prepare the model have no coefficients processed or connected with them. Let $A = A_1 ... A_n$ be the observed random variables vector termed as features, wherein every feature deems values from its D_i domain. The collection of each feature vector denotes$\Omega = D_i \times ... \times D_n$. Consider C as an unobserved random variable specifies the class, C takes m values$c \in \{0, ..., m-1\}$;

The function$h : \Omega \rightarrow \{0, ..., m-1\}$, here $h(a) = C$ denotes the concept of arrhythmia detection in ECG data, which always assigns the same class to disjunctive and conjunctive concepts yields the random function$h(a)$.

Naïve Bayes is defined as $h : \Omega \rightarrow \{0, ..., m-1\}$ a function assign to every class i with $f_i(a), i = 0, ..., m-1$ discriminant function, and then the classifier selects the maximal discriminant function with$h(a) = \arg\max_{i \in \{0,..m-1\}} f_i(a)$. In naïve Bayes classifier $h*(a)$ utilizes discriminant function in class posterior probabilities specified to the feature vector. In Arrhythmia detection applying Bayes rules as$Q(C = i|A = a) = \frac{Q(A=a|C=i)Q(C=i)}{Q(A=a)}$, where $Q(A = a)$ is identical for all classes. This yields Bayes discriminant function is described in Eq. (5)

$$f_i^*(a) = Q(A = a|C = i)Q(C = i) \tag{5}$$

where $Q(A = a|C = i)$ implies class conditional probability distribution, the detection mechanism is described in Eq. (6)

$$h * (a) = \underset{i}{max} Q(A = a|C = i)Q(C = i) \tag{6}$$

The maximum posteriori probability (MAP) hypothesis of a is determined. The direct assessment of $Q(A = a|C = i)$‡ from specified set of training samples is complicated while the feature space has a higher dimension. So approximations are generally employed. The naive Bayes classifier $NB(a)$ computed by discriminant functions in Eq. (7)

$$f_i^{NB}(a) = \prod_{j=1}^{n} Q(A_j = a_j|C = i)Q(C = i) \tag{7}$$

The probability of a classification error, classifier$g$, is articulated as,

$$\begin{aligned} S(g) = Q(h(A) \neq h(A)) &= \sum_{a \in \Omega} Q(g(a) \neq h(a))Q(A = a) \\ &= E_a\{Q(g(a) \neq h(a))\} \end{aligned} \tag{8}$$

where E_a the expectation is over and $a.S* = S(g*)$ denotes the Bayes error. Then the classifier g is optimal on a specified issue if its risk coincides. A product refers to every feature that is independent of identifying the output class of arrhythmia.

3.4.3 Random *forest classifier*

In this section, arrhythmia detection is done with the help of the proposed random forest (RF) classifier. Non-parametric, interpretable, and effective categorization method that delivers excellent categorization exactness for a variety of applications is called Random Forest (RF). By lessening the variance, a unique method of random sampling and collection of decision trees aids in better classification. In a classification challenge, each tree votes, and the most popular class is chosen as the final outcome. In this, the extracted features from ECG data are given to RF classifier [50]. The proposed random forest classifier constructs DT decision trees$\{T_s(e)\}(s = 10.17em, ..., DT)$. Where e denotes the extracted feature of $RELBP$ from with length l. The final decision$f_{RF}(e)$, by the random forest by taking the majority votes of the decision trees, is scaled by Eq. (9),

$$f_{RF}(e)\frac{1}{DT}\sum_{s=1}^{DT} T_s(e) \tag{9}$$

A tree-shaped diagram acts as the decision tree. Here, each branch represents the possible decision to define the course of action. In a random decision forest classifier, the classification or decision outcome is carried via the leaf node attribute. The decision node contains 2 or more branches. The topmost decision node is nothing but root node attributes. The various decision tree majority votes basis the random forest works for accurate arrhythmia class. It deals with the overfitting issue by combining the results of various decision trees.

3.4.4 Ensemble classifier

The major advantage of the proposed ensemble learning technique is that it evades the overfitting problem by reducing the complexity of the model. An ensemble of classifiers is a collection of classifiers these specific verdicts (habitually by weight or unweight voting) are amalgamated in some way to identify novel events. The primary contribution of the proposed ensemble scheme is as follows:

- Engender Q classifiers
- Train every classifier solely
- Amalgamate the Q classifiers which predict class labels based on the majority vote of Q ML classifiers. For instance, if a classifier is to be trained, all instances are deemed as a positive class, and other classes are deemed as a negative class. All classifiers vote as an ensemble to categorize unknown cases. The classifier receives one vote if the prediction made by the random forest model is positive; however, if negative prediction, the remaining classes receive one vote.

The average of all classifiers affords the much-desirable generalization of the model by plummeting variance and model complexity. Finally, the proposed ensemble classifier correctly classifies the arrhythmia as normal (N), supraventricular ectopic beat (S), ventricular ectopic beat (V), fusion beat (F), and unknown beat (Q).

4 Results and discussion

This section describes the ensemble classifier fostered detection of arrhythmia using ECG data. The entire implementation of the proposed scheme is carried out by Python version 3.6 using Keras, a deep learning tool. The performance metrics are analyzed to analyze the efficacy of the proposed system. The outcomes are estimated to the existing AD-Ensemble CNN-LSTM-RRHOS [25], AD-Ensemble CNN-LSTM [26], and AD-Ensemble MLP-NB-RF models [27].

4.1 Dataset description

MIT-BIH Arrhythmia Database contains 109,446 ECG sample. In this work, 80% are randomly selected for training purposes and 20% are randomly selected for testing purposes.

4.2 Performance metrics

To assess system performance, certain parameters, like sensitivity, precision, f-Measure, specificity, accuracy, and error rate, are examined. To measure the performance metrics, the given confusion matrix is deemed,

- True positive($T(P)$): normal perfectly identified into normal.
- True negative($T(N)$): abnormal perfectly identified into abnormal
- False positive($F(P)$): abnormal imperfectly identified into normal
- False negative($F(N)$): normal imperfectly identified into abnormal

4.2.1 Accuracy

Accuracy is calculated as the number of all correct predictions divided by the total number of the dataset. The best accuracy is 1.0, whereas the worst is 0.0. This is determined by Eq. (10),

$$Accuracy = \frac{(T(P) + T(N))}{(T(P) + T(N) + F(P) + F(N))} \tag{10}$$

4.2.2 Precision

Precision is determined as a count of real positive predictions divided by the entire count of positive predictions. This is named positive predictive value (PPV). The best precision indicates 1.0, and the worst indicates 0.0. This is determined by Eq. (11),

$$\mathrm{Pr}ecision = {}^{T(P)}\!/_{(T(P)+F(P))} \tag{11}$$

4.2.3 Sensitivity

Sensitivity is defined as the count of real positive predictions divided by the overall count of positives. This is termed as recall or true positive rate. The best sensitivity indicates 1.0, worst indicates 0.0. This is scaled by Eq. (12),

$$Sensitivity = \frac{T(P)}{F(N) + F(P)} \tag{12}$$

4.2.4 Specificity

It is computed as the count of real negative predictions divided by the overall count of negatives. This is termed a true negative rate. The best specificity indicates 1.0, and worst indicates 0.0. It is computed by Eq. (13),

$$Specificity = \frac{F(N)}{F(P) + F(N)} \tag{13}$$

4.2.5 F-Measure

It is the harmonic mean of precision or recall. This is computed by Eq. (14),

$$F - Measure = \frac{2\,T(P)}{2\,T(P) + F(P) + F(N)} \quad (14)$$

4.3 Simulation result

Figures 2, 3, 4, 5, 6, 7, and 8 depict the simulation results of the ensemble classifier fostered detection of arrhythmia using ECG data. The performance metrics are analyzed to check the robustness of the proposed approach. The performance of the proposed AD-Ensemble SVM-NB-RF is analyzed with existing AD-Ensemble CNN-LSTM-RRHOS [25], AD-Ensemble CNN-LSTM [26], and AD-Ensemble MLP-NB-RF [27] methods respectively.

Figure 2 represents the accuracy analysis for arrhythmia identification. The accuracy of AD-Ensemble SVM-NB-RF classifier for Supraventricular ectopic beat (S) and fusion beat (F) classes (98.40%, 99.71%) is much better than majority voting (86.65%, 93.39%). Both models have a comparable presentation on the ventricular ectopic beat (V) class. Contrary to the majority vote, the ensemble classifier improves Supraventricular ectopic Beat (S) identification. For non-ecotic beats, the proposed AD-Ensemble SVM-NB-RF method provides 56.43%, 49.34%, and 45.79% better accuracy analyzed to the existing AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and AD-Ensemble DGEC models respectively. For supraventricular ectopic beats, the proposed AD-Ensemble SVM-NB-RF method provides 45.57%, 50.41%, and 27.49% higher accuracy compared with the existing methods like AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and AD-Ensemble DGEC respectively. For ventricular ectopic beats, the proposed AD-Ensemble SVM-NB-RF method provides 34.48%, 23.57%, and 27.68% higher accuracy compared with the existing methods like AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and AD-Ensemble DGEC respectively. For fusion beats, the proposed AD-Ensemble SVM-NB-RF method provides 31.47%, 27.76%, and 33.91% better accuracy assessed with existing AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and AD-Ensemble DGEC models respectively. For unknown beats, the proposed AD-Ensemble SVM-NB-RF method provides 21.63%, 30.51%, and 32.63% better Accuracy analyzed with existing AD-Ensemble CNN-LSTM-RRHOS, AD-Ensemble CNN-LSTM, and AD-Ensemble MLP-NB-RF models respectively.

Figure 3 implicates sensitivity analysis for the detection of arrhythmia. The sensitivity of the existing ensemble classifier is lower than the proposed AD-Ensemble SVM-NB-RF classifier; even though the entire presentation is better. If the testing sample is categorized as negative through every Ensemble SVM-NB-RF classifier, normal class (N) is labeled. For sensitivity, the proposed technique has maximal value for normal class (N) (97.03%) as well as ranked third for ventricular ectopic beat (V) (97.91%) compared to the existing ensemble classifier. The sensitivity of fusion (F) and supraventricular ectopic beat (S) (98.33%, 98.51%) are not amongst the better results owing to the SVM network lessening these classes' true positive values instead of substantially lessening in false-positive values. For non-ecotic beats, the proposed AD-Ensemble SVM-NB-RF method provides 53.91%, 62.48%, and 49.21% better Sensitivity analyzed to the existing AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and AD-Ensemble DGEC models respectively. For supraventricular ectopic beats, the proposed AD-Ensemble SVM-NB-RF method provides 34.98%, 59.41%, and 21.86% higher sensitivity compared with

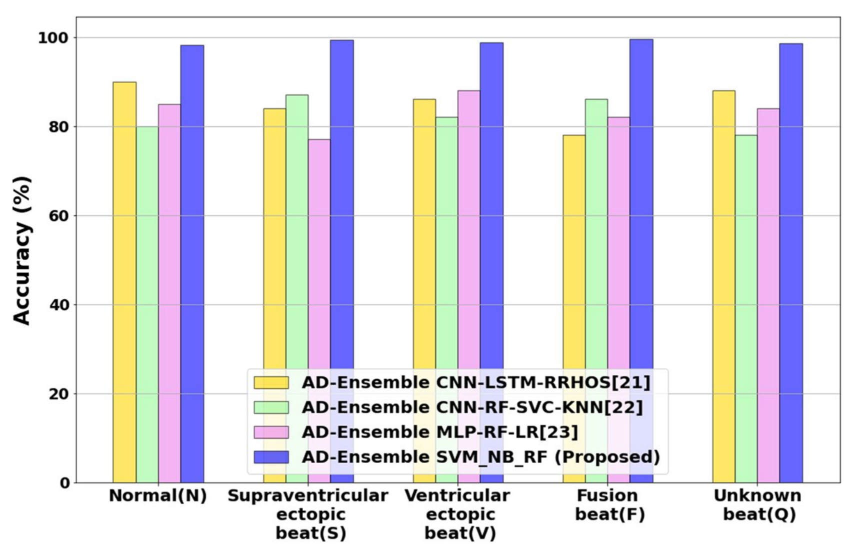
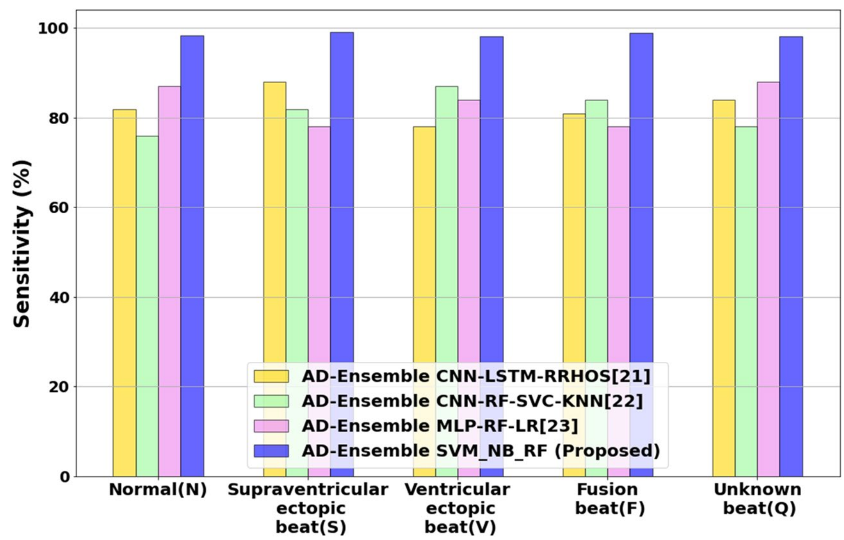


Fig. 2 Performance of accuracy

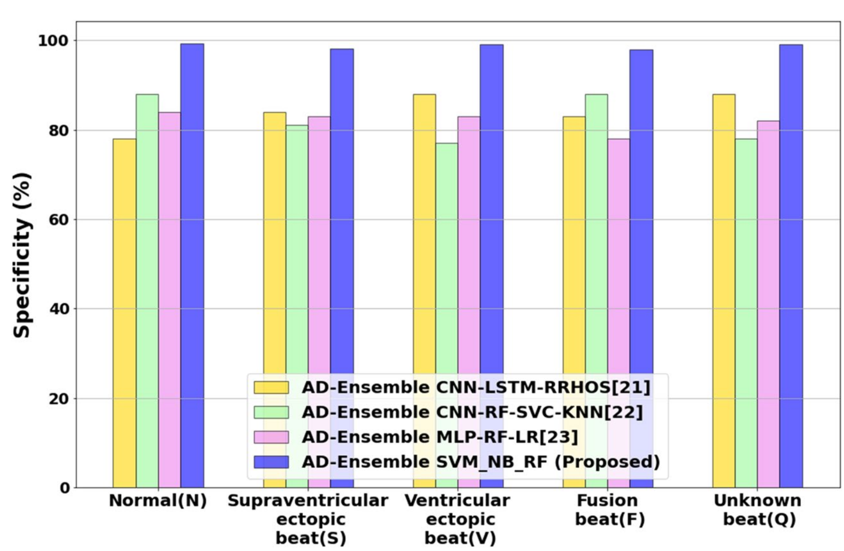
Fig. 3 Performance of sensitivity



existing AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and AD-Ensemble DGEC models respectively. For ventricular ectopic beats, the proposed AD-Ensemble SVM-NB-RF method provides 26.47%, 22.75%, and 24.64% better Sensitivity assessed to the existing AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and AD-Ensemble DGEC models respectively. For fusion beats, the proposed AD-Ensemble SVM-NB-RF method provides 36.63%, 27.88%, and 33.69% better Sensitivity assessed with existing AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM and AD-Ensemble DGEC models respectively. For unknown beats, the proposed AD-Ensemble SVM-NB-RF method provides 24.54%, 31.76%, and 27.71% higher Sensitivity compared with existing methods like AD-Ensemble CNN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and AD-Ensemble MLP-NB-RF respectively.

Figure 4 represents the Specificity analysis for the detection of arrhythmia. Specificity scales the capacity of the test to make negative reports for a disease. The specificity of the proposed technique is less than other models in the case of supraventricular ectopic beat (S) detection due to a greater count of normal beats being misclassified as supra-ventricular beats. Due to their comparable statistical properties, the atrial escape beat in Normal (N) and atrial premature beat in Supraventricular ectopic beat (S) are difficult to distinguish from one another. For specificity, the proposed technique achieves Ventricular ectopic beat (V), Supraventricular ectopic beat (S), and fusion (F) (96.62%, 98.56%, and 96.79%). For non-ecotic beats, the proposed AD-Ensemble SVM-NB-RF method provides 49.15%, 60.73%, and 51.33% greater specificity estimated to the existing AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and

Fig. 4 Performance of specificity



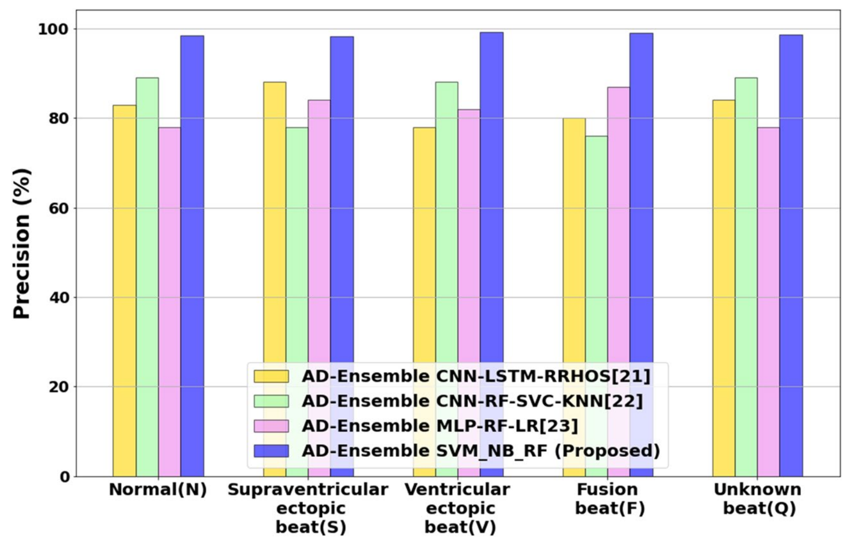


Fig. 5 Performance of precision

AD-Ensemble DGEC models respectively. For supraventricular ectopic beats, the proposed AD-Ensemble SVM-NB-RF method provides 43.27%, 53.40%, and 29.65% greater Specificity assessed with existing AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and AD-Ensemble DGEC models respectively. For ventricular ectopic beats, the proposed AD-Ensemble SVM-NB-RF method provides 31.49%, 28.52%, and 20.84% higher Specificity compared with existing methods like AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and AD-Ensemble DGEC respectively. For fusion beats, the proposed AD-Ensemble SVM-NB-RF method provides 28.64%, 25.69%, and 30.42% greater specificity assessed with existing AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and AD-Ensemble DGEC models respectively. For unknown beats, the proposed AD-Ensemble SVM-NB-RF method provides 31.63%, 32.26%, and 29.13% better specificity evaluated to the existing AD-Ensemble CNN-LSTM-RRHOS, AD-Ensemble CNN-LSTM, and AD-Ensemble MLP-NB-RF models respectively.

Figure 5 represents the Precision analysis for arrhythmia identification. In precision, the overall classification performance of the ventricular ectopic beat (V) is better than that of the supraventricular ectopic beat (S). For non-ecotic beats, the proposed AD-Ensemble SVM-NB-RF method provides 43.21%, 54.11%, and 49.28% better precision compared with existing AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and AD-Ensemble DGEC models respectively. For supraventricular ectopic beats, the proposed AD-Ensemble SVM-NB-RF method provides 39.41%, 59.90%, and 21.45% greater precision assessed with existing AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and

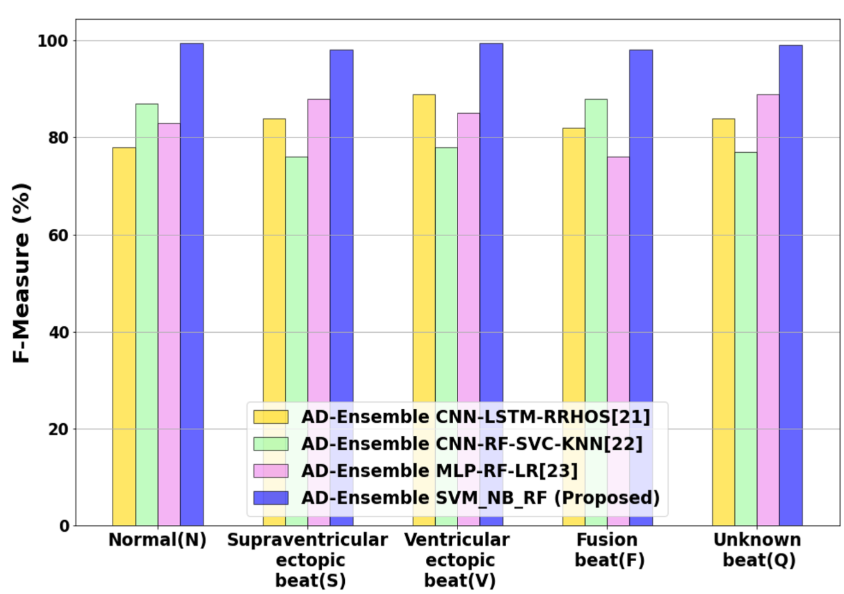


Fig. 6 Performance of F-Measure

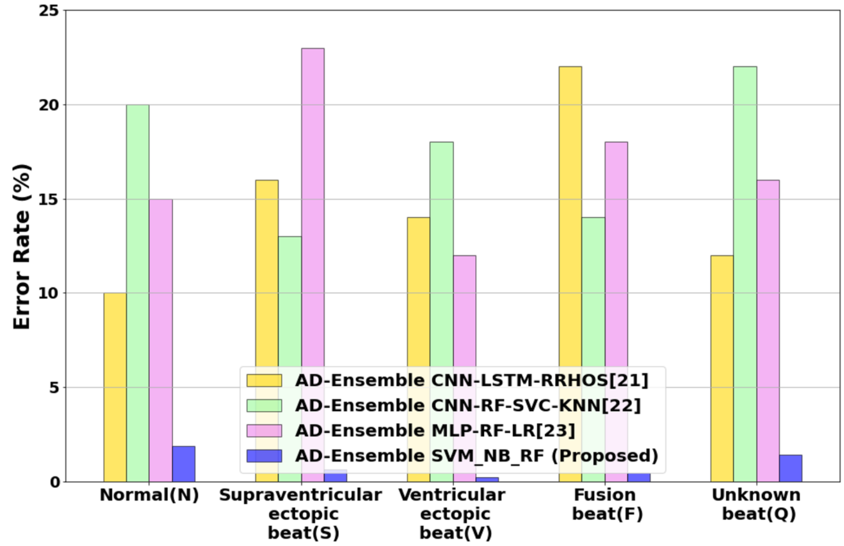


Fig. 7 Performance of error rate

AD-Ensemble DGEC models respectively. For ventricular ectopic beats, the proposed AD-Ensemble SVM-NB-RF method provides 25.42%, 21.73%, and 20.71% higher precision compared with existing methods like AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and AD-Ensemble DGEC respectively. For fusion beats, the proposed AD-Ensemble SVM-NB-RF method provides 23.41%, 18.99%, and 30.23% better precision analyzed with existing methods, like AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM and AD-Ensemble DGEC respectively. For unknown beats, the proposed AD-Ensemble SVM-NB-RF method provides 26.61%, 29.55%, and 20.15% higher precision compared with existing methods like AD-Ensemble CNN-LSTM-RRHOS, AD-Ensemble CNN-LSTM, and AD-Ensemble MLP-NB-RF respectively.

Figure 6 implicates F-Measure analysis for arrhythmia identification. The proposed technique has the highest F-Measure for supraventricular ectopic beat (S), ventricular ectopic beat (V), and fusion (F). From this, the proposed method recognizes the abnormal classes effectively. For non-ecotic beats, the proposed AD-Ensemble SVM-NB-RF method provides 45.89%, 64.21%, and 43.19% better F-Measure compared to existing AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and AD-Ensemble DGEC models respectively. For supraventricular ectopic beats, the proposed AD-Ensemble SVM-NB-RF method provides 41.14%, 62.39%, and 19.52% higher F-Measure compared with existing methods like AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and AD-Ensemble DGEC respectively. For ventricular ectopic beats, the proposed AD-Ensemble SVM-NB-RF method provides 22.31%, 19.48%, and 15.61% higher F-Measure compared with existing methods like AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and AD-Ensemble DGEC respectively. For fusion beats, the proposed AD-Ensemble SVM-NB-RF method provides 18.21%, 15.74%, and 25.09% higher F-Measure compared with existing methods like AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and AD-Ensemble DGEC respectively. For unknown beats, the proposed AD-Ensemble SVM-NB-RF method provides 17.52%, 25.05%, and 10.68% better F-Measure assessed to existing AD-Ensemble CNN-LSTM-RRHOS, AD-Ensemble CNN-LSTM, and AD-Ensemble MLP-NB-RF models respectively.

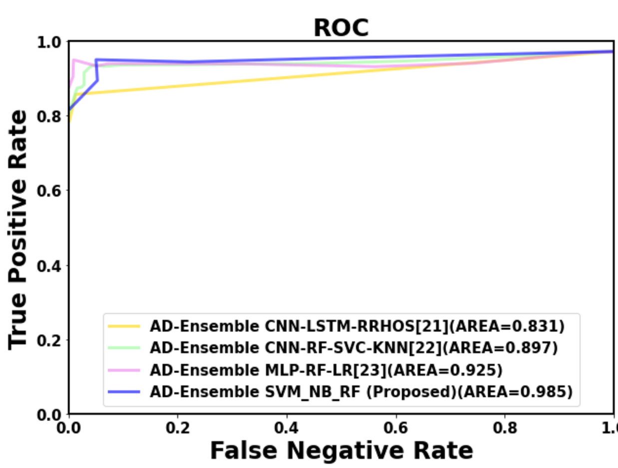


Fig. 8 Performance of ROC

Figure 7 represents the error rate analysis for arrhythmia detection. For non-ecotic beats, the proposed AD-Ensemble SVM-NB-RF method provides 33.29%, 27.49%, and 28.63% lower error rates compared with existing methods, like AD-Ensemble CNN-LSTM-RRHOS, AD-Ensemble CCN-LSTM and AD-Ensemble DGEC respectively. For supraventricular ectopic beats, the proposed AD-Ensemble SVM-NB-RF method provides 30.45%, 31.89%, and

29.44% lower error rates compared with existing methods like AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and AD-Ensemble DGEC respectively. For ventricular ectopic beats, the proposed AD-Ensemble SVM-NB-RF method provides 35.54%, 20.56%, and 29.19% lower error rates compared with existing methods like AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and AD-Ensemble DGEC respectively. For fusion beats, the proposed AD-Ensemble SVM-NB-RF method provides 34.12%, 25.18%, and 35.62% lesser error rates examined with existing AD-Ensemble CCN-LSTM-RRHOS, AD-Ensemble CCN-LSTM, and AD-Ensemble DGEC models respectively. For unknown beats, the proposed AD-Ensemble SVM-NB-RF method provides 21.19%, 29.41%, and 19.91% lesser error rates analyzed with existing AD-Ensemble CNN-LSTM-RRHOS, AD-Ensemble CNN-LSTM, and AD-Ensemble MLP-NB-RF models respectively.

Figure 8 depicts the ROC curve for the detection of arrhythmia. The test capacity properly identifies normal or abnormal by the area under the ROC curve. Also, accuracies are scaled. Area 1 indicates the valid test; area 0.5 indicates the invalid test. The point system categorizes diagnostic test accuracy. When the area is among 0.90 and 1 system is well, betwixt 0.80 and 0.90 is well, betwixt 0.70 and 0.80 is also well, betwixt 0.60 and 0.70 is bad, and betwixt 0.50 and 0.60 faults. Then, the ROC of the proposed AD-Ensemble SVM-NB-RF Method provides 2.01%, 3.33%, and 3.19% higher area under the curve (AUC) than the existing methods, like AD-Ensemble CNN-LSTM-RRHOS, AD-Ensemble CNN-LSTM, and AD-Ensemble MLP-NB-RF respectively.

5 Conclusion

The accurate Arrhythmia Detection using an ensemble classifier (AD-Ensemble SVM-NB-RF method) is implemented successfully in this work for classifying the Arrhythmia accurately. The proposed AD-Ensemble SVM-NB-RF is done in Python and the efficacy is assessed utilizing performance metrics. The proposed AD-Ensemble SVM-NB-RF method attains 32.63%, 24.88%, and 31.69% higher Sensitivity; 34.63%, 28.26%, and 32.13% higher Specificity; 27.61%, 28.55%, and 19.15% higher precision and 23.19%, 19.41% and 31.91% lower error rate analyzed with existingAD-Ensemble CNN-LSTM-RRHOS, AD-Ensemble CNN-LSTM, and AD-Ensemble MLP-NB-RF models.

Data availability Nil.

Code availability Nil.

Declarations

Ethical approval Nil.

Conflict of interest The authors declare no competing interests.

Consent to participate Nil.

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