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CaP: Cardiovascular Disease Prediction using a Delta Layer based Center Vector Activation-centric DCNN

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Abstract— Cardiac disease stands as a primary contributor to mortality, representing a prevalent category of chronic and life-threatening conditions. Therefore, early detection is imperative. While existing research has sought to predict heart disease (HD) through Electrocardiogram (ECG) signals, there remains room for enhancement. This study introduces a novel approach for early HD detection based on the Delta Layer with Center Vector Activation-centric Deep Convolutional Neural Network (DLCVA-DCNN) within its research framework, namely: CaP. Initially, the input ECG signals undergo preprocessing using a Weighted Covariance Kalman Filter (WCKF) to eliminate noise. Subsequently, the preprocessed data is bifurcated: one branch transforms it into a binary image, while the other decomposes the signal to identify peak segments. The decomposition employs the Bivariate Ensemble Empirical Mode Decomposition (BEEMD) method, and the Pan-Tompkins Algorithm (PTA) is applied to ascertain the highest-frequency segments. The coupling information is then extracted from these peaks. Simultaneously, depth features are extracted from the binary image. The Linear Approximate Functional Walrus Optimization Algorithm (LAFWOA) is employed to select pertinent features from the coupling and depth features. These selected features are input into the DLCVA-DCNN classifier to discriminate disease and standard signals. The experimental analysis compares the proposed methodology with conventional frameworks based on performance metrics, revealing that the proposed approach achieves higher accuracy than existing techniques.

Keywords- Depth Features; Coupling Information; Delta Layer; Linear Approximate Functional Walrus Optimization Algorithm (LAFWOA); Weighted Covariance Kalman Filter (WCKF); and Bivariate Ensemble Empirical Mode Decomposition (BEEMD).

I. INTRODUCTION

ECG analysis has been integral to diagnosing cardiovascular pathology since the 20th century. The ECG signal reflects the heart's electrical activity, and its waveform or rhythm alterations indicate underlying cardiovascular issues [1]. The signal is derived from the standard 12-lead ECG, which calculates electrical potential from ten electrodes positioned on various parts of the body surface—six on the chest and four on the limbs [2]. Sudden Cardiac Death (SCD) is a significant preventable cause of natural death, with a potential annual incidence of about 5 million cases worldwide [3]. Therefore, continuous heart monitoring is crucial. The ECG signal proves highly beneficial in early HD prediction. However, its quick variations in morphology, duration, and amplitude pose a challenge for effective classification in HD detection [4]. Several studies have recently focused on automatic HD detection. Neural Networks (NNs) have gained popularity for their adoption in models addressing the nonlinear-ity of heart anomaly classification. Relevant features of the signal are input into NN models for classification. Frequency domain features such as lower frequency, higher frequency, and significantly lower frequency are considered for ECG signal classification. Features are extracted from the PQRS wave, where the P wave reflects atrial activity, the PR interval measures the time for electrical conduction between nodes, and the QRS complex represents ventricular activity, with the QRS interval measuring the corresponding conduction time. Various Machine Learning (ML) and Deep Learning (DL) mechanisms have been employed to learn features for HD detection [10]. However, existing ML models often require signal processing steps involving feature extraction, selection, reduction, and classification, with limitations in identifying and utilizing appropriate features from ECG signals. To address these limitations, the proposed CaP model enhances the early HD prediction model by incorporating a DLCVA-DCNN-based approach using depth features and coupling information.

A. *Research Gap*

Research on cardiac disease and its early prediction using electrocardiogram (ECG) signals has seen significant advancements, but a notable research gap still exists. Despite numerous existing studies focusing on HD prediction, improvements are deemed necessary in the current methodologies. The proposed CaP model introduces a novel framework for early HD detection, aiming to address the existing gaps in the field.

One critical gap lies in the preprocessing stage, where the input ECG signals are subjected to a Weighted Covariance Kalman Filter (WCKF) for noise removal. While this step contributes to signal enhancement, the effectiveness of the WCKF in different noise scenarios and its adaptability to diverse datasets require further investigation. Additionally, converting preprocessed data into a binary image introduces a novel element in the research. However, the robustness of this binary representation across various ECG patterns and its impact on subsequent analyses necessitate deeper exploration.

Composing the preprocessed signal for peak segment detection using Bivariate Ensemble Empirical Mode Decomposition (BEEMD) is another area that merits attention. The choice of BEEMD as the decomposition method and its comparative analysis with alternative decomposition techniques could provide insights into the most suitable approach for identifying peak segments in ECG signals. Moreover, using the Pan-Tompkins Algorithm (PTA) to determine the highest-frequency segments raises questions about its sensitivity and specificity, urging further investigation into its performance across diverse datasets.

The proposed methodology's innovative aspects are the extraction of coupling information from peaks and the concurrent extraction of depth features from binary images. However, the precise impact of these features on the overall classification accuracy and their generalizability to different populations and demographics remain open research questions. The Linear Approximate Functional Walrus Optimization Algorithm (LAFWOA) for feature selection introduces a unique element.

The experimental analysis showcasing improved accuracy compared to prevailing techniques is promising. However, a comprehensive understanding of the proposed methodology's performance across different datasets, patient demographics, and pathological conditions is crucial for its robustness and reliability. Addressing these research gaps will contribute to refining and validating the proposed CaP model, fostering advancements in early detection and prediction of cardiac diseases.

B. Motivation

The motivation behind this research stems from the profound impact of cardiac disease on mortality, marking it as a prevalent category of chronic and life-threatening conditions. Recognizing the urgency of early detection, previous research has delved into predicting HD through analyzing Electrocardiogram (ECG) signals. Despite these efforts, there exists an opportunity for improvement in the existing methodologies.

To address this gap, the study introduces an innovative CaP approach for early HD detection based on DLCVA-DCNN technique within its research framework. The journey begins with the preprocessing of input ECG signals, employing a Weighted Covariance Kalman Filter (WCKF) to eliminate noise and enhance signal quality. The subsequent steps involve a bifurcation of the preprocessed data: one branch transforms it into a binary image, while the other undertakes signal decomposition to identify peak segments.

The decomposition process utilizes the Bivariate Ensemble Empirical Mode Decomposition (BEEMD) method, and the Pan-Tompkins Algorithm (PTA) is applied to pinpoint the highest-frequency segments. Concurrently, coupling information is extracted from these identified peaks, and depth features are derived from the binary image. The selection of relevant features from both the coupling and depth features is achieved by applying the Linear Approximate Functional Walrus Optimization Algorithm (LAFWOA). These carefully chosen features are then fed into the DLCVA-DCNN classifier to discern between disease and standard signals, marking a significant advancement in the classification process. The experimental analysis thoroughly compares the proposed methodology and conventional frameworks, evaluating their performance based on established metrics. The outcomes demonstrate that the introduced approach outperforms existing techniques, attaining higher accuracy in discriminating disease and standard signals.

The significant contributions of this study are stated as follows:

i) The noises of the ECG signals are removed utilizing our proposed CaP approach.
ii) The signal is decomposed noise-free with the help of BEEMD.
iii) The accuracy level is improved by extracting coupling information from the signal and the depth features from the image.
iv) The training time of the model is reduced by using LAFWOA.

The remaining sections of this study are organized as follows: Section 2 presents the literature review. Section 3 defines the system architecture and problem formulation of the proposed CaP model. Section 4 describes about the used dataset for the formation of the CaP model. Section 5 outlines the proposed CaP model. Section 6 presents the experimental analysis of the proposed mechanism. Section 7 concludes our study and presents a few future works.

II. LITERATURE REVIEW

Jahmunah et al. devised a model to classify ECG signals into standard signals. Also, this model analyzed Myocardial Infarction (MI), Coronary Artery Disease (CAD), and Congestive Heart Failure (CHF) classes by utilizing a Convolutional Neural Network (CNN) along with unique GaborCNN models [11]. The GaborCNN model [11] demonstrated higher accuracy and the fastest computing process in experimental evaluation. However, the CNN model used general features, neglecting depth features associated with the disease, resulting in error output.

Plawiak & Acharya proposed a three-layer Deep Genetic Ensemble of Classifiers (DGEC) for arrhythmia detection using ECG signals [12]. With numerous features, the model achieved superior recognition accuracy and was deemed suitable for telemedicine models. However, it exclusively targeted arrhythmia disease, limiting its applicability to other types of heart diseases.

Fang et al. showcased ECG signal classification based on the Radial Basis Neural Network [13]. The K-means clustering approach was employed for sample screening, followed by using Radial Basis Function (RBF) NN for ECG information analysis. However, the final classification yielded better results, and the accuracy for recognizing abnormal signals was relatively low.

Li et al. recommended a multi-modal technique for predicting cardiovascular disease based on ECG and Phonocardiogram (PCG) features [14]. Utilizing prevailing NNs, they extracted deep-coded features from ECG and PCG. The genetic algorithm was employed for screening the amalgamated features, resulting in improved model performance compared to single-model mechanisms. However, the approach's networks were optimally adjusted for limited datasets.

Atal & Singh proposed an automated arrhythmia classification model using an optimization-centric deep CNN [15]. The Bat-Rider Optimization Algorithm (BaROA), combining the Rider Optimization Algorithm (ROA) and Multi-Objective Bat Algorithm (MOBA), achieved enhanced outcomes in experimental analysis. However, it focused only on manual features, neglecting dynamic features that could affect the output.

Sharma et al. presented a hybrid scheme for ECG signal classification involving preprocessing, Discrete Wavelet Transformation (DWT) signal decomposition, and feature vector optimization with Cuckoo Search (CS) [16]. The Support Vector Machine (SVM) with Feed-Forward Back-Propagation NN (FFBPNN) was employed for classification, resulting in better performance. However, fewer abnormal classes were identified, raising concerns about reliability for other abnormal classes.

Goharrizi et al. recommended a multi-lead ECG classification scheme using 1-dimensional total variation regularization for denoising [17]. The Histogram of Oriented Gradients technique extracted feature images for ECG signal classification, utilizing SVM with a fully connected NN. However, the model achieved better performance and was only partially automatic.

Palczy & Smigiel proposed a Deep Neural Network (DNN) for automatic primary ECG signal classification [18]. Features were extracted from input signals, and superior classification outcomes were attained by the convolutional network with entropy features. However, a convolutional network without entropy-centered features demonstrated higher computational efficiency but lower successful outcomes, potentially due to a considerably low number of neurons.

Rath et al. employed an imbalanced number of ECG samples to train various classification models for heart disease classification [19]. Multiple ML models were utilized, and based on performance metrics, the presented approach outperformed others. However, the Logistic approach, assumed as the baseline, might yield inaccurate results.

Panganiban et al. introduced a classification technique for ECG arrhythmia using CNN with images based on spectrograms, eliminating the need for enduring ECG visual examination [20]. Google Inception Net retained CNN's final layer, resulting in higher accuracy than other studies. However, the direct input of the signal into the classification process raised concerns about potential inaccuracies.

III. System Architecture & Problem Formulation

A. *System Architecture*

Designing a system architecture for Cardiovascular Disease (CVD) prediction using the DLCVA-DCNN technique involves several key components. Below is a high-level overview of the CaP architecture:

i. *Data Analysis:* We used the PTB Diagnostic ECG Database [21] for developing our CaP model. Then we perform data normalization followed by data pre-processing to deal with the missing values.
ii. *Feature Engineering:* We extract all relevant features from the dataset [21] that are likely to contribute to CVD prediction. For that, we consider incorporating domain-specific knowledge to enhance the feature set.
iii. *Architecture of the CaP model:*
   a. *Input Layer:* Accept the preprocessed features as input.
   b. *Convolutional Layers:* We use 300 convolutional layers to learn hierarchical representations from the input data automatically.
   c. *Activation Function:* We use the Delta Layer-based Center Vector Activation for enhancing non-linearity and feature learning.
   d. *Pooling Layers:* We employ pooling layers to reduce spatial dimensions and extract dominant features.
   e. *Fully Connected Layers:* We connect the convolutional layers to densely connected layers for global feature learning.
   f. *Output Layer:* A single output neuron with a sigmoid activation function is used for the binary classification of CVD.
   g. *Delta Layer and Center Vector Activation:*
      i. Integrate the Delta Layer to enhance the feature learning process by capturing local variations in the data.
      ii. Utilize the Center Vector Activation to introduce non-linearity and capture complex relationships in the data.
   h. *Loss Function:* We binary cross-entropy as our loss function to deal with the binary classification problem.
   i. *Optimization Algorithm:* We use Adam as our optimized to minimize the loss function during training.

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j. *Regularization and Dropout:*
   i. We apply dropout layers to prevent overfitting.
   ii. We use L1 regularization techniques to avoid model complexity.

k. *Model Evaluation:*
   i. We split the dataset [21] into training (80% of data), validation (10% of data), and test (10% of data) sets.
   ii. Evaluate the CaP model on the validation set to fine-tune hyperparameters and prevent overfitting.
   iii. Assess the final CaP model on the test set for unbiased performance evaluation.

l. *Hyperparameter Tuning:* The best hyperparameters configuration is described in table 1 to optimize the CaP model performance.

TABLE I. HYPERPARAMETER CONFIGURATION

Hyperparameter	***Value***
Optimizer	Stochastic Gradient Descent
Kernel size	1X1
Activation	Relu
Dropout Rate	0.1
Learning Rate	0.0005
Number of Convolutional Layer	300
Number of Max Pooling Layer	150
Number of Convolutional Layer Parameters	150X150X160
Epoch	2000
Batch Size	68

m. *Deployment:* Once the CaP model is trained and evaluated, deploy it in a production environment by considering various factors like latency, scalability, and accessibility.

B. *Problem Formulation*

Existing research efforts have primarily focused on enhancing the heart disease (HD) detection model. However, several research drawbacks have been identified, which are elaborated as follows:

i. *Feature Extraction Approach:* Many prevailing research methods directly extract features from signals, but they often fail to DLCVA-DCNN ture the intri-cate details in the signal. The frequency domain, known for its complexity, poses challenges in extracting comprehensive information for disease prediction.

ii. *Utilization of Lightweight Features:* The adoption of lightweight features in existing research has resulted in error-prone outputs, indicating a limitation in accurately representing the complexities of the underlying signals.

iii. *Impact of Non-Stationary Data Sequences:* The presence of non-stationary data sequences in samples increases the likelihood of overestimating the effect of sympathetic control. This, in turn, adversely affects the DLCVA-DCNN ability of statistical testing.

iv. *Noisy ECG Signal Handling:* The input ECG signal is inherently noisy. However, in conventional research, the heartbeat is often directly segmented from the input image without addressing power line interference and electromagnetic interference. This oversight may lead to inaccurate results.

v. *Decomposition Process:* In traditional research methodologies, decomposition is applied to extract peak segments from the signal. However, this process introduces noise, potentially resulting in a noisy output and inaccurate outcomes.

IV. DATASET

To develop the CaP model, we use the PTB Diagnostic ECG Database [21]. The PTB Diagnostic ECG Database comprises 549 high-resolution 15-lead electrocardiograms (ECGs). These ECGs consist of the standard 12, and Frank XYZ leads. Clinical summaries accompany each record. There are one to five available ECG records for each of the 294 subjects represented in the database. The subjects encompass healthy individuals and patients presenting a range of heart diseases.

V. PROPOSED CAP MODEL

The proposed DLCVA-DCNN method introduces HD detection using a Delta Layer based Center Vector Activation-centric Deep Convolutional Neural Network, incorporating depth features and coupling information. This approach encompasses eight distinct phases: i) pre-processing, ii) signal decomposition, iii) peak detection, iv) extraction of coupling information, v) image conversion, vi) extraction of depth features, vii) feature selection, and viii) classification. The block diagram of the proposed model is depicted in figure 1.

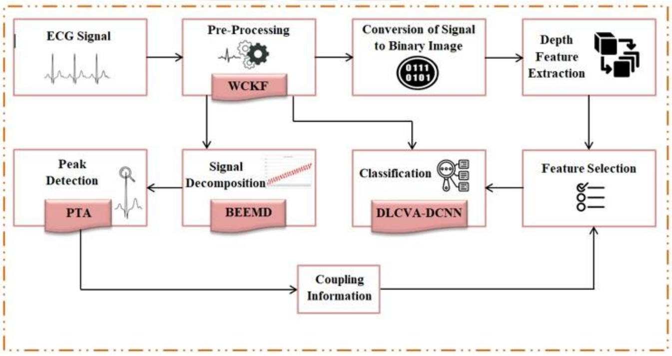

Figure 1. Block Diagram of Our Proposed CaP model.

Figure 1 depicts the general flow of our proposed CaP model. To achieve the desired result from the CaP model, we used the best hyperparameter set up to train the CaP model as described in the table 1.

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i. *Pre-processing:*

Initially, the input ECG signals ($D_{1,l}$ = 1, 2, ..., n) undergo pre-processing to eliminate various noises, including muscle artifact, power line interference, and baseline wander, commonly encountered during signal recording. The objective is to achieve an error-free outcome by removing these noises. In this context, the Kalman Filter (KF) is employed for noise reduction. Filters that lack output prediction introduce phase shifts, and using a predictive filter is essential to eliminate this issue. The KF is one of the most effective filters, justifying its application in this research methodology. However, in instances where the covariance process is smaller, round-off errors can lead to the computation of a smaller positive eigenvalue as a negative number. To address this, the research methodology employs the weighted covariance, ensuring the prevention of obtaining negative values. This modified filter is referred to as the Weighted Covariance Kalman Filter (WCKF) algorithm.

The process begins with the initialization of the system state for the input signal (S_1) and the system state error covariance (E_1). Subsequently, the system state (S_2) and system state error covariance (E2) are re-initialized. Following this, the system state and error covariance undergo prediction using the following equations (1) and (2):

$$Sn = Z * S2 \quad (1)$$
$$En = \omega * (Z * E2 * ZT) \quad (2)$$

Subsequently, the Kalman Gain (KG) is computed as per the following equation (3).

$$KG = En * LT\,(L * En * LT + \omega * R)-1 \quad (3)$$

Following the calculation of KG, the estimation of the system state (SS) and the system error covariance (SEC) is performed using equations (4) and (5).

$$SS = Sn + KG * (\alpha - L * Sn) \quad (4)$$
$$SEC = En - KG * L * En \quad (5)$$

Here, SS represents the state variable of the signal, SEC symbolizes the state covariance matrix, influenced by the weight function ω. α signifies the measurement, L epitomizes the state-to-measurement matrix, Z specifies the state transition matrix, R is the measurement covariance matrix, KG denotes the Kalman gain, and Pd characterizes the output of the pre-processed data.

ii. *Binary Image Conversion:*

On one hand, the signal undergoes noise removal before being transformed into a binary image. Extracting depth information from the signal poses challenges due to its non-linear nature. Employing an image-based process proves advantageous for extracting pixel information, as the frequency variance becomes evident in the pixels. The conversion process involves normalization, which unfolds in two steps: first, signal data points are partitioned into equivalent segments divisible into the total signal points without data loss. In the second phase, these segmented signals are reshaped into binary images. The resulting converted image is denoted as (Ds) in equation (6).

$$Ds = \text{Conversion(Signal after Noise Removal)} \quad (6)$$

iii. ***Depth Feature Extraction***:

After transforming the signal into a binary image, depth features are derived from this image. The depth features pertain to the most concealed points within the image. Specifically, edge features, correlation, entropy, contour-based features (external and internal contours), and slope-centered features (horizontal, positive, vertical, and negative) are extracted from the converted image. This set of extracted features is defined in equation (7).

$$Fs=\{F1,F2,..........,Fn\} \quad (7)$$

Here, Fs denotes the feature set and implies the n number of features from the converted image.

iv. Signal Decomposition:

On the flip side, the pre-processed signal (Pd) undergoes decomposition. This decomposition process is an effective way of identifying model information within time domain signals. The research employs the Ensemble Empirical Mode Decomposition (EEMD) algorithm for signal decomposition. The rationale behind selecting this algorithm lies in its automatic selection of fluctuations within a time series. However, this algorithm initially introduces Gaussian noise to address the inter-symbol interference problem. Since randomly added noise might impact the original data, this research methodology employs the bivariate function. In this function, noise is added to the input signal's imaginary and real parts. The proposed algorithm is named Bivariate Ensemble Empirical Mode Decomposition (BEEMD). The input signal is combined with a white noise time series during the initial stage. To prevent the loss of the original signal, the signal is segregated into its imaginary and real parts as the bivariate process. The bivariate process is computed by the following equation (8).

$$Hr\,(t) = (Ig(Pd) + Rl(P-d)) + br(t) \quad (8)$$

Here, Hr (t) represents the signal affected by noise, Ig denotes the imaginary component of the signal, Rl illustrates the real part of the signal, and the Gaussian white noise is represented as br (t). Subsequently, the signal containing noise is decomposed into a collection of Intrinsic Mode Functions (IMFs) along

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with a residual term, expressed as the following equation (9).

$$Hr(t) = \sum M_f(t) + Df(t) \quad (9)$$

M_f (t) represents the Intrinsic Mode Function (IMF) derived from each decomposition, and Df (t) signifies the residual. The ultimate IMF is achieved by averaging the overall IMF ($M^{avg}{}_f(t)$), and it is defined as the following equation (10).

$$M^{avg}{}_f(t) = 1/N * \sum M_f(t) \quad (10)$$

The results obtained from the system depend on both the selection of the ensemble number (N) and the amplitude of the added noise (T). Additionally, it is necessary to satisfy the following equation (11).

$$\gamma = T/\sqrt{N} \quad (11)$$

Here, the final standard deviation error is represented as the disparity between the original signal and denoted as γ.

iv. *Peak Detection*:

Following the signal decomposition, peaks are detected within the decomposed signal using the Peak-Tracing Algorithm (PTA) to extract valuable features. Broadly, the PTA is employed as a real-time QRS detection method. However, this algorithm incorporates an integrated window's width, slope, and amplitude. The algorithm encompasses two stages: pre-processing and decision-making. In the initial stage, a bandpass filter eliminates unwanted signals. This removal process involves both a low-pass filter and a high-pass filter. The transfer function of the low-pass filter is expressed as the following equation (12).

$$Lo(w) = (1 - w^{-6})^2/(1 - w^{-1})^2 \quad (12)$$

Here, Lo(w) denotes the low pass filter at the w transfer function. Afterward, the high pass filter HG(w) at the w transfer function is expressed as the following equation (13).

$$HG(w) = w^{-16} - (1 - w^{-32})/(1 - w^{-1}) \quad (13)$$

Subsequently, to gather insights into the signal's slope, the input signal's derivative is computed. Following differentiation, each point's value is squared to ensure all values are positive. Subsequently, the squared signal undergoes averaging. The next step involves integrating the averaged signal to extract information about the slope. These processes collectively contribute to the detection of waves.

v. *Coupling Information Extraction*:

The coupling information is derived from the identified waves. Coupling analysis can potentially delineate the electrical and mechanical characteristics of the heart based on the functional state and dynamic changes in the cardiovascular system. This information proves valuable for disease detection. Mutual Information (MI), multiscale cross approximate entropy, Cross Power Spectral Density (CPSD), phase synchronization, cross fuzzy measure entropy, and joint symbolic dynamics information are extracted in this context. The extracted coupling information is then articulated as the following equation (14).

$$Ci = C1, C2, \ldots, Cn \quad (14)$$

Here, the extracted coupling information set is symbolized as $Ci \in R+$.

vi. *Feature Selection:*

In this context, significant features are selected from the extracted depth features in the binary image and the extracted coupling information from the signal to minimize error output and training time. The proposed methodology employs the LAFWOA for the feature selection process.

In the Walrus algorithm, adults identify their large whiskers and tusks. A parameter is utilized to determine the algorithm's exploration ability, inducing substantial and extensive changes in the walrus's position. Incorrect selection of this parameter can lead to premature convergence issues. Hence, the research methodology utilizes the linear approximation function to choose the parameter value. The population is initially initialized, where the extracted depth features and coupling information are treated as attributes of the walrus. The initialization of the population is expressed in equation (15).

$$Jq = J1, J2, \ldots, Jn \quad (15)$$

Here, Jq exemplifies the combination of extracted feature set and coupling information where, $Jq \in R+$.

In this study, HD classification serves as the fitness criterion. Following the initialization phase, the fitness is computed. The population update process is initiated if the fitness value does not align with the predetermined threshold. This update process involves three phases: i) feeding strategy, ii) migration, and iii) escaping and fighting against predators.

vii. *Classification*:

In the context of HD prediction, the DLCVA-DCNN classifier receives the selected features and the original input signal as input. The random assignment of weight values in a CNN can result in error output. Thus, the utilization of the delta layer is introduced. This layer indicates that the adjustment in a node's weight is proportional to the product of the error and the input, where the error represents the disparity between the desired and actual output. Additionally, CNN employs the softmax activation function, known for its instability and vanishing gradient problem. Therefore, this research

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incorporates the neuron's center vector with the input of the activation function. Convolution layers extract features from the input image, and the dense layer uses the output from these layers to produce the final output. Subsequently, the convolutional layer's output is fed into the pooling layer, which reduces the number of parameters in the input and introduces some information loss. The output is fully connected through nodes in the fully connected layer, followed by activation in the output layer. Figure 2 illustrates the structure of our proposed DLCVA-DCNN classifier, while algorithm 1 defines the CaP model.

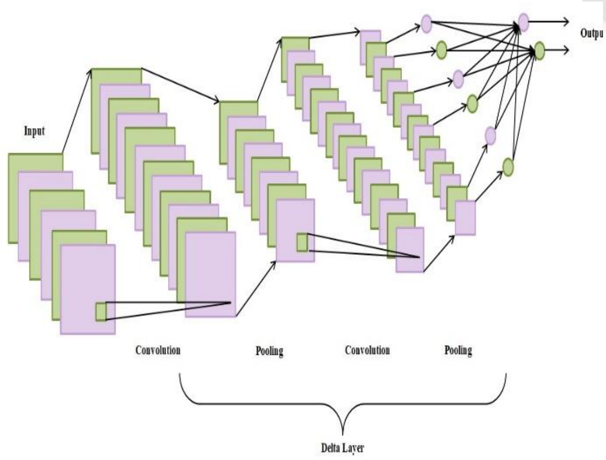

Figure 2. Structure of the DLCVA-DCNN classifier

Algorithm1. Cardiovascular Disease Prediction using CaP Model

Input: Input features for cardiovascular disease prediction
Output: Predicted cardiovascular disease status

Begin

i. Initialization:
   a. Initialize the deep convolutional neural network with a delta layer based center vector activation.
ii. Set hyperparameters, such as learning rate, batch size, and the number of epochs.
iii. Input Processing:
   a. Preprocess input data, including normalization and feature extraction.
iv. Model Architecture:
   a. Assume a simplified CNN architecture with multiple layers. For example, a convolutional layer followed by a pooling layer and a fully connected layer:

      Convolutional Layer: h(1) = σ(W (1) ∗ X + b(1))
      Pooling Layer: h(2) = max pooling(h(1))
      Fully Connected Layer: h(3) = σ(W (2)h(2) + b(2))

   Here, h(i) represents the output of layer i, W (i) is the weight matrix, b(i) is the bias, ∗ denotes convolution, and σ is the activation function.
v. Model Training:
   a. Train the deep convolutional neural network using a suitable loss function, such as cross-entropy:

$$\mathcal{L}(\theta) = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)] \quad (16)$$

   Here θ represents the model parameters, N is the number of samples, yi is the true label, and ˆyi is the predicted probability.
vi. Prediction:
   a. New input data into the trained model to predict cardiovascular disease status.
   b. The final prediction can be obtained by applying a threshold to the predicted probability:

$$\text{Prediction} = \begin{cases} 1, & \text{if } \hat{y} \geq \text{Threshold} \\ 0, & \text{otherwise} \end{cases} \quad (17)$$

vii. Return the predicted cardiovascular disease status.

End

VI. Evaluation Results & Discussion

A. Evaluation Results

The CaP model's effectiveness is assessed based on its performance in filtering, classification, decomposition, and feature selection processes, aligning with established research methodologies.

Network loss of the proposed CaP model is evaluated through the binary cross-entropy (BCE) metric.

BCE is computed by the following equation (18).

$$BCE = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(p_i) + (1-y_i)\log(1-p_i)] \quad (18)$$

Here, N denotes the total number of samples. y_i represents the true label of the i^{th} sample (either 0 or 1). pi is the predicted probability that the i^{th} sample belongs to class 1.

B. Performance Analysis based on Filtering Process

To analyze the performance of our proposed CaP model based on filtering process, we designed WCKF filter. Therefore, the performance of the CaP model using our proposed WCKF filter is analyzed through the Peak Signal Noise Ratio (PSNR) and Mean Squared Error (MSE) metrics. PSNR and MSE can be computed by the following equations (19) and (20).

$$\text{PSNR} = 10 \cdot \log_{10}\left(\frac{\text{MAX}^2}{\text{MSE}}\right) \quad (19)$$

Here, MAX is the maximum possible pixel value. MSE is the Mean Squared Error between the original and the reconstructed signal.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \quad (20)$$

Here, n is the number of samples. Yi and ˆYi are the actual value and the predicted value for the ith sample, respectively.

The outcomes of the CaP model based on WCKF filter are compared with Kalman Filter (KF) [23], Band Pass Filter (BPF) [24], Chebyshev Filter (CF) [25], and Notch Filter (NF) [26] techniques. Table 2 describes the comparison results among all techniques.

TABLE II. COMPARISON OF TECHNIQUES WITH PERFORMANCE METRICS BASED ON FILTERING PROCESS

Techniques	*PSNR (%)*	*MSE (%)*
Kalman Filter (KF) [23]	68	60.3
Band Pass Filter (BPF) [24]	64	49.2
Chebyshev Filter (CF) [25]	59	31.3
Notch Filter (NF) [26]	65	24.23
CaP with WCKF (Proposed Technique)	**73**	**10**

From table 2, we observed that the CaP model with WCKF achieves superior PSNR and a lower MSE value, which mitigates favorable outcomes of our proposed CaP model. Our CaP model exhibits a PSNR of 73% and an MSE of 10%. Higher PSNR and lower MSE values indicate higher prediction accuracy. In contrast, the KF demonstrates an average PSNR and MSE of 68% and 60.3%, respectively. Similarly, the other algorithms perform less than the proposed CaP model. From the above observation, we can understand that the noise removal process employed by the CaP model proves highly effective for eliminating baseline wander, muscle artifacts, and other forms of noise.

C. Performance Analysis of CaP Model based on Signal Decomposition

Performance Analysis of CaP Model based on Signal Decomposition is computed through the recall, sensitivity, precision, and F1-Score metrics. The recall, sensitivity, precision, and F1-Score metrics can be computed by using the following equations (21), (22), (23), and (24).

Recall = True Positives/(True Positives + False Negatives) (21)
Sensitivity = False Positives/(True Positives + False Negatives) (22)
Precision = True Positives/(True Positives + False Positives) (23)
F1-Score = 2 ∗((Precision ∗ Recall)/(Precision + Recall)) (24)

The performance of the CaP model using BEEMD method is compared with the conventional Empirical Mode Decomposition (EMD) [27], Fourier Decomposition Method (FDM) [28], Ensemble Empirical Mode Decomposition (EEMD) [29], and Variational Mode Decomposition (VMD) [7] methods. The comparison result is described in table 3.

TABLE III. COMPARISON OF METHODS WITH PERFORMANCE METRICS BASED ON SIGNAL DECOMPOSITION

Methods	*Precision (%)*	*Recall (%)*	*F1-Score (%)*
Empirical Mode Decomposition (EMD) [27]	93.2	91	88
Fourier Decomposition Method (FDM) [28]	89	85.2	80.29
Ensemble Empirical Mode Decomposition (EEMD) [29]	79	71.3	69.98
Variational Mode Decomposition (VMD) [7]	69	64.23	60.98
CaP with BEEMD (Proposed Method)	**96**	**94**	**95**

Table 3 shows that the proposed CaP with the BEEMD method demonstrates precision, recall, and F1-Score values of 96%, 94%, and 95%, respectively. In contrast, the compared methods exhibit lower precision values: 93.2% for EMD, 89% for FMD, 79% for EEMD, and 69% for the VMD methods. Additionally, the existing research exhibits inferior performance across various metrics compared to the proposed CaP model because the utilization of the bivariate function in the CaP model safeguards against noise and mode mixing problems.

D. Performance Analysis of CaP Model based on Feature Selection

Performance analysis of CaP model based on feature selection is computed by using LAFWOA algorithm. Here, the performance of CaP model with LAFWOA algorithm is compared with the existing Walrus Optimization Algorithm (WOA) [6], Salp Swarm Optimization (SSO) [5], Dove Swarm Optimization (DSO) [9], and Egret Swarm optimization (ESO) [8] algorithms.

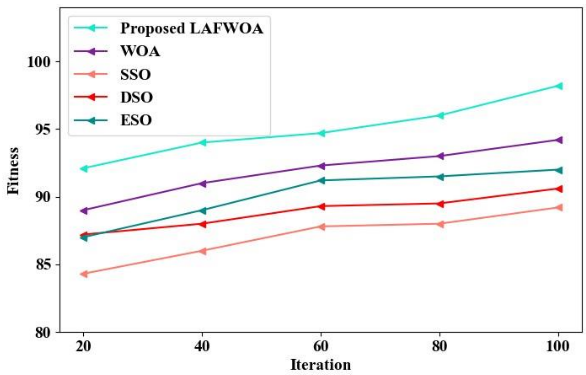

Figure 3. Fitness Vs Iteration Analysis Comparison.

Figure 3 illustrates a graphical representation of the analysis of fitness versus iteration. In this study, accuracy serves as the fitness function. The fitness level exhibits variations based on the iteration count. At an iteration count of 80, the proposed CaP with the LAFWOA algorithm achieves a fitness of 96%, surpassing the fitness values obtained by existing research approaches at the exact iteration count. Moreover, the presented CaP with the LAFWOA algorithm consistently demonstrates superior outcomes for the remaining iteration counts. Solving the premature convergence problem in CaP with the LAFWOA algorithm contributes to its enhanced performance in each iteration.

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E. Performance Analysis of CaP Model based on HD Classification

This phase compares the performance of our proposed CaP model (based on DLCVA-DCNN classifier) with the conventional Recurrent Neural Network (RNN) [22], Artificial Neural Network (ANN) [5], Deep Convolutional Neural Network (DCNN) [15], and Deep Neural Network (DNN) [18] models using specificity, sensitivity, and accuracy metrics as described in table 4.

TABLE IV. COMPARISON OF METHODS WITH PERFORMANCE METRICS BASED ON HD CLASSIFICATION

Models	*Specificity (%)*	*Sensitivity (%)*	*Accuracy (%)*
Deep Convolutional Neural Network (DCNN) [15]	83.2	81	80.8
Deep Neural Network (DNN) [18]	69	68.23	68.98
Artificial Neural Network (ANN) [5]	80	79.3	79.98
Recurrent Neural Network (RNN) [22]	75	74.23	73.98
CaP (Proposed Model)	**97**	**98**	**98.5**

From table 4, we observed the HD classification of the state-of-the-art models using specificity, sensitivity, and accuracy metrics. The existing DNN model [18] attains the lowest value based on all the mentioned metrics (i.e., 69% for specificity, 68.23% for sensitivity, and 68.98% for accuracy). In contrast to existing approaches, the DCNN [15] model attains better results. However, it also has lower performance than the proposed CaP model because the proposed methodology is enhanced by introducing a delta layer with the center vector neuron activation process. The specificity, sensitivity and accuracy values of the proposed approach are 97%, 98%, and 98.5%, respectively.

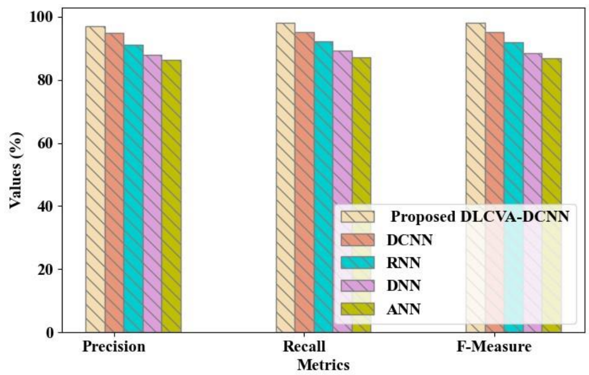

Figure 4. Analysis of Proposed DLCVA-DCNN and Existing Classifiers based on Precision, Recall, and F1-Score Metrics.

Figure 4 presents an analysis based on i) Precision, ii) Recall, and iii) F1-Score metrics comparing the proposed CaP model with DLCVA-DCNN classifier with the existing classifiers. In this comparison, the presented CaP model consistently outperforms conventional systems. The F1-Score value achieved by the proposed CaP model is 98%, surpassing the F1-Score values of existing DCNN [15], RNN [22], DNN [18], and ANN [5] are 2.8%, 6.1%, 9.5%, and 11.1%, respectively. This observation highlights the efficiency prominently demonstrated by the proposed DLCVA-DCNN classifier

VII. CONCLUSION & FUTURE WORK

This study introduces an efficient system for detecting Heart Diseases (HD) based on DLCVA-DCNN. Both coupling information and depth features are extracted to enhance the system's effectiveness. The proposed methodology is evaluated using the PTB-ECG diagnostic database. Performance comparison with conventional mechanisms is conducted in the experimental evaluation. Using PSNR and MSE metrics, the proposed WCKF is compared with other filters, achieving 73% PSNR and 10% MSE. The decomposition algorithm is analyzed with respect to recall, precision, F1-Score, and sensitivity metrics. The primary phase involves HD classification using a classifier. The proposed DLCVA-DCNN is contrasted with other algorithms based on performance metrics, achieving a higher accuracy (98.5%) than existing classifiers. The proposed classifier is also compared with literature approaches. However, peak detection is crucial for extracting information from the input, particularly in effectively detecting QRS and other significant peaks. Therefore, the proposed CaP model could be further enhanced by adopting an efficient approach for peak detection and considering additional features for HD prediction in future research.

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