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Optimized CNN for Cardiac Disease Detection Using Hybrid Crow Search and Dragonfly Algorithms

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Abstract: Cardiovascular Disease (CVD) is a hazardous condition for humans that is rapidly expanding around the globe in developed as well as developing nations, eventually resulting in death. In this disease, the heart often fails to supply sufficient oxygen to other parts of the body so that they are cannot able to perform their normal activities. It is critical to identify this problem immediately and precisely in order to save patients lives and avoid additional damage.Henceforth, this work proposes an efficient image processing strategy based on a hybrid algorithm optimised Convolutional Neural Network (CNN) classifier, which is used in this present research for precise identification of cardiac vascular disease.In the beginning, the Electrocardiogram (ECG) images are obtained and processed by removing noise using an adaptive median filter. The pre-processed ECG image is then divided into different regions using the Fuzzy C-Means (FCM) algorithm, which improves the accuracy of heart illness detection.Following segmentation, the Grey level Co-occurrence Matrix (GLCM) is employed to efficiently extract high-ranked features. Subsequently, the characteristics are considerably identified using a novel hybrid Crow Search Optimization (CSO) Dragon Fly Optimisation (DFO) algorithm-based CNN classifier for optimally categorising the cardiacvascular illness.The entire work is validated in Python software, and the results show that the novel method produces the best possible outcomes with a maximum precision of 98.12%.

Index Terms: Adaptive Median Filter, ECG, Fuzzy C-Means, GLCM, Hybrid CS-DF Optimized CNN Classifier.

1. Introduction

Heart disease is one of the foremost causes of death on a broad scale throughout the world. According to the World Health Organisation (WHO), heart disease accounts for 33% of all deaths worldwide, or 18 million people every year [1]. Cardiovascular diseases (CVDs) are another term for heart-related disorders. Strokes and heart attacks account for approximately 86% of CVD deaths [2]. Due to the reasons of Poor diets, insufficient exercise, drunkenness, and tobacco use are some of the main risk factors that raise the risk of heart disease. As a result, people are reported to have intermediate-risk disorders such high blood pressure, being overweight, and being obese [3, 4].Current medical research has demonstrated significant and effective ways to deal with heart-related issues. In the modern era, medical problems are able to be resolved using innovative technological approaches [5]. The ECG, a coronary screening, and blood test are the three main methods used to identify heart disease. The ECG test is also known as a diagnostic aid for detecting heart conditions [6].Cardiovascular disease can be identified throughan ECG, an accessible, affordable, and noninvasive method of discoveringthe heart's electrical activity [7]. In this research, the ECG images data of patients with cardiac conditions is utilised to explore the potential of deep learning algorithms to predict the four main cardiac abnormalities:myocardial infarction, abnormal heartbeatand normal person classes.Using electrodes on the outermost layer of the body to identify voltage changes, the ECG is a visible signal that gets recorded or measured (Figure 1). Early prediction of cardiovascular disease has been the subject of several studies. These are presented below in an elaborative manner.The authors of [8] have presented a novel strategy for digitising ECG data from previously preserved paper or photographed format using traditional image processing methods. With an average of more than 95% correlation pairing, the method reconstructs ECGs. However, the majority of disease trends depend on inaccurate information and inaccurate stepwise algorithms.The end-to-end adaptable cross-domain transfer learning model for based on information detection of CVDs is described in ref [9], which could promote making choices and therefore enhance patient care. The suggested structure is tested on two sets of data, and the findings demonstrate that utilising transfer learning, superior performance is attained. However, utilising an auto-encoder capable of concurrently optimise the classification and reconstruction errors would help to reduce the high-dimension of CNN features.The ECG and PCG signals are combined for CAD detection according to research published in [10], which also led to the development of a dual-input neural network structure. The experimental findings demonstrated that the suggested technique had a classification accuracy on the ECG and PCG records of 95.62%. But,it should be noted that the suggested approach needs a lot of annotated data for supervised learning, and some of the retrieved features aren't very helpful for categorization.

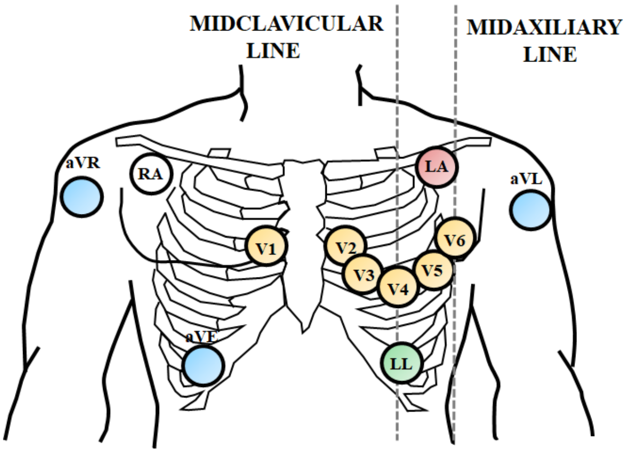

Fig.1. ECG electrodes

For a better screening system, the author of [11] offers a CNN-LSTM method that integrates two separate generalised CAD markers into one hybrid structure. Here, the more affordable ECG sensor is utilised. However, neither of the bio-markers discussed in this research is always present at the outset of CAD. As a result, this method misses some patients who are on the borderline.A multi class classification issue is accurately handled in this study [12]. The problem of temporal difficulty and training time is addressed, and a DCNN design is presented. This shortens the overall training period. The suggested model works better than the methods used in previous research, obtaining the best accuracy with a minimal time complexity. However, this method has significant drawbacks, which include recognising that the data became extremely unbalanced and containing only a certain amount of images. Therefore, in this work propose an a hybrid optimized CNN to tackle the aforementioned issues. According to the proposal, the following are its major contributions:

- Implementation of Adaptive Median Filter to enhance the ECG images by reducing noise without dramatically obscuring the image's structures.
- An application of FCM to segment noise-free ECG images into multiple regions to facilitate disease diagnosis.
- Using GLCM method, the required features are extracted in effective manner.
- Deployment of Hybrid CS-DF optimized CNN results in accurate CVD prediction with a minimal time complexity.

The proposed approach significantly advances existing research by addressing key limitations in prior works, such as reliance on imbalanced datasets, high training complexity and limited feature relevance. Unlike traditional methods that depend on annotated data or are susceptible to noise interference, this study introduces a hybrid optimized CNN framework that integrates multiple advanced techniques for improved accuracy and efficiency. Firstly, the use of an Adaptive Median Filter ensures superior ECG image quality by effectively removing noise while preserving essential structural information. The FCM segmentation divides the denoised images into meaningful regions, enhancing diagnostic precision. Feature extraction using the GLCM captures texture-based patterns crucial for distinguishing cardiac conditions. Most notably, the hybrid CS-DFO algorithm fine-tunes the CNN classifier, optimizing both classification performance and computational efficiency. The proposed system is implemented in Python platform to validate its effectiveness, from the simulation results the proposed system attains maximum prediction acuracy value of 98.12%. The following section contains an in-depth description of the present research.

2. Proposed System Description

The adoption of a hybrid CS-DF optimised CNN-based image processing method for recognising CVD at the earliest phase is extensively clarified in this paper to achieve the supreme goal of determining the presence of cardiac conditions without difficulties because this method has the capability of forecasting the disease with the utmost precision. Figure 2 shows a block diagram depicting the flow of the proposed technique.

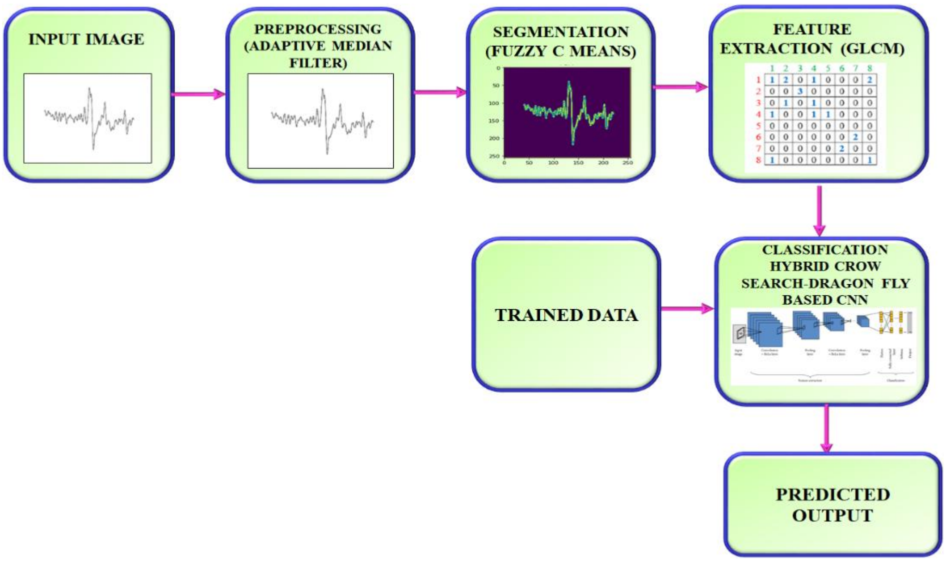

Fig.2. Early cardiovascular disease prediction using hybrid optimized CNN

The input ECG image is first pre-processed to efficiently remove any unforeseen or unwanted noises from the images. This serves to enhance the image in the best possible way. This ensures that the input to subsequent stages is of high quality, reducing the likelihood of false detections. Following denoising, the FCM algorithm segments the ECG image into distinct regions based on pixel similarity, which improves the localization of relevant patterns associated with different cardiac conditions. The denoised image is segmented into several parts in the following step with the support of FCM to increase the accuracy of illness identification. By isolating meaningful segments and eliminating irrelevant or noisy regions, FCM enhances feature clarity and ensures that the extracted features are more representative of the underlying pathology. These refined inputs allow the feature extraction and classification stages, especially the CNN classifier to operate on more informative data, ultimately contributing to improved classification performance. After segmentation, the features in the segmented images are successfully extracted in the following stage employing the FCM method, which substantially decreases the difficulty in determining the presence of CVD. The segmented features are then accurately classified in the following stage through a hybrid CS-DF optimised CNN classifier, which helps considerably in identifying the types and stages of the disease.

3. Proposed System Modelling

3.1. Pre-processing using Adaptive Median Filter

Adaptive Median Filter is employed in the present research for removing unwanted noise as it includes in maintaining the specifics of the image whereas removing the electrical impulse noises without causing interruptions because the ECG image is highly susceptible to the unavoidable noises, making it exceptionally essential to remove noise from the input image via the application of suitable filters. In Figure. 3 the denoising of the image is impressively and effectively described.

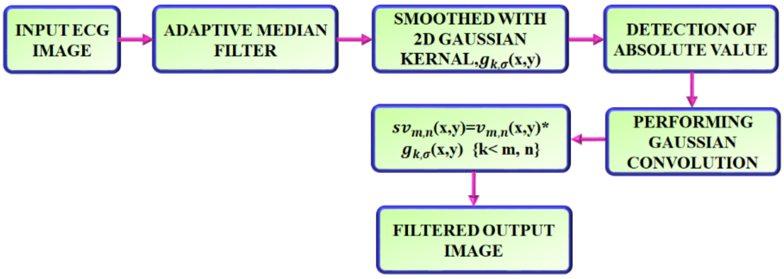

Fig.3. ECG image pre-processing using adaptive median filter

Following median filtering the input image, the variance between the filtered and original image is calculated and is represented as,

$$d_{m,n}(x,y) = f_{m,n}(x,y) * med_N\left[f_{m,n}(x,y)\right] \tag{1}$$

For the purpose of to soften the input image, the 2D Gaussian kernel, $g_{k,\sigma}(x,y)$ is convoluted with the original image as follows:

$$s_{m,n}(x,y) = f_{m,n}(x,y) * g_{k,\sigma}(x,y)\{k < m,n\} \tag{2}$$

In this case, the amount of σ and the degree of flattening are proportionate.The variancebetween the original image and smoothed image is then taken to be,

$$v_{m,n}(x,y) = \mid f_{m,n}(x,y) - s_{m,n}(x,y) \mid \tag{3}$$

A function of Gaussian convolution is applied to $v_{m,n}(x,y)$ in order to achieve the smoothed form of the difference.

$$s_{m,n}(x,y) = v_{m,n}(x,y) * g_{k,\sigma}(x,y)\{k < m,n\} \tag{4}$$

The smoothing variability splits the difference in equation 1 as follows for achieving the ratio.

$$r_{m,n}(x,y) = \frac{d_{m,n}(x,y)}{sv_{m,n}(x,y)} \tag{5}$$

Following the completion of all of the preceding stages, the improved output image is obtained, and the filtered image is then passed to the subsequent stage, called segmentation.

3.2. Segmentation using Fuzzy C Means Method

A collection of data in FCM serve as a member of several clusters. The membership value reveals the similarity. A data sample's membership value in FCM is determined by the proximity the sample is to the cluster centre. The membership values range from 0 to 1, with higher values designating greater similarity.The clustering at the final stage of the clustering procedure is determined by defuzzification. As a repeated algorithm, FCM updates the cluster centre and membership value repeatedly to arrive at the desired result. The cost function must be solved to generate these updating equations. The data containing N data samples is signifiedby $X = \{x_1, x_2, x_3, ..., x_N\}$. In order to divide it into c-clusters, the next cost function needs to be minimised**.**

$$J = \sum_{j=1}^{N}\sum_{i=1}^{c} u_{ij}^{m} \left\| x_j - v_i \right\|^2 \tag{6}$$

Where $\|.\|$ is a norm metric, v_i is the centre of the ith cluster, u_{ij} indicates the membership of x_j with the ith cluster, and $'m'$ is a constant. The subsequent partition's fuzziness is determined by the parameter m. The subsequent equations are reached by calculating the derivative of the equation and setting it equal to zero utilising the Lagrange method.

$$v_i = \frac{\sum_{j=1}^{N} u_{ij}^{m} x_j}{\sum_{j=1}^{N} u_{ij}^{m}} \tag{7}$$

$$u_{ij} = \sum_{K=1}^{C} \left(\frac{\left\| x_j - v_i \right\|}{\left\| x_j - v_K \right\|} \right)^2 \tag{8}$$

Following the segmentation process, the image is passed to the following stage for the extraction of the best features.

3.3. Feature Extraction using GLCM Method

The features in the photos are essentially generate the increased precision, however a large number of features increases the difficulty of the procedure, which consumes a greater amount of time and memory, and may cause overfitting problems. To solve this problem, GLCM is used, a feature extraction technique of second order that makes use of a co-occurrence matrix to indicate the neighbour relationships between picture pixels for various directions and spatial distances. The GLCM is selected as the feature extraction method in this study due to its proven effectiveness in capturing texture-based information, which is particularly important in analyzing ECG images where subtle variations in pixel intensity patterns can indicate underlying cardiac abnormalities. Unlike basic statistical or gradient-based feature extraction techniques, GLCM analyzes the spatial relationships between pixels, enabling the extraction of second-order texture features such as contrast, correlation, energy and homogeneity. These features provide a more comprehensive representation of the structural characteristics present in ECG signals. Additionally, GLCM is computationally efficient and well-suited for grayscale medical images, making it a practical choice for integration with deep learning models. Its ability to enhance the discriminative power of the classifier, especially when combined with optimized CNN architectures, justifies its selection over other conventional methods for this application. Below is a list of the features that were extracted and used for classification.

A. Energy

It delivers information about the size of the concentration of pair with anexact grey intensity in the co-occurrence matrix,

$$Energy = \sum_{i=1}^{L} \sum_{j=1}^{L} q(i, j)^2 \tag{9}$$

B. Contrast

It is provided by and it describes the size of the dispersion of inertia moments or changes in the picture matrix,

$$Contrast = \sum_{i}^{L} \sum_{j}^{L} |i - j|^2 \, q(i, j) \tag{10}$$

C. Homogeneity

The term "homogeneity" describes the level of homogeneity of a gray-scale image and is provided by,

$$Homogeneity = \sum_{i=1}^{L} \sum_{j=1}^{L} \frac{q(i, j)^2}{1 + (i - j)^2} \tag{11}$$

D. Dissimilarity

It is defined asthe measurement of the variations in grey level image,

$$Dissimilarity = \sum_{k} \sum_{I} P(k, I) |k - 1| \tag{12}$$

E. Correlation

Correlation is defined as the calculated value of the linear correlation of the grey currency matrix with respect to the picture and is given by,

$$Correlation = \sum_{i=1}^{L} \sum_{j=1}^{L} \frac{(i - \mu_i)(j - \mu_i) \, p(i, j)}{\sigma_i \sigma_j} \tag{13}$$

Thus, by using the GLCM technique, the features are successfully extracted from the image and then applied to the proposed classifier.

3.4. Hybrid CS-DF Optimized CNN for Classification

CNN Classifier

The structure of a fundamental CNN for classification of images is shown in Figure 4. Convolutional and pooling layers are the two primary layer types in the CNN. Depending on the quantity of predetermined filters (or weights), convolutional layers produces set of feature maps. The input data is subjected to a convolution using these features. The feature convolves over a small area of the data using a sliding window method, creating an output that becomes the input for the following layer. After computing the feature maps, a nonlinear activation function is used.

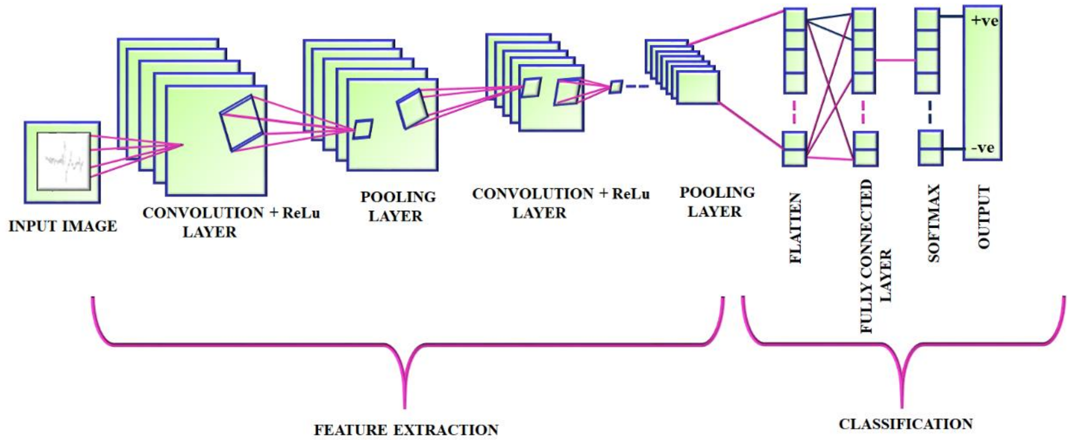

Fig.4. CNN structure

Semantically related features (the convolutional layer's outcome) are combined into a single output value using pooling layers. Max-pooling, which uses the maximum result from a sub-sampling zone as the output value, is one of the most frequently employed pooling method. After pooling layers, fully-connected layers are added to classify or predict using the input data. To ensure that the proposed CS-DF-CNN model generalizes effectively to unseen data, cross-validation techniques are employed during the training and evaluation phases. Specifically, k-fold cross-validation is used, wherein the dataset is divided into *k* equal subsets. The model is trained on *k-1* subsets and validated on the remaining subset, and this process is repeated *k* times with each subset serving once as the validation set. The average performance across all *k* iterations provides a more robust estimate of the model's generalization ability. This approach minimizes the risk of overfitting by exposing the model to diverse partitions of the data. Additionally, the use of the hybrid CS-DF optimization helps the CNN avoid local minima and over-tuned configurations by continuously adjusting its parameters for optimal performance across various data segments. As a result, the model maintains high predictive accuracy and performs reliably when applied to new, unseen ECG image data.

A. Hybrid CS-DF Algorithm

A method for learning the network structure and updating the weight is proposed. While adjusting the weight and bias in CNN, weight optimisation is essential to acquire the desired result. As a result, the hybrid CS-DF optimisation approach is implemented in this case. Although having numerous positive components, the CSO Algorithm has concerns with convergence and precision, which are addressed by including the DF Algorithm. The combination of these algorithms assists in achieving optimal results with fewer parameters and faster convergence. This combination is strategically designed to integrate the strengths and overcome the limitations of each individual algorithm. CS, inspired by the intelligent food-hiding and retrieval behavior of crows, excels in global exploration of the search space but may suffer from premature convergence and local optima entrapment. On the other hand, the DF algorithm, which mimics the static and dynamic swarming behaviors of dragonflies, offers strong local exploitation capabilities and smooth convergence but may lack sufficient global search diversity. By integrating CS's exploratory prowess with DF's fine-tuning and exploitation efficiency, the hybrid CS-DF algorithm achieves a balanced optimization strategy. This combination enables more accurate tuning of the CNN’s hyperparameters such as learning rate, batch size, number of filters and kernel sizes, ultimately leading to enhanced classification performance, faster convergence and better generalization. Thus, the hybrid model benefits from a diverse and adaptive search process that improves the reliability and precision of cardiovascular disease detection from ECG images.

B. Crow Search Algorithm

Crow search algorithm is another bio-inspired technique that mimics crows' cognitive behaviour in memorising the locations where they bury their food and can retrieve it even after months.

Procedure for CSO

- Assume that the populace has N different options or solutions.
- Let S represent the population size.
- To initialise the position of each crow vector is used,

$$X_c^i = [X_c 1^i X_c 3^i .....X_c d^i] \tag{14}$$

Where d denotes the dimensions of the search space and i is the iteration index

- The entire population

$$X = \begin{bmatrix} \\ X_{11i} & X_{12i} & \dots & X_{1di} \\ X_{21i} & X_{22i} & \dots & X_{2di} \\ . & . & \dots & . \\ . & . & \dots & . \\ X_{s1i} & X_{s2i} & \dots & X_{sdi} \end{bmatrix} \tag{15}$$

- Memory can be set up as follows:

$$M = \begin{bmatrix} \\ m_{11i} & m_{12i} & \dots & m_{1di} \\ m_{11i} & m_{22i} & \dots & m_{2di} \\ . & . & \dots & . \\ . & . & \dots & . \\ m_{s1i} & m_{s2i} & \dots & m_{sdi} \end{bmatrix} \tag{16}$$

- Determine the likelihood of being aware.
- The optimal option is selected by assessing the fitness value at each iteration.
- The crows' position is modified appropriately to establish the location of the hidden food.
- The created location's feasibility is confirmed, and the fitness value for the newly updated position is determined.
- If the fitness value is greater than the existing memory value, the memory value should be updated.
- Repeat steps 6–10 until the termination conditions are met.

C. Dragon Fly Algorithm

The dragonfly spends the majority of its life as a nymph before metamorphosing into an adult. Swarming characteristics of dragonflies, including static and dynamic, are being replicated in DF. Dragonflies form tiny flocks and fly to and from a nearby location for food hunting during the stationary swarm stage. A static swarm's main features include sudden alterations and localization within the flying route. A huge number of dragonflies in a dynamic swarm cause the swarm to move across long distances in a given direction.The position update of swarm individuals is divided into five types based on the two behaviours mentioned above: attraction, control cohesion, alignment, separation distraction. Equation (17) indicates the parting of the $i^t h$ dragonfly indicated as D_i to form its neighbour.

$$D_i = -\sum_{i=1}^{NI'} \left(Z' - Z'j \right) \tag{17}$$

The currently positioned individual's location is given as Z', the j^{th} surrounding individual's location is supplied as $Z'j$, and the number of related to individuals is given as NI'. The alignment of such dragonflies is estimated by Equation (18). The speed of the i^{th} neighbouring individual is denoted as $V'j$ in this case. Equation (19) depicts the procedure for calculating of cohesiveness. The assessment of inclination over the food source is explained in Equation (20). Fd specifies the position of the food source in this case. The mathematical calculation of distraction across external foes is shown in Equation (21). Eny provides the enemy's location as that.

In current individual's position is given as Z', the j^{th} neighbouring individual's position is denoted as $Z'j$, and count of neighbouring individual is specified as NI'. Equation (18) evaluates the alignment of such dragonflies. Here, velocity of i^{th} neighbouring individual is defined as $V'j$. Equation (19) represents the calculation of cohesion. Equation (20) describes the estimation of attraction over food source. The food source position is indicated by Fd. Equation (21) displays the computation of distraction over the external enemies. In this, the position of the enemy is specified by Eny.

$$AI_i = \frac{\sum_{j=1}^{NI'} V'j}{NI'} \tag{18}$$

$$Ch_i = \frac{\sum_{j=1}^{NI'} Z'j}{NI'} - Z' \tag{19}$$

$$Fs_i = Fd - Z' \tag{20}$$

$$EE_i = Eny + Z' \tag{21}$$

The following five correction strategies are used to study dragonfly behaviour. The location of dragonfly revisions, in addition to their simulation's motions, are calculated in search space utilising two vectors, location Z' and step ZD'. The step vector is identical as the vector of velocity of the PSO method, and the DF method is built on top of it. The step vector that determines dragonfly motion is depicted in Equation (22).

$$\Delta Z'_{t+1} = \left(d' + D_i + a'^{AI_i} + c'^{Ch_i} + f'^{Fs_i} + e'^{EE_i} \right) + \delta \Delta Z'_t \tag{22}$$

where d0 represents the amount of separation weight, D_i represents the ith individual segregation, a' represents the position weight, and AI_i represents the ith individual alignment The cohesion weight is written as c', the first individual cohesion is written as Ch_i, the food aspect is written as f', the i^{th} individual food source is written as Fs_i, the enemy factor is written as e0, the i^{th} Sensors individual enemy position is written as EE_i, the coefficient of inertia is written as d, and the iteration count is written as t. Equation (23) is used to estimate the location vector.

$$Z'_{t+1} = Z'_t + \Delta Z'_{t+1} \tag{23}$$

In which t represents the current iteration. When there is no neighbouring an approach the dragonflies have to fly in random directions over a search space (Levy flight) to enhance their unpredictable behaviour, inconsistency, and exploration. Equation (24) is used to modify the location of the dragonflies at this stage.

$$Z'_{t+1} = Z'_t + Levy(h) \times Z'_t \tag{24}$$

Flow chart of proposed hybrid CS-DF optimized CNN classifier is illustrated in Figure 5. Initially, a population of candidate CNN configurations is generated. The CS algorithm updates these candidates by adjusting their positions based on memory of best-known solutions, aiming to discover optimal hyperparameter settings. However, to overcome CS's tendency to stagnate or converge prematurely, the DF algorithm is integrated. It introduces dynamic swarm behaviors such as alignment, separation and cohesion to diversify the search and refine local exploration. Together, CS ensures global search capability while DF strengthens convergence by refining promising regions. This hybrid CS-DF optimization loop continues through several iterations, constantly evaluating CNN performance as the fitness function, ultimately leading to a robust and high-performing CNN model designed for cardiac disease classification.

Key CNN hyperparameters such as the number of convolutional layers, filter sizes, stride values, learning rate, batch size and number of neurons in the fully connected layers are adjusted dynamically using the hybrid algorithm. The Crow Search component helps explore the global search space effectively, integrating memory-based learning to guide the search process, while the Dragonfly Optimization component addresses local exploitation by simulating natural swarming behaviors. By combining these strategies, the hybrid algorithm mitigates issues of premature convergence and local optima entrapment, which are common in individual optimization methods. The result is a well-tuned CNN model capable of delivering high classification accuracy with improved generalization and reduced training time.

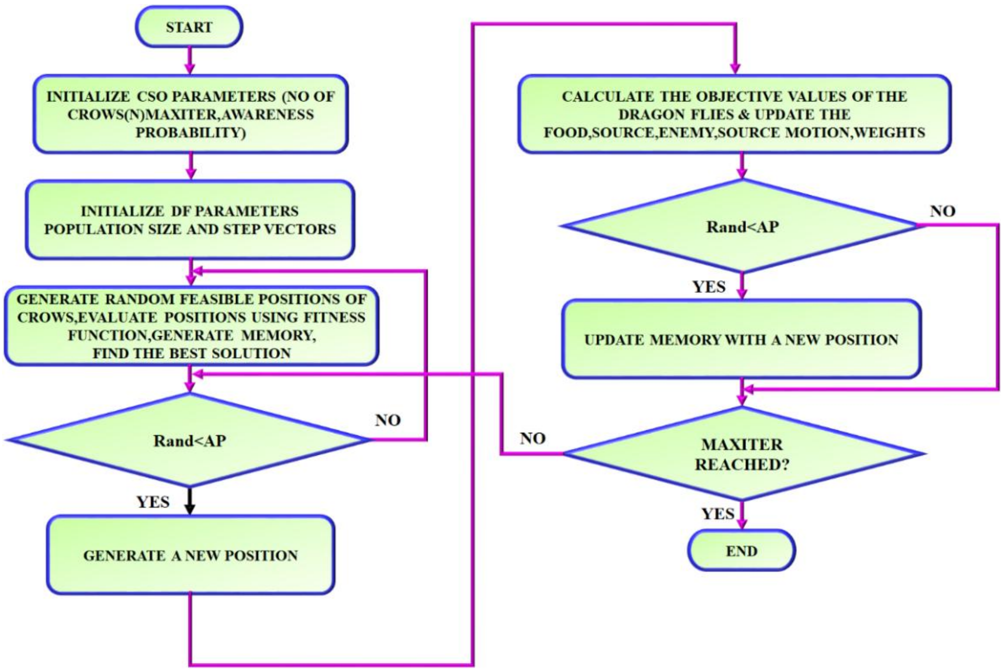

Fig.5. Flowchart of proposed hybrid algorithm

4. Results and Discussion

The present research provides a thorough explanation of the process used to develop an innovative hybrid optimization-based CNN classifier for the precise detection of CVD utilising GLCM-based feature extraction with Adaptive median filter and the results of this method are clearly described in the next part. The given research has been optimally validated using the MATLAB Simulink. The MIT-BIH arryhthmia dataset is used in which the training data used is 5042 and testing data used is 1341.Arrhythmia is one form of cardiac disease that is triggered from constricted heart attack, faulty heart valves, heart arteries, heart failure, previous heart surgery, cardiomyopathy and extra types of heart injury.An aberrant heartbeat, which may happen individually or in sequential order, is frequently used to diagnose an arrhythmia. Five categories of heartbeats can be illustrated: fusion (F), supra ventricular (S), ventricular (V), non-ectopic (N)and unknown beats (Q). However, the dataset used is of imbalanced type and hence data augmentation approach is adopted for tackling the imbalance issues. Data augmentation helps by artificially increasing the number of samples in the minority classes through operations such as rotation, scaling, flipping or adding noise, ensuring a more balanced representation across all classes.

4.1. Fusion Beat (F)

When electrical impulses from many sources act simultaneously on the same area of the heart, it results in a fusion beat. Atrial fusion beats are created when collision currents in the atrial chambers collide, whereas ventricular fusion beats are created when they act on the ventricular chambers. The F-beat image is pre-processed with segmented using adaptive median filter & FCM method respectively as seen in Figure 6, which is helps to divine the cardiac disease in accurate manner.

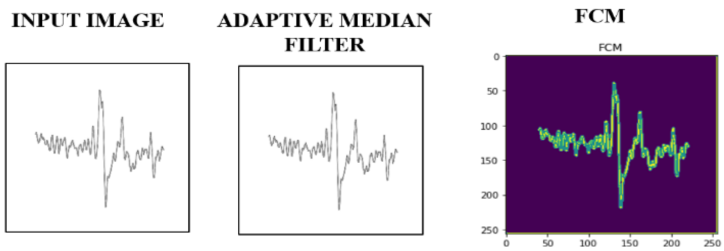

Fig.6. F-beat ECG image using adaptive median filter and FCM

4.2. Non-ectopic Beat (N)

Non-Ectopic heartbeats are deviations from a normally occurring heartbeat. These modifications cause additional or skipped heartbeats. Frequently, there is no obvious reason behind these adjustments. The N-beat image is pre-processed with segmented using adaptive median filter & FCM method respectively as seen in Figure 7, which is supports to detect the cardiac disease in exactmethod.

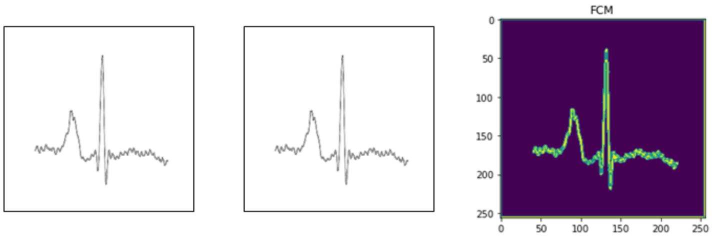

Fig.7. N-beat ECG image using adaptive median filter and FCM

4.3. *Unknown Beats Beat (Q)*

Paced beats and beats that combine paced and normal beats are included in the class Q that corresponds to unknown beats. The Q-beat image is pre-processed with segmented using adaptive median filter & FCM method respectively as seen in Figure 8, which helps to accurately predict cardiac disease.

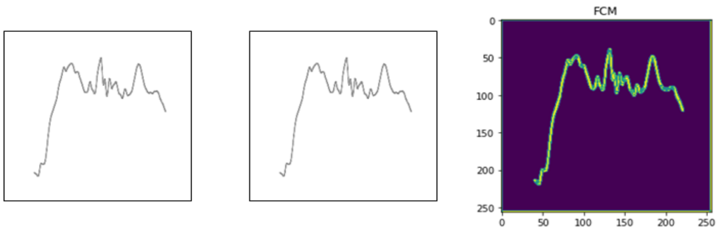

Fig.8. Q-beat ECG image using adaptive median filter and FCM

4.4. *Supra Ventricular Beat (S)*

Supraventricular tachycardia is characterised by an erratic rapid heartbeat. It occurs when poor electrical connections in the heart trigger a string of early heartbeats in the upper chambers (atria).S-beat image is pre-processed with segmented using adaptive median filter & FCM method respectively as seen in Figure 9, which is aids to anticipate the cardiac disease in perfectway.

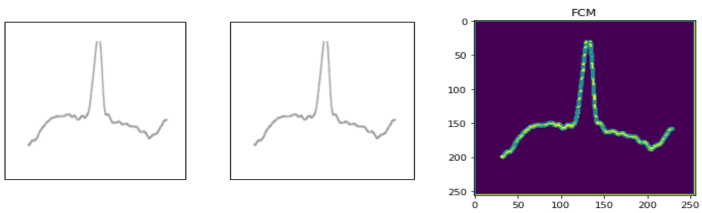

Fig.9. S-beat ECG image using Adaptive median filter and FCM

4.5. *Ventricular Beat (V)*

Irregular heartbeats termed ventricular arrhythmias start in the lower chambers of your heart, known as the ventricles. These arrhythmias make your heart beat too rapidly, obstructing oxygen-rich blood from reaching your brain and body and perhaps causescardiac arrest. The V-beat image is pre-processed with segmented using adaptive median filter & FCM method respectively as seen in Figure 10, which helps to precisely predict cardiac disease.

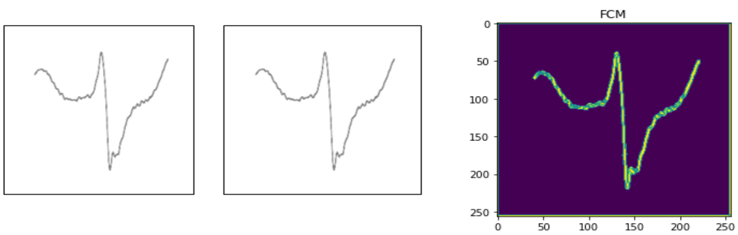

Fig.10. V-beat ECG image using adaptive median filter and FCM

The input F, N, Q, S and V ECG images shown in the aforementioned Figures demonstrate a variety of deformations or noises, which reduces the detection capability over a broader range. As a result, it is essential to remove the noise information from the input image to get the optimal resultsin the identification of CVD. The Adaptive Median Filter is effectively utilized to removenoise from input ECG images, and the resultant output of the pre-processed image is clearly demonstrated to be effective, demonstrating the remarkably superior ability of the proposed filter in denoising the input ECG images.Following pre-processing stage, the input F, N, Q, S and V ECG pictures are segmented with the help of FCM technique in several regions to increase the accuracy of disease identification.

Table 1. Feature extraction using GLCM

Beats	Feature extraction				
	Correlation	**Homogeneity**	**Energy**	**Dissimilarity**	**Contrast**
F-Beat	0.05113	0.82138	0.80792	8.45429	840.364
N-Beat	0.09844	0.82791	0.81883	7.40166	593.466
Q-Beat	0.19209	0.84410	0.81758	10.4752	778.566
S-Beat	0.31353	0.79818	0.78492	8.52146	769.187
V-Beat	0.15526	0.82099	0.81812	17.68832	366.018

Table 1 mentioned above displays the data collection for the extraction of features such as homogeneity, energy, dissimilarity contrast, and correlation. The datasets for the F, N, Q, S, and V beat ECG pictures had been employed to obtain outcomes using the GLCM approach.

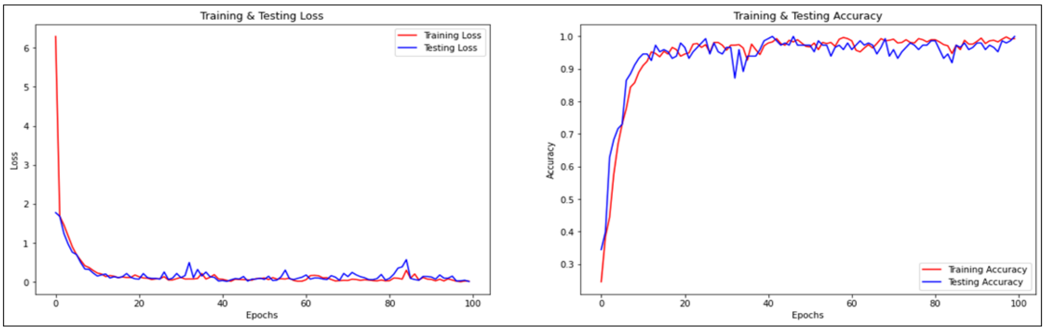

Fig.11. Testing & training results of hybrid CS-DF optimized CNN classifier

Figure 11 shows the proposed classifier's precision as well as loss during testing and training. The proposed hybrid optimised CNN classifier has better accuracy with minimized testing & training loss, as shown by the graph. The proposed approach successfully recognises CVD in the input ECG images as an outcome.

4.6. Comparison Analysis

Table 2. Observations of SNR, PSNR, RMSE and MSSIM attained by different noise removal methods

Techniques	SNR (Signal-to-Noise Ratio)	RMSE (Root Mean Square Error)	PSNR (Peak Signal-to-Noise Ratio)	MSSIM (Multi Scale Structural Similarity)
Median Filter	16.2600	213.40	16.2603	0.649
Wiener Filter	15.8175	245.40	24.2349	0.638
Bilateral Filter	20.3197	0.0055	77.0425	0.994
Adaptive Median Filter	23.4259	0.0038	80.6537	0.996

In accordance with the results in Table 2, while contrasted with additional three filters, such as the wiener ,bilateral and median filters, the proposed adaptive filter technique provides superior MSSIM, SNR, and PSNR values, in addition to lower RMSE values. This means that it keeps the image features after the elimination procedure. Table 3 illustrates the comparison evaluation of segmentation techniques, which is prove that the proposed FCM achieves less time consumption than K-means algorithm. The corresponding plot represented in Figure 12.

Table 3. Comparison analysis of segmentation techniques

Methods	Final Cluster Centre Value	No.of iterations	Time Consumption (sec)
K-means algorithm	234.78	50	35
FCM	225.14	50	20

Table 4. Performance matrices comparison

Methods	Accuracy	Specificity	Sensitivity
Random Forest [13]	89.9	90.4	89.7
Support Vector Machines [13]	91.2	91.8	90.2
ANN [13]	93.6	95.6	94.1
Hybrid CS-DF optimized CNN	98.12	98.2	97.5

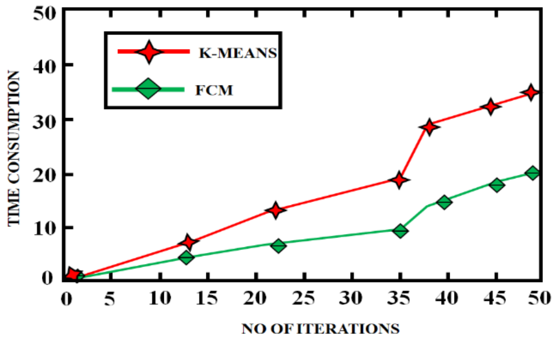

Fig.12. Time consumption comparison

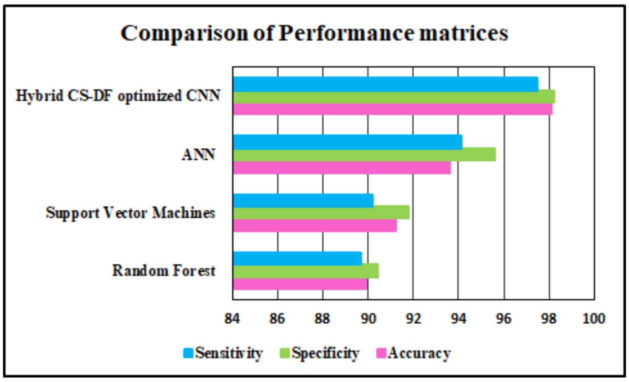

Fig.13. Performance matrices comparison

Table 5. Classification comparison analysis

Classification Methods	Accuracy %
Bi-CLSTM [14]	94%
DMLNN [15]	95.87%
LSTM [16]	88.08%
K-nearest Neighbour [17]	80%
Proposed classifier	98.12%

The performance matrices comparison of proposed classifier with other classifier is presented in Table 4, and Figure 13denotes the corresponding plot. From the graph, it is evident that, the proposed hybrid CS-DF optimized CNN is superior to other existing classifier, in terms of accuracy, specificity and sensitivity 98.12 %, 98.2% & 97.5 % respectively. Similarly, the Table 5 indicates the comparison analysis of classification accuracy, from that the proposed classifier obtains highest accuracy value of 98.12%.

5. Conclusions

Cardiovascular disease (CVD) causes heart and blood vessel disorder, which frequently results in fatality or physiological paralysis. As a result, quick and computerised identification of CVD is capable of saving many lives. To identify cardiac vascular disease in a precise manner, this research proposes an efficient image processing method based on a hybrid CS-DF optimized CNN classifier.The ECG pictures are initially gathered and analysed by reducing noise with an adaptive median filter. The FCM algorithm divides the pre-processed ECG image into separate zones, improving the reliability of heart disease identification. The GLCM is used after segmentation to effectively retrieve prominent features. The features are then significantly detected utilising a unique hybrid CS-DF optimisation based CNN classifier for properly categorising the cardiac vascular disease.According to the simulation findings, the proposed hybrid CS-DF optimised CNN outperforms other current classifiers in terms of accuracy, specificity, and sensitivity (98.12%, 98.2%, and 97.5%, respectively). The proposed hybrid CS-DF optimized CNN model demonstrates strong potential for real-time applications due to its high classification accuracy, rapid convergence and efficient computational design. By employing advanced image preprocessing, precise feature extraction through GLCM and optimal parameter tuning using the hybrid CS-DF algorithm, the model achieves fast and reliable performance suitable for practical deployment in clinical environments. Its ability to accurately detect cardiovascular abnormalities from ECG images in minimal time makes it highly applicable for real-time monitoring systems and automated diagnostic tools. While the hybridization of the CS and DF algorithms with the CNN significantly enhances classification accuracy and convergence speed, it also introduces additional complexity that presents challenges for practical implementation. Future work should focus on simplifying the optimization pipeline by exploring lightweight hybrid strategies that retain performance benefits without significantly increasing the model's operational cost or development overhead.

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