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Research Article

ML-DLNN-based Heartbeat Detection System for Diagnosing Cardiac Arrhythmia Disease using ECG Signal

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ABSTRACT

A condition when the heart rate is irregular either the beat is too slow or too fast is named Cardiac Arrhythmia (CA). Sudden Cardiac Death (SCD) could be caused by risky arrhythmia disorders. Early detection is required for reducing the fatality rate. In current years, several techniques have been developed for automatic Electrocardiogram (ECG) beat classification. Hence, a novel Memory layer with a Logistic BCM function-based Deep Learning Neural Network (ML-DLNN)-based CA disease detection based on fiducial point detection using ECG signal is proposed. Primarily, by utilizing the First Order Derivation based Kaiser Derived Bessel (FOD-KDB), the noises are removed from the input signal, and the isoelectric line is corrected. Afterward, the waves are detected from the obtained signal using PTA and it is decomposed using Deviation Measure based Ensemble Empirical Mode Decomposition (DM-EEMD). The fiducial point is accurately detected from the decomposed signal using CPA. From the fiducial point, the relationship betwixt each interval is computed and the features are extracted. Next, by utilizing Frechet Distribution-based Lemurs Optimization Algorithm (FD-LOA), the important features are selected. For classifying the conditions, both of them are given into the ML-DLNN. The proposed mechanism's experimental outcomes are contrasted with the conventional approaches, which exhibit the proposed one's higher detection accuracy

Keywords: First Order Derivation based Kaiser Derived Bessel (FOD-KDB) filter, Deviation Measure based Ensemble Empirical Mode Decomposition (DM-EEMD), Chebyshev Polygonal Approximation (CPA), Frechet Distribution-based Lemurs Optimization Algorithm (FD-LOA) and Memory layer with a Logistic BCM function-based Deep Learning Neural Network (ML-DLNN) algorithm

I. INTRODUCTION

Worldwide, Cardiovascular Disease (CVD) has become one of the prominent causes of non-infectious as well as non-transmissible disease deaths (Yang & Wei, 2020). The greatest number of deaths since 2016 is owing to Ischemic Heart Disease (IHD), which is mostly caused by CA; also, the risk of SCD could be decreased by earlier detection. Owing to chaotic electrical activities, CA is caused in which most of them are associated with CVD (Abubakar et al., 2021). Atrial Fibrillation (AF), atrial futter, ventricular tachycardia, and supraventricular tachycardia are the various sorts of arrhythmias. Generally, cardiac diseases are diagnosed with ECG signals (Devi & Kalaivani, 2020). Currently, electrocardiography-centric signals are broadly utilized for automating the study of arrhythmia classification as well as heart disease diagnosis (S et al., 2020).

The evaluation of the heart's electrical activity over a while is named ECG, which is wielded for determining the heartbeat's rate along with regularity, the chamber's position, as well as the presence of any harm to the heart (Qamar, 2022) (Xie et al., 2020). In the ECG signal, the individual notated waves are P, Q, R, S, T, and U. Also, the major features are QRS width, PP, PR, RR, and ST intervals, peak amplitudes, and wave duration. QRS-complex's irregular form is given by the malfunctions of pacemakers, associate position in the ectopic center, and ventricular region

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blockage. For detecting irregularities, QRS-complex is a significant segment (Sikdar et al., 2018). But, the measured ECG waveforms generally deform because of such obstacles caused by power-line interference, motion artifacts, muscle contraction, along with baseline drift owing to respiration (Bae & Kwon, 2021). Hence, automatic and computerized systems are more beneficial. The conventional automatic arrhythmia recognition system comprises pre-processing, feature extraction (QRS complex, Wavelet Transform (WT), morphological learning, beat segmentation, R-peak or R-R interval, time-frequency), and classification (Gupta et al., 2021). For arrhythmia classification, the combination of Deep Learning (DL) systems like Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), Deep Neural Networks (DNNs), and Recurrent Neural Networks (RNNs) have gained popularity (H. Ullah et al., 2022). However, these approaches are still challenging to provide accurate classification.

1.1 Problem Statement & Objectives

Despite developing several ML and DL-based models for CA disease detection, certain limitations are still needed to be solved for better classification. Some of the limitations of existing models are framed as follows,

- The prevailing approaches only extract features and classify the Atrial Filtration (AF). Arrhythmia comprises numerous diseases, not just AF.
- The input ECG signal has many noises. However, in the existing research, the heartbeat was directly segmented from the input image without solving power line interference and electromagnetic interference, which may produce an inaccurate result.
- The prevailing research detects the disease with the shorter segment, which affects the recognition rate. Moreover, the research was proved with a less number of samples.

To overcome these issues, the paper proposes CA disease detection with the help of accurate fiducial point detection using an ECG signal. It comprises some research objectives, which are enlisted further,

- For removing the noises from the ECG signal, a novel filtering is applied.
- For understanding the sensitive information of the signal, a novel decomposing technique is employed.
- For reducing the proposed system's training time, a feature selection model is utilized.
- For mounting the detection accuracy, a novel neural network is proposed.

This remaining paper is systemized as: the associated works are elucidated in Section 2; Section 3 elucidates the proposed technique; Section 4 exemplifies the outcomes and discussion grounded on performance metrics. Lastly, the paper is winded up in section 5.

II. LITERATURE SURVEY

(Chen et al., 2021) propounded an AF detection system grounded on multi-feature extraction as well as atrial activity's CNN through electrocardiograph signals. Also, its detection is contrasted grounded on the Support Vector Machine (SVM), one-versus-one rule, along with cluster analysis. The developed model's detection accuracy is illustrated by the outcomes. However, analyzing P waves from the small amplitude was difficult.

(Dias et al., 2021) proffered an automatic mechanism to classify arrhythmias by utilizing single-lead ECG signals. A combination of high-order statistics, signal morphology, and RR intervals were utilized by the scheme. Here, by adding a jitter to the R-wave positions specified by the database, the model's robustness was tested against the segmentation errors. The outcomes exhibited the system's higher sensitivities for the taken classes. But, owing to the noise present in ECG data, the chances of irrelevant feature incorporation were more.

(Mathunjwa et al., 2021) established a DL system to accurately classify arrhythmia. In the initial phase, the categories of noise and Ventricular Fibrillation (VF) were separated. In the second phase, Normal, Premature VF, AF, and Premature AF categories were identified. Comparing the categorization findings to the author's earlier work, this work was better. But, given the huge number of dimensions in the data, the calculation complexity was significant; also, it was challenging to mitigate the data imbalance effects.

(Sangaiah et al., 2020) explored a whole approach to detect an arrhythmia from the basic noise removal stage to the classification stage. (1) Noise removal from the ECG signal, (2) feature extraction and feature selection, and (3) ECG signal classification into 5 sorts of arrhythmia were the 3 phases comprised here. In an experimental evaluation, the presented research displayed a low error rate than the prevailing approaches. But, since the chosen features were not customized for the particular model, the final classification accuracy was not higher.

(Wang et al., 2020) illustrated a technique for automatic AF identification using two-lead ECG readings. The Wavelet Packet Transform (WPT) along with the random process theory's correlation function was wielded for creating an efficient feature extraction methodology for physiological signal assessment and creating the associated histogram. Following that, wavelet coefficient series correlations were used to extract multivariate statistical features. On the correlation betwixt the wavelet coefficient series, multivariate statistical features were then built. As per the numerical outcomes, superior classification performance was yielded by the presented technique. Nevertheless, its inherited noise challenged its apt interpretation.

(Pławiak & Acharya, 2020) revealed the classifiers' deep genetic ensemble for arrhythmia detection utilizing ECG signals. To strengthen the characteristic ECG signal feature, the spectral power density was assessed centered on Welch's system as well as the discrete Fourier transform. The proper direction of the presented idea's development led to attaining superior outcomes. The network wanted to be trained longer time owing to a large number of data.

(Sharma et al., 2021) propounded an effective hybridized mechanism for ECG sample classification into crucial arrhythmia classes for detecting heartbeat abnormalities. The QRS complex's feature vectors were optimized with the Cuckoo Search (CS) approach. The SVM was trained for classifying signals among five classes. Simulation results illustrated the developed ECG classification model's success in accurately classifying ECG signals for arrhythmia classification. However, the developed model focused only on five diseases.

(Ahmed & Zhu, 2020) proffered an early detection of AF grounded on ECG signals. For developing a lower-cost as well as easier-to-use device, this developed research was performed. Here, the heartbeat variations and varying periods betwixt ECG signal's successive R peaks were measured and evaluated; then, the outcome was contrasted with the heart rate and RR intervals. A reasonable success rate of AF detection was yielded by the outcomes. However, its suitable interpretation was challenged by its complexity and inherited noise.

(A. Ullah et al., 2021) established a reliable technique that properly classified the ECG data even when there was background noise. This study built 2 down-sampling layers, a fully connected layer, and a one-dimensional (1D) CNN encompassing 2 convolutional layers. The identical 1D data was converted into 2D images for enhancing the system's classification accuracy. Yet, the misclassificationhas occurred in the model owing to considering the single ECG signal.

(Arumugam & Sangaiah, 2020) provided arrhythmia classification and identification in ECG signals utilizing a wavelet-centered methodology. The developed work included 3 stages: (1) the ECG noise suppression, (2) RR and PR intervals' extraction from the ECG signal, and (3) the ECG classification. Using a specific wavelet design, the created methodology successfully located and measured the ECG signal's P, Q, R, S, and T sub-waves. According to experimental findings, the ECG signal had higher energy levels throughout a decomposition phase.Nevertheless, owing to the large frequency range, the filter's noise-reduction effect with a fixed threshold was very limited.

III. PROPOSED METHODOLOGY FOR BEAT RHYTHM CONDITIONS CLASSIFICATION USING ACCURATE FIDUCIAL POINT

This work proposes a novel ML-DLNN-centric CA disease detection with the help of accurate fiducial point detection using an ECG signal for diagnosing heart disease. Here, from the preprocessed signal, the waves are detected and then the fiducial points aredetected. From that, time intervals and features are gathered and given into the developed network for classifying the heartbeat types. Figure 1 displays the proposed mechanism's block diagram.

3.1 The ECG waveform

A representation of the heart's electrical activity is the ECG waveform, which is a critical diagnostic tool to determine heart health. As a result, the proposed technique uses the ECG signal as an input for categorizing the beat rhythms

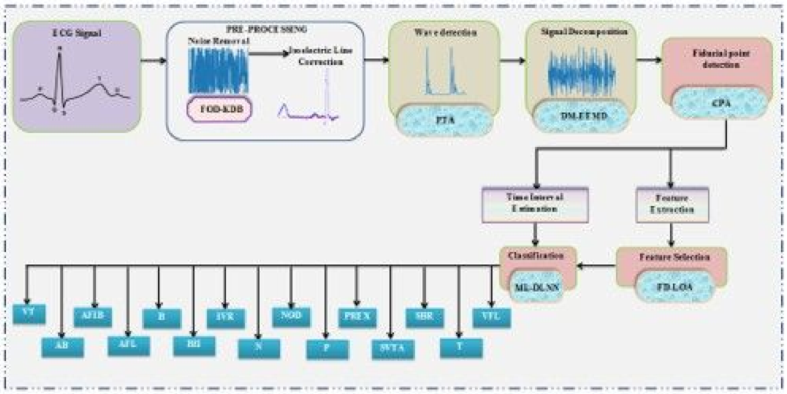


Fig. 1. Block diagram of the proposed methodology

for diagnosing the disease. P waves, a QRS complex, and T waves are the three main components of an ECG trace. Then, the input signals $(\wp)$ for each patient are expressed as,

$$\wp = \{\wp_1, \wp_2, \wp_3, ...\wp_\hbar\} \tag{1}$$

Here, $\hbar$ symbolizes the number of signals.

3.2 Pre-processing

The actual signals are distorted by the artifacts present in the ECG, which also degrade its processing ability for accurate disease diagnosis. Hence, these artifacts are removed from the signal. These artifacts enclose noises and baseline wandering.

3.2.1 Noise Removal

Here, by utilizing the FOD-KDB filter, the various noises present in the input signals $(\wp)$ are eliminated for increasing the Signal to Noise Ratio (SNR), which is advantageous for the following fiducial point detection and heartbeat classification. The prevailing Bessel filter has a better shaping factor. However, there are issues with passband, ringing, overshoot, loss of information, and delay. As a result, the paper uses the Kaiser Window. The shape factor has been adjusted to the design for the appropriate passband and stopband ripples by keeping the window length constant. Thus, *the passband as well as the stopband ripple size is not affected*. The signal is therefore protected against overshoot, ringing, and passes band issues. Moreover, utilizing the first-order derivation, the frequency is chosen.

Primarily, the ECG signal $(\wp)$ is windowed using Kaiser Window. The Kaiser window $(\wp^W)$ and its Fourier transform are given by,

$$\wp^W = \begin{cases} \dfrac{1}{L}\dfrac{b_0\left[\pi\beta\sqrt{1-(2/L)}\right]}{b_0[\pi\beta]}, & |\alpha| \le L/2 \\ 0, & |\alpha| > L/2 \end{cases} \tag{2}$$

Here, b_0 and L are the zeroth order Bessel function and window duration, correspondingly, β symbolizes the non-negative real number that determines the window's shape, and α signifies the control parameter. Kaiser-Bessel window strikes a balance amongst the numerous conflicting goals of amplitude accuracy, side lobe distance, along with side lobe height. Hence, it gives better minimum stop-band attenuation characteristics. The windowed signal is fed into the FOD-KDB filter, which is an all-pole filter, and is having maximally flat time delay. Thus, the normalized transfer function for the Bessel filter $B_{fil}(\wp^W)$ is expressed by,

$$B_{fil}(\wp^W) = \frac{\gamma(0)}{\gamma(\wp^W/f)} \tag{3}$$

Where, the Bessel polynomial is specified as $\gamma(0)$, which is given by,

$$\gamma(0) = \lim_{\wp^W \to 0} \phi(\wp^W) \tag{4}$$

Here, f epitomizes the cut-off frequency, which is chosen by using first-order derivation, which averts the filter's cut-off frequency point from being affected by changes in the impedance of the load (l). Thus, the cut-off frequency is given by,

$$f = \frac{1/\chi}{l + 1/\chi} \tag{5}$$

Where l symbolizes the Brownian motion and χ exemplifies the drift. Lastly, the noise-removed signal is obtained from the filter, which is epitomized as $\wp^{remove}$.

3.2.2 Isoelectric Correction Line

The filtered ECG signal $\left(\wp^{remove}\right)$ is first processed to correct the baseline wander for minimizing the changes in beat morphology. *For the isoelectric line correction, the minimum amplitude value is extracted (i.e., the amplitude level is equal to zero level) and it is subtracted from the whole signal. Afterward, the signal after removing the drift is signified as* $\wp^{pre}$.

3.3 Wave detection

The received ECG signature $\wp^{pre}$ is characterized by a repetitive wave sequence of *P*, QRS, and *T* waves associated with each heartbeat. Hence, Pan-Tompkins Algorithm (PTA) is wielded for detecting each wave, which is useful for arrhythmia classification since more information about the heartbeats is obtained. For highlighting this rapid heart depolarization's frequency content, a series of baseband filters is applied by the PTA, which removes the background noise. After that, it squares the signal for amplifying the waves. Lastly, it applies adaptive thresholds (T) for detecting the peaks of the filtered signal. The detected waves $\left(W_{\wp^{pre}}\right)$ in the signals are represented as,

$$W_{\wp^{pre}} = \begin{cases} W^{QRS} & if\ T < A \\ W^{T} & if\ T = A \\ W^{P} & if\ T > A \end{cases} \tag{6}$$

Here, W^{QRS}, W^{T}, and W^{P} symbolize the detected wave of QRS, P, and T, correspondingly, A signifies the amplitude of the signal.

3.4 Signal Decomposition

After detecting the waves, the wave-detected signals $\left(W_{\wp^{pre}}\right)$ are decomposed using the DM-EEMD for collecting and understanding sensitive information sent via various ECG signals. The existing Ensemble Empirical Mode Decomposition (EEMD) model provides a high time-frequency resolution. However, in the conventional model, the noise is added to the original input signal to solve the mode mixing problem of IMF. If the noise is added over, then it degrades the important information of the input signal. To solve that issue, this research methodology calculates the standard deviation after randomly adding noise to the signal. If it has more deviation, then the added noise is reduced. DM-EEMD is applied according to the following algorithm:

- Add white noise to the wave-detected signals according to the following equation,

$$Y = W_{\wp^{pre}} + X_J \quad for\ J = 1,2,3,..M \tag{7}$$

  Here, Y symbolizes the signal with white noise according to the ensemble number (M), X exemplifies the white noise.
- Evaluate the standard deviation $\left(S^{Y}\right)$ of the signal.

$$S^{Y} = \sqrt{\frac{\sum_{i=1}^{N}\left(Y_i^{amp} - Y^{amp}\right)}{N-1}} \tag{8}$$

Here, Y_i^{amp} and Y^{amp} signify the i^{th} amplitude of the signal component and the mean of signal components, correspondingly, N signifies the number of amplitude. It estimates the deviation of the signal from the original signal after adding the white noise by considering the mean of signal components.

- Compare the deviation with the limited level of noise $\left(X^{\lim it}\right)$. Afterward, the noise level $\left(Y^{noise}\right)$ in the signal is determined as,

$$Y^{noise} = \begin{cases} add\,noise, & if\ S^{Y} < X^{\lim it} \\ reduce\,noise, & if\ S^{Y} < X^{\lim it} \end{cases} \tag{9}$$

- Signal decomposition $\left(Y^{de}\right)$ of Y^{noise} into several IMF with the residue.

$$Y^{de} = \sum_{z=1}^{Z-1} IMF_z^J + R_z^J \tag{10}$$

Here, Z notates the total amount of IMF decomposed form, IMF_z^J implies z^{th} mode, and R_z^J elucidates the remainder obtained in the J^{th} experiment.

- Reiterating the first and second stages while varying the white noise that is introduced to the signal.
- Compute the average IMF IMF_z^{avg} of the several ensembles M.

$$IMF_z^{avg} = \frac{1}{M}\sum_{J=1}^{M} IMF_z^J \tag{11}$$

- Lastly, the obtained decomposite signal is notated as $\wp^{decom}$.

3.5 Fiducial Point Detection

Here, the fiducial points of the decomposite signals are detected from $\wp^{decom}$ using the CPA approach for approximating the shape of a signal's curve by utilizing a polygon whose vertices are specified by a subset of points on the curve. Here, these points are considered as fiducial points. The interval betwixt each initial vertex is wielded for choosing further vertices using the existing Sequential polygonal approximation. The additional vertices effectively express the fiducial points, but the significant inaccuracy is problematic. To resolve this issue, the paper proposes a Chebyshev distance rather than calculating geometric distance because it is calculated as the maximum absolute difference between the elements of the vectors. It reduces the error problem and makes the system faster.

Primarily, the coordinate points (Vertices) $\left(g_0, h_0\right) \in \wp^{decom}$ over the signal curve are assumed. Afterward, the increments $\left(\Delta h_v, \Delta g_v\right)$ are computed and moved to the next point $\left(g_v, h_v\right)$ from $\left(g_0, h_0\right)$. Then, the accumulation $\left(\rho_v\right)$ is performed as,

$$\rho_v = \rho_{v-1} + \Delta\rho_v \tag{12}$$

$$\Delta\rho_v = g_v \cdot \Delta h_v - h_v \cdot \Delta g_v \tag{13}$$

Here, ρ_{v-1} epitomizes the previously accumulated parameter, and $\Delta\rho_v$ symbolizes the moving parameter. Following this, the current line segment's length (ϑ) from the starting vertex is computed using Chebyshev distance as,

$$\vartheta = \max\left(g_v - h_v\right) \tag{14}$$

Afterward, the next vertex for shape forming is evaluated grounded on the following criteria and is applied as,

$$\left|\rho_v\right| \le \varphi \cdot \vartheta \tag{15}$$

Here, the maximum allowed area deviation per length unit of the approximating segment is exemplified as φ. If the above criterion is satisfied, then the movement is performed towards another point. Else, the allowable segment has been considered and the latter vertex is considered as the starting point of the next segment and also considered as one of the fiducial points. The process is repeated until the points are processed. After completing the whole process, the obtained fiducial points are notated as ω.

3.6 Time interval evaluation

Here, for determining whether the heartbeat is normal or abnormal, the relationship betwixt each wave is calculated from ω since the time interval between each wave is different for normal and abnormal heartbeats. Therefore, the time interval $(\iota \in \omega)$ betwixt each wave, namely the PR interval (ι^{PR}), PQ interval (ι^{PQ}), QRS duration (ι^{QRS}), ST interval (ι^{ST}), and QT interval (ι^{QT}) is measured and is expressed as,

$$\iota = \{\iota^{PR}, \iota^{PQ}, \iota^{QRS}, \iota^{ST}, \iota^{QT}\} \tag{16}$$

3.7 Feature Extraction

While measuring the time interval between the waves, the features are extracted from P for gathering information about the ECG signals. Therefore, the primary features (F_c), namely standard deviation, Root Mean Square acceleration, skewness, margin factor, impulse factor, B-factor, mean acceleration, variance, peak acceleration, kurtosis, crest factor, shape factor, and A-factor are extracted and it is expressed as,

$$F_c = \{F_1, F_2, F_3, ...F_C\} \quad where\ c = 1,2,3,......C \tag{17}$$

Here, C implies the feature.

3.8 Feature Selection

Here, the important features are selected from F_c using FD-LOA for reducing the proposed model's training time. By conducting an exhaustive search, the exact solution could be found by the existing Lemurs Optimization Algorithm (LOA). But, the new population is updated in the current model grounded on the Free Risk Rate (FRR) calculation. For calculating the FRR value, the predefined values are utilized, which may select the unnecessary features or may avoid important features. As a result, the Frechet distribution function is wielded in this study methodology to calculate the high-risk rate and low-risk rate, which will improve feature selection. The modified model is named FD-LOA. The mathematical model for FD-LOA is,

Primarily, the set of lemurs (Extracted features) is signified in the matrix form as,

$$F_c = \begin{bmatrix} F_1^1 & F_1^2 & \cdots & F_1^d \\ F_2^1 & F_2^2 & \cdots & F_2^d \\ \vdots & \vdots & \vdots & \vdots \\ F_C^1 & F_C^2 & \cdots & F_C^d \end{bmatrix} \tag{18}$$

Here, d epitomizes the decision variables. Then, each solution in the decision variable Ω in the solution c is randomly generated as,

$$F_C^{\Omega} = r \times (U - L) + L \tag{19}$$

Here, r symbolizes the random number, U and L exemplify upper and lower bound limits. Then, the fitness of each lemur is calculated as,

$$f^{best} = \max_{acc}(F_c) \tag{20}$$

The evaluation is done grounded on attaining classification accuracy. The lemurs are then arranged according to their fitness in every single iteration, with one lemur picked as the global best lemur (G) and one lemur chosen as the best neighbour for each lemur (B). Centered on selecting the lemur, the position of the current lemur $(F(c,\Omega))$ is updated using,

$$F_c^{\Omega} = \begin{cases} F(c,\Omega) + F((c,\Omega) - F(G,\Omega)) * (r - 0.5) * 2; & r < \Re^{FER}, \\ F(c,\Omega) + F((c,\Omega) - F(B,\Omega)) * (r - 0.5) * 2; & r > \Re^{FER}, \end{cases} \tag{21}$$

Here, the global best lemur is signified as $F(G,\Omega)$, $F(B,\Omega)$ specifies the j value of the best nearest lemur for $(F(c,\Omega))$, and the risk rate of all lemurs in the troops is elucidated as $\Re^{FER}$. The likelihood of the $\Re^{FER}$ is the primary coefficient of the FD-LOA algorithm, according to this formulation. This coefficient's formula is provided using the Frechet distribution function as,

$$\Re^{FER} = e^{-\left(\frac{H-\lambda}{it_{\max}}\right)^{it}} \tag{22}$$

Here, H and λ symbolize the high and low-risk rates, correspondingly, $it_{\max}$ and it are the maximum and current iterations, correspondingly. The Frechet distribution, which is a special case of the generalized extreme value distribution, is also named the inverse Weibull distribution. Therefore, an extreme level of risk rate is determined appropriately to prevent the lemur from wrong decision for moving. The updated position is considered as the selected feature and it is represented as F_c^{sel}. The pseudocode of the proposed FD-LOA is,

---

Input: Extracted Features (F_c)

Output: Selected features (F_c^{sel})

Begin

Initialize Population, Ω, d

While $it \le it_{\max}$

Evaluate the Objective function of all F_c

Calculate FRR

Update the global best lemur

For each lemur, **do**

Update best nearest lemur

`**For** each lemur variable, **do**

Set random number

If $(r < \Re^{FER})$ {

Update position to global best

} **Else** {

Update Best nearest lemur position

}

End if

End for

End for

End while

Return $\left(F_c^{sel}\right)$

End

3.9 Heartbeat Classification

Here, the ML-DLNN network is wielded for classifying the heartbeat types by utilizing the time intervals (ι) and selected features $\left(F_c^{sel}\right)$. Both inputs are commonly signified as Φ_k. The conventional DL Neural Network (DLNN) only can allow models for becoming more efficient at learning complex features and performing more intensive computational tasks. But, it has a higher computation burden and overfitting problem, which is raised by the random updation of weight value. Thus, to solve that issue, this research methodology uses the memory layer, which stores the previous training information. With the help of that layer, the weight value is derived for the current iteration using the logistic BCM function. In conventional postsynaptic, the activation function was executed, which was not considered the real input value. Hence, this research considers the logistic function of the post activities. Figure 2 exhibits the proposed ML-DLNN's architecture,

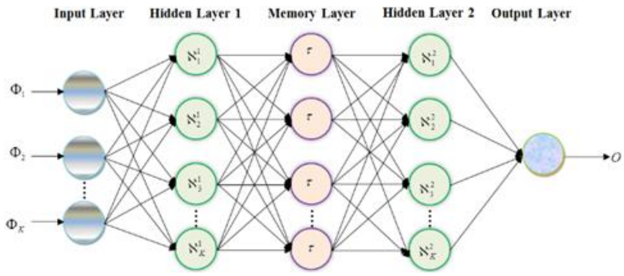


Figure 2: Architecture of the proposed ML-DLNN model

Initially, the outputs of the selected features and time intervals are given to the input layer. From the input layer, the data is given to the hidden layer, where the hidden unit $(\aleph_k)$ is computed for the input by utilizing,

$$\aleph_k = B + \sum_{k=1}^{K} \Phi_k . \xi \tag{23}$$

Where, the number of neuron layers is specified as K. The bias parameter is exemplified as B, Φ_k epitomizes the k^{th} input, and ξ symbolizes the weight parameter obtained using the logistic BCM function that is calculated as,

$$\xi = \varepsilon \Psi \left(\Phi_k / \Im \right) \tag{24}$$

Where, ε symbolizes the previous weight, Ψ is the learning rate, and $\Im$ signifies the difference between the expected and calculated error in the previous iteration. All of the data from the previous iteration is stored in the memory layer. The logistic BMC function's parameters are implemented using this knowledge to estimate the weights of real input values in subsequent iterations. Therefore, the hidden layer output is given as input to the output layer, where the exponential activation function is calculated as,

$$\tau = \frac{\Gamma}{e^{\Gamma(\aleph_k - \xi)} + B} \tag{25}$$

Where, τ signifies the output unit and Γ is the carrying capacity. The logistic function observes the real input values to adjust or cut off the generated hidden layer output by considering the limits of capacity. Hence, by the process, the final output (O) classified the heartbeats as Atrial Bigeminy (AB), Atrial Flutter (AF), Idioventricular Rhythm (IVR), Nodal (A-V junctional) rhythm (NOD), Pre-excitation (PREX), Supraventricular tachyarrhythmia (SVTA), Ventricular flutter (VFL), Atrial Fibrillation (AFIB), Ventricular bigeminy (B), 2° heart block (BII), Normal sinus rhythm (N), Paced rhythm (P), Sinus Bradycardia (SBR), Ventricular trigemini (T), and Ventricular tachycardia (VT). The pseudo-code of the proposed ML-DLNN is,

---

Input: Time intervals (ι) and Selected features $\left(F_c^{sel}\right)$

Output: classification of Heart beats (O)

Begin

Initialize parameters $\Phi_k\ \aleph_k, \xi$.

Transfer all the inputs to input layer

Update weight value //using logistic BCM function

Update Bias

Execute the operation Hidden layers

For $k = 1 to\ K$

While $k = 1$

Compute Hidden layer

$$\aleph_k = B + \sum_{k=1}^{K} \Phi_k . \xi$$

Evaluate activation function //using logistics function

$$\alpha = \frac{\Gamma}{e^{\Gamma(\aleph_k - \xi)} + B}$$

End while

End for

Flattening all the layers

Return classified Heart beats

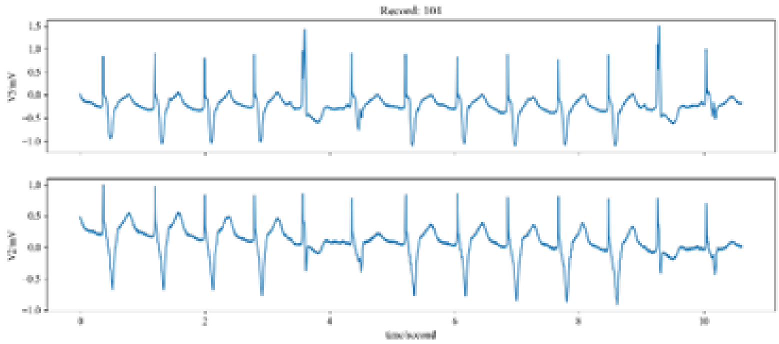
End begin

IV. RESULTS AND DISCUSSIONS

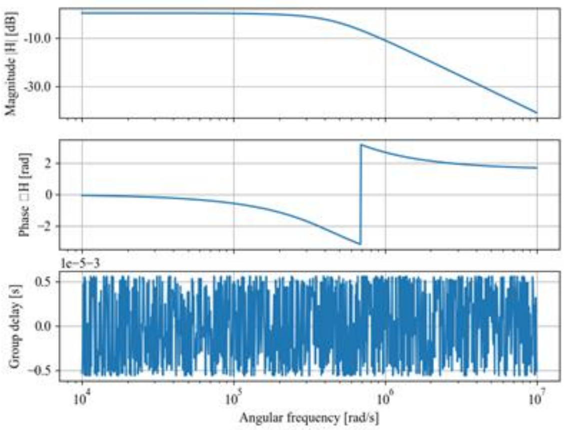
Here, the experiments conducted in the working platform of PYTHON are presented for validating the proposed scheme's performance.

4.1 Dataset Description

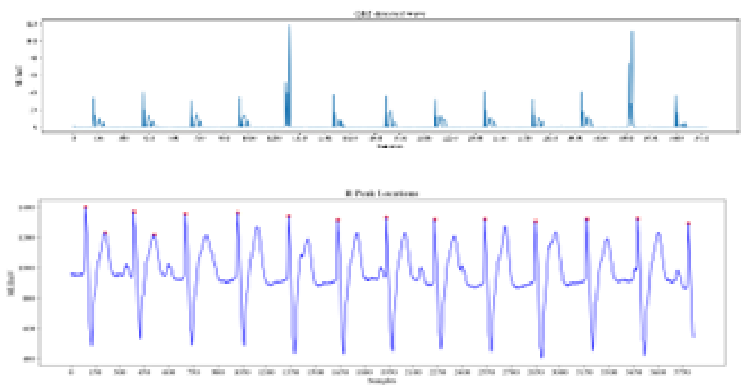
For the performance analysis, the research methodology uses the MIT-BIH dataset, which has been collected from publically available sources. The MIT-BIH Arrhythmia Database comprises 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory betwixt 1975 and 1979. From the dataset, 80% and 20% are wielded for training and testing, correspondingly. Figure 3 displays the ECG signals' sample input and output images.



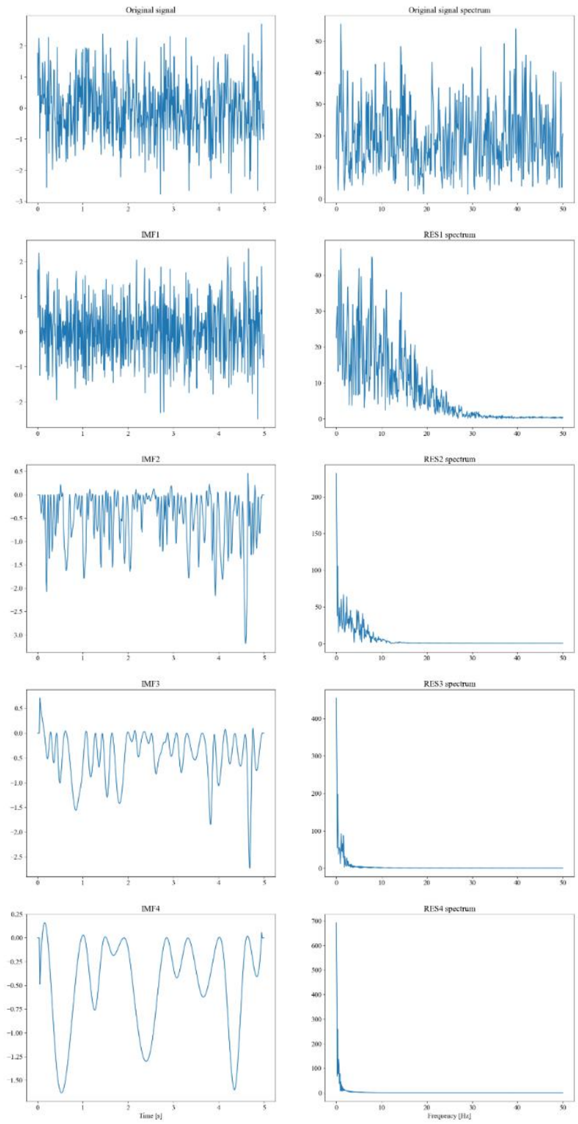
(a)



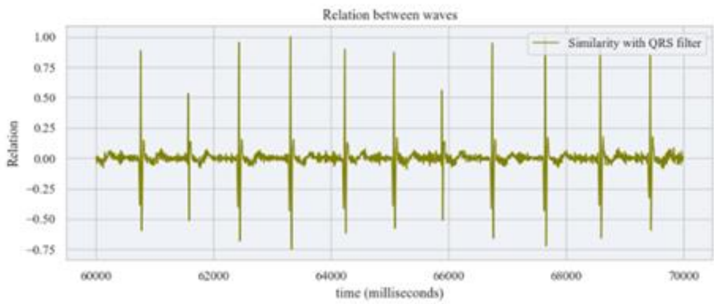
(b)



(c)



(d)

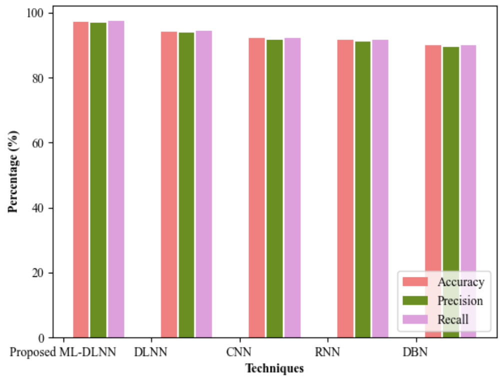


(e)

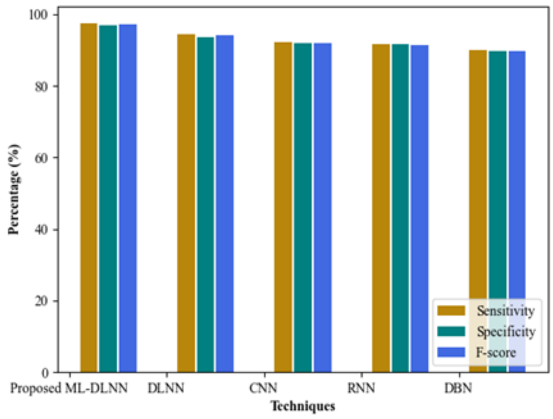
Figure 3: (a) Input ECG signal, (b) Noise removed signal, (c) QRS detected signal, (d) Time interval relation between waves

4.2. Performance Analysis of Heartbeat Classification

The proposed ML-DLNN's performance analysis is validated and contrasted with the existing models like CNN, Deep Belief Network (DBN), DLNN, and RNN.



(a)



(b)

Figure 4: Performance analysis of the proposed ML-DLNN and existing models in terms of (a) Accuracy, Precision, and Recall (b) Sensitivity, Specificity, and f-measure

Figure 4 exhibits the proposed ML-DLNN and the existing models' performance evaluation. The proposed model's better performance is indicated by the higher values of the above-mentioned metrics. The proposed model's accuracy is 97.08%, which is higher than the existing DLNN (94.08%), CNN (92.06%), RNN (91.67%), and DBN (89.85%). Here, the sensitivity and recall of the proposed models are the same and reached 97.4%. Similarly, the proposed model's precision, specificity, and f-measure are attained at 96.81%, 96.77%, and 97.10%, correspondingly. When compared to the existing models, these values are higher. Therefore, the investigation found that the proposed system performs better.

Table 1: Performance Analysis of Proposed ML-DLNN and existing models

Techniques	FRR	FPR	FNR
Proposed ML-DLNN	0.013052	0.032258	0.026
DLNN	0.028084	0.063265	0.055227
CNN	0.038153	0.079612	0.079002
RNN	0.04012	0.083495	0.082988
DBN	0.049197	0.102564	0.100204

Concerning FPR, FNR, and FRR, the performance analysis of the proposed ML-DLNN and existing models is illustrated in Table 1. The lower value of FPR, FNR, and FRR values results in the proposed technique's better performance. The FRR of the proposed model shows an improvement of 53% than the existing DLNN, 65.79% than

CNN, 67.46% than RNN, and 73.46% than DBN. Likewise, the FNR and FPR of the proposed model are 0.032258 and 0.026, correspondingly, which displays the improvement of the developed model. Thus, from the results of these metrics, it is concluded that the proposed ML-DLNN shows better performance for the classification of Heartbeats.

Table 2: Performance Analysis of Proposed ML-DLNN and existing models

Techniques	MCC	NPV
Proposed ML-DLNN	0.945	0.976
DLNN	0.885	0.944
CNN	0.821	0.912
RNN	0.833	0.919
DBN	0.785	0.895

Grounded on MCC and NPV, the proposed ML-DLNN and existing techniques' performance assessment is exhibited in Table 2. Higher values of both metrics show the model's higher performance. MCC of the proposed one is improved by 0.55 than DLNN, 0.124 than CNN, and 00.11 than RNN. Similarly, the NPV of the proposed model is 0.976, which is also higher than the existing systems.

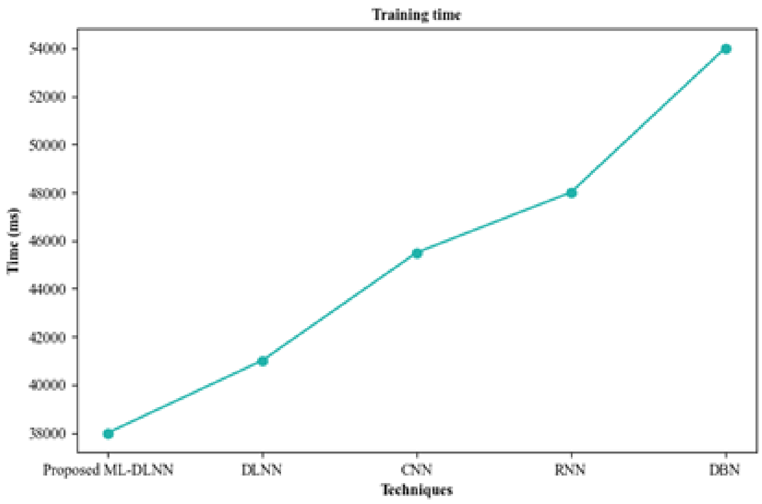


Figure 5: Computation time analysis

Concerning computation time, the proposed and current models' performance is depicted in Figure 5. The existing DLNN, CNN, and RNN each need 41015.1ms, 45501.9ms, and 48009.2 ms to train, compared to 38008.7 ms for the proposed model. In the existing DLNN model, induced optimal weight updation and a logistic function-based activation function were used for obtaining overall good performance. Therefore, the proposed mechanism's performance is superior to the existing systems.

4.3 Performance Analysis of Feature Selection

Here, the proposed FD-LOA's performance is assessed and contrasted with conventional methodologies like LOA, Drops on Surface Optimization (DSO), Social Learning Optimization (SLO), and Salp Swarm Optimization (SSO).

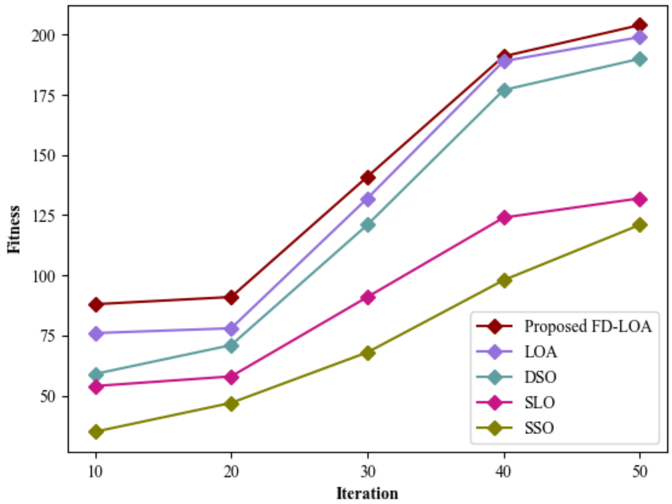


Figure 6: Fitness Vs Iteration Analysis

Figure 6 displays the proposed FD-LOA's performance grounded on fitness vs. iteration. In the proposed methodology, fitness is centered on attaining classification accuracy. For the proposed system, when the number of iterations varies from 10 to 50, the fitness value ranges from 10 to 50. When iteration is 10, the fitness of the proposed model is 88%. For iteration 20, the fitness is 91%. But, the existing techniques show a gradual decrease. This demonstrates how the optimal feature selection process has been improved by utilizing the Frechet distribution technique in the proposed system. Hence, the proposed work reaches superior performance compared to the conventional frameworks.

4.4 Performance Analysis of Noise Removal

For proving the developed framework's superiority, the proposed FOD-KDB's performance is assessed and contrasted with the prevailing techniques like *Bessel Filter (BF), Butter Worth Filter (BWF), Chebyshev Filter (CF), and* Berkeley Packet Filter (BPF) *grounded on the Peak Signal Noise Ratio (PSNR) metric.*

Table 3: PSNR analysis

Method	PSNR (dB).
Proposed FOD-KDB	38.911
BF	34.54265
BWF	31.8803
CF	26.1458
BPF	18.4249

The evaluation of the proposed and current models' performance is assessed in Table 3. Higher values show the better performance of the proposed model. PSNR of the proposed FOD-KDB is 38.911 dB, which is improved by 4.36835dB than BF, 7.0307dB than BWF, and 12.7652 dB. The overall achievement was attained by inducing the Kaiser window and first-order derivation in the selected filter, which provides better-filtering results in the previous studies. Finally, the proposed model is highly efficient than the prevailing technique.

4.5 Comparative Analysis with Literature Paper

Here, grounded on accuracy, the proposed technique and previous studies mentioned in the literature survey's comparative is explicated.

Table 4: Accuracy Analysis

Method	Accuracy (%)
Proposed Model	97.08
(Mathunjwa et al., 2021)	93..5
(Sangaiah et al., 2020)	99.7
(Sharma et al., 2021)	98.3

Table 4 illustrates the performance measure grounded on its accuracy. The proposed technique is contrasted with the conventional approaches like recurrence plot and CNN introduced by (Mathunjwa et al., 2021), An intelligent learning approach to improve ECG signal classification by (Sangaiah et al., 2020), and A novel hybrid DL method with CS algorithm for classification by (Sharma et al., 2021). Here, the proposed model attained a detection accuracy of 97.08% for the 15 classes, while the existing (Sangaiah et al., 2020) attained 99.7% only for two classes, (Mathunjwa et al., 2021) attained 93.5% for 6 classes, and (Sharma et al., 2021) attained 98.3% for 5 classes. But, the existing model shows higher accuracy than the proposed model, and it shows better results only for a minimum number of classes. However, the proposed model shows lower accuracy with more classes. As per these comparative results, the proposed recognition system has higher efficiency than the prevailing model.

V. CONCLUSION

A novel ML-DLNN-based CA disease detection with the help of accurate fiducial point detection using an ECG signal has been proposed in this research work. The proposed work undergoes the following steps, namely preprocessing, wave detection, signal decomposition, fiducial point detection, time interval estimation, feature extraction, feature selection, and classification. Afterward, the performance, as well as comparative assessment, are performed. From the experimental analysis, the proposed framework achieves an accuracy of 97.08% and a computation time of 38008.7ms. Moreover, the performance is analyzed utilizing some quality metrics like sensitivity, precision, specificity, recall, MCC, and NPV. Therefore, the proposed mechanism is better and more efficient than the other prevailing techniques. The proposed work only concentrated on classifying the heartbeats for diagnosing the disease. Thus, the work will be extended in the future with some advanced techniques for analyzing the risk factor to provide treatments reliant on that.

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