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Machine Learning-based ECG Classification using Wavelet Scattered Features

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Abstract-----**Cardiac abnormalities are one of the leading causes of mortality and morbidity among the population. Changes in the morphology and rhythm of the cardiac signals associated with cardiac abnormalities need to be identified and classified. Advances in artificial intelligence pave the way for precise classification. The preprocessed ECG signal segments undergo wavelet scattering to extract the low variance features with reduced dimensions are rearranged and the key features are selected using Minimum Redundancy and Maximum Relevance (MRMR) feature selection algorithms chosen by comparatively analyzing different feature selection algorithms and the selected features are fed to the machine learning models. Classification of ECG signals is comparatively analyzed using different Machine Learning models such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Decision tree, and Artificial Neural Network (ANN) models with 10-fold cross-validation. The performance is improved by optimizing each model by tuning the hyperparameters. Among the twenty models, the cubic SVM model achieves the highest accuracy of 99.84 percent.**

Index Terms---**Arrhythmia, Electrocardiography, Machine Learning, Support vector machine (SVM)**

I. Introduction

The electrical activity of the heart is recorded by a process called electrocardiography. The electrocardiograph signal obtained provides a lot of information about the activities of the cardiac muscle's contraction and relaxation, blood flow, and electrical conductivities of the cardiac muscles. The normal functioning of the heart involves the proper generation of electric impulses, conduction of electrical stimuli to muscles all over the heart, contraction, and relaxation of muscles, opening and closing of valves, and flow of blood without stagnation.

The time interval of each action has been a key factor concerning the normal functioning of the heart. Any deviation in the processes as mentioned above and timing results in cardiac abnormalities. ECG shows notable changes corresponding to such deviations which makes noninvasive diagnosing possible. The ECG has P, Q, R, S, and T waves where the P wave, QRS complex, and T wave corresponds to atrial depolarization, ventricular depolarization, and ventricular repolarization, respectively.

All cardiac arrhythmias are the results of deviations in automaticity and conductivity, the two physiological properties of the five electrophysiology of the heart. The various arrhythmias such as atrial fibrillation, atrial flutter, supraventricular tachycardia, ventricular fibrillation ventricular tachycardia, are the types of tachycardia (condition with increased heart rate), in addition to bradycardia (condition with decreased heart rate) and premature beats [1]. CHF commonly referred to as heart failure is a condition where the heart fails to supply enough oxygenated blood to the body. CHF is a serious condition where without enough blood flow all the organs struggle to work normally. CHF may occur because of arrhythmias, cardiac muscle damage, or injury commonly known as ischemia, diabetes, obesity, and heart attack [2]. The cardiac chamber enlargement is found to be common among people with heart failure. In addition, there are noticeable changes in the P waves, the height of the R wave, and RR intervals [3]. This study focuses on classifying the ECG signal segments corresponding to arrhythmias, CHF, and NSR ECG segments. The machine learning and deep learning models learn the underlying patterns of the abnormalities in the ECG signal which is used to classify the segments. The artificial learning model will help to diagnose with great accuracy at the initial stages preventing the severe later effects of the problem. The limitations faced by the manual diagnosis are overcome by using A.I.-based models providing the advantage of remote diagnosis possible to large populations.

II. Related Works

The arrhythmic signals are classified using various machine learning and deep learning models. The ECG signals used for arrhythmia detection and classification are from the PhysioNet database which provides huge varieties of arrhythmia ECG signals. The MIT-BIH arrhythmia database is used by [4], [5], [6], [7], the BIDMC coronary Heart Failure database is used by [8], PTB dataset is used in [9]. The ECG

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signals are preprocessed, the features are extracted, and key features are selected and classified using classifiers. In [4] the signals are primarily normalized twice before and after segmenting. [10] preprocess the signal through a series of processes. Firstly, the signal using Stationary Wavelet Transform (SWT), is filtered the signal using a combination of two median filters and a Savitzky Golay (SG) filter, and the original signal is retrieved back using inverse SWT. The combination of SWT and SG filter effectively removes the baseline wander and powerline interferences. Wavelet Packed Decomposition (WPD) is used to decompose the signal into various scales which makes it easy to remove the low-frequency noise scale from the signal [6]. The low-frequency scale of 3 Hz includes noises like baseline drift caused by breathing and motion artifacts are removed effectively using WPD. In [11] the wavelets generated are filtered employing the 6th-order Butterworth filter which gets rid of the noises. The dual Q tunable Q factor wavelet transformation is used to denoise the signal in [12]. The signal is simply smoothened using Gaussian Assisted Signal Smoothing (GASS) [13]. The simple high pass and band pass filters are used to filter out the noises as in [14] which is effective and simple and the works dealing with deep learning prefer using raw signals with minimal preprocessing [15].

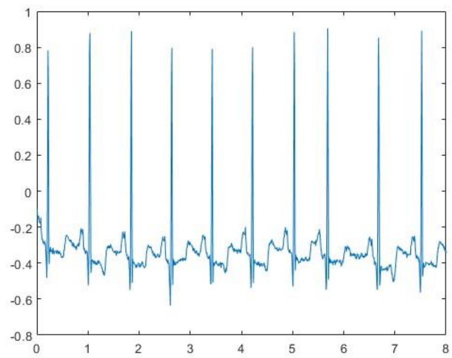
The preprocessed signals are up-sampled or down-sampled to common value while dealing with multiple datasets. The segmented data among the classes are balanced for effective results. This is achieved by employing synthetic data augmentation models like ROS and SMOTE [16] but faces the drawback of adding noise to the rhythm. Various algorithms are used to extract features that highlight the signal characteristic components. The feature extraction holds the advantage of reducing the data size for training the classifier models. Thus, helping to reduce the training time and computational complexity. Autoencoders [5], wavelet scattering [9], and complex wavelet transform are actively employed to extract the features from the time series data. Certain works use both shallow and deep layers of convolutional networks to extract features from the signals. Feature selection plays a significant role in accuracy and training time. The selection of key features is done using attention modules [17], simply selecting inter and intra features such as the dimensional and morphological values.

The selected features are fed to machine learning and deep learning models for classification. The Bi-LSTM model is used by the existing works [4], [5], [10] and achieves high accuracies as shown in the table (7). As the model goes deep the computational cost and the training time increase. [7], [9], [14] achieves comparable accuracies using machine learning models like SVM, KNN, PNN, ANN, and more. Among different machine learning algorithms, the SVM [18], SVM with Gaussian Kernel [19], ensemble-based SVM model [20], the ANN model [21], ANN with MEMD [22] and KNN model [9] perform better in classifying ECG signals. [17] proposes Expert Knowledge Attention Network (EKANet) for classifying four tachyarrhythmias. The EKANet model comprises six CNN layers with a Gated Recurrent Unit (GRU). [23] uses the LSTM model for detecting and classifying CHF from NSR signals. [24] uses the modified ResNet model with the combination of scatter transform in the residual blocks to perform temporal down sampling. This modified ResNet block improves the performance by speeding up the convergence process. In the proposed work. The signals are preprocessed, resampled, and segmented into 1024 samples, totaling 10368 ECG segments. The features are extracted using wavelet scattering, and the dimensionality of the features is reduced using a feature selection process based on MRMR. The selected features are fed to machine machine-learning model for classification.

Section 3 provides information on various datasets used, and section 4.1 explains the preprocessing and segmentation processes of the ECG signals. Section 4.2 gives an insight into the feature extraction process. Different feature selection models adopted to analyze are discussed in section 4.3 and in section 4.4 the splitting of data and the validation adopted are mentioned. Section 4.5 discusses the different machine learning models and their performances in classifying the data segments in terms of validation accuracies and test accuracies. In the next section, the results are statistically analyzed and discussed.

III. DATABASE

The ECG signals from three different datasets are used for classification the MIT BIH Normal Sinus Rhythm [25] dataset includes eighteen long-term ECG recordings from five men and thirteen women subjects of the arrhythmia laboratory at Boston’s Beth Israel Hospital. These signals are found to be free from any abnormalities.



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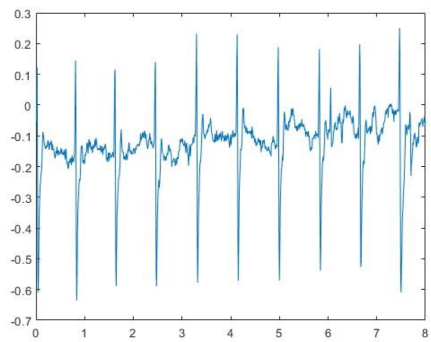

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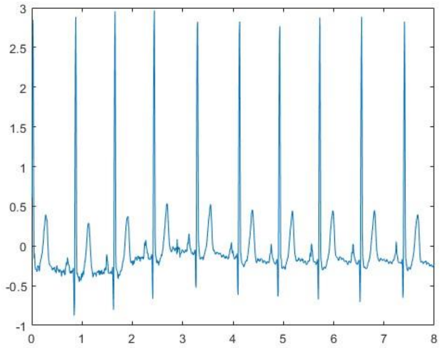


(c)

Fig.1. ECG signals (a) ARR, (b) CHF and (c) NSR

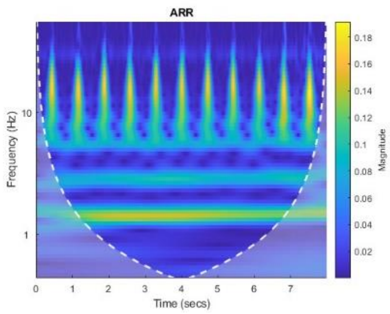
The forty-eight ambulatory ECG signals [26] obtained from forty-seven subjects each of 30-minute duration recorded and studied by the MIT arrhythmia laboratory in the years 1975 to 1979. The samples consist of different arrhythmia cases. The dataset [27] consists of the original recordings from fifteen subjects (11 men and four women) who suffered from Congestive Heart Failure recorded at Boston's Beth Israel Hospital. The signals are sampled at different frequencies. These three datasets are combined to form the final dataset which consists of eighty-one recordings grouped into three classes NSR, CHF, and all other arrhythmias are grouped as class ARR.

IV. METHODOLOGY

The classification of ECG signal segments is conducted following the preprocessing, segmenting, feature extraction, and feature selection processes. All such processes are discussed in this section.

A. *Preprocessing*

The signals are initially filtered to remove the noises present in the signals. The basic filtering is done using the low pass filter, median filter, and high pass filter to eliminate the artifacts like the power line interferences, outliers, and baseline wanders respectively as it achieves a good denoising effect as used in [14].



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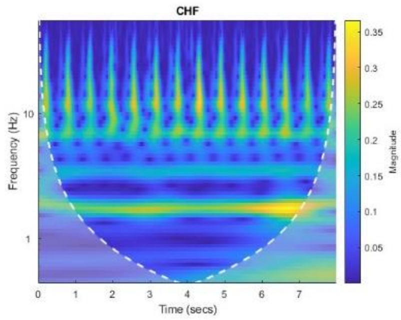

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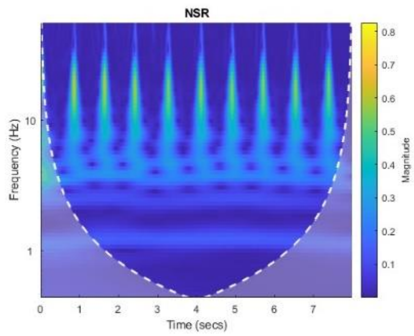

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Fig.2. Scalogram representation of the ECG signals (a) ARR, (b) CHF, and (c) NSR

The recordings are of different lengths and have been sampled at different frequencies. The signals are resampled at 250 HZ. The signals are initially resampled and segmented into short sequences of 1024 samples. In total 10368 segments with three classes of 6144 (ARR), 1920 (CHF), and 2304 (NSR) segments. The signals possess unique changes in their morphological features that can be easily noticeable using their scalogram representations as shown in Fig.(2). The 2000 ARR signal segments, 1920 CHF signal segments, and 2000 NSR signal segments are accounted to balance the distribution to get an efficient classification result using machine learning models. These noticeable changes captured by the variance features are learned by the model to classify them while testing.

The classification is done in MATLAB R2022a software using i5 Intel(R) Core (TM) -7400 CPU @ 3.00GHz with 8 GB RAM.

B. *Feature Extraction*

The features are extracted using the wavelet scattering process as it provides the advantage of lesser training time and complexity [28]. In Wavelet scattering, the long real-valued signal data is minimized into characteristic low variance features for further processing in machine learning models and deep learning models [9]. The minimization of the time series data helps to achieve reduced processing time. Wavelet scattering involves three processes, the first generation of low variance features and second step involves introducing nonlinearity, and lastly, the lowpass scaling function. The low variance features are the wavelets generated using the convolution process. The morlet wavelet representation is the most common wavelet representation used in the case of wavelet scattering. The scaling function is done to average the values. The main advantage of wavelet scattering is preserving the key information in the signal and dropping the uninformative translations in the case of signals and uninformative rotations in the case of images.

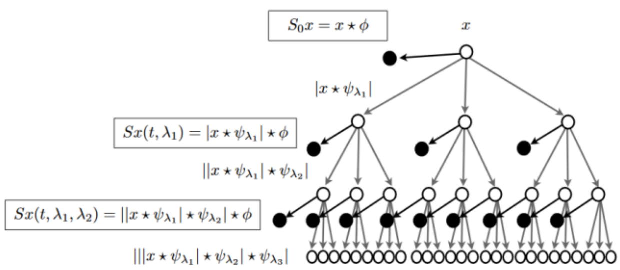


Fig.3. Wavelet scattering principle.

The wavelet scattering can be replaced for deep CNN when the availability of the dataset is minimal as the deep CNN requires a huge amount of data. Both the DCNN and wavelet scattering networks involve convolution, nonlinearization, and pooling processes. In DCNN the filter weights are learned by the network along the process whereas in wavelet scattering the filter weights are fixed. The two-stage wavelet scattering process involves both linear operation convolution and the nonlinearization process by taking modulus on the results achieved from the stage 1 scaling function later the dimensionality reduction is done by averaging as shown in Fig. (3).

C. *Feature selection*

From the features generated through wavelet scattering, the key features are selected by the feature selection process. The feature set generated is 102 x 8 in dimension for each of the 10368 ECG segments. Among the 816 low-variance features the highly ranked features are selected using different feature selection processes and the results are compared as shown in the table (1). The number of features selected is the value with which the Cubic SVM model achieves maximum accuracy for each selection model. In Table (1) the importance score is the resulting optimized value based on the trial-and-error method

TABLE I
ECG CLASSIFICATION PERFORMANCE COMPARISON USING DIFFERENT FEATURE SELECTION ALGORITHMS

S.No.	Feature selection model	Importance score	Feature selected	Accuracy
1	ReliefF	≥ 0.02	309	99.4
2	Chi-square	∞	452	99.2
3	ANOVA	≥ 0.05	481	99.4
4	MRMR	≥ 0.01	600	99.8

1) *ANOVA*

It stands for Analysis of Variance is a statistical method that checks the significant differences of the mean of two or more groups.

$$F= (SSB/df_b) / (SSW/df_w) \qquad (1)$$

It calculates the f-value that compares the variance between and within groups. The f-value is calculated by using the equation number (1) where SSB stands for the sum of squares between which focuses on the sum of squared value between the classes and SSW stands for the sum of squares within which focuses on the sum of square values within the classes.

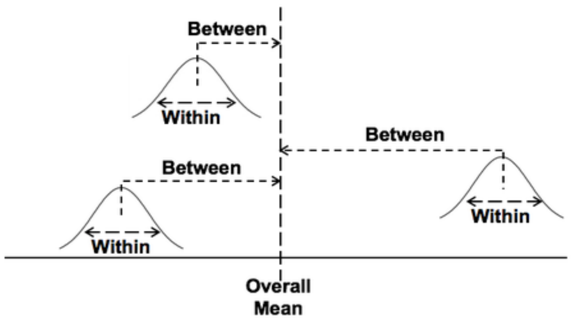


Fig.4. Variation of the mean within and between groups.

Among the 816 features, the top 481 features with an importance score of 0.05 and above using the ANOVA statistical method-based ranking are considered. The selected features are utilized for the classification of data using the Cubic SVM model achieving an accuracy of 99.4%. The 481 is the minimum count at which the model provides the highest accuracy and when the feature count is further reduced the performance of the model degrades.

2) *Minimum Redundancy Maximum Relevance (MRMR)*

It is an algorithm that selects features based on the prediction capability ranking. The features that predict target effectively are considered as highest ranked features having relevance and redundancy as important components. The highest-ranked feature has no redundancy and the most relevant one. The highest-ranked 342 features with an importance score of 0.01 and above are selected and used for classification achieving the highest classification accuracy of 99.6%.

3) *ReliefF*

The basic concept in Relief algorithms is to calculate the attribute quality based on how well it can distinguish instances from the nearby ones. The nearby instances are estimated using the K- nearest neighbor algorithm. The Relief algorithm is restricted to two class classifications and for multiclass classification the extended version of Relief (ReliefF) is used since the classification of three classes is concerned. Among the 816 features, the features with an importance score of 0.02 and above are selected which includes 309 highest-ranked features. The cubic SVM-based machine learning model achieves an accuracy of 99.4%.

4) *Chi-square*

This inferential statistical test focuses on evaluating the likelihood of test data termed as "Goodness of Fit" statistic to measure how well the data distribution fits with the expected distribution which is derived from the equation number (2) where the O represents the observed values, E represents the expected values and c represents the degrees of freedom. The target is achieving features that are highly dependent on the response satisfying the "Test of Independence" "the null hypothesis test.

$$O^2 = \sum \frac{(O_i - E_i)^2}{E_i} \qquad (2)$$

In the Chi-square test the dependency is also given by the equation (2). Among the 816 features, the 452 features with the highest scores are selected for classification achieving an accuracy of 99.2%.

D. *K- fold Cross-validation*

The data is split in the 80:20 ratio with the allocation of 4736 signal segments for training and 1184 signal segments for testing.

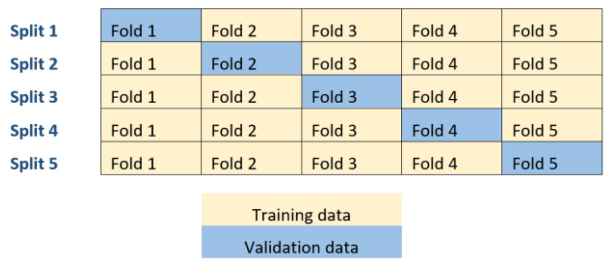


Fig.5. 5-fold cross-validation

With the availability of limited data, the model achieves efficient accuracies which necessitates the evaluation of the model. The cross-validation evaluates the model by validating the model using the data allocated for training. 80 percent of the data is further divided into five parts in 5-fold cross-validation as shown in Fig.(5). Each split is used for validation iteratively with the rest splits for training the model. The overall validation accuracy was obtained by averaging the accuracies of each iteration. The cross-validation helps to avoid overfitting and evaluating the generalizability of the model. The different k-fold cross-validations with k=5, k=6, and k=10 are used to evaluate the performance of the cubic SVM model in terms of different performance metrics [31] as shown in Table (7).

E. *Classification models*

The features extracted using wavelet scattering are rearranged and the highest-ranked features are selected using the MRMR feature selection method. The selected features are fed to the classifier to classify the signals into NSR, ARR, and CHF classes. Various machine learning models like KNN, SVM, Decision tree, and ANN models are trained and comparatively evaluated on classifying the ECG segments.

1) *Support Vector Machine*

SVM is a supervised learning algorithm, that classifies the data by generating the best hyperplane. The SVM models with different kernel functions are used for classifying the features among which the Cubic SVM model achieves the highest training and test accuracy of 99.7% and 99.8% respectively. The accuracies of linear, quadratic, cubic, and Gaussian kernel models are compared as shown in Table 2.

The kernel is the algorithm that analyses the pattern used in the case of nonlinear problems with linear classifiers like SVM. The kernel trick used in SVM helps the classifier to form the best boundary about the higher dimensional relationships of the observations to derive better solutions. The polynomial kernel is defined by the equation.

$$K(x_1, x_2) = (x_1 * x_2 + 1)\ d \qquad (3)$$

where d stands for the degree of polynomial. Since SVM normally supports binary classification problems the multiclass classification is broken down into multiple binary classifications which are of two types rest and one-to-one classification problems. Optimization SVM regularizes parameters to derive an optimal hyperplane avoiding misclassifying training examples. Bayesian optimization uses the Bayes theorem in directing the search for better hyperplanes. The data are initially standardized to avoid the influence of data scale on deriving hyperplanes. The standardization process normalizes the data with zero mean and the variance with a value equal to one which brings the feature to a common scale. The table (2) shows the performance of the SVM models employing different kernels.

TABLE 2
ECG CLASSIFICATION PERFORMANCE COMPARISON USING SVM MODELS

S. No	SVM model's kernel	Selected features using MRMR	Validation accuracy (%)	Test accuracy (%)
1	Linear	600	99.2	99.5
2	Quadratic	600	99.5	99.7
3	**Cubic**	**600**	**99.6**	**99.8**
4	Fine Gaussian	600	89.8	90.4
5	Medium Gaussian	600	99.5	99.8
6	Coarse Gaussian	600	93.4	95.1

The cubic SVM model classifies the signals with a high training accuracy of 99.6% and test accuracy of 99.8% employing a 5-fold cross-validation and MRMR feature selection process selecting 600 highly ranked features for classification.

2) *K- Nearest Neighbor*

It is a supervised model known as a non-parametric model as it does not make any assumption on the underlying pattern of data distribution. The classification is done by categorizing the elements and identifying the nearest neighbor based on the similarity of features. The distances are calculated using different distance metrics like Euclidean, Manhattan, Hamming, and Minkowski distances to find the nearest neighbor. All the models analyzed here predominantly use Euclidean distance. The KNN models are computationally expensive, but the model has a faster training time.

TABLE 3
ECG CLASSIFICATION PERFORMANCE COMPARISON USING KNN MODELS

S. no	KNN model	No. of neighbors	Distance metric	Distance weight	Validation accuracies (%)	Test accuracy (%)
1	Fine	1	Euclidean	Equal	**99.4**	**99.7**
2	Medium	10	Euclidean	Equal	98.9	99.1
3	Coarse	100	Euclidean	Equal	86.8	93.5
4	Cosine	10	Cosine	Equal	98.3	97.9
5	Cubic	10	Euclidean	Equal	98.5	99.0
6	Weighted	10	Euclidean	Square inverse	99.0	99.2

The different KNN models like fine, medium, coarse, cosine, cubic, and weighted KNN are trained and their hyperparameters with performances in terms of distance weight, distance metric validation accuracy, training time, and test accuracy are tabulated as shown in the table (3). The models differ based on the number of predefined neighbors and the distance metric used. The fine KNN model with only one neighbor achieves 99.4% validation accuracy and 99.7% test accuracy performing better than all other KNN models.

3) *Decision tree*

It is a supervised learning model classifying the data in a way resembling the hierarchical tree structure where the root node stands for the feature and, the leaf node represents the outcomes. The model uses the Gini diversity index which prefers the large partitions whereas the information gain model prefers the smaller partitions with distinct values. Three different tree models namely fine, medium, and coarse based on the maximum number of splits such as 100, 20, and 4 respectively achieving validation and test accuracies as shown in Table (4). The model's performances are moderate with the largest training times.

TABLE 4
ECG CLASSIFICATION PERFORMANCE COMPARISON USING DECISION TREE MODELS

S.No.	Decision tree models	Splits	Validation accuracies (%)	Test accuracy (%)
1	Fine	100	93.8	94.8
2	Medium	20	91.4	92.1
3	Coarse	4	80.6	80.9

4) *Artificial Neural Network*

The neural network model mimics the nervous system by signaling connections along the series of neurons to find the underlying patterns. Based on the number of layers the neural networks are classified as narrow, medium, and wide with 10, 25, and 100 layers, respectively.

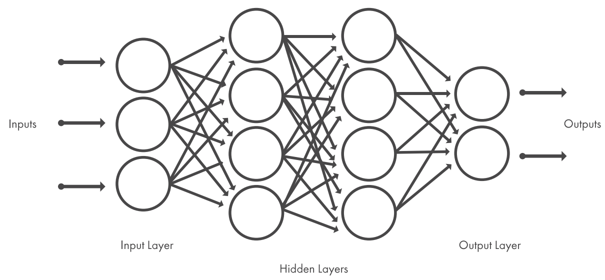


Fig.6. Pictorial representation of simple neural network

The neural network consists of an input layer, a hidden layer, and an output layer followed by a fully connected layer as shown in Fig.(6). The neuron in the hidden layers extracts the underlying patterns in the features to classify the ECG signals into three classes. Each neuron consists of an activation unit that activates the neurons firing the information to pass into the next layer. The activation layer used is the Rectified Linear Unit (ReLU). The network is trained in an iterative manner where the cost and weights are continuously updated in such a way the output approaches the desired value. The models used here vary with the number of layers used as shown in the third column of Table (5). As the count of layers increases, the complexity of the model increases. In addition to the three networks, the bi-layered and tri-layered models with two and three ten-layer networks are stacked using two and three fully connected layers, respectively.

TABLE 5
ECG CLASSIFICATION PERFORMANCE COMPARISON USING ANN MODELS

S. No.	ANN models	No. of layers	No. of fully connected layer	Validation accuracies (%)	Test accuracy (%)
1	Narrow	10	1	99.5	99.7
2	**Medium**	**25**	**1**	**99.7**	**99.7**
3	Wide	100	1	99.5	99.5
4	Bi-layered	20	2	99.4	99.7
5	Tri-layered	30	3	99.4	99.0

The wide ANN model uses the maximum number of layers greater than all other models. The ANN models perform comparatively better than all other machine learning models.

The existing works on ECG arrhythmia classification are compared as shown in table (6) highlighting the classification classes, feature extraction methods, classification models, and the accuracies achieved. The SVM classifier provides better accuracies in classifying the bio-signals. The classification employing deep learning models uses a Bi-LSTM network in the classification of time-series data. The usage of wavelet-based models in feature extraction and denoising seems to be prevalent among the state-of-the-art models [29], [9], [28], [30], [8], [12]. In [32] transfer learning-based model is used to classify the wavelet scattered features of the ECG signal with better accuracy.

TABLE 6
COMPARISON OF THE CLASSIFICATION PERFORMANCE OF EXISTING WORK WITH THE PROPOSED WORK

S.no.	Papers	Year	Class	Feature extraction	Classification model	Accuracy
1	Sahoo et al [24]	2017	4	DWT + temporal and morphological features	SVM	98.39%
2	Jagdeep et at. [19]	2021	3	R.R. interval +8 statistical features	SVM with Gaussian kernel	99.51%
3	Pandey et al [20]	2020	4	Wavelet transform + statistical features and Morphological features and R.R. intervals	Ensemble-based SVM	97.2%
4	Wang et al [21]	2021	2	Wavelet packet transform + correlation function	ANN	98.9%
	Murawwat et al [22]	2021	2	R.R. interval and heart rate	MEMD + ANN	89.8%
5	Kim et al [15]	2022	5	ECG raw signal	Bi-LSTM using Bayesian optimization	99.0%
6	Rahul et al [4]	2022	2	1D ECG signal 2D instantaneous frequency and spectral entropy	Bi-LSTM	98.85% (1D) 99.84% (2D)
7	Ramkumar [5]	2022	6	Autoencoder	Bi-LSTM	97.15%
8	Rahul et al [10]	2022	4	Six-layer CNN	Bi-LSTM	99.41%
9	Liu et al [9]	2020	5	Wavelet scattered features	KNN	99.3%
10	**Proposed model**	**2022**	**3**	**Wavelet scattered features**	**Cubic Kernel SVM**	**99.84%**

V. RESULTS AND ANALYSIS

The classification of arrhythmia, CHF, and NSR has been done using different machine learning and neural network models. The performance of the models in terms of model hyperparameters, validation accuracy, training time, and test accuracies are tabulated and analyzed. The features extracted are classified using machine learning models like SVM, KNN, Decision tree, and ANN models with different model hyperparameters accounting for twenty different models. Table (2) compares the performances of SVM models in which the cubic SVM model shows the highest accuracy of 99.8% and the quadratic SVM model also performs well with 99.7% test accuracy. The KNN models mentioned in table (3) differ in allotment of the number of neighbors and the distance metric is trained on the features to classify ECG signals. Among the six different models fine KNN model performs well with 99.4% test accuracy uses the Euclidean distance metric and achieves validation accuracy of 99.4%.

The decision tree model performs moderately in classifying the features achieving the highest test accuracy of 94.8%. The ANN models provide better classification accuracy in comparison with all other models. Among the five models, the medium neural network achieves higher validation and test accuracy of 99.7% about 4.36 percent speedier when compared with the cubic SVM model.

TABLE 7
PERFORMANCE METRICS COMPARISON USING K=5,6,10-FOLD CROSS-VALIDATIONS

Class	Cross-validation	Precision	Recall	Specificity	F1-score	accuracy
1	K=5	99.43	99.68	99.71	99.55	99.7
	K=6	99.73	99.47	99.75	99.59	99.74
	K=10	99.81	99.81	99.90	99.81	99.87
2	K=5	99.62	99.5	99.71	99.55	99.70
	K=6	99.60	99.73	99.81	99.66	99.78
	K=10	99.75	99.75	99.8	99.75	99.83
3	K=5	99.5	99.8	99.7	99.64	99.80
	K=6	99.86	99.6	99.93	99.72	99.83
	K=10	99.87	99.8	99.93	99.83	99.89

In comparison with all trained models cubic SVM and medium neural network model performs well with accuracies of 99.8 and 99.7 percent, respectively. In concern of complexity and cost of computation, the cubic SVM model is more effective than the medium neural network.

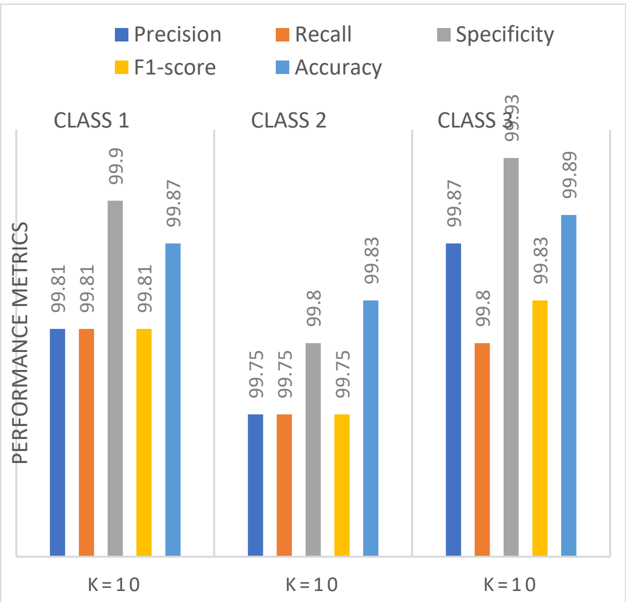
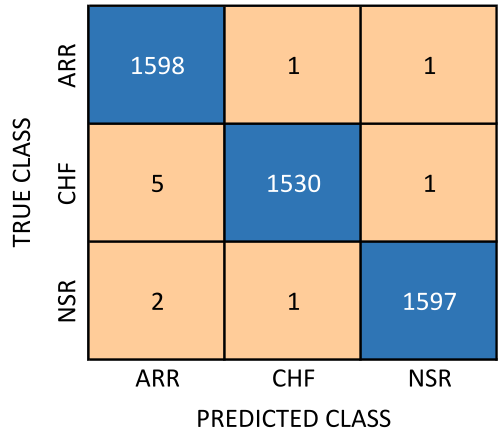
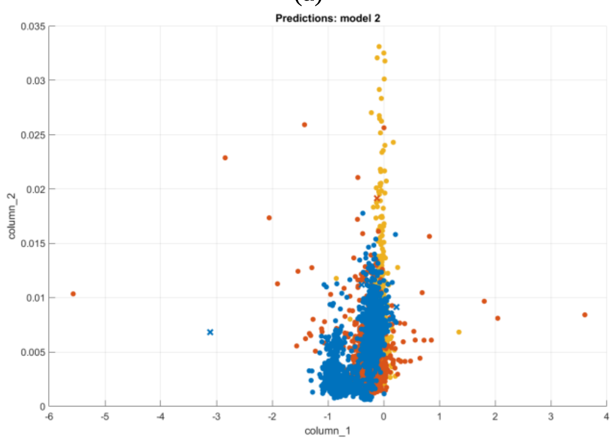


Fig.7. Graphical representation of performance metrics achieved on classifying ECG signals using Cubic SVM with k =10 cross-validation

The effect of feature selection algorithms is compared using the cubic SVM model as shown in Table (1) considering the highly ranked features producing the highest accuracies. Different feature selection algorithms with highest highest-ranked features are chosen for classifying the data and the MRMR feature selection algorithm achieves the highest accuracy. Fig. (8) shows the confusion matrix and scatter plot of the cubic SVM model. The selection process of K-fold cross-validation [31] for ECG signal classification is done and comparatively analyzed. The performance metrics include accuracy, specificity, sensitivity, and F1 score, and accuracy achieved in classifying the three class ECG signals with 5, 6, and 10-fold cross-validations are shown in Table (7) The performance metrics achieved in classifying all three classes using 10-fold cross-validation is represented graphically using a bar graph as shown in Fig. (7).



(a)



(b)

Fig.8. (a) Confusion matrix, (b) Scatterplot of the Cubic SVM model

From the confusion matrix the performance metrics like precision, recall, specificity, and F1- score are calculated by accounting for the true positive, true negative, false positive, and false negative of the three classes. The wavelet scattering-based Cubic SVM model achieves 99.81% precision, 99.78% recall, 99.87% specificity, and 99.79 % F1 score.

The analysis of the above is carried out with the recent database launched by Chapman University and Shaoxing People's Hospital [33] consisting of 10-second segments of 12 lead ECG signals with a sampling rate of 500Hz collected from 10,646 patients. The dataset comprises 11 types of rhythms unevenly distributed. The classification of the ECG signals belonging to various rhythms namely Sinus Bradycardia, Sinus Tachycardia, and Atrial Fibrillation is done using the proposed model. To address data imbalance in a classification task, an approach has been taken where each class is represented by 1200 signals. This ensures an equitable distribution of data across all classes The classification of wavelet scattered features using the Ensemble Boosted trees model achieves a maximum accuracy of 94.1%. The achieved classification accuracy explains the generalizability of the model.

The study faces some limitations like data imbalance which poses a great drawback in the analysis, this can be overcome by employing various data augmentation algorithms. In the future, the categorization of ECG signals of different medical conditions will be done involving time domain features, and spectral domain features alongside morphological features. This will pave the way to study the changes that occur in the cardiac system in relation to other medical conditions like stress, and depression etc., Expanding the automated analysis through deep learning models will prove beneficial in uncovering additional underlying features correlated with these conditions. The analysis will be conducted in real time, facilitating a more comprehensive exploration of the relationship between bio-signals and various health conditions.

VI. Conclusion

The classification ECG signals of NSR, CHF, and arrhythmia classes are detected and classified using different machine learning and neural network models. The ECG signals are initially preprocessed, resampled, and segmented into segments of 1024 samples with a sampling frequency of 250 Hz. The segments of three classes are balanced and the features are extracted using wavelet scattering. The wavelet scattering extracts the low variance features reduced in dimension holding the intra-class differences. The highest-ranked features are selected using the MRMR feature selection algorithm chosen after analyzing the different feature selection models. the models employ an 80:20 percentage splitting of data for training and testing, respectively. The model performance is evaluated using 5-fold and 10-fold cross-validation. The Cubic SVM model achieves an accuracy of 99.8%. The F1 score, sensitivity, specificity, and precision of the model are 99.79%,99.78%, 99.87%, and 99.81% respectively. In the future, the generalizability of the deep learning models with wavelet scattered features will be evaluated with another type of abnormalities.

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