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DEEP LEARNING OPTIMIZED FRAMEWORK FOR DETECTION OF ARRHYTHMIA FROM ECG

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ABSTRACT

Early detection of heart diseases has become the need of hour due to surging heart disease occurrence and mortality across world. Electrocardiogram (ECG) test is the most adopted screening test for heart diseases. Various methods have been proposed to extract various features from ECG and use it for classification of heart diseases, still it is open research area due to the need to provide higher accuracy with lower false positives. Optimizations were proposed in various stages like data acquisition, feature engineering, classification stages for achieving higher accuracy. But existing feature engineering approach can be improved with extracting spatial characteristics across multi modalities and temporal characteristics over longer widow duration. This work proposes an optimized deep learning framework to detect Arrhythmia from ECG by extracting spatial characteristics found from multi modalities and temporal correlation over longer time window. Optimization is done in two areas of feature engineering and model parameter fine tuning to provide higher accuracy and lower false positives. The proposed optimization increased the accuracy by 3.5% compared to classifiers without optimization

Keywords: *Heart Diseases, Arrhythmia, Deep Learning, Optimization, Feature Engineering*

1. INTRODUCTION

Heart diseases are the leading cause of death worldwide. Every year more than 60 million people develop heart disease across the world and one in three deaths globally are attributed to some form of heart disease. Recent estimates from British heart foundation [1] are that on average 56,000 people die each day and one death every 1.5 seconds due to heart diseases. This surge in heart disease mortality is alarming and warrants early detection/treatment to reduce the casualties. Electrocardiogram (ECG) test is the most adopted screening method to diagnose heart diseases. ECG recordings from heart are collected from multiple leads and these ECG readings are analyzed to diagnose heart diseases. It is often cumbersome to analyze the ECG recordings manually and this gap is bridged by machine learning based automatic diagnosis methods. These machine learning tools extracts various intricate features from ECG recordings and use trained machine learning classifier models to classify the features to various heart diseases. But variations in recording mode, subject introduced variations, external noises during data acquisition etc make accurate classification a challenge. To increase the accuracy and reduce the false positives in diagnosis, various techniques have been proposed. The existing machine learning based methods can be classified to two categories of: conventional and deep learning methods. Conventional methods extracts various handcrafted features using methods like principal component analysis (PCA)[2], Fourier transform [3], wavelet transform [4] etc and classifies them using various classifiers like K-nearest neighbor, support vector machine , artificial neural networks, random forests and decision trees etc to recognize heart diseases. Deep learning methods use advanced classifiers like convolutional neural networks (CNN), recurrent neural networks (RNN), deep belief networks etc to learn more intricate features from the data and classifies them. Due to its ability to learn more intricate features, deep learning methods usually have higher accuracy when trained with more samples without bias. Deep learning approaches for ECG classification works in two modes: 1D and 2D. In 1D mode, the features from ECG are used to learn intricate features and used for classification. In 2D mode, the ECG is processed as image. Approaches [5-6] generate 2D representation of ECG signals through segmentation and stacking. This 2D matrix is then processed like images by the deep learning models. Though many deep learning models have been proposed, achieving higher accuracy necessitate optimizations in terms of deep learning models, feature engineering and organizing them as inputs for deep learning models. In addition, temporal contexts information must also be added to increase accuracy and reduce false positives. This work proposes hybrid approach where spatial features extracted from multiple ECG leads are selected for higher correlation to Arrhythmia. These features are then stacked to 2D representation. Resnet model is then used to convert the stacked 2D representation to encoded representation. This encoded representation is then temporal correlated over longer time widow by long short term memory (LSTM).The hyper parameters of the deep learning models are then optimized using particle swarm optimization algorithm.

Following are the novel contributions of the work

(i) An optimized feature engineering approach to stack ECG spatial characteristics from multi modal perspective and select the best set of features with higher correlation to Arrhythmia.

(ii) Including temporal correlation over longer time window along with selected multi modality spatial characteristics in classification of Arrhythmia.

(ii) Optimization of hyperparameters of the deep learning model using particle swarm optimization algorithm with fitness function designed to reduce error in classification.

Paper organization is as follows. Section 2 presents the existing deep learning solutions for heart disease classification. Section 3 presents the proposed hybrid approach for Arrhythmia classification. Section 4 presents the results of proposed solution in comparison to existing works. Section 5 presents the conclusion and scope for future research

2. SURVEY

Xia et al [7] proposed a 1D CNN for heart ECG signal classification. Features extracted using 1D CNN was optimized to select best features using active learning. By optimizing features, the accuracy of classification increased. But the method was not tested for heart disease recognition. Pourbabaee et al [8] recognized paroxysmal atrial fibrillation from ECG signals using deep CNN. Using deep CNN allowed learning more intricate features. But the training volume must be higher and bias must be removed from the dataset. Tripathy et al [9] detected myocardial infarction (MI) from multi lead ECG signals using a multiscale CNN. Authors used 1D CNN based approach wherein the subband signals extracted using wavelet filter back were classified by 1D CNN to MI classes. Chen et al [10] classified MI from 3 lead ECG signals using a light weight CNN. Wavelet filters extracted from ECG signals are fused and then classified by CNN to MI classes. Shaker et al [11] used 1D CNN for MI classification. Authors solved the data imbalance problem using GAN based data augmentation and enrich the dataset. Using enriched dataset increased the accuracy of CNN classification. Wang et al [12] classified heartbeat types from ECG signals using an fully connected neural networks. Wavelet features are extracted from multi leads ECG are classified by neural networks and then results are fused to get classify heart beat types. In all of the above [7-12] approaches, only spatial context was considered and temporal context or the correlation between multiple leads ECG was not considered to increase classification accuracy. Chen eta [13] proposed a solution to combine spatial with temporal characteristics. Author combined CNN with LSTM to classify beat types in the ECG signals. Though the work used only a shorter window for temporal correlation, the accuracy improved applying temporal correlation. Porumb et al [14] classified heart disease using CNN with majority voting on a small time scale. Voting on results over time scale increased the accuracy of classification. But this solution needed large unbiased dataset. Rahhal et al [15] proposed a 2D based approach for ECG signal classification. ECG signals were converted to image using a GAN transformer. The image is then classified using a dense CNN. Focal loss function for used to reduce the training loss. But for a long duration of ECG signal, the segments to be used for image conversion were not defined in this work. Izci et al [16] segmented ECG to beats and converted each beat to a image. This image is then classified by 2D CNN. But the classification did not consider temporal correlation between beats. Mathunjwa et al [17] proposed 2D CNN approach to classify arrhythmia. The ECG signal were split to 2 second duration segments and segments are classified by 2D CNN. Authors did not consider temporal correlation between the segments. Pham et al [18] compared the performance of 2D CNN, 1D CNN and traditional machine learning classifiers to classify Arrhythmia. Scatter plot is made for ECG from the R-R interval. This plot image is then processed by Resnet to classify Arrhythmia. Time series of ECG signals were processed by 1D Resnet in 1D CNN mode to classify Arrhythmia. Author also classified time series by Xgboost algorithm to classify Arrhythmia. From the experimental results authors found that considering temporal context information increases even with Xgboost classifier. Fang et al [19] extracted QRS features from ECG signals and classified it with RBF neural networks to classify heart diseases. A novelty in this approach is that QRS feature extraction which has higher correlation to heart disease. But the temporal correlation between QRS features of each segment was not considered for increasing accuracy. Rouhi et al [20] extracted 56 features related to heart rate variability and used it to classify Atrial Fibrillation detection using cascaded classifiers. Authors identified the best feature combination for higher accuracy using a game theory based concept called as Shapely additive explanations (SHAPE) Best features selected by this method are then classified by Random forest classifier to provide higher accuracy. Authors concluded that by optimizing feature engineering process higher accuracy can be achieved even with traditional machine learning classifiers. Bridge et al [21] proposed a 2D approach to detect abnormal EEG recordings. EEG printout images are processed by a Inception V3 deep learning architecture to classify abnormal heart beat. But the study did not provide details on the segment duration to be used as image for classification. Mahfuz et al [22] extracted SHAPE values from time frequency representation of ECG signals and classified it using VGG16 based CNN to abnormal heart beats. Authors concluded that temporal features selected using SHAPE provided higher accuracy. But the temporal correlation was only on short term interval. Sattar et al [23] extracted ECG segments from ECG signals and trained three different machine learning models of CNN, LSTM and self supervised auto encoders. CNN achieved higher accuracy compared to other models considering only spatial characteristics of the signal. Authors did not consider temporal correlation of ECG segments and spatial correlation across multi lead for achieving higher accuracy. Bhatia et al [24] combined deep CNN with Bidirectional LSTM to classify Arrhythmia. The ECG signal was split to beat segments and processed as whole by CNN-BiLSTM without any feature selection or parameter optimization. Essa et al [25] proposed an ensemble of LSTM classifier to classify Arrhythmia. The ECG segment was processed as whole without giving importance to segment level details, so model becomes over fit. Mulam et al [26] extracted statistical and time domain features and then used it as input to Luong attention based LSTM to classify Arrthymia. But due to segment overlap and redundancy in temporal feature collection, the classifier becomes over fit.

From the survey, it can be seen that most approaches did not consider spatial correlation of ECG across multiple modalities in feature engineering and temporal correlation over a longer time window in classification stage. As the result their classification accuracy was reduced and false positives were higher. This work attempts to solve this problem by proposing a multimodality-based feature analysis in spatial and temporal context (both short term and long term) to increase the accuracy and reduce false positives.

3. DEEP LEARNING OPTMIZED FREAMEWORK

The proposed solution involves optimization in two stages of feature engineering and model parameters fine tuning for increasing the accuracy of Arrhythmia classification. The architecture of the solution is given in Figure 1. The ECG is split to beat segments. These beat segments are then analyzed from multiple modality views and featuresare extracted. From those, the best set of features with higher correlation to Arrhythmia is found, using entropy analysis. The spatial features over a K sequence of beat are augmented to generate the spatio temporal features. The best value for K is found using clustering analysis. These spatio temporal features are processed by Resnet to get more intricate features. The features are then classified by two different classifiers of random forest and multi attribute LSTM classifiers with hyper parameter optimized using PSO. Thus the proposed solution involved optimization in two stages of feature engineering and classification Feature engineering selected optimal features considering both spatial and temporal context which is different from existing works on feature selection only based on spatial context. The details of each stage of feature engineering and classification are detailed in below subsections.

3.1 FEATURE ENGINEERING

Feature engineering proposed in this approach selected optimal features considering both spatial and temporal characteristics. The ECG signal is segmented to beats using Pan Tompkins algorithm [27] as shown in Figure 2. Spatial features are extracted over multiple modalities. There different modalities of 1D convolutional features, heart rate variability (HRV) features and

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QRS features are extracted from each beat. The beat signal is processed by the network

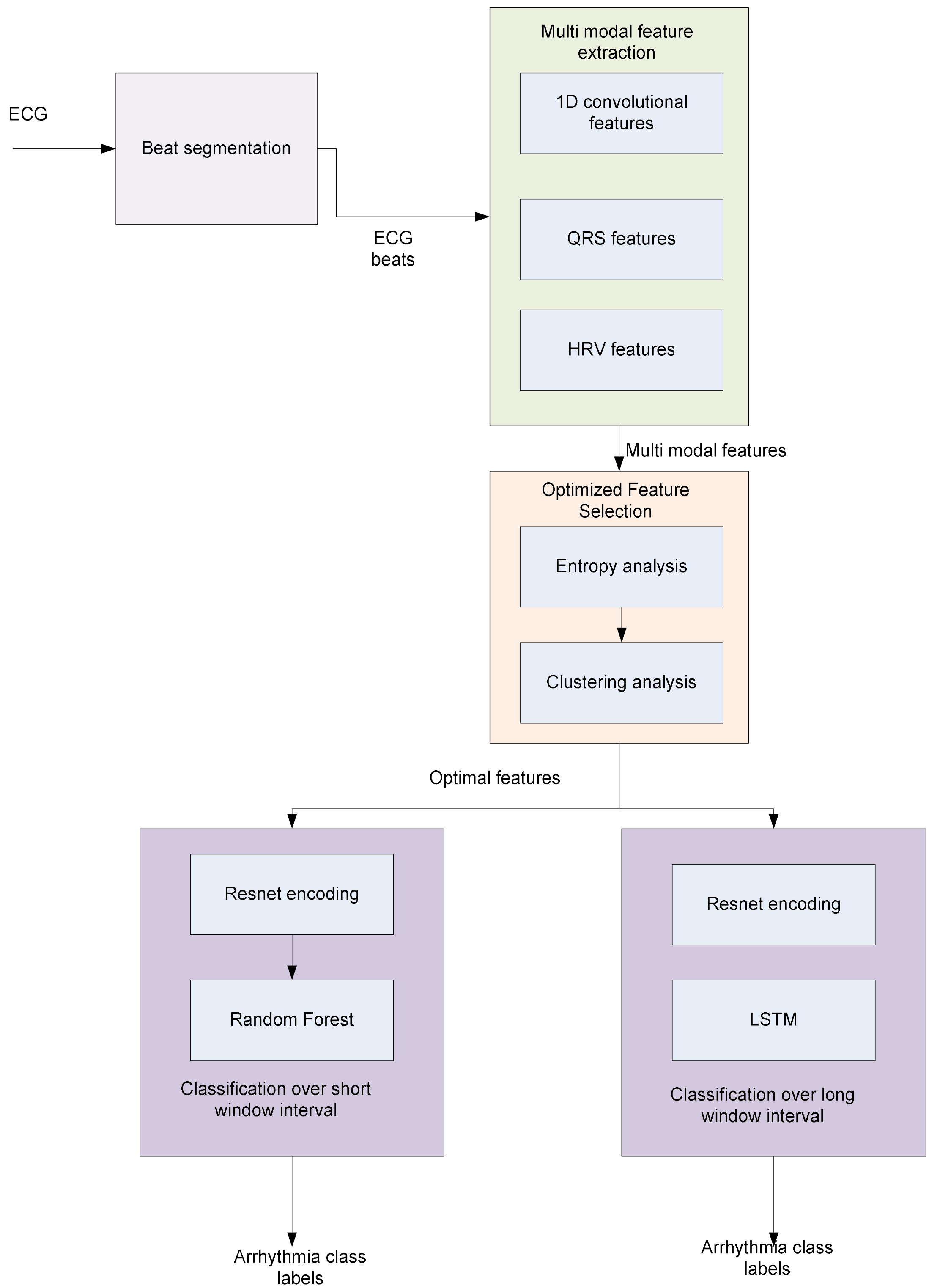

Figure 1 Deep learning optimized framework

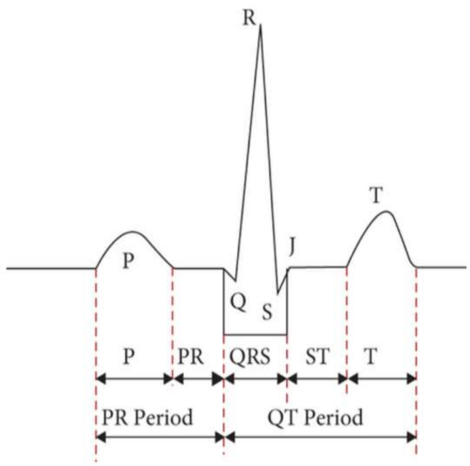

Figure 2 ECG Beat

configuration given in Table 1 to extract convolutional features.

Table 1 Configuration to extract convolutional features

Layer	Configuration
Input	1*512
Convolutional 1D	10*128, ReLU, Stride=2
MaxPool 1D	Size=2,Stride=2
Convolutional 1D	10*128, ReLU, Stride=2
MaxPool 1D	Size=2,Stride=2
Convolutional 1D	8*128, ReLU, Stride=2
Convolutional 1D	8*128, ReLU, Stride=2
Flatten	-
Dense	1*128,ReLU

The QRS features extracted from ECG beats are given in Table 2.

Table 2 QRS features

Feature	Description
QT	QT interval
PR	PR interval
TL	T wave length
PL	P wave length
PA	P wave amplitude
STA	Amplitude of ST segment
QRST	Segment length between QRS and T
PRL	PR segment length
RA	R peak amplitude
TA	T peak amplitude

The HRV features extracted from ECG beats are given in Table 3.

Table 3 HRV features

Feature	Description
NN	NN interval to next beat
RR	RR interval to next beat
TINN	Baseline width of RR interval
QRSD	Distance to next QRS wave
PSF	Power spectral frequency

From these features, the best features are selected using entropy analysis. Between each of the feature to class label (Arrhythmia/Not), correlation factor (CF) is calculated as

$$CF(a,b) = \frac{2 \times MI(a,b)}{H(a)+H(b)} \quad (1)$$

Where MI is the mutual information and H is the Shanon's entropy. MI is calculated as

$$MI = \sum_a \sum_b PDF(a,b)\, log \frac{PDF(a,b)}{p(a) \times p(b)} \quad (2)$$

PDF(a) is the probability density function for the variable a and PDF(a,b) is the joint probability density function. H(a) is calculated in terms of shanon's entropy as

$$H(a) = -\int PDF(a)\, log\big(PDF(a)\big) dx \quad (3)$$

when the CF(a,b) is above 0.75, the feature a selected as significant feature. After selection of significant features, the number of beats to be grouped (K) as temporal feature is found using clustering analysis. Starting from 2 to K consecutive beats, Clustering of features is done for each combination and three measures of cohesion (C), separation (S) and Silhouette coefficient (SC) are calculated as

$$C = \sum_i \sum_{x \epsilon C_i} (x - m_i)^2 \quad (4)$$

Where x is the data point within cluster and m_i is the median of the cluster.

$$S = \sum_i |C_i| \, (m - m_i)^2 \qquad (5)$$

Where $|C_i|$ is the size of the cluster i, and m is the centroid of whole feature set

$$SC = \begin{cases} 1 - \frac{a}{b}, & if\ a < b \\ \frac{b}{a} - 1 & if\ a \geq b \end{cases} \qquad (6)$$

For a individual point, a is average distance of i to the points in its cluster and b is minimum of average distance of i to points in another cluster.For a good clustering, C should be minimum, S should be maximum and SC should be maximum. Based on this observation, clustering score is calculated for each clustering combination as

$$CS_i = \frac{1}{C} + S + SC \qquad (7)$$

The clustering combination providing highest value for CS_i is the optimum combination of beats to be used for temporal correlation.

The optimal features found from entropy analysis and arranged in form of 2D matrix with each row being the optimal features corresponding to each beat and there are K rows where K is the optimal number of beats found using clustering analysis. The feature selection process is summarized in the pseudo code below

Algorithm: Feature selection

Input: 1D convolution features(a), QRS features(b), HRV features(c), Arrhythmia classes(d) , M beats

Ouput: SigFeat, MaxC

$$FM \leftarrow a \cup b \cup c$$

SigFeat← {}

For each column ct in FM

Calculate CF (ct , d) as in Eq. 1

If CF (ct , d) > 0.75

SigFeat← SigFeat ∪ ct

MaxC←0

MaxV←0

For K=1 to M

D←Create dataset with SigFeat for J=1:K beats

Cluster D

temp←Calculate CS_i for D

If temp> MaxV

MaxV←temp

MaxC←K

3.2 CLASSIFICATION

The optimal feature 2D matrix is processed like a image and converted to feature encoding using Resnet block. The Resnet block used for feature encoding is given in Figure 3.The feature encoding from Resnet block is classified in two modes of short term temporal and long term temporal. Short term temporal classification is realized by classifying the Resnet output feature encoding using random forest classifier. Long term temporal classification is realized by classifying using LSTM classifier. LSTM is an improved recurrent neural network with gating mechanism. This gating mechanism allows LSTM to retain or forget a level of information. This allows LSTM to control the learning rate. Each LSTM cell takes current input vector and previous hidden state as input. The cell activation is calculated as weighted sum of inputs along with bias b. The cell activation is processed by a hyperbolic tangent activation function to provide output.

$$c_t = \emptyset_t(W_c x_t + U_c h_{t-1} + b_c) \qquad (8)$$

c_t is the candidate cell activation. x_t is the input vector. W and U are the weight matrices.h_{t-1} is the hidden state vector at the previous time step and b_c is the bias.The information level to be trained or forget is controlled by gates. The level to retain is controlled by input gate. The level to forget is controlled by forget gate. Hidden state information is calculated by the final gate.

$$f_t = \emptyset_s(W_f x_t + U_f h_{t-1} + b_f) \qquad (9)$$

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$$i_t = \emptyset_s(W_i x_t + U_i h_{t-1} + b_i) \quad (10)$$

$$o_t = \emptyset_s(W_o x_t + U_o h_{t-1} + b_o) \quad (11)$$

f_t is the forgot gate vector. i_t is the input gate vector.o_t is the output gate vector.In this work, a multi attribute LSTM is used for Arrhythmia classification. The LSTM takes the $Z = (Z_1, Z_2, \ldots Z_T)$, where T observation are used to predict the Arrhythmia at time T+1 and each Z_i is the feature embedding given by Resnet block. The hyper parameters of random forest and LSTM classifier is optimized using PSO.

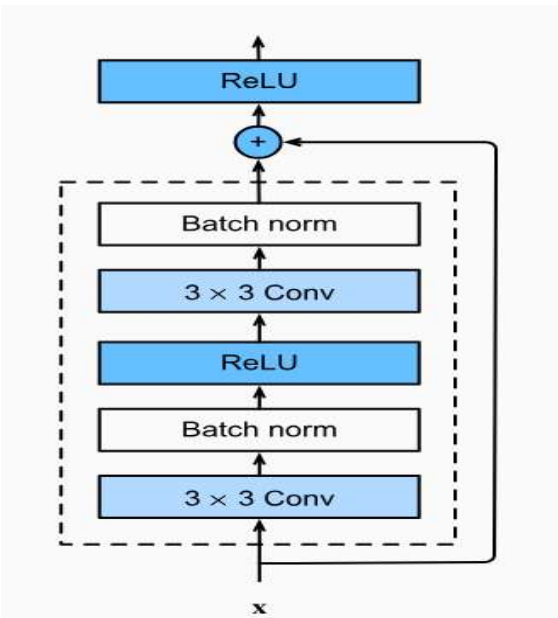

Figure 3 Resnet block

PSO is a swarm intelligence algorithm simulating the social behavior of swarm of organisms. This method is popular for solving optimization problems due it its simplicity, flexibility and versatility. Each organism updates their position by moving randomly with different velocities. Each candidate solution is a 'particle'. Each particle tries to attain its best velocity based on its own local best (p_{best}) value and its neighbor's global best (g_{best}). Each particle's next position depends on the current position, current velocity, distance from current position to p_{best}, distance from current position to g_{best}. The movement of particle in its search space depends on its velocity. For a particle X, it current position X_i and current velocity V_i is updated as

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (12)$$

$$V_i(t+1) = wV_i(t) + c_1 r_1\big(p_{besti}(t) - X_i(t)\big) + c_2 r_2\big(g_{besti}(t) - X_i(t)\big) \quad (13)$$

In the above equations, t is the iterative value. $c_1$and c_2 are acceleration coefficients, $r_1$and r_2 are random numbers, w is the inertia weight. The iteration is repeated till termination condition is met.PSO is used for finding the optimal values for hyperparameters. Say there are P hyperparameters, K particles with each particle have P parameters each corresponding to a hyperparameter is initialized with random values within range of each hyperparameters. PSO iteration is then started. At each iteration fitness value for each particle is calculated as

$$F = \frac{1}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - A_i)^2}} \quad (14)$$

Where $P_i$is the prediction result and $A_i$is the actual result calculated for n test items of classifier built with corresponding values of hyperparameters in the particle. The hyperparameters of the best particle found at end of PSO iteration is the optimal parameters for fine tuning the classifier. The hyper parameters considered for optimizing random forest and LSTM are given in Table 4 and Table 5 respectively.

Table 4 Hyperparameters of random forest

Hyperparameters	Range
Maximum depth	[10 to 30 in interval of 5]
Maximum sample split	[100 to 500 in interval of 50]
Maximum terminal nodes	[25 to 200 in interval of 25]
Minimum samples in leaf	[500-3000 in interval of 500]
Number of estimators	[50-500 in interval of 50]

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Table 5 Hyperparameters of LSTM

Hyperparameters	Range
Number of kernels in the convolutional layer	[16,24,32,40,48,52,64]
Number of columns of the kernel	[2-11]
Number of rows of the kernel	[2-11]
Stride of x-axis	[1-4]
Stride of y-axis	[1-4]
Units of fully connected layer	[50-150]
The size of a training batch.	[10-30]

4. RESULTS

The performance of the proposed solution is tested against MIT-BIH dataset [28]. The database created due to joint effort of Massachusetts Institute of Technology (MIT) and the Beth Israel Hospital (BIH) is a collection of 7 long duration ECG recordings each around 14 to 22 hours. It is the standard dataset used for testing cardiac arrhythmia. The performance is measured and compared in terms of four standard metrics of: accuracy, precision, recall and F1-score. Results were validated using 5 fold cross validation. The performance of the proposed solution is compared against CNN-BiLSTM proposed by Bhatia et al [24], RRHOS-LSTM proposed by Essa et al [25] and LSTM with Luong Attention Mechanism (LSTM-LAM) proposed by Mulam et al [26]. The comparison results are given in Table 6. The proposed solution Resnet + LSTM faired slightly higher than LSTM-LAM in terms of accuracy, precision, recall and F1- accuracy. This is due to combined feature selection optimization and hyper parameter optimization in proposed solution. The accuracy of proposed solution for each class of Arrhythmia are given in Table 7 and Table 8. The average accuracy in Resnet + LSTM is higher compared to Resnet + RF. This is due to long term temporal correlation in Resnet + LSTM. In both the proposed solution, the accuracy is consistent for all Arrhythmia classes. The results of the proposed solution for different K fold validation values are given in Table 9. With increasing K value, the accuracy increases in both the proposed Resnet+RF and Resnet+LSTM classifiers. The performance of the two proposed classifier with and without feature selection optimization is measured in terms of accuracy and the result is given in Figure 4.

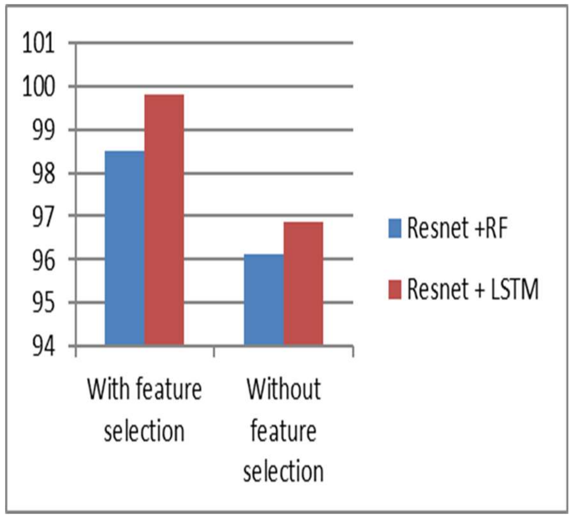

Figure 4 Feature selection comparison

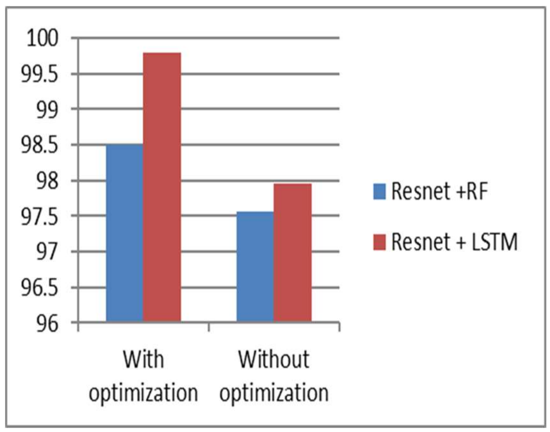

Figure 5 Classifier optimization comparison

The accuracy of Resnet + RF increased by 2.39% due to inclusion of feature selection optimization. The accuracy of Resnet + LSTM increased by 2.94% due to inclusion of feature selection optimization. On average inclusion of feature selection optimization has increased the accuracy by 2.6%. Selecting significant features in spatial and temporal context reduces the over fit problem in classification. This has contributed positively to increase of accuracy. The accuracy of two proposed classifiers with and without hyper parameter

Table 6 Comparative results

Solution	Accuracy	Precision	Recall	F1-score
CNN-BiLSTM[24]	98.36	89.4	94.24	91.67
RRHOS-LSTM [25]	95.81	N/A	69.20	71.06
LSTM-LAM [26]	99.75	96.34	99.67	99.58
Proposed Resnet+ RF	98.50	94.85	98.10	98.65
Proposed Resnet + LSTM	99.80	97.1	99.74	99.67

Table 7 Results for Proposed Resnet + RF

Classes	Accuracy	Precision	Recall	F1-score
N	98.94	98.61	95.48	97.89
SVEB	98.17	97.86	96.89	98.10
VEB	98.89	97.23	97.12	98.23
F	98.12	98.21	97.23	98.34
Q	97.25	96.89	97.87	97.47

Table 8 Results for Proposed Resnet + LSTM

Classes	Accuracy	Precision	Recall	F1-score
N	99.94	99.41	99.18	99.89
SVEB	99.27	98.86	98.99	99.30
VEB	98.99	98.83	98.52	98.80
F	98.92	99.21	98.78	98.94
Q	98.35	97.89	98.87	98.87

Table 9 K fold cross validation results

K values	Accuracy		Precision		Recall		F1-score	
	Resnet+ RF	Resnet+LSTM	Resnet+ RF	Resnet+LSTM	Resnet+ RF	Resnet+LSTM	Resnet+ RF	Resnet+LSTM
3	96.65	97.99	92.25	95.89	96.55	98.11	96.89	97.88
4	97.67	98.36	93.11	96.75	97.56	98.67	97.86	98.22
5	98.50	99.80	94.85	97.1	98.10	99.74	98.65	99.67

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optimization is measured and the results are given in Figure 5. The accuracy of Resnet +RF classifier has increased by 0.9% due to hyperparameter optimization. The accuracy of Resnet + LSTM has increased by 1.84% due to hyperparameter optimization. This implies, the impact of hyper parameter optimization is higher in LSTM deep learning classifier compared to traditional RF classifier. The accuracy of proposed classifiers with and without both optimization of feature selection and hyper parameters fine tuning is measured and results are given in Figure 6.

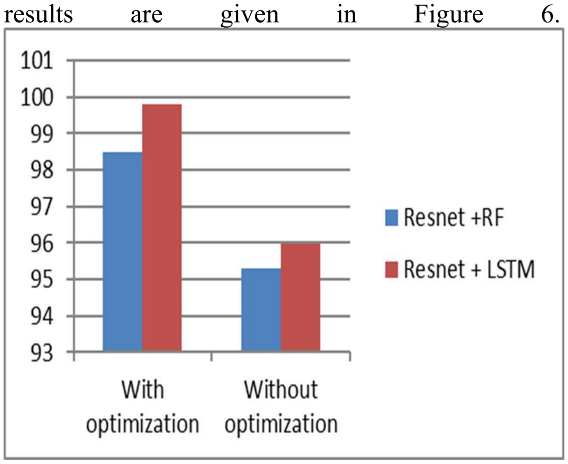

Figure 6 overall optimization comparison

The overall optimization in two stages of feature selection and hyperparameter fine tuning has increased the accuracy of Resnet + RF by 3.19% and accuracy of Resnet + LSTM by 3.83%. Thus, optimization in feature selection and hyper parameter fine tuning has increased the overall accuracy by 3.5%.

Discussion: Though deep learning has been used in CNN-BiLSTM proposed by Bhatia et al [24], RRHOS-LSTM proposed by Essa et al [25] and LSTM with Luong Attention Mechanism (LSTM-LAM) proposed by Mulam et al [26], the proposed solution performed better than these works in all measures of accuracy, precision, recall and F1-score. The performance improvement is due to the way the input ECG signal was processed in the proposed solution. Bhatia et al [24] split the ECG signal to segments and processed as whole by CNN-BiLSTM without any feature selection or parameter optimization. But in proposed solution best set of features are identified and those features were used in both temporal and spatial context. Though temporal context was considered by Essa et al [25], ECG signal was processed as whole without considering segment importance. As result, the model become overfit. But the proposed solution isolated important segments though feature analysis. The overfit problem was also seen in works of Mulam et al [26]. In addition, the redundancy between segments were higher. But the proposed solution was able to solve the problem of redundancy and overfit using entropy-based feature selection and stacking of multi view features. Thus through intelligent combination of feature engineering, stacking long term and short term dependency through multiple classifiers and hyper parameter tuning of the classifiers, the proposed solution achieved higher performance compared to existing works.

AUTHORS CONTRIBUTION:

The first author conceptualized, implemented and documented the paper work.

The second authors reviewed the paper work and improvised it.

5. CONCLUSION

Achieving higher accuracy and reduced false positives in Arrhythmiaclassification was a problem addressed in this work. A deep learning optimized framework integrating multimodality feature engineering, stacking multiple classifiers and optimization of the classifiers was proposed to solve the problem. The solution involved optimization in two stages of feature engineering and classification. Feature engineering selected optimal features from both spatial and temporal context. Classification considered both short term and long-term temporal correlation. In addition, hyper parameters of classifier model were optimized. Through performance analysis, the proposed optimizations in combined feature selection and hyper parameter fine tuning have increased accuracy by atleast 3.5% and reduced false positives by 1%. By this way the proposed solution was able to realize the objective of achieving higher accuracy with reduced false positives. Though the proposed solution achieved higher performance, it was tested only against a single dataset. Testing the performance of the proposed solution against diverse datasets and optimizing the hyperparameters through hybrid meta-heuristics is in scope of future work.

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