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A Novel Hybrid Deep Learning System for Cardiovascular Detection and Salient Feature Extraction from ECG Data

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Abstract— The Cardiovascular system is responsible for the circulation of blood throughout the body. Abnormalities in the cardiovascular system can lead to various diseases such as arrhythmia, heart failure, and myocardial infarction. The Electrocardiogram (ECG) is unique and commonly used diagnostic tools for detecting cardiovascular diseases. The conventional methods of ECG analysis require expert interpretation and are time-consuming. Automated ECG analysis systems cantered on machine learning and also deep learning techniques have been proposed to overcome the limitations of conventional methods. In this research, we propose a hybrid deep learning-based cardiovascular detection system that can accurately detect various cardiovascular diseases by extracting salient features from ECG data. The suggested approach combines feature extraction using a convolutional neural network with wavelet transform and principal component analysis. The fused signals obtained from the previous steps are optimized using Sequential Minimal Optimization (SMO) algorithm to improve classification accuracy. Therefore, the development of a reliable and automated ECG analysis system is highly desirable testing on a publicly available ECG dataset from MIT-BIH Arrythmia.

Keywords- Cardiovascular, Electrocardiogram, Deep Learning, Abnormalities, Feature Extraction

I. Introduction

CVDs are considered as most dangerous to the patients who neglect their health by risking it with unhealthy food plan and also risky lifestyle [1-2]. ECG is a non-invasive and extensively used diagnostic tool for cardiovascular diseases. The ECG records the heart's electrical signals as it beats, and provides valuable information about the heart's function and any abnormalities [3]. ECGs are routinely used in clinical settings to diagnose and monitor a range of cardiovascular conditions, such as arrhythmias, myocardial infarction, and heart failure [4]. However, conventional ECG analysis methods are time-consuming and require expert interpretation [5-6]. To overcome these limitations, there has been growing interest in developing automated ECG analysis systems based on deep learning techniques. Early detection of these diseases can play a vital role in reducing the mortality rate.

Deep learning-based techniques have yielded encouraging outcomes for ECG analysis in recent years [7]. Deep learning is a machine learning discipline that use artificial neural networks to acquire knowledge from data [8-10]. These networks can identify patterns and features in the ECG signals that are difficult for human experts to discern. In this context, the proposed research intentions to design a hybrid deep learning centered cardiovascular detection system that can accurately detect various cardiovascular diseases by extracting salient features from ECG data. The system integrates wavelet transform and principal component analysis for feature extraction, as well as a traditional neural network for detection. The suggested system has the possible to be employed in medical settings as a reliable and automated ECG analysis system, assisting in the early detection and management of cardiovascular illnesses.

A. Contribution

The current study seeks to advance the field of cardiovascular disease diagnostics by providing a hybrid deep learning-based cardiovascular detection system. The cardiovascular system is responsible for circulating blood throughout the body, and any anomalies in this system can Ea result in a variety of catastrophic disorders such as arrhythmia, heart failure, and myocardial infarction.

While the ECG is a frequently used diagnostic tool for diagnosing cardiovascular problems, traditional methods of ECG analysis are time-consuming and rely on professional interpretation. To address these shortcomings, machine learning and deep learning-based ECG analysis methods have been developed.

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By extracting prominent features from ECG data, we offer a unique hybrid deep learning-based cardiovascular detection system that considerably improves the accuracy of detecting various cardiovascular disorders. The suggested approach combines wavelet transform and principal component analysis for feature extraction, with the goal of identifying important patterns and information from ECG data.

Furthermore, the system employs a Convolutional Neural Network (CNN) for classification, which has demonstrated exceptional performance in pattern recognition tests. The suggested system is aimed to autonomously classify ECG data and detect probable cardiovascular issues correctly and efficiently by harnessing the power of deep learning.

The merging of the retrieved features from the wavelet transform and principal component analysis, optimising the classification process using the Sequential Minimum Optimisation (SMO) algorithm, is the key originality of this research. This combination of features and optimisation improves overall classification accuracy, making the system more dependable for automatically diagnosing various cardiovascular illnesses.

Extensive testing is done on a publicly accessible ECG dataset from MIT-BIH Arrhythmia to confirm the efficiency and performance of the anticipated system. The use of a well-established and extensively used dataset ensures the suggested method's robustness and generalizability.

B. Paper formulation

The organized preparation of the article is presented as, Section 2 evaluates the associated works done in the field of detection of Cardiovascular disease. Section 3 designates the particulars of the suggested methodology with algorithm. In section 4, investigational evaluation and discussion is carried out. Section 5 explains conclusions of the paper.

II. Related Work

This literature review aims to deliver an indication of the existing literature on the use of deep learning-based approaches for cardiovascular disease detection and feature extraction from ECG data.

In 2022 [11], sawano et al., suggested a fully connected network based 2D CNN. Fully connected network based 2D CNN does not take into account the temporal information present in ECG signals, as it processes each segment of the ECG signal independently. This can limit its ability to capture the active changes in the ECG over time, which is essential for precise analysis and monitoring of cardiovascular diseases.

Tongtong Liu suggested in 2021 [12] a technique for identifying CAD based on Support Vector Machine (SVM) with almost 90% of accuracy. The performance of SVM is extremely dependent on the choice of hyperparameters, such as kernel type, kernel width, and regularization parameter. Tuning these parameters requires significant expertise and trial-and-error, which can be time-consuming and computationally expensive.

In 2020 [13], Siddiqui et al. proposed a machine learning approach using Fuzzy Logic with 87 % of accuracy in detecting the anomalies related to Heart to issues. Fuzzy logic systems are complex, and it can be difficult to interpret the decision-making process. This lack of transparency can make it challenging for clinicians to understand and trust the results of the analysis

In 2019, Jalil Nour Mohammadi-Khiarak proposed an amalgamated system with K-nearest neighbour with a less accuracy of 91 % [14]. KNN is known to perform poorly with high-dimensional data.

In 2018, Reddy et al. proposed a feature reduction-based detection procedure involving Fuzzy classifier with a very less accurate value of 76.51% [15]. Therefore, it was observed that the proposed work utilized less dataset and also provided less accuracy.

In 2018, the authors developed a CNN model with Multi perceptron layer for early detection of CVD diseases [16]. This combination both did poorly in this trial, with 88.7 percentage and 83.5 percent, respectively.

In 2017 Chen et al. [17] planned a multisection convolutional besides residual system (MBCRNet). Therefore, it was observed that the proposed work utilized less dataset and also provided less accuracy of around 87 %.

The research gap in CVDs is to be focused on improving prediction accuracy by combining multiple factors with traditional classification methods. Following a first-hand comprehensive survey of the most recent 5 years of research papers corresponding to CVD detection with various algorithms, the following limitations and gaps have been identified that must be addressed and solved in this work.

- Attainment of Less Accuracy from previous methods.
- Usage of less relevant dataset to carry training and testing
- Potential bias in Patient dataset or using non-standardized dataset
- Inherent limitation of in-built methods such K-nearest neighbour as it is sensitive to the selected data.

III. Multimodal Fusion Framework

The data base of ECG signals from and MIT-BIH arrythmia[18] via Kaggle CVD datasets is collected. The data consists of varied databases with documents of differing modalities and varying characteristics. The Deep Learning algorithms with Multi modal fusion of ECG Signals for which implementations are available named as Hybrid Deep Learning System will be considered for the purpose.

The process flow of the work is provided in Fig.1

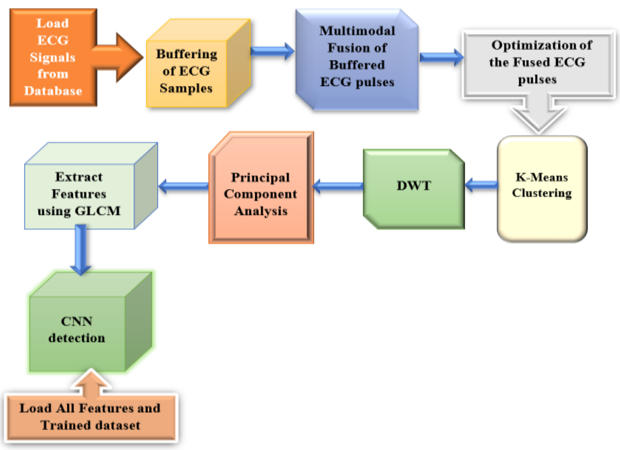

Fig. 1 Block diagram of Multimodal Fusion Framework

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A. Algorithm

Step i. Download the 48 half-hour odds and ends of the two-channel based ambulatory ECG recordings from the voluntarily participated 47 patients who were the subject of BIH Arrhyt hmia Laboratory investigations.

Step ii. These signals are buffered, as it ensures that no data is lost during the processing of the ECG signal. ECG signals can be affected by noise and other artifacts, and buffering allows for the removal of these artifacts before analysis.

Step iii. Multimodal Fusion of Buffered signals, as it can provide additional benefits compared to processing individual signals separately, including improved signal quality, enhanced diagnostic accuracy, robustness to sensor failure, and improved feature extraction.

Step iv. Optimization of the Fused signals is carried out using Sequential minimal optimization (SMO), is an algorithm used for resolving quadratic programming (QP) problems, which can be used for optimizing fused ECG signals. QP problems are optimization problems where the objective function is quadratic and the constraints are linear.

The basic mathematical model of the SMO algorithm is as follows:

- Given a QP problem in the form:

minimize:1/2(x^T P x + q^T x) ……………(1)
subject to: G x ≤ h, A x = b

- where x is the variable vector, P is a symmetric positive-definite matrix, q is a vector, G is a matrix, h is a vector, A is a matrix, and b is a vector.
- The SMO algorithm starts by initializing the variable vector x and a set of Lagrange multipliers α to zero.
- It then selects two Lagrange multipliers αi and αj to optimize, subject to the constraints.
- The optimization problem for αi and αj is given by:

maximize: L(αi,αj) ……………………….(2)

subject to: 0 ≤ αi, αj ≤ C, αi y_i + αj y_j = constant
Where y_i and y_j are the labels of the data points corresponding to αi and αj, C is a constant that controls the trade-off between maximizing the margin and minimizing the classification error, and L(αi, αj) is the objective function provided in equation(3).

L(αi,αj)=1/2 (K(i,i)αi^2+ K(j,j)αj^2- 2K(i,j)αi αj)- y_i αi - y_j αj + constant… (3)

- where K(i,j) is the kernel. The SMO algorithm solves the optimization problem for αi and αj using analytical methods, and updates the variable vector x and the Lagrange multipliers α based on the solution. It then repeats the process of selecting two Lagrange multipliers to optimize until convergence is achieved.
- In the context of optimizing ECG signals, the variables x can represent the fused ECG signal, and the Lagrange multipliers α can represent the weights assigned to each individual ECG signal in the fusion process.
- The kernel function K(i,j) can be chosen based on the characteristics of the ECG signals, and the objective function L(αi, αj) subject to constraints such as ensuring the fused ECG signal is smooth or has a certain frequency content.

Step v. The optimized Fused signals are subjected to K-Means which is a popular unsupervised machine learning algorithm used for clustering data points into k groups. In the context of optimizing fused ECG signals, K-Means clustering will be applied to group similar signals together based on their feature vectors. The mathematical model of the K-Means clustering algorithm can be defined as follows:

- Assumed a set of n points x_1, x_2, ..., x_n and a pre-defined number of clusters k
- Initialization of the k cluster centroids in a Random fashion referred by c_1, c_2, ..., c_k.
- Use a distance measure to assign each data point to the nearest centroid. The Euclidean distance is a typical distance metric utilized in K-Means clustering.
- Calculate the mean for the Corresponding data points.
- Repeat steps 2 and 3 until convergence, where convergence is achieved when the cluster assignments no longer change.
- The distance metric used in K-Means clustering can be defined as

$$d(x_i, c_j) = \left\|x_i - c_j\right\|^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Step vi. The Clusters of optimized signals are then applied to DWT to decompose signals into subbands

- The DWT decomposes a signal into a set of wavelet coefficients at different scales and positions, allowing for analysis.
- The basic mathematical model of the DWT is as follows:
- Given an ECG signal

$$x[n], where\ n = 0, 1, \ldots, N-1 \ldots\ldots\ldots\ldots\ldots(5)$$

- the DWT computes a set of wavelet coefficients w[j,k] at different scales j and positions k, where j = 0, 1, ..., J-1 and k = 0, 1, ..., 2^j-1.
- The DWT is defined by a pair of wavelet functions ψ(t) and φ(t), where ψ(t) is the detail wavelet function and φ(t) is the scaling function.
- The DWT is computed by convolving the signal x[n] with a set of wavelet filters, consisting of a low-pass filter denoted by h[n] and a high-pass filter which is denoted by g[n].
- In this work here, the filters are chosen based on the wavelet functions ψ(t) and φ(t), and are applied at different scales and positions to compute the wavelet coefficients w[j,k].

The DWT can be expressed mathematically as:

$$w[j,k] = \frac{1}{sqrt(2^j)}\ sum_n x[n]h[n-2^{jk}]\ 2^{\frac{j}{2}}\text{………(6)}$$

for detail coefficients

$$\mathrm{w[j,k]} = \frac{1}{\mathrm{sqrt(2^j)}} * \mathrm{sum_n x[n]g\left[n-2^{jk}\right]} * \ 2^{\frac{j}{2}}\text{….(7)}$$

for approximation coefficients

where j and k are the scale and position indices, respectively.

In the context of optimizing ECG signals, the DWT can be used to decompose the fused ECG signal into different scales and positions, allowing for analysis.

The DWT coefficients can be used as features for further analysis or classification of the ECG signals.

Step vii. The DWT coefficients are then subjected to PCA Algorithm. The mathematical model of PCA can be defined as follows:

1. where the scale and position indices are j and k, respectively:
2. Calculate the mean of the data opinions:

$$mu\ =\ \left(\frac{1}{n}\right)\ sum_i x_i\ \text{………………….(8)}$$

3. Calculate the covariance matrix of the data opinions:

$$S\ =\ \left(\frac{1}{n}\right)\ sum_i (x_i - \ mu)(x_i - \ mu)^T \ldots \text{(9}$$

where T denotes the transpose operator.

4. Compute the eigen vectors as well as the eigen values of the corresponding values. Which is denoted by covariance matrix S:

$$S\ x\ v_i\ =\ lambda_i\ x\ v_i\text{………(10)}$$

- where lambda_i is the i-th eigenvalue and v_i is the corresponding eigenvector.
- Categorise the eigenvectors in descendant order of the respective eigenvalues.
- Select the k eigenvectors with the largest eigenvalues, where k is the desired dimensionality of the reduced feature space.
- Transform the original data points into the reduced feature space:

$$\mathrm{y_i}\ =\ \mathrm{U^T}\ (\mathrm{x_i} -\ \mathrm{mu})\text{……….(11)}$$

- where U is the matrix of the k selected eigenvectors, and y_i is the reduced mode of the feature vector for the available i-th data point.

Step viii. The feature space is in case as input to the GLCM stage, which is a widely used texture analysis technique in image processing. In the context of feature extraction from ECG signals, GLCM can be used to extract texture features from the PCA reduced feature space.The mathematical model of GLCM can be defined as follows:

- Given an input image I with N gray levels, the GLCM algorithm works as follows:
- Define a displacement vector

$$d\ =\ (dr,dc)\ \text{…………(12)}$$

- where dr and dc are denoted as the corresponding row and column offsets, respectively.
- For each pixel in the image, compute the corresponding GLCM:

$$G(i,j)\ =\ sum_k sum_l I(k,l) * \ I(k\ +\ dr,l\ +\ dc)\text{…(13)}$$

- where I(k, l) is the concentration of the pixel at spot (k, l) and I(k + dr, l + dc) is the concentration of the pixel at place (k + dr, l + dc).
- Normalize the GLCM by dividing each element by the sum of all elements:

$$P(i,j) = \frac{G(i,j)}{sum_k sum_l G(k,l)}\text{……….(14)}$$

- Compute the statistical measures from the normalized GLCM. A common set of statistical measures used in GLCM analysis are:

Contrast: measures the local variations in intensity between adjacent pixels.

Energy: measures the uniformity of the texture.

Homogeneity: measures the similarity of intensity values between adjacent pixels.

Correlation: measures the linear dependence between neighboring pixels.

The statistical measures can be computed as follows:

$$Contrast\ =\ sum_i sum_j (i\ -\ j)^2\ P(i,j)\ \text{……(15)}$$

$$Energy\ =\ sum_i sum_j P(i,j)^2\text{……….…...….(16)}$$

$$\text{Homogeneity}\ = \frac{\mathrm{sum_i sum_j P(I,j)}}{(1 + (\mathrm{I - j})^2)}\text{…………….…..(17)}$$

Correlation is given by

$$Corr. = \frac{sum_i sum_j (i\ \ j * P(i,j) - mu_i\ mu_j)}{(sigma_i\ x\ sigma_j)}\ \text{…..(18)}$$

- where mu_i and mu_j are the mean values of the row and column projections of P, respectively, and sigma_i and sigma_j are the corresponding standard deviations.
- The feature vector of statistical measures are then subjected to Deep Learning stage i.e Convolutional Neural Networks (CNN) of customized layers for

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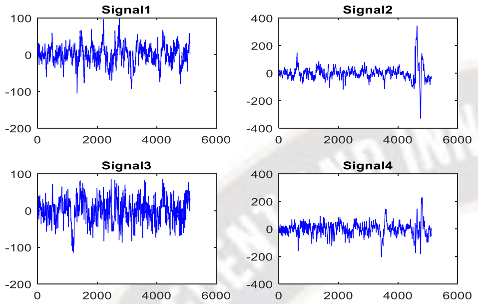
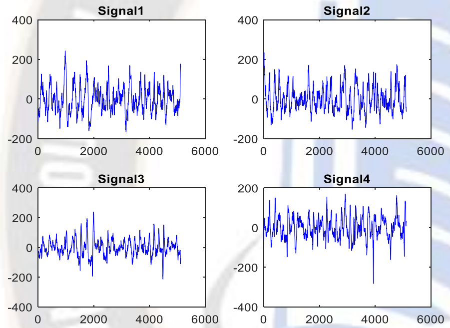
the detection of abnormalities based on Trained data.

IV. EXEPERIMENTAL SETTINGS

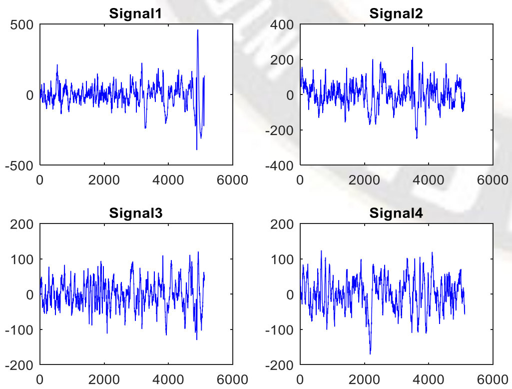
In the beginning, the electrocardigram's are obtained in order to identify and categorize cardiovascular disorders. In this work the ECG signals of 4 patients represented as subjects and denoted by S-l, S-2, S-3 and S-4 are acquired from public database like Kaggle and are shown in Figure 2.



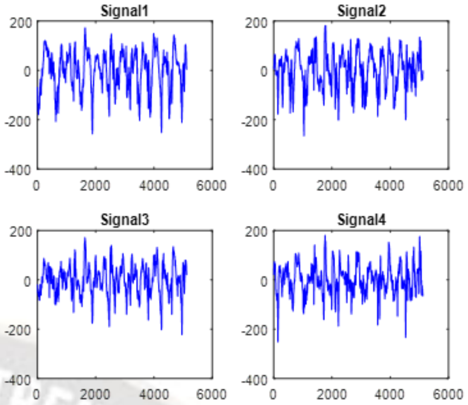
(a)



(b)



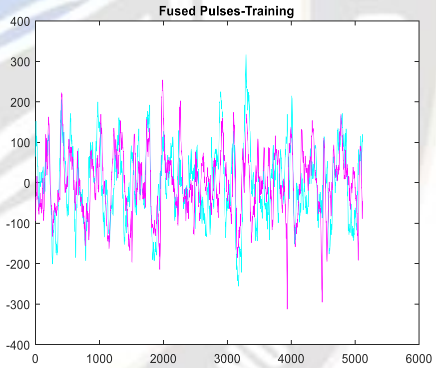
(c)



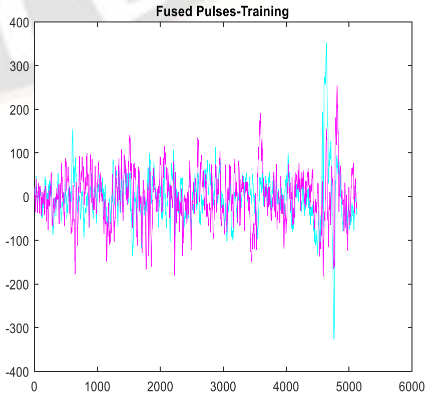
(d)

Figure 2 ECG signals (a) S-1, (b) S -2, (c)S -3, (d) S-4

ECG accounts the electrical movement of heart over time. As a screening tool for identifying and diagnosing a number of heart problems, ECG signals are still frequently employed today. It has also developed into a crucial element of any thorough medical evaluation. The ECG signal contains a affluence of statistics concerning the structure and function of the heart. Figure 2 depicts ECG signals obtained from various nodes of the patient.



(a)



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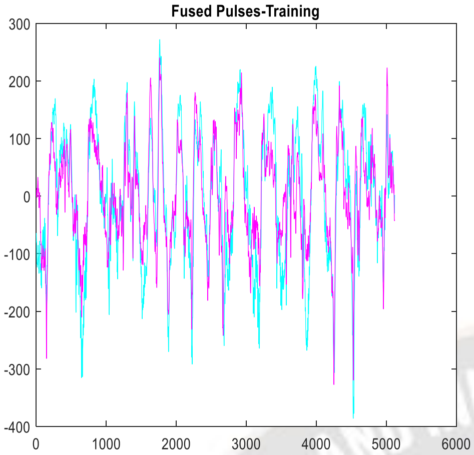

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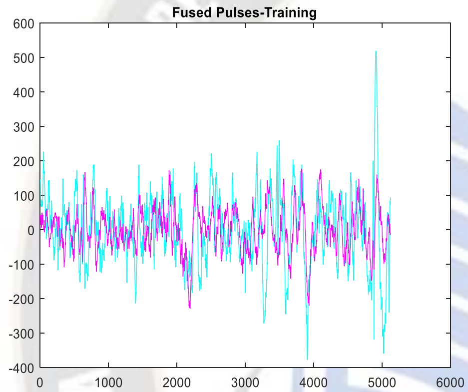
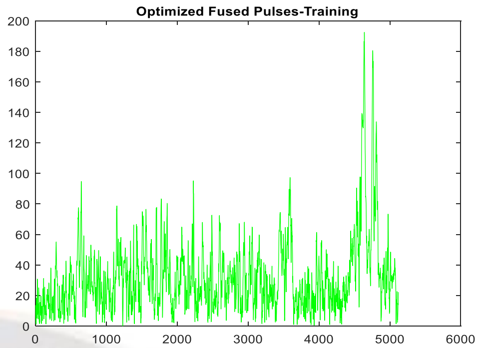


(d)

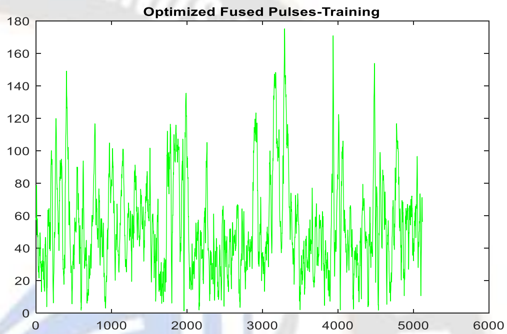
Figure 3 Fused ECG Signals (a) S-1, (b) S-2, (c) S-3, (d) S-4

After acquiring of ECG signals at different nodes of the patient are stored at buffer. After recording all the ECG signals then, they are fused. The process of combining two or more entities into a singular entity is known as fusion. Fusion can enable or enhance the approximation to more complex structured results. Multimodal fusion combines data from a variety of sheathes into a single command. Usually for a single patient 4 ECG signals are acquired at 4 different nodes. It is difficult to process all four signals at the same time. As a result, the four ECG signals of patients are merged to lessen the process's complexity.

The fused signals of patient-1(S-1), patient-2 (S-2), patient-3 (S-3) and patient-4 (S-4) are shown in figure 3.



(a)



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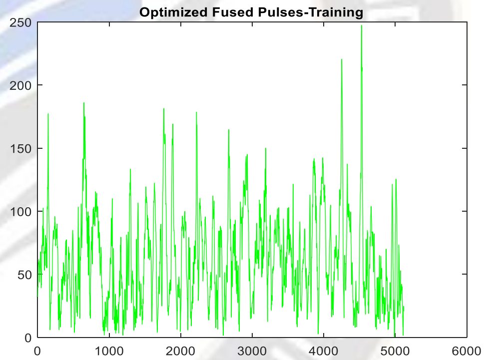

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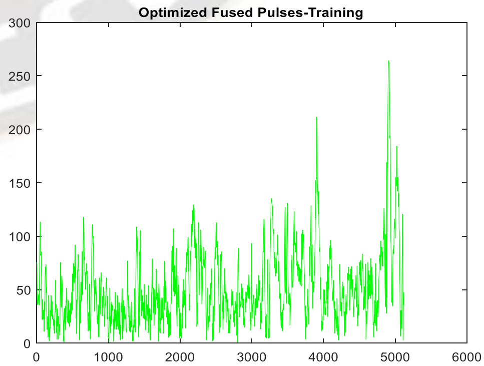

(d)

Figure 4 Optimized ECG signals (a) S-1, (b) S-2, (c) S-3, (d) S-4

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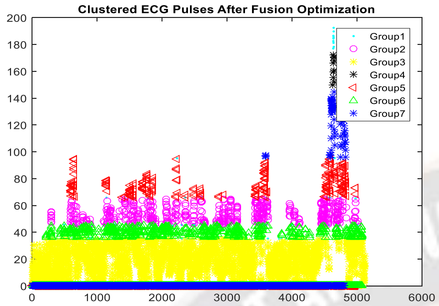
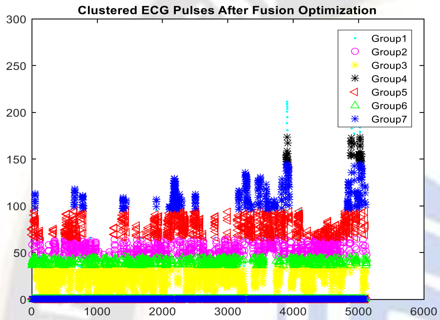
The fused signals are individually then subjected to Sequential minimal optimization (SMO) process to form a one resultant vector to create a base for forming the Clustering into groups for easiest feature extraction process. The optimized signals of different patients are shown in figure 4.

(a)





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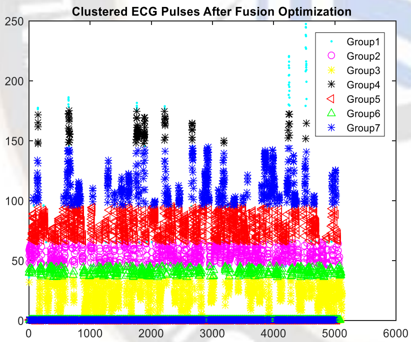
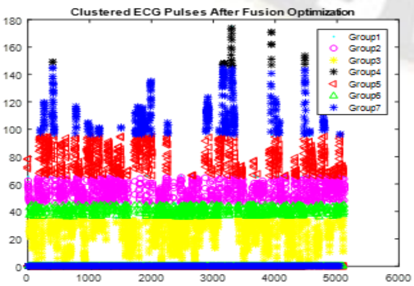


©

(c)



(d)

Figure 5 Clustered ECG pulses (a) S-1, (b) S-2, (c) S-3, (d) S-4

The optimised signals are sent into the clustering process. The K-Means algorithm divides the given dataset into an existing number of clusters, and the optimised ECG signals are clustered based on their magnitude. The total amount of clusters is 7 groups and clustered ECG signals of different patients are shown in figure 5.

A. Feature Extraction Stage

The optimised outcome of seven groups is applied to the Discrete wavelet transform (DWT) to divide signals into subbands with narrower bandwidths and shorter sample rates. These decomposed signals are fed into PCA, which reduces the complexity of high-dimensional data while preserving trends and patterns. GLCM is applied to the simplified data to compute statistics supplied in the form of a matrix. These characteristics are divided into two types: static and dynamic. The static features are those whose values do not vary with change in subject data such as Energy, Entropy, Homogeneity, Contrast and Correlation which are provided in Table 1 and their graphical plot is shown in Fig.6 for easy perception except contrast which is an adverse value.

TABLE 1 STATIC FEATURES EXTRACTED

Features Extracted	***Values***
Energy	0.500
Entropy	0.8113
Homogeneity	0.5625
Contrast	24.500
Correlation	1.000

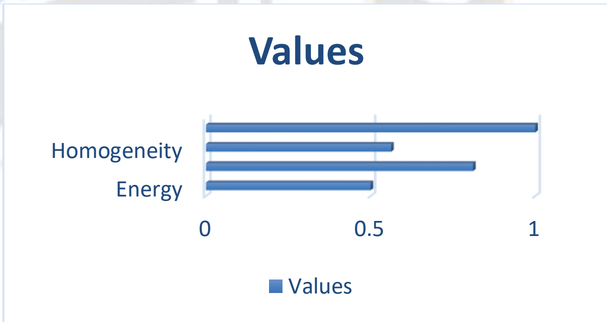


Fig. 6 Static features

The Dynamic Features are those whose values change with change in subject data and are shown in Table 2 with representing them in graphical plot as shown in Fig. 7.

TABLE 2 DYNAMIC FEATURES EXTRACTED

Dynamic Features Extracted	***Subjects***			
	S-1	***S-2***	***S-3***	***S-4***
Max and Min	192.448	175.10	247.31	250.7952
Mean	31.89	53.0719	62.55	66.91
Median	26.5868	47.3641	58.1006	56.70
RMS	40.0864	60.6366	72.6898	79.05

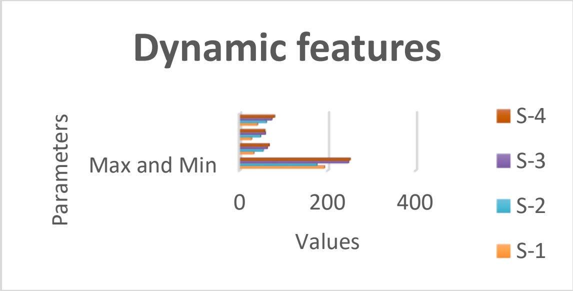


Fig. 7 Dynamic features

The static features and dynamic features in vector form are given to Customised CNN, and the corresponding results are also provided after the features and detection process for identifying CHF, Myocardial Infarction, and Valvular Stenosis has been carried out in the same table. Thus, the main focus of this work has been on the design of a Hybrid deep learning process with customizable CNN in conjunction with PCA, GLCM, and DWT for feature extraction.

V. CONCLUSION

In conclusion, the proposed hybrid deep learning-based cardiovascular detection system has demonstrated the effectiveness of extracting salient features from ECG signals using various techniques such as wavelet transform, principal component analysis, and GLCM with their concerned standard algorithms with customized CNN based deep learning-based which detects the abnormalities based on the features. Performance of the proposed system was assessed using the MIT-BIH arrhythmia database. The proposed system's future scope includes investigating the use of CNN with adding few more algorithms. In future the training the features and testing them for varied dataset along with the performance evaluation will be carried out. Moreover, the proposed system's effectiveness can be further improved by integrating it with other signal processing techniques and clinical data to enhance its diagnostic capabilities.

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