

Detection of cardiac arrhythmia using deep CNN and optimized SVM

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ABSTRACT

Deep learning (DL) has become a topic of study in various applications, including healthcare. Detection of abnormalities in an electrocardiogram (ECG) plays a significant role in patient monitoring. It is noted that a deep neural network when trained on huge data, can easily detect cardiac arrhythmia. This may help cardiologists to start treatment as early as possible. This paper proposes a new deep learning model adapting the concept of transfer learning to extract deep-CNN features and facilitates automated classification of electrocardiogram (ECG) into sixteen types of ECG beats using an optimized support vector machine (SVM). The proposed strategy begins with gathering ECG datasets, removal of noise from ECG signals, and extracting beats from denoised ECG signals. Feature extraction is done using ResNet18 via concept of transfer learning. These extracted features are classified using optimized SVM. These methods are evaluated and tested on the MIT-BIH arrhythmia database. Our proposed model is effective compared to all State of Art Techniques with an accuracy of 98.70%.

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1. INTRODUCTION

Heart attacks are the major cause of death globally. 17.9 million people die each year due to cardiac abnormalities, estimating 31% of worldwide deaths [1]. Half of the cardiovascular deaths are due to cardiac arrhythmias. Any disturbance or changes that alter the normal functioning of the heart causes cardiac arrhythmia. Doctors often recommend patients with arrhythmia to wear Holter for continuous monitoring of ECG for 24 hours. As this recorded data is large, there is a necessity to categorize the type of each heartbeat automatically using the computer-aided diagnosis tool. The advancement and adoption of artificial intelligence have surged in the last few years. Traditional machine learning techniques or kernel-based neural network (NN) needs domain experts to identify important features for the analysis of ECG waveform [2].

Researchers have proposed different methodologies for the classification of arrhythmia [3]. Morphological and temporal characteristics are mostly considered for ECG signal analysis. The methodologies begin with the collection of data from MIT-BIH arrhythmia database [4], pre-processing data, feature extraction and classification. ECG signal is affected by various types of noises like powerline interference, baseline wander, Motion artifacts and EMG noise [3]. These noises are removed by pre-processing the data using DWT [5], [6], Filtering [7], [8]. The Denoised ECG signal is further considered for feature extraction. Time domain analysis [9], frequency domain analysis [10], [11], time-frequency analysis [12],

statistics-based analysis [13] and hybrid feature-based methods [14] is done for feature extraction. These extracted features can be classified using artificial neural networks (ANN) [15], support vector machines (SVM) [16]-[21], Naïve Bayes [22], decision tree (DT) [23], K-nearest neighbor (KNN) [24], and linear discriminant algorithms (LDA) [25].

Machine learning techniques require feature extraction, which indeed needs a domain expert to identify efficient features [26], [27]. Deep learning models incrementally learn features without the need for domain experts [28], [29]. Deep learning models are layered architectures that learn features at different layers. Input layers extract features using the convolutional layer, and these features are analyzed and classified using output layers.

It is observed from the literature that, as we increase the number of ECG classes for classification, the accuracy decreases. The main problem observed is to obtain besy accuracy when more abnormal classes are considered. Most of the methodologies require domain experts for extracting features. To avoid the need for domain experts, our work mainly emphases extracting features using a transfer learning-based CNN model-ResNet18.

Rest of the paper is systematized as follows. Section 2 describes our proposed methodology, including pre-processing (removal of noise and ECG beat segmentation), feature extraction (using Deep CNN-ResNet18 model), and classification (using optimized SVM). In section 3, investigative results are presented and compared with the existing state-of-art model. Section 4 concludes our work.

2. METHODOLOGY

The purpose of this study is to detect abnormalities in ECG signals. Transferring the learned knowledge utilizing pre-trained deep learning models empowers us to gather information required to study new data. We here explored the deep learning model-ResNet18 and extracted intrinsic Deep-CNN features. Utilizing these features classification is done using optimized-SVM. Figure 1 represents the methodology of our proposed work.

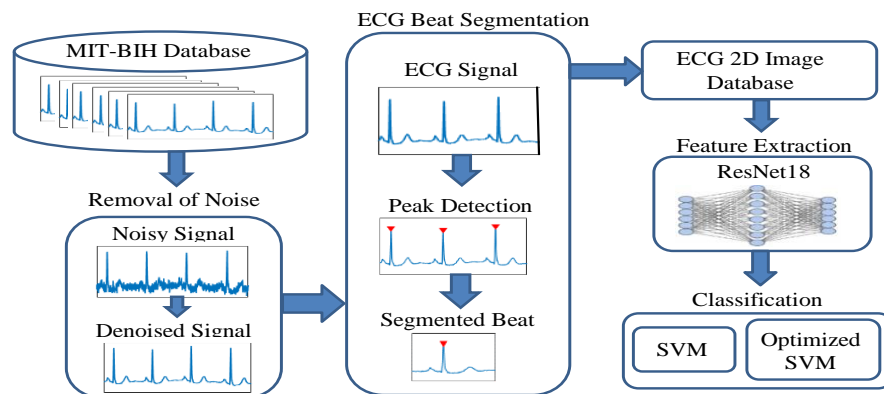


Figure 1. Block diagram of proposed approach

2.1. Pre-processing data

ECG signals are taken from MIT-BIH arrhythmia database [5]. It contains 48 records, each with 30 minutes duration. All records together contain 16 types of beats, of which one is normal, 14 classes of arrhythmia, and one unclassified beat. Types of beats considered are normal beats (N), left bundle branch block beats (L), right bundle branch block beats (R), premature ventricular contraction beats (V), atrial premature beats (A), paced beats (P), fusion of normal and paced beat (f), fusion of ventricular and normal beat (F), ventricular flutter wave (!), nodal (junctional) escape beat (j), blocked atrial premature beat (X), aberrated atrial premature beat (a), ventricular escape beat (E), nodal (junctional) premature beat (J), atrial escape beat (e), unclassified beat (Q).

2.1.1. Removal of noise

ECG signals are most frequently affected by various noises like power line interference, baseline drifts, motion artifacts and electromyography (EMG) noise. In this work, noise is removed using Savitzky-Golay filters. These filters smooth out noisy signals with a large frequency span. In general, filtering replaces each value of a signal with points that measure nearly the same underlying value. In moving average filters, total window length of $L = 2k + 1$ samples is replaced by its average value as;

$$x_s \rightarrow \hat{x}_s = \frac{1}{L} \sum_{r=-K}^K x_{s+r} \tag{1}$$

Savitzky-Golay filters generalize this idea by least-squares fitting a p^{th} - order polynomial through the signal values in the window and taking the calculated central point of the fitted polynomial curve as the new smoothed data point. Let the degree p polynomial considered as

$$f(x + i) = \sum_{k=0}^p \frac{i^k f^{(k)}(x)}{k!} \tag{2}$$

After convolving the polynomial and rearranging the summations we get

$$g(x + i) = \sum_{i=-m}^m \sum_{k=0}^p \frac{i^k f^{(k)}(x)}{k!} c_i = \sum_{k=0}^p \frac{f^{(k)}(x)}{k!} \sum_{i=-m}^m i^k c_i \tag{3}$$

Following equation must be satisfied for reproducing the values of degree p .

$$\sum_{i=-m}^m i^k c_i = \begin{cases} 1 & k = 0 \\ 0 & k = 1, 2, \dots, p \\ \neq 0 & k > p \end{cases} \tag{4}$$

2.1.2. ECG beat segmentation

Considering noise-free signal, the next step is to extract Beats. MIT-BIH arrhythmia database also provided annotation files with this database. They recorded the location of R-peak and the type of each heartbeat. R peaks are identified using annotation files. The average RR interval is calculated by averaging preRR interval and postRR interval. An onset duration of 1/3rd of average interval and offset duration of 2/3rd of average interval is selected to extract one ECG beat. Simulated results of noise removal and beat segmentation procedure are shown in section 3. These beats are further considered for feature extraction.

2.2. Feature extraction through transfer learning

Training a deep network from scratch with data scarcity is time-consuming. An alternative approach is to use the concept of transfer learning to extract features. Deep models extracts features by utilizing convolutional layers. These layers have a group of filters that convolves with layer kernels to generate a tensor of features. Depending on the 'stride' filter will move from one point to the next in each progression. Zero paddings are done to the filters if the convolutional layer does not cover the entire ECG beat. Each layer of a CNN Model produces a response, or activation, for a given input beat. However, only a few layers within a CNN Network are suitable for extracting features. The initial layers of the network capture basic ECG features, such as edges, slopes and curves. As more layers are added deep features like small curves, slopes get extracted. This builds up intuition as to why the features extracted from CNNs work so well for detecting abnormal ECG signals. The tensor of feature maps generated is determined through a rectified linear unit (ReLU) as an activation function. Convolution operation between convolutional filters and kernels is defined as

$$x_k^l = f(\sum_{i \in N_k} x_i^{l-1} * w_{ik} + b_k) \tag{5}$$

N_k is a range of convolution kernels with kernel size 5 or 3, x_k^l gives output of neuron k at layer l , b_k is the bias of neuron k , w_{ik} is the weight kernel neuron i at layer $l - 1$ and neuron k at layer l . $f(.)$ represents activation function ReLU. We have explored CNN architecture resnet18 for extracting features. The layered architecture of Resnet18 and internal architecture of residual blocks is shown in Figure 2. Resnet18 has one convolution layer, eight residual blocks and one fully connected layer. Each residual block has two convolutional layers i.e., ResNet18 has a total of 18 layers. ResNet-18 has been trained using the ImageNet dataset on more than a million images and can classify images into 1000 object categories. The input layer requires an image of size 224 x 224 for training. Hence, data augmentation is performed. In this study, on-the-fly data augmentation is performed on each beat before extracting features. This technique generates more accurate and robust beat with specified size and avoids loss of information. Augmentation reduces the risk of overfitting drastically. This augmented database adapts ResNet18 configuration. The convolution kernel size and activations in the residual blocks of ResNet18 remain unchanged. The existing fully-connected layer with 1000 nodes is discarded and an activation ReLU is used after the pooling layer. For a wide range of images, the ResNet18 model has learned features. Adapting the same weights and activations, the model learns required features. The final pooling layer pools the input features over all spatial locations, giving N -by- C feature set in total. N represents the total number of observations and C represents a

number of features extracted for each observation. Pooling layer has 512 nodes which after activations gives 512 features. Total observations considered in this study are 45943. Hence, a Feature set of size 45943 -by- 512 is extracted. Illustration of Feature extraction using transfer learning Via ResNet18 is shown in Figure 3. The Features extracted using this model are further given for classification.

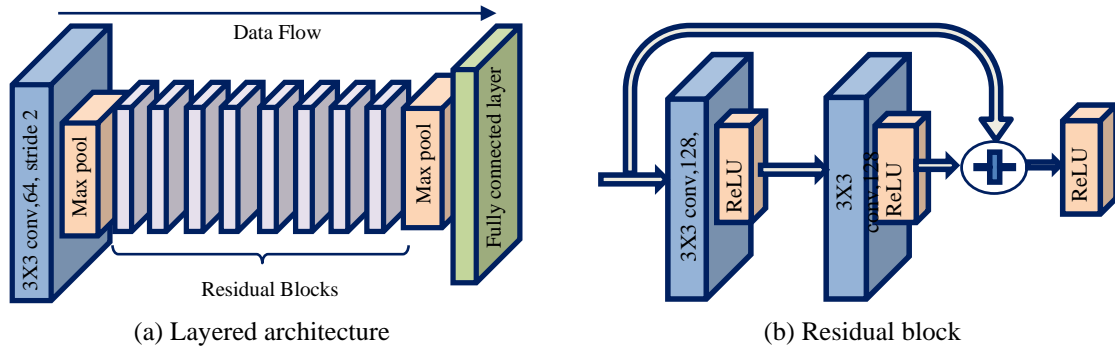


Figure 2. Architecture of Resnet18 pretrained model

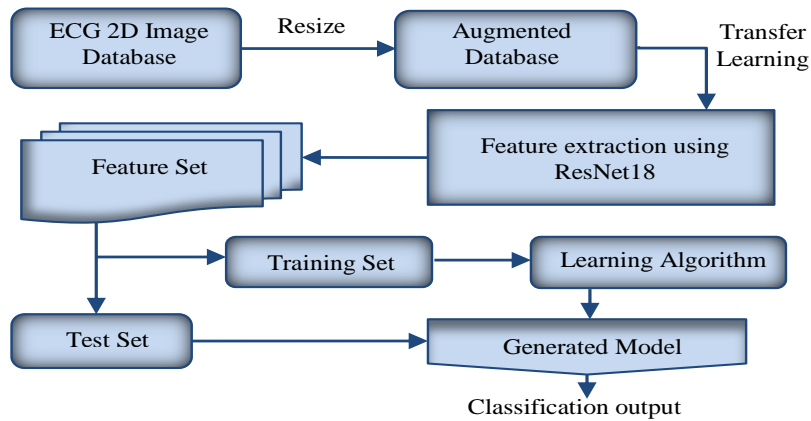


Figure 3. Illustration of feature extraction and classification using transfer learning via ResNet18 and optimized SVM

2.3. Classification using optimized- SVM

The feature set extracted of size 45943 -by-512 has input data $X = \{X_1, X_2, \dots, X_n\}$, $X_i = \{x_1, x_2, \dots, x_n\}$ with learning targets $y = \{y_1, y_2, \dots, y_n\}$. This feature set is split into training and testing feature sets. Using the training feature set the SVM is trained to obtain hyperplane expressed as $wX + b = 0$.

Here n is the number of labels/classes, w is normal vector and b is the intercept of hyperplane. When minimum of $\|w\|$ is achieved then this plane becomes optimum hyperplane. To avoid overfitting stochastic gradient descent (SGD) optimizer is implemented to minimize the objective function. The objective function of SVM classifier is given as

$$F = \min \frac{1}{2} w^T w + C \sum_{i=1}^l \epsilon_i \tag{6}$$

where ϵ is relaxation variable.

The loss function measures the fit between the actual and predicted values. As the loss function decreases, robustness increases. The loss function is the crucial Measure for a model to converge. Considering this constrain, the objective function of SVM becomes;

$$F = \min \frac{1}{2} w^T w + C \sum_{i=1}^l \max [0, 1 - y_i w^T x_i] \tag{7}$$

Local optimum of SVM is found out using SGD algorithm. To update the parameters samples are randomly selected. Accordingly, the objective function is formulated as;

$$F = \min \frac{1}{2} w^T w + \frac{c}{l} \max[0, 1 - y_i w^T x_i] \tag{8}$$

Process of dataset learning becomes very fast when sample gradient is used to update gradient. The gradient is noted as follows.

$$g_t = w - I[y_i w^T x_i > 1] \frac{c}{l} y_i x_i \tag{9}$$

Here second term is an indicator function, which becomes 1 when $y_i w^T x_i > 1$ or else it becomes 0. Iterations can be defined as;

$$w^{t+1} = w^t - \eta_t g_t \tag{10}$$

$$\eta_t = \frac{\eta_0}{1 + \lambda \eta_0 t}, \quad \eta_0 = 1 \tag{11}$$

where η is the stride, that determines the time elapsed by model to reach the optimal value. After training the SVM classifier, it is tested using testing feature set. To justify the effectiveness of optimization, we have classified ECG beats using SVM and the compared its performance with optimized SVM.

3. RESULTS AND DISCUSSIONS

In this study, MIT-BIH arrhythmia database is considered. The proposed model is simulated and tested using MATLAB software (2020b) package installed on Windows 10 platform with system configuration Intel core i7-9th Gen, 3.6 GHz CPU, 16 GB RAM, and NVIDIA GeForce GTX 1060 4GB GPU. The simulated results are shown and discussed in the following sections. Noise is removed using S-Golay Filtering mentioned in section 2.1.1. ECG Signal after removal of Noise from Noisy ECG signal is as shown in Figure 4.

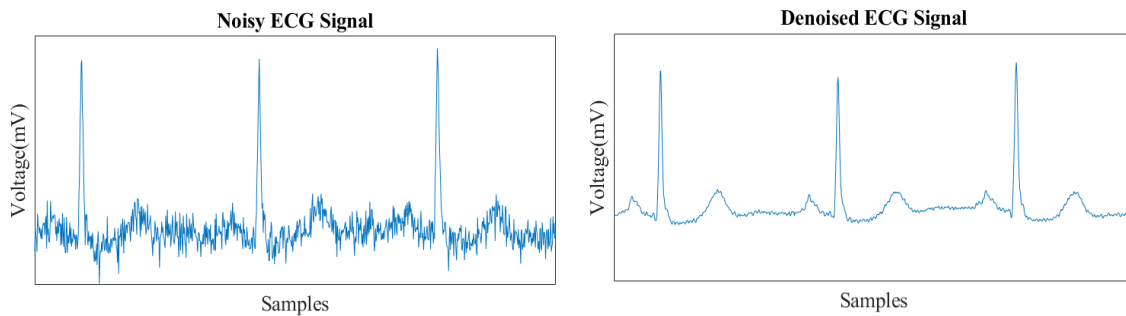


Figure 4. Removal of noise from ECG signal

As each record has different types of ECG beats, we need to segment the beats and label as per the abnormalities. ECG beat segmentation is done as discussed in section 2.2.1. Figure 5 shows ECG peaks detected and Figure 6 shows segmented ECG beat.

These segmented ECG beats are stored as ECG images and considered for further processing. A total of 45,943 ECG beats are extracted of which 36,753 beats are used for training and 9,190 beats are used for testing. Table 1 summarizes the total beats considered after segmentation. Feature extraction is done using Transfer learning based ResNet18 model as discussed in section 2.2 and classified using optimized-SVM as discussed in section 2.3.

The confusion chart depicts the performance of the model. It depicts how the particular trained model is performing on a given test dataset for which the actual values are already known. Predicted class of ECG beat is considered on X-axis and true class of ECG beat is considered on Y-axis. Figure 7 shows the confusion chart obtained using Resnet18+SVM and Figure 8 shows the confusion chart obtained using Resnet18+optimized SVM.

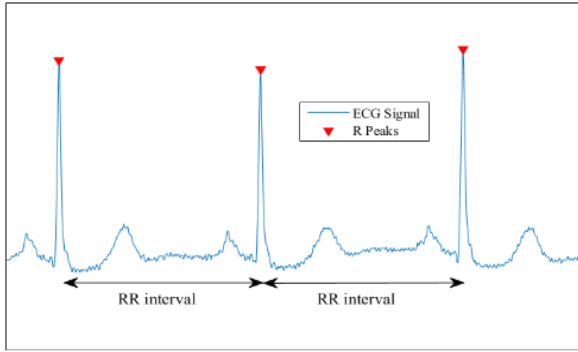


Figure 5. EEG peak detection

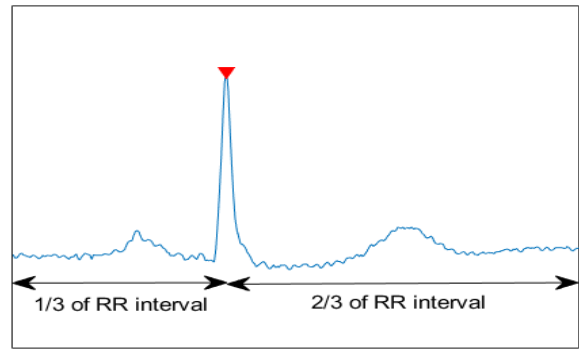


Figure 6. Segmented EEG bear

Table 1. Summary of ECG beats

	N	L	R	V	P	A	f	F	!	j	X	a	E	J	e	Q	Total Beats
Training Beats	8670	6460	5807	5704	5622	2037	786	642	378	183	154	120	85	66	13	26	36753
Testing Beats	2168	1615	1452	1426	1406	509	196	161	94	46	39	30	21	17	3	7	9190
Total Beats	10838	8075	7259	7130	7028	2546	982	803	472	229	193	150	106	83	16	33	45943

True Class	Predicted Class															
	N	L	R	V	P	A	f	F	!	j	X	a	E	J	e	Q
N	2166	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0
L	1	1611	0	2	0	1	0	0	0	0	0	0	0	0	0	0
R	8	0	1379	0	0	65	0	0	0	0	0	0	0	0	0	0
V	1	36	2	1385	1	0	0	1	0	0	0	0	0	0	0	0
P	0	1	0	19	1385	0	1	0	0	0	0	0	0	0	0	0
A	13		3	1	0	491	0	0	0	1	0	0	0	0	0	0
f	0	1	0	0	1	1	193	0	0	0	0	0	0	0	0	0
F	0	0	0	0	0	0	0	161	0	0	0	0	0	0	0	0
!	0	0	1	3	0	0	0	0	90	0	0	0	0	0	0	0
j	0	0	0	0	0	0	0	0	0	46	0	0	0	0	0	0
X	0	0	0	0	0	0	0	0	0	0	39	0	0	0	0	0
a	9	0	0	0	0	0	0	0	0	0	0	21	0	0	0	0
E	0	0	0	0	0	0	0	0	0	0	0	0	21	0	0	0
J	0	0	0	0	0	0	0	0	0	0	0	0	0	17	0	0
e	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0
Q	0	0	0	0	1	1	0	0	0	1	0	0	0	0	0	4

Figure 7. Confusion chart using Resnet18+SVM

True Class	Predicted Class															
	N	L	R	V	P	A	f	F	!	j	X	a	E	J	e	Q
N	2163	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0
L	0	1603	1	2	9	0	0	0	0	0	0	0	0	0	0	0
R	0	1	1447	0	1	3	0	0	0	0	0	0	0	0	0	0
V	0	5	2	1411	7	1	0	0	0	0	0	0	0	0	0	0
P	0	0	1	0	1405	0	0	0	0	0	0	0	0	0	0	0
A	10	6	8	5	23	457	0	0	0	0	0	0	0	0	0	0
f	0	4	0	0	8	1	184	0	0	0	0	0	0	0	0	0
F	0	0	0	0	0	0	0	161	0	0	0	0	0	0	0	0
!	0	0	1	1	1	0	0	0	91	0	0	0	0	0	0	0
j	0	0	0	0	0	0	0	0	0	46	0	0	0	0	0	0
X	0	0	0	0	0	0	0	0	0	0	39	0	0	0	0	0
a	0	2	0	0	0	0	0	0	0	0	0	28	0	0	0	0
E	0	0	0	0	0	0	0	0	0	0	0	0	21	0	0	0
J	0	0	0	0	0	0	0	0	0	0	0	0	0	17	0	0
e	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0
Q	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	5

Figure 8. Confusion chart using Resnet18+optimized SVM

To check the efficiency of developed classifiers, we evaluate the precision, specificity, recall, F-score, mathews correlation coefficient (MCC) and accuracy. Formulae are listed below

$$Precision(Pr) = \frac{Tp}{Tp+Fp} \tag{12}$$

$$Recall(Re) = \frac{Tp}{Tp+Fn} \tag{13}$$

$$Specificity(Sp) = \frac{Tn}{Fp+Tn} \tag{14}$$

$$F - Score(Fs) = \frac{Tp}{Tp+0.5(Fp+Fn)} \tag{15}$$

$$MCC = \frac{(Tp*Tn)-(Fp*Fn)}{\sqrt{(Tp+Fp)(Tp+Fn)(Tn+Fp)(Tp+Fn)}} \tag{16}$$

$$Accuracy = \frac{Tp+Tn}{Tp+Fp+Fn+Tn} \tag{17}$$

Where *Tp* gives True positives, *Tn* gives True negatives, *Fp* gives False positives and *Fn* gives False negatives. Performance Measures of each ECG class are summarized in Table 2. Average precision, Recall, specificity, F score and MCC achieved by SVM is 98.47%, 94.25%, 99.87%, 98.80%, 95.95%. Average precision, Recall, specificity, F score and MCC achieved by Optimized SVM is 99.51%, 96.42%, 99.92%, 97.78%, 97.80%. Overall accuracy achieved by SVM is 98.06% and accuracy achieved by Optimized-SVM is 98.7%.

Table 2. Performance measures using Resnet18 features+ SVM

Labels / Notation	Resnet18+SVM					Labels / Notation	Resnet18+optimized-SVM				
	Pr (%)	Re (%)	Sp (%)	Fs (%)	MCC (%)		Pr (%)	Re (%)	Sp (%)	Fs (%)	MCC (%)
N ('1')	98.54	99.90	99.97	99.22	98.98	N ('1')	99.54	99.76	99.92	99.65	99.54
L ('2')	97.69	99.75	99.94	98.71	98.44	L ('2')	98.89	99.25	99.84	99.07	98.87
R ('3')	99.56	94.97	99.06	97.12	96.74	R ('3')	99.11	99.65	99.93	99.38	99.26
V ('4')	98.15	97.12	99.61	97.63	97.32	V ('4')	99.36	98.94	99.85	99.15	99.04
P ('5')	99.78	98.50	99.80	99.14	99.03	P ('5')	96.23	99.92	99.99	98.04	97.80
A ('6')	87.83	96.46	99.81	91.94	91.61	A ('6')	99.13	89.78	99.46	94.22	94.06
f ('7')	99.48	98.46	99.96	98.97	98.95	f ('7')	100	93.87	99.87	96.84	96.82
F ('8')	98.77	100	100	99.38	99.37	F ('8')	100	100	100	100	100
! ('9')	100	95.74	99.95	97.82	97.82	! ('9')	100	96.80	99.96	98.37	98.37
j ('10')	95.83	100	100	97.87	97.88	j ('10')	100	100	100	100	100
X ('11')	100	100	100	100	100	X ('11')	100	100	100	100	100
a ('12')	100	70	99.90	82.35	83.62	a ('12')	100	93.33	99.97	96.55	96.59
E ('13')	100	100	100	100	100	E ('13')	100	100	100	100	100
J ('14')	100	100	100	100	100	J ('14')	100	100	100	100	100
e ('15')	100	100	100	100	100	e ('15')	100	100	100	100	100
Q ('16')	100	57.14	99.96	72.72	75.58	Q ('16')	100	71.42	99.97	83.33	84.50
Average	98.47	94.25	99.87	98.80	95.95	Average	99.51	96.42	99.92	97.78	97.80
Overall Accuracy = 98.06 %						Overall Accuracy = 98.70%					

Several state of art studies attempted by many researchers is shown in Table 3. Our proposed model, outperformed all State of art Techniques and classified 16 types of ECG beats with an accuracy of 98.70%.

Table 3. Comparisons with state-of-art models

Study	Beats	Classes	Method	Performance
Melgani <i>et al.</i> [16]	40438	6	PSO+SVM	Acc 89.72 %
Li <i>et al.</i> [17]	720	5	k-ICA+SVM	Acc 97.78 %
Osowski <i>et al.</i> [18]	12785	13	HOS+SVM	Acc 95.91 %
Venkatesan <i>et al.</i> [19]	-	2	HRV + SVM	Acc 96.00 %
Yang <i>et al.</i> [20]	104986	15	AKMC+KNN	Acc 97.70 %
Rodriguez <i>et al.</i> [26]	64260	16	Morphology+Decision	Acc 96.13 %
Oh <i>et al.</i> [27]	16499	5	CNN+LSTM	Acc 98.10 %
Mousavi <i>et al.</i> [28]	750	5	CNN-LSTM	Acc 92.50 %
Proposed Model	45943	16	ResNet18+SVM	Acc 98.06%
			ResNet18+ Optimized SVM	Acc 98.70 %

4. CONCLUSION

Deep learning-based CNN models have been proposed to classify 16 types of ECG beats. MIT-BIH arrhythmia database has been considered in this study. To remove the noise from signals S-Golay filtering has been performed. Considering noise-free signal, a total of 45,943 ECG beats are extracted using ECG beat segmentation technique. Feature extraction is done using deep learning model and classified using the proposed optimized-SVM. Multiclass SVM with error-correcting output code was used and then optimized using SGD optimizer. Optimization improved the performance of our model. Our model recorded the best accuracy of 98.70% compared to all the related works.

REFERENCES

- [1] A. S Go, D. Mozaffarian, E. J Benjamin, D. K Arnett, and M. J. Blaha, "American Heart Association Council on Epidemiology and Prevention Statistics Committee and Stroke Statistics Subcommittee," *Heart Disease and Stroke Statistics-2018 Update: a report from the American Heart Association, Circulation*, vol. 137, no. 12, pp. e67-e492, 2018.
- [2] R. J. Martis, U. R. Acharya, and L. C. Min, "ECG beat classification using PCA, LDA, ICA and discrete wavelet transform," *Biomed. Signal Process. Control*, vol. 8, no. 5, pp. 437-448, Sep. 2013, doi: 10.1016/j.bspc.2013.01.005.
- [3] Mohebbanaaz, Y. Padma Sai and L. Rajani Kumari, "A review on arrhythmia classification using ECG signals," *2020 IEEE International Students' Conference on Electrical Electronics and Computer Science (SCEECS)*, 2020, pp. 1-6, doi: 10.1109/SCEECS48394.2020.9.
- [4] G. B. Moody and R. G. Mark, "The impact of the MIT-BIH Arrhythmia Database," in *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 3, pp. 45-50, May-June 2001, doi: 10.1109/51.932724. L. V.
- [5] L. V. Rajani Kumari, Y. Padma Sai, and N. Balaji, "R-Peak Identification in ECG Signals using Pattern-Adapted Wavelet Technique," *IETE Journal of Research*, 2021, doi: 10.1080/03772063.2021.1893229.
- [6] P. Sri Lakshmi and V. Lokesh Raju, "ECG De-noising using Hybrid Linearization Method," *Indonesian Journal of Electrical Engineering and Computer Science (IJECS)*, vol. 15, no. 3, pp. 504-508, 2015.
- [7] P. Sarthak, and N. M. Mihir, "Impulsive Noise Cancellation from ECG Signal using Adaptive Filters and their Comparison," *Indonesian Journal of Electrical Engineering and Computer Science (IJECS)*, vol. 3, no. 2, pp. 369-376, 2016, doi: 10.11591/ijeecs.v3.i2.pp369-376.
- [8] H. Rahmad, L. Ninik Sri and Herawati, "An approach of adaptive notch filtering design for electrocardiogram noise cancellation," *Indonesian Journal of Electrical Engineering and Computer Science (IJECS)*, vol. 22, no. 3, pp. 1303-1311, 2021, doi: 10.11591/ijeecs.v22.i3.pp1303-1311.
- [9] S. Raj, K. Maurya, and K. C. Ray, "A knowledge-based real time embedded platform for arrhythmia beat classification. Biomed," *Eng.Lett.* vol. 5, no. 4, pp. 271-280, 2015, doi: 10.1007/s13534-015-0196-9.
- [10] Q. Li, C. Rajagopalan and G. D. Clifford, "Ventricular Fibrillation and Tachycardia Classification Using a Machine Learning Approach," in *IEEE Transactions on Biomedical Engineering*, vol. 61, no. 6, pp. 1607-1613, June 2014, doi: 10.1109/TBME.2013.2275000.
- [11] L. V. Rajani Kumari, Y. Padma Sai and N. Balaji, "ECG Signal Preprocessing Based on Empirical Mode Decomposition," *Microelectronics, Electromagnetics and Telecommunications. Springer, New Delhi*, pp. 673-679, 2016.
- [12] L. D. Sharma and R. K. Sunkaria, "Inferior myocardial infarction detection using stationary wavelet transform and machine learning approach," *Signal Image Video Process*, vol. 12, no. 2, pp. 199-206, 2017, doi: 10.1007/s11760-017-1146-z.
- [13] M. Mohanty, S. Sahoo, P. Biswal and S. Sabut, "Efficient classification of ventricular arrhythmias using feature selection and C4.5 classifier," *Biomedical Signal Processing and Control*, vol. 44, pp. 200-208, 2018, doi: 10.1016/j.bspc.2018.04.005.
- [14] M. Sharma, R. S. Tan, and U. R. Acharya, "Automated heartbeat classification and detection of arrhythmia using optimal orthogonal wavelet filters," *Informatics in Medicine Unlocked*, vol. 16, p. 100221, 2019, doi: 10.1016/j.imu.2019.100221.

- [15] S. C. Matta, Z. Sankari, and S. Rihana, "Heart rate variability analysis using neural network models for automatic detection of lifestyle activities," *Biomed. Signal Process Control*, vol. 42, pp. 145-157, 2018, doi: 10.1016/j.bspc.2018.01.016.
- [16] L. V. Rajani Kumari, Y. Padma Sai and N. Balaji, "Performance Evaluation of Neural Networks and Adaptive Neuro Fuzzy Inference System for Classification of Cardiac Arrhythmia," *International Journal of Engineering & Technology*, vol. 7, pp. 250-253, 2018.
- [17] F. Melgani and Y. Bazi, "Classification of Electrocardiogram Signals With Support Vector Machines and Particle Swarm Optimization," in *IEEE Transactions on Information Technology in Biomedicine*, vol. 12, no. 5, pp. 667-677, Sept. 2008, doi: 10.1109/TITB.2008.923147.
- [18] H. Li, X. Feng, L. Cao, H. Liang, and C. Miao., "Novel ECG signal classification based on KICA nonlinear feature extraction," *Circuits, Syst., Signal Process*, vol. 35, no. 4, pp. 1187-1197, 2016, doi: 10.1007/s00034-015-0108-3.
- [19] S. Osowski, L. T. Hoai, and T. Markiewicz "Support vector machine based expert system for reliable heart beat recognition," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 4, pp. 582-589, 2004, doi: 10.1109/TBME.2004.824138.
- [20] C. Venkatesan, P. Karthigaikumar, A. Paul, S. Satheeskumaran and R. Kumar, "ECG Signal Preprocessing and SVM Classifier-Based Abnormality Detection in Remote Healthcare Applications," in *IEEE Access*, vol. 6, pp. 9767-9773, 2018, doi: 10.1109/ACCESS.2018.2794346.
- [21] H. Yang and Z. Wei, "Arrhythmia Recognition and Classification Using Combined Parametric and Visual Pattern Features of ECG Morphology," in *IEEE Access*, vol. 8, pp. 47103-47117, 2020, doi: 10.1109/ACCESS.2020.2979256.
- [22] L. B. Marinho, N. D. M. M. Nascimento, J. W. M. Souza, M. V. Gurgel, P. P. R. Filho and V. H. C. de Albuquerque, "A novel electrocardiogram feature extraction approach for cardiac arrhythmia classification," *Future Gener. Comput. Syst.*, vol. 97, pp. 564-577, Aug. 2019, doi: 10.1016/j.future.2019.03.025.
- [23] M. Sharma, R. S. Tan, and U. Rajendra Acharya, "Automated heartbeat classification and detection of arrhythmia using optimal orthogonal wavelet filters," *Informatics in Medicine Unlocked*, vol. 16, p. 100221, 2019, doi: 10.1016/j.imu.2019.100221.
- [24] Mohebbanaaz, L. V. Rajani Kumari, and Y. Padma Sai, "Classification of Arrhythmia Beats Using Optimized K-Nearest Neighbor Classifier," In: *Udgata S.K., Sethi S., Srirama S.N. (eds) Intelligent Systems. Lecture Notes in Networks and Systems*, Springer, Singapore, vol. 185, 2021, doi: 10.1007/978-981-33-6081-5_31.
- [25] R. Varatharajan, G. Manogaran, and M. K. Priyan, "A big data classification approach using LDA with an enhanced SVM method for ECG signals in cloud computing," *Multimedia Tools Appl.*, vol. 77, pp. 10195-10215, 2018, doi: 10.1007/s11042-017-5318-1.
- [26] S. Sabar, S. Djanggan, P. S. Setyawan, and S. Andarini, "The Peak of the PQRST and the Trajectory Path of Each Cycle of the ECG 12-Lead Wave," *Indonesian Journal of Electrical Engineering and Computer Science (IJECS)*, vol. 4, no. 1, pp. 169-175, 2016, doi: 10.11591/ijeecs.v4.i1.pp169-175.
- [27] J. Rodriguez, A. Goni, and A. Illarramendi, "Real-time classification of ECGs on a PDA," *IEEE Trans. Inf. Technol. Biomed.*, vol. 9, no. 1, pp. 23-34, 2005, doi: 10.1109/TITB.2004.838369.
- [28] S. L. Oh, E. Y. K. Ng, R. S. Tan, and U. R. Acharya, "Automated diagnosis of arrhythmia using combination of CNN and LSTM techniques with variable length heart beats," *Comput. Biol. Med.*, vol. 102, pp. 278-287, Nov. 2018, doi: 10.1016/j.compbiomed.2018.06.002.
- [29] S. Mousavi, A. Fotoohinasab, and F. Afghah, "Single-modal and multi-modal false arrhythmia alarm reduction using attention-based convolutional and recurrent neural networks," *PLoS One*, vol. 15, no. 1, p. e0226990, 2020, doi: 10.1371/journal.pone.0226990.