Automatic Heart Disease Classification Using Ensemble Features Extraction Mechanism from ECG Signals

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Received April 26, 2021; Accepted August 23, 2021
ISSN: 1735-188X
DOI: 10.14704/WEB/V18I2/WEB18354

Abstract

The heart disease detection and classification using the cost-effective tool electrocardiogram (ECG) becomes interesting research considering smart healthcare applications. Automation, accuracy, and robustness are vital demands for an ECG-based heart disease prediction system. Deep learning brings automation to the applications like Computer-Aided Diagnosis (CAD) systems with accuracy improvement compromising robustness. We propose the novel ECG-based heart disease prediction system using the hybrid mechanism to satisfy the automation, accuracy, and robustness requirements. We design the model via the steps of pre-processing, hybrid features formation, and classification. The ECG pre-processing is aiming at suppressing the baseline and powerline interference without loss of heartbeats. We propose a hybrid mechanism that consists of handcrafted and automatic Convolutional Neural Network (CNN) lightweight features for efficient classification. The hybrid feature vector is fed to the deep learning classifier Long Term Short Memory (LSTM) sequentially to predict the disease. The simulation results show that the proposed model reduces the diagnosis errors and time compare to state-of-art methods.

Keywords

Convolutional Neural Network, Electrocardiogram, Heart Disease Detection, Classification, Smart Healthcare.

Introduction

Nowadays, Computer-Aided Diagnosis (CAD) becomes the essential component for ECG-based heart disease detection. Several standard techniques were proposed for the automatic detection of abnormal heart conditions (Ponikowski, P., 2014). The ECG signals are examined to recognize these abnormal conditions directed by utilizing auto-correlation work, frequency area features, time-frequency investigation, and wavelet change. Even though there exist great outcomes on recognizing ordinary and strange patients, isolation between anomalous ECG signals and their worthy arrangement is yet to be consummated (Mahajan, H.B., 2021; Rajpurkar, 2017; Mahajan, H.B., 2018). The feature extraction from the ECG signal is vital as it consists of different types of heartbeats or waves. After pre-processing, the ECG signal is consists of dissimilar types of waves such as Q wave, R wave, S wave, P wave, T wave, etc. that mainly represents the heart conditions of the human being. The Q, R, and S wave is known as the QRS complex that addresses ventricular depolarization. The P wave addresses atrial depolarization and the T wave addresses the repolarization of the ventricle.

The ECG-based heart disease prediction is mainly designed in two steps after the pre-processing such as features extraction and characterization. The Q, R, and S wave is known as the QRS complex that addresses ventricular depolarization. The P wave addresses atrial depolarization and the T wave addresses the repolarization of the ventricle. fluctuation, and so forth or in the frequency space to find varieties in QRS-complex power spectra among ordinary and arrhythmia waveforms, time-frequency area to show simultaneously ECG frequency and time features. The second step is the classification has been established by several methods, such as the Artificial Neural Network (ANN), Support Vector Machine (SVM), Naïve Bayes (NB), k-Nearest Neighbors (KNN), etc. The features extraction step is quite challenging compared to the classification step as it is important to extract the accurate and unique QRS complex as features. Feature removal techniques incorporate wave shape functions (deChazal, P., 2004), Hermite functions (Lagerholm, M., 2000), wavelet-based features (Ince, T., 2009), and statistical features (De Lannoy, G., 2012). Techniques to organize certain extracted features incorporate decision trees (Rodríguez, 2005), SVM (Rodríguez, 2005), KNN Jung, W.-H., 2017), linear discriminants (Jiang, W., 2007) and ANN (Jiang, W., 2007). Existing automatic ECG identification systems normally rely on a pattern-matching structure that represents the ECG signal as a series of stochastic patterns. They need complex feature removal techniques and large sampling rates and are consequently time-consuming. For real-time implementation in the hospital at a reduced cost, certain practices must use a modest set of features and a cheaper sampling rate. However, such systems undergo various difficulties in achieving perfect heart disease classification in terms of scalability, robustness, and efficiency.

Different combinations of deep learning methods are widely used for image verification, object classification, object recognition, speech recognition, and action recognition. It brings complete automation for such applications with improved accuracy. Deep learning methods are explored to create a deep and multistage architecture for unsupervised learning and recognition systems. ECG-based heart disease detection using deep learning techniques like CNN's had shown improved performances. These methods have shown accuracy improvement using automated features learning and extraction on specific ECG datasets, but yet it comes with challenges of scalability and robustness. The beat classification from ECG signal is a vital part of accurate heart disease classification and can further utilize by the cardiologist for treatment purposes. CNN extracts the multi-layer automatic features rather than such heartbeats-specific features. It motivates to offer the novel framework of ECG-based heart disease detection using the hybrid mechanism of features extraction. We first design the ECG processing to remove the artifacts from the raw ECG signal. Then we propose the hybrid approach of features extraction using the Stationary Wavelet Transform (SWT) and automatic CNN features. The hybrid features are reduced using manifold learning and normalized before feeding to the deep learning classifier LSTM for disease detection. Section 2 presents the related works to this research. Section 3 presents the methodology for ECG-based disease detection. Section 4 presents simulation results and discussions. Section 5 presents the conclusion and future works.

Related Works

This section presents a review of some recent works for ECG-based heart disease detection. The reviewed methods mainly focused on feature extraction either using handcrafted or deep learning methods. The QRS complex detection algorithm using the computation of time-dependent entropy of ECG signal proposed in (Farashi, S., 2016). The computation of entropy was performed at various temporal resolutions to enhance the QRS detection accuracy. Another novel technique of QRS complex detection using the deterministic finite automata proposed in (Hamdi, S., 2017). They used regular grammar for extracting QRS complexes and interpreting normalized ECG signals. The enhanced and accurate QRS beat detection proposed in (Sheetal, A., 2019) using the hybrid filtering technique. They designed hybrid filtering using maximum mean minimum and derivative filtering techniques. The Independent Component Analysis (ICA) was used to pre-process the raw ECG signal in (Gupta, V., 2020) followed by the chaos analysis for QRS complex extraction. Some other methods for Heart disease classification using different approaches reported using the handcrafted features. The recent automatic approach of heart disease diagnosis using the Discrete Wavelet Transform (DWT) and Principle Component Analysis (PCA) approach was introduced in (El-Saadawy, 2017). They designed the dynamic segmentation policy to consider the heart rate variation, and DWT was used to extract such beat features followed by PCA to reduce the dimension. Another DWT-based method recently proposed for the ECG wave's detection and features extraction in (Gutiérrez-Gnecchi, J., 2017). They used the Probabilistic Neural Network (PNN) for the classification process. The mechanism of ECG heartbeats segmentation had proposed in (Bognár G., 2020) using the adaptive transformation exploring the rational functions. They segmented the input ECG signal into waves like T, P, and QRS.

The deep learning-based method proposed in (Huang, J., 2019) for ECG arrhythmia grouping using 2D CNN. The Short-Time Fourier Transform (STFT) was applied to input ECG data. The spectrogram generated by STFT fed to 2D CNN for automatic heart disease classification. This model was called STFT-CNN. The deep learning-based effective model was proposed in (Tabaa, M., 2019) using time-frequency and convolutional unit presentations. The CNN was used to automatically train the ECG signals and classify them in either of the classes. Another recent CNN-based architecture had proposed in (Tyagi, A., 2021) for the classification of heart diseases using the ECG data. The hybrid CNN model had proposed using Grasshopper Optimization Algorithm (GOA) to address the challenges related to artifacts and noises. They used pre-processing and DWT-based features extraction techniques rather than relying on automatic CNN features for the GOA-CNN model. The novel architecture for heart disease classification automatically using the CNN proposed in (Avanzato, R., 2020). The raw ECG signals were directly passed to 5 Layer CNN (5L-CNN) for automatic feature extraction and classification. The deep learning technique was recently proposed in (Zhang, X., 2020) for automatic disease detection and classification from input ECG signals. They trained 18 Class CNN (18C-CNN) to predict cardiovascular heart disease in raw ECG signals. The recent CNN-based ECG heartbeat segmentation and classification approach had proposed in (Qiu, X., 2021). They achieved the segmentation and classification simultaneously using the speedy R-CNN model. Another study used the deep learning model called Restricted Boltzmann Machine (RBM) for the ECG-based arrhythmias classification in Pandey, S.K., 2021).

The deep learning methods received more attention recently over the semi-automatic techniques, but there are some challenges that yet to address using automatic methods for ECG-based heart disease detection. Automatic feature extractions from the raw ECG signals lead to erroneous results considering the real-time health practices. Also, they are a possibility of a loss of heart wave-specific features using the CNN-based approach directly. To address these limitations, we propose the novel approach of ECG-based heart disease detection in which we design the steps pre-processing, hybrid features extraction, and deep learning classifier. The contributions are summarized as:

- Adaptive and robust ECG signal pre-processing technique to remove the baseline wander, power line interference, and noises without loss of original data related to heartbeats.
- Hybrid approach for features extraction using dynamic handcrafted and robust CNN techniques. The handcrafted features extracted using dynamic threshold-based QRS complex extraction using 3rd level SWT decomposition. The CNN-based automatic features extracted by passing pre-processed ECG signal to lightweight 3 layer CNN model. The handcrafted features and CNN-features are ensemble, reduced and normalized to enhance the classification performance.
- Deep learning model LSTM for classification purpose where automatically probabilities computed for early prediction of ECG disease accurately.
- Performance analysis of the proposed model with state-of-art classifiers and methods using publically available research dataset.

Proposed System

Figure 1 shows the architecture of the proposed system for ECG-based heart disease detection. The input raw ECG signal is pre-processed to remove baseline wander, cancellation of powerline interference, and removal of other types of noises. For that purpose, we design robust and adaptive filtering in this paper. After pre-processing, hybrid feature extraction performs using handcrafted features and automatic CNN-based features. The handcrafted and CNN features are fused, then the manifold learning technique has applied to reduce the high-dimensional features followed by the features normalization. It generates the outcome of the hybrid feature extraction block of the proposed architecture. The LSTM classifier performs the early prediction of heart disease by taking normalized feature vectors as sequential input. The output layer of LSTM classifies the input ECG signal either of heart disease classed based on probability score (the class with a high probability score). The goal of the proposed integrated approach has to address the challenges related to scalability, accurate QRS-complex extraction, fast disease detection, and classification accuracy.

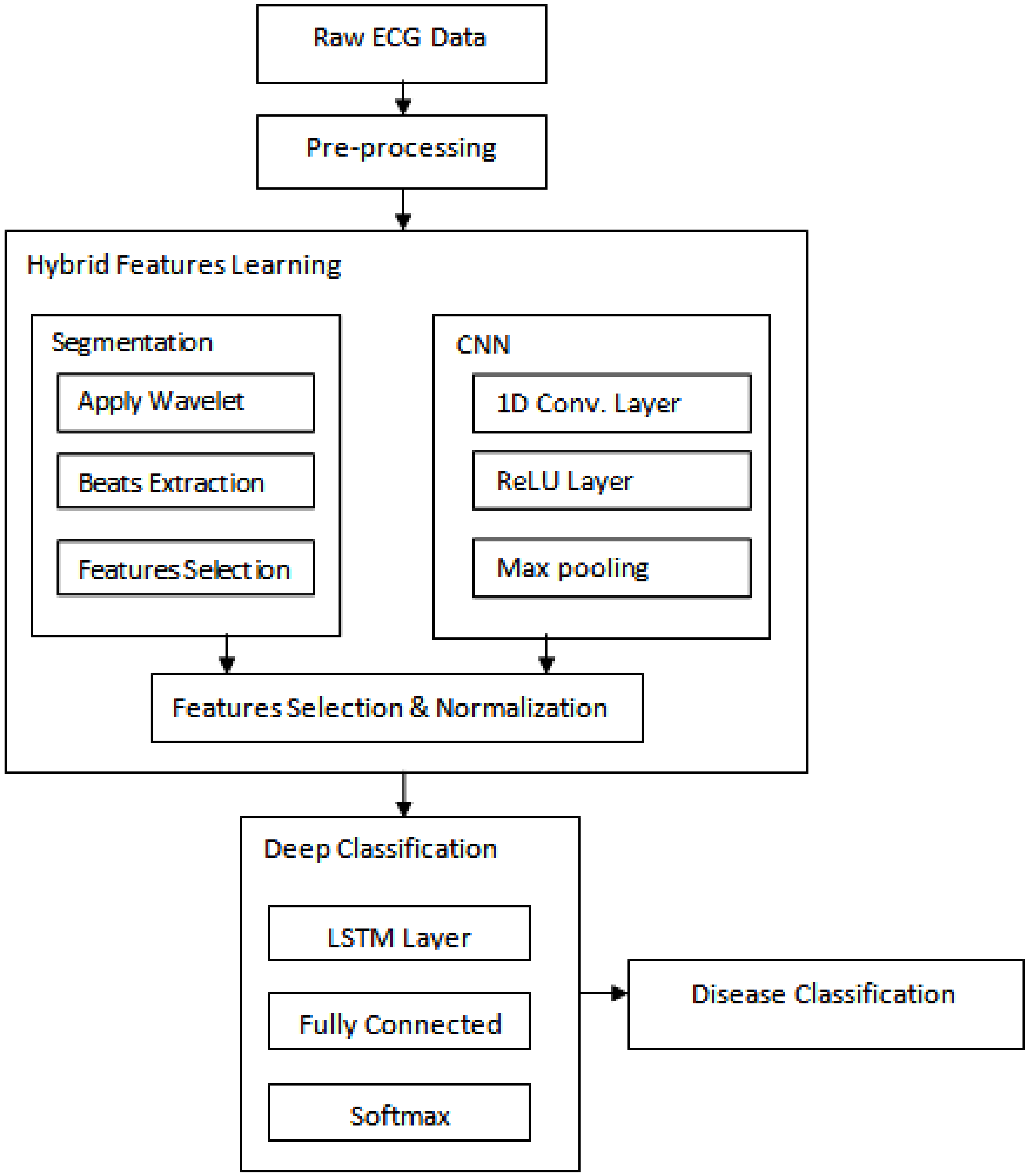

Figure 1 Proposed framework of ECG-based heart disease detection

A. Signal Pre-processing

We design the pre-processing algorithm using the 1D median filtering of different widths and second-order notch filtering in this paper. To remove the baseline wander, we apply 1D median filters twice to prevent data loss while removing the baseline wander artifact from the input signal I. As the baseline wander presents in ECG signal due to the respiration having the low incidence components, two median filters of 200 ms and 600 ms widths applied respectively. The outcome of both filters represents ECG signal baseline and hence subtracted directly from the original ECG signal to get the ECG indication without baseline wander. To remove another ECG artifact called powerline interference, the simple yet effective second-order notch filtering of 60 Hz frequency component. The notch cutoff frequency is 35 Hz. The use of twins of median filtering followed by notch filtering ensures the removal of noises along with baseline wander and powerline interferences with the minimum computational burden. The output of these steps is I^P.

B. Hybrid Features Extraction

This step consists of three sub-steps such as heartbeat segmentation, CNN-features extraction, and features optimization. We segment ECG signal to get QRS beats using adaptive transform domain function applied. The CNN applied on pre-processed ECG signal to extract the automatic features. Finally in features optimization step, the features of both handcrafted and CNN ensembled. The ensembled feature vector processed for dimensionality reduction and features normalization.

I. Dynamic Heartbeat Segment

We apply the third level SWT decomposition for the segmentation of pre-processed ECG signal segmentation and QRS features extraction. Algorithm 1 shows the working of proposed handcrafted features vector construction using Normalized SWT (NSWT). Before using the SWT decomposition, the pre-processed ECG signals normalized to overcome the challenges in accurate wave detection for complex ECG signals. The pre-processed ECG signal I^P is normalized and represented as I^N:

$$I^N = \frac{I^{p^2}}{\max|I^{p^2}|} \tag{1}$$

After the signal normalization, the 3rd level NSWT decomposition using Haar wavelet was applied to get the approximation and detailed coefficients. The third level approximation (AAA) and detailed coefficients (DDD) have been used to detect the QRS beats A^{QRS} and D^{QRS} respectively in this paper. The QRS beats A^{QRS} and D^{QRS} are extracted using the dynamic thresholding technique. The adaptive mechanism of QRS extraction overcomes the challenges of scalability and data loss. This is the first time that both approximation and detailed coefficients are used for the QRS estimation independently and then QRS complex are represented by the fusion of both coefficients F^{AD} for accurate estimation of QRS features of the input normalized ECG signal.

Algorithm 1: Dynamic Heartbeat Segmentation and Features Extraction
Inputs $I^P: pre-processed\ ECG\ signal$ $A^{QRS} = [null]: QRS\ features\ detected\ as\ approximate\ coeff.$ $D^{QRS} = [null]: QRS\ features\ detected\ as\ detailed\ coeff.$ *Output* $F^{AD}: feature\ vector\ using\ approximate\ (A) and\ Detailed\ (D) Coeff.$

1. I^N: Normalize I^P using Eq. (1)
2. $[SA, SD] = swt\ (I^N, 3,\ haar)$
3. Extract 3rd level Approximate and Detected Coefficients
4. $AAA = SA\ (3,:)$
5. $DDD = SD\ (3,:)$
6. Compute the thresholds T^A and T^D using Eq. (2) and (3) respectively
7. Compute the QRS complex as:
8. For $i = 1: size\ (AAA)$
If $(AAA(i) > T^A)$
$A^{QRS} = (A^{QRS}; AAA(i))$
End If
End For
9. For $i = 1: size\ (DDD)$
If $(DDD(i) > T^D)$
$D^{QRS} = (D^{QRS}; DDD(i))$
End If
End For
10. $F^{AD} = ((A^{QRS}), dct(D^{QRS}))$
11. $return\ F^{AD}$

After extracting the 3rd level coefficients i.e. AAA and DDD, the dynamic threshold T^A and T^D respectively for each coefficient as:

$$T^A = \frac{|\max(AAA)|}{2} \tag{2}$$

$$T^D = \frac{|\max(DDD)|}{2} \tag{3}$$

II. CNN-Features Extraction

After extracting the handcrafted features, the automated approach of lightweight CNN features extraction designed. It takes input I^P pre-processed ECG signal and produces the automatically extracted CNN features F^{CNN}. As compared to recent CNN-based methods, we focused on lightweight design CNN layers to extract features from input 1D ECG data. The CNNs are a specialized type of neural network automatically. Table 1 show the design of the proposed 3L-CNN model to extract the features from input pre-processed ECG signals with reduced computational costs. At the first convolutional layer, the kernel size is set to 40 elements which are further reduced for the second and third convolutional layer to 3. This significantly reduces computational efforts. After every 1D convolutional layer, we applied the batch normalization to overcome the challenges of parameter explosion and vanishing gradients. For quick and effective extraction of features, we applied 1D ReUL followed by the max-pooling in 3L-CNN. The output of the third layer is 128x4 features extracted from the input ECG signal of size 1x10000.

Table 1 Configuration of proposed 3L-CNN for automatic features extraction

Layers	**Convolutional Layer**	**Batch Normalization**	**ReUL Layer**	**Pooling Layer**
LAYER 1	**Conv1D (1, 64, 40, 4):** *Input*: 1 channels *Output*: 64 channels *kernel size*: 40 *Stride*: 4	**BatchNorma1D (64):** Features: 64	**ReUL1D(64):** Features: 64	**MaxPool1D(64):** kernel size: 4
LAYER 2	**Conv1D (64, 64, 3, 4):** *Input*: 1 channels *Output*: 64 channels *kernel size*: 4 *Stride*: 3	**BatchNorma1D (64):** Features: 64	**ReUL1D(64):** Features: 64	**MaxPool1D(64):** kernel size: 4
LAYER 3	**Conv1D (64, 128, 3, 4):** *Input*: 1 channels *Output*: 128 channels *kernel size*: 4 *Stride*: 3	**BatchNorma1D (128):** Features: 64	**ReUL1D(128):** Features: 128	**MaxPool1D(128):** kernel size: 4

Using above structure of 3L-CNN, we extracted the features vector. The 1D convolutional layer, batch normalization layer, ReUL layer, and max pooling layer consolidated in one squashing layer. This leads output of max pooling layer with additive bias as:

$$F_j^l = tanh\left(pool_{max}\left(\sum_i f_j^{l-1} * kij\right) + b_j^l\right) \qquad (4)$$

Where,

- F_j^l: are the feature maps produced by the ReUL l of j^{th} max-pooling kernel
- f_j^{l-1}:are the feature maps of the previous ReUL $l-1$,
- $kij:$ are the i trained convolution kernels

- b_j^l: the additive bias
- $pool_{max}(\cdot)$: the max-pooling operation
- $tanh(\cdot)$: the hyperbolic activation function.

The final layer F_j^l stored into the output variable F^{CNN} as 2D feature vector.

III. Features Selection and Normalization (FSN)

The extracted features vectors F^{AD} and F^{CNN} are first resized to standard size for entire dataset in this step. F^{AD} and F^{CNN} are then fused to form the feature vector of size 256 x 1 into variable F^{Ens} as:

$$F^{Hyb} = [F^{AD}, F^{CNN}] \quad (5)$$

As the size of extracted features F^{Hyb} is high, features selection becomes vital to enhance the prediction accuracy and minimize the computational efforts. We applied the manifold learning for features selection on extracted features. This technique builds the reliable and unique features compared to other features selection techniques. The features from each vector selected up to 50 using manifold technique as:

$$F^{Hyb} = [manifold(F^{AD}, 50),\ manifold(F^{CNN}, 50)] \quad (6)$$

After the features reduction, we normalize them using log 10 approach as:

$$F^{norm} = -sign(F^{Hyb}) * log10|F^{Hyb}| \quad (7)$$

This approach not only helps to reduce the space and time complexity but also improve the heart disease detection performance significantly.

C. Classifiers

In this paper, we used CNN for automatic features extraction, but for classification, we design the LSTM sequential classifier for disease prediction. The hidden LSTM units consist of memory blocks that are controlled by memory cells, an input and output gate, a forget gate, and peephole connections. The LSTM layer, fully connected layers, and softmax layer operations are performed in the LSTM model to classify the input features into either of heart disease classes. We design the LSTM with the number of hidden layers 150 and epoch 27. For comparative analysis, we applied the other classifiers also. All the performances are measured by portioning the dataset in 70 % training and 30 % testing ratio.

Simulation Results

We implement and evaluate the proposed model using MATLAB on Windows 10 OS with an I3 processor and 4GB RAM. All experiments are performed on a publically available research dataset PTB Diagnostic ECG Database [47]. This dataset consists of the collection of ECG data from 290 subjects. The ECG records were collected under several classes such as myocardial dead tissue, Cardiomyopathy/Heart disappointment, Pack branch square, Dysrhythmia, Myocardial hypertrophy, Valvular heart disease, Myocarditis, Miscellaneous, and healthy control. We first investigate the performance of the proposed hybrid mechanism of features extraction using different classifiers such as LSTM, Ensemble Classifier, ANN, SVM, and KNN. After that, we present the comparative analysis with state-of-art methods. The performance parameters such as accuracy, precision, recall, F1-score, and prediction time are measured.

Table 2 Accuracy performance analysis

	Raw Features	FSN
KNN	79.65837	82.41837
SVM	81.34072	85.77209
ANN	86.34364	88.15356
ESEMBLE	87.33431	88.6415
LSTM	94.72072	98.27595

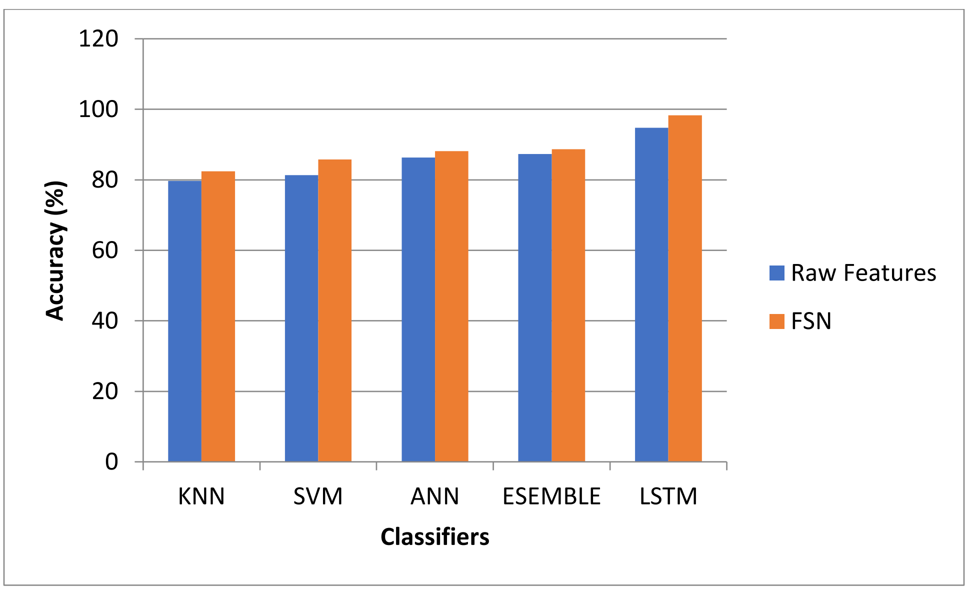

Figure 2 Heart disease classification accuracy analysis

Table 3 Precision performance analysis

	Raw Features	FSN
KNN	79.0529	81.37
SVM	77.31	81.19
ANN	78.94949	82.2091
ESEMBLE	82.33308	82.99
LSTM	94.03	97.66595

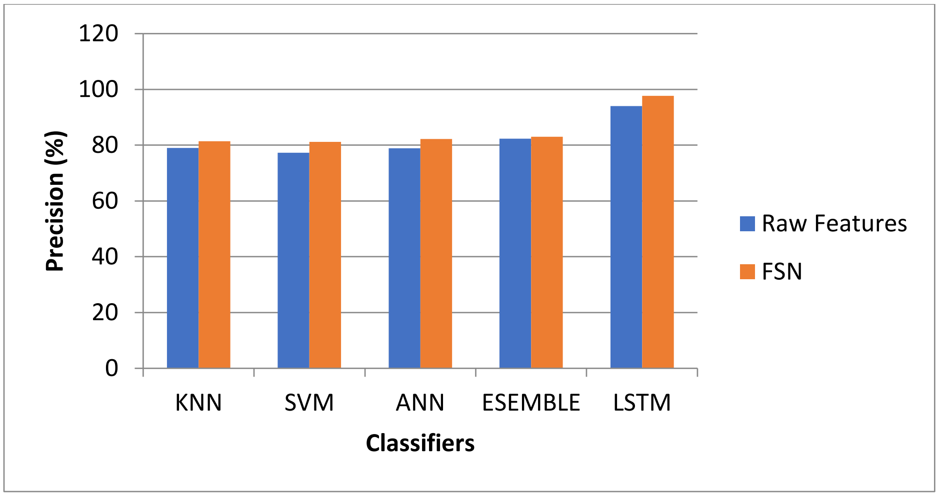

Figure 3 Heart disease classification precision analysis

Table 4 Recall performance analysis

	Raw Features	FSN
KNN	84.58	86.41
SVM	85.71	88.32
ANN	89.77351	91.70688
ESEMBLE	90.33	91.51
LSTM	95.92	100

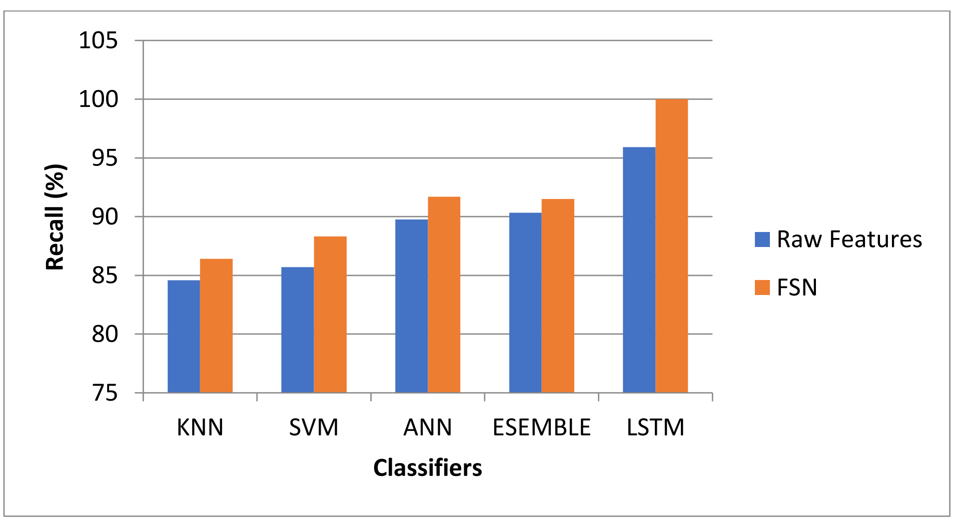

Figure 4 Heart disease classification recall analysis

Table 5 F1-score performance analysis

	Raw Features	FSN
KNN	81.72311	83.8143
SVM	81.29358	84.60505
ANN	84.01431	86.69865
ESEMBLE	86.14635	87.042
LSTM	94.9656	98.81919

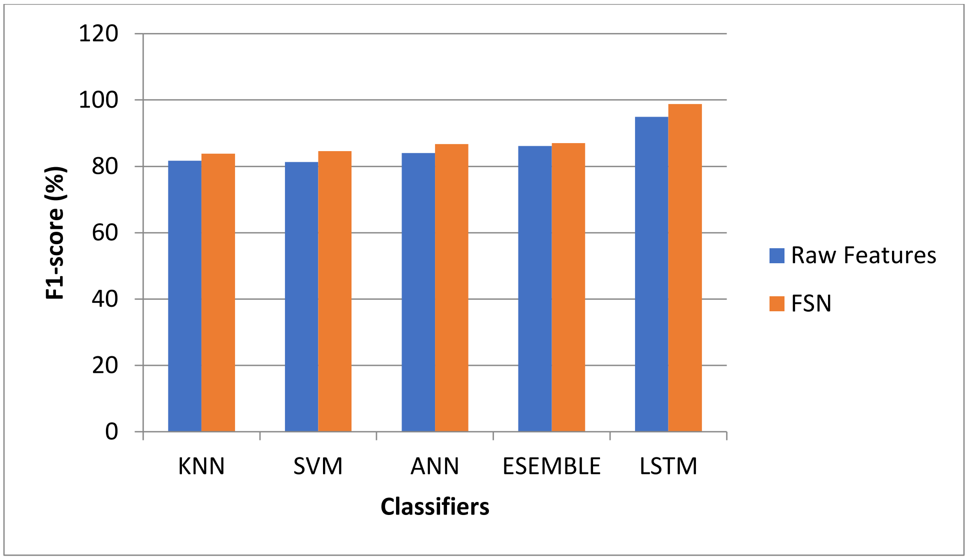

Figure 5 Heart disease classification F1-score analysis

Table 2-5 (figures 2-5) shows the outcome of heart disease classification accuracy, precision, recall, and F1-score using different classifiers. From these results, it seems that FSN with LSTM produces better performances compared to other classifiers. It is because LSTM addresses the problem of gradient exploding, overfitting, and class imbalance effectively compared to other classifiers. The performance mainly improved due to the probabilistic LSTM classifier with sequential hybrid features as input for early prediction heart disease. Among SVM, KNN, ANN, and EC classifiers, the EC shows superior performance for all these parameters due to the ability to minimize misclassification compared to other classifiers. The KNN classifier is shown poor performance among all the classifiers. The F1-score parameter indicates another form of prediction accuracy analysis of classifiers.

On the other side, we compared the raw hybrid features with the FSN features to shows the effect of applying feature selection and normalization on classification performance. The performances are significantly enhanced using the FSN for each classifier. Manifold learning able to reduce redundant features by selecting the meaningful and unique features from the high-dimensional hybrid feature vector. The result of manifold learning has normalized to reduce classification flaws further. The advantages of manifold learning followed by feature normalization reduce misclassification and training errors. Moreover, feature normalization does the clear process of distance calculation in machine learning techniques. The normalized range of all features guides to efficient weight calculation during the training and classification.

Finally, we compare the performance of the proposed model with state-of-art ECG-based heart disease classification using deep learning techniques (Alhayani, B., 2021). We have implemented recent methods such as STFT-CNN (Tabaa, M., 2019), GOA-CNN (Tyagi, A., 2021), 5L-CNN (Avanzato, R., 2020), 18C-CNN (Zhang, X., 2020). Table 6 demonstrates the accuracy, F1-score, and average training-detection time. The comparative results claim that the proposed model of heart disease classification produces the efficiency of ECG-based heart disease classification in reduced computational burden significantly compared to all existing deep learning-based methods. The effective pre-processing algorithm, adaptive QRS-complex extraction, lightweight CNN-features extraction, features optimization using manifold learning and normalization, and LSTM for classification overcomes the challenges of the existing model. And this is confirmed by the performances demonstrated in this paper.

Table 6 Performance analysis with state-of-art methods

	Accuracy	F1-score	Time
STFT-CNN	95.67	96.03	4780
GOA-CNN	95.99	96.43	4982
5L-CNN	96.72	96.56	3789
18C-CNN	95.71	96.15	5890
Proposed	**98.27**	**98.81**	**3184**

Conclusion and Future Works

The goal of this paper was to present a novel approach for ECG-based heart disease classification. We designed the integrated mechanism that brings the automation without the loss of vital heart wave's related data. The adaptive heartbeats segmentation leads to the accurate representation of heart functionality with the automated features learning by CNN. It helps to reduce misclassification errors. As the features vector builds by CNN and QRS complex features, the FSN approach delivers a more effective and reliable features set for the accurate classification of heart diseases. The experimental results confirm that the proposed model produces better performances compared to other deep learning-based methods. For future work, we suggest investigating a more number of datasets to access the performance reliability of the proposed model.

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