Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

A Multi-Folded Dynamic Regularized Dual Crossed CNN with A Self-Adaptive Metaheuristic Aware Cardiovascular Disease Prediction

Raja Aswathi R[1], K. Pazhanikumar[2]

[1]*Department of Computer Science and Research Centre, S.T. Hindu College, Nagercoil, Affiliated to Manonmaniam Sundaranar University, India.*
[2]*Department of Computer Science and Research Centre, S.T. Hindu College, Nagercoil, Affiliated to Manonmaniam Sundaranar University, India.*
*E-mail: *rajaaswathirk@gmail.com*

Cardiovascular Disease (CVD) prediction is becoming a complex task in research, where enormous work is being carried out to provide a highly efficient prediction system. Deep learning-based prediction is a highly significant task for achieving a robust detecting system, which prevents death through early diagnosis. However, the existing system has the challenges of overfitting, improper feature learning, imbalanced dataset, high false positive rate, and high false negative rate. Therefore, the proposed model has introduced a novel multi-folded regularized Convolutional Neural Network (CNN) based on dynamic regularized dual crossed CNN, Fuzzy C-Means based feature aggregation, a Self-adaptive Whale Optimization Algorithm (SWOA) with the Optimized Information Gain (IG). The proposed multi-folded dynamic regularized dual crossed CNN framework, implemented in Python, achieves superior performance in heart disease prediction, with metrics such as accuracy (99.1234), Sensitivity (98.9876), specificity (99.4321), and also other metrics significantly outperforming existing methods in terms of Precision, F-Measure, MCC, NPV, FPR, and FNR.
Keywords: Cardiovascular Disease prediction, Convolutional Neural Network, ECG Signals, Heart Disease, and Robust Detecting System

1. Introduction

One of the more dangerous medical disorders is cardiac arrest, which occurs when the heart stops beating suddenly and stops supplying oxygen to the majority of the organs. With high rates of illness and mortality documented, it poses a serious threat to global public health (Nallamothu, et. al., 2023). Early identification and treatment of this illness can save lives; every minute that passes reduces the likelihood of survival. An estimated 17.5 million deaths worldwide are attributed to heart disease and stroke each year, according to the World Health Organization (Thapa, et. al., 2021). Over 75% of heart disease-related deaths take place in nations with middle-class and lower-class populations (Sandroni, et. al., 2022). Furthermore, 80% of all deaths from Cardio Vascular Disease are attributable to heart attacks and strokes. An early and precise prognosis and management plan is crucial because cardiac arrest continues to be a top cause of death globally, despite advancements in the medical sciences (Pareek, et. al., 2020).

Commonly utilized diagnostic techniques, including dual-source CT exams, cardiac magnetic resonance imaging (MRI), X-rays, and transthoracic echocardiography (TTE), are expensive, time-consuming, and logistically difficult. They also rely significantly on the assessment of skilled cardiologists (Muhammad, et. al., 2020). In the absence of contemporary technology and medical professionals, heart disease diagnosis and treatment are exceedingly challenging. A proper diagnosis and treatment course can save many lives (Wong, et. al., 2020). The European Society of Cardiovascular approximates that 3.6 million novel Heart Disease (HD) cases are diagnosed annually, with 26 million new cases reported. Heart disease affects the majority of individuals in the United States (Ali, et. Al., 2020). The traditional method for diagnosing HD is the physician's examination of the patient's history, physical examination, and symptoms (Khan and Algarni, 2020). Nevertheless, the diagnosis obtained through this approach is unreliable for the patient with HD (Ghosh, et. al., 2021).

Several studies used Machine Learning (ML) techniques like Support Vector Machines (SVM), Artificial Neural Networks (ANN), Decision Tree (DT), Linear Regression (LR), and Random Forest (RF) to evaluate health information and forecast cardiac problems. In a recent study, the scientists used ML algorithms to estimate the chance of developing heart disease in a multiethnic community. To stratify CVD risks, the scientists used a large collection of data from electronic medical records and linked it with sociodemographic data (Ali, et. al., 2020). The models had an excellent accuracy in predicting the risk of CVD in the multiethnic group. Similarly, another research used a Deep Learning (DL) system to predict the event of Coronary Artery Disease (CAD) (Bharti, et. al., 2021). The investigators trained the DL model on clinical information and and Coronary Computed Tomography Angiography (CCTA) images (Rahim, et. al., 2021). Recent advancements in deep learning have demonstrated reliable and cardiologist-level ECG analysis capabilities, including the ability to detect features that human experts are not typically able to perceive (Nadeem, et. al., 2021). Previous studies have shown that DL models can benefit from both automatically generated characteristics of ECG waveform information along with features derived from wavelet transformations and conceptual features used by human experts (Pathan, et. al., 2022). Few combined all of those different kinds into an end-to-end DL frame that did just automatic, efficient, and almost ideal fusing (Pan et al., 2020).

DL offers many advantages concerning medical diagnosis, especially the prediction of heart disease. The most important advantage is the autonomous extraction and learning of complex details in raw data, including those derived from ECG signals, without human intervention. Thus, its predictions are far more trustworthy and accurate than conventional or earlier models because DL models can detect tiny patterns and anomalies that even a human expert misses. Furthermore, DL models are scalable and robust in practical applications because the management of big and varied datasets has been made effective. Then, this paper introduces a novel multi-folded regularized Convolutional Neural Network (CNN) framework that comes to eradicate the limitations mentioned above. The following is the work's main contribution:

- Preprocessing techniques by the system utilize strong preprocessing; these include removing redundant data and attribute replacement that improves feature representations, ensures that quality data is collected, and in turn, preps the input for the CNN to learn.
- A dynamic regularized dual-crossed CNN is proposed for improving feature extraction and reducing overfitting during robust learning from medical data like ECG signals. The proposed architecture can ensure model accuracy with the challenges of imbalanced datasets and high false positive/negative rates.
- The combination of SWOA and IG features optimizes the selection of features and tuning of hyperparameters. This may enhance learning efficiency by using more essential features and adaptation of SWOA to changes in the dataset to improve prediction accuracy.

These sections are organized as follows: Section 2 discusses some relevant research and literature reviews, Section 3 introduces the proposed framework, Section 4 provides a detailed analysis of the observed results and discussions, and the final assessment for this study is offered in Section 5.

2. Literature Review

Several recent studies of multi-organ rare disease prediction were reviewed in this section.

(Li, et. al., 2020) have put out an accurate and effective approach that uses machine learning approaches to diagnose cardiac problems. It used several classification methods such as K-nearest neighbor (KNN), support vector machines (SVM), decision trees (DT), artificial neural networks (ANN), Naïve bays, and logistic regression (LR). For the issue of choosing characteristics, they suggested a new fast conditional data source exchange feature selection approach. The objective of feature selection algorithms is to enhance classification precision and minimize the categorizing system's execution time.

(Mehmood, et. al., 2021) introduced a technique known as CNN (convolutional neural networks) that applied deep learning for the CardioHelp approach, designed to predict a patient's susceptibility to cardiovascular illness. CNN is used in the suggested strategy to model temporal data for HF detection at the early stage. They produced a dataset on heart disease and examined the outcomes using innovative methods, obtaining positive outcomes.

(Alqahtani, et. al., 2022) developed a group-based approach that employs machine learning (ML) and deep learning (DL) models to calculate a person's risk of cardiovascular illness. They predict the incidence of heart disease by employing six distinct categorization systems. A dataset of cardiovascular illness patients that is openly accessible is used for training the models. They extract significant cardiovascular disease variables using random forest (RF).

(Abdellatif, et. al., 2022) have offered an effective strategy that utilizes the Synthetic

Minority Oversampling Technique (SMOTE) to address the problem of unbalanced distribution, to determine the patient's condition, six different machine learning classifiers were used., and Hyperparameter Optimization (HPO) to determine the optimal hyperparameter for the SMOTE in combination with an ML classifier. To develop and verify a framework with every characteristic, two public datasets were used. The outcomes demonstrate that Extra Trees (ET) and SMOTE enhanced with hyperband outperformed the state-of-the-art approaches and produced superior outcomes than the other models.

(Oyeleye, et. al., 2022) have investigated several potent based on data models, such as the autoregressive integrated moving average (ARIMA) model, decision tree regressor, support vector regression (SVR), linear regression, k-nearest neighbor (KNN) regressor, long short-term memory (LSTM) recurrent neural network and random forest regressor technique for the evaluation of accelerometer information in the request to generate the future HR estimations based on univariant HR time series information from the accelerometers gathered from healthy people. The models' effectiveness was evaluated throughout a range of periods.

(Ogunpola, et. al., 2024) have concentrated on employing machine learning algorithms for the early identification of the heart conditions, such as myocardial infarction. It addresses the issue of data imbalances by performing an extensive literature review to find workable solutions. To enhance the accuracy of heart disease predictions, seven machine learning and deep learning classifiers were used, which are Support Vector Machine, Convolutional Neural Network, K-Nearest Neighbors, Logistic Regression, Random Forest, XGBoost, and Gradient Boost.

(Sharma and Parmar, et. al., 2020) have presented the use of deep-learning neural network models for predicting cardiac disease. This also points out that Deep learning supports medical research in terms of identifying illnesses and solving medical-related problems. This study apart from pointing out a possibility for generally improving the quality of categorization of diseases, provides a method to forecast cardiovascular conditions. Various classification techniques, including SVM, KNN, Random Forest, and Naïve Bayes, are discussed, and the Heart Disease UCI dataset is used as a demonstration.

(Pandey, et. al., 2024) developed an approach for the diagnosis and classification of heart illness by combining blockchain computing with a CNN-Bidirectional Long Short-Term Memory (CNN-BiLSTM) model that depends on a modified mixed attention-enabled searching optimizer (M2MASC enabled CNN-BiLSTM). To improve the extraction of features and overall accuracy in forecasting, the innovative model integrates a pre-trained VGG16 classifier. Utilizing IoT devices' continuous monitoring capabilities, real-time patient data collection serves as a dynamic source for the CNN-BiLSTM model. Table 1 addresses the aim, methodology, advantages, and drawbacks of the existing works.

Table 1 Review of various authors about the existing works

Author	Aim	Methodology	Advantage	Drawback
Li, et al., 2020	To create an effective and precise system that uses machine learning approaches to identify heart disease.	Naïve Bayes, KNN, ANN, SVM, LR, and DT.	Improves system efficiency, decreases execution time, and raises classification accuracy.	Large datasets may require a lot of computing power to use the feature selection method.

Mehmood, et al., 2021	To forecast cardiovascular illness by combining CNN and deep learning for the prediction of early-stage heart failure.	Utilized Convolutional Neural Networks (CNN)	Proficient in anticipating cardiac disease in its early stages.	Non-temporal datasets may not be well suited for temporal data modeling.
Alqahtani, et al., 2022	To forecast the probability of cardiovascular illness by employing deep learning and ensemble-based machine learning algorithms.	Employed six classification algorithms and Random Forest (RF)	The ensemble method increases forecast accuracy by combining the strength of several models.	High processing power is needed to train several models at once.
Abdellatif, et al., 2022	To improve the identification of heart disease and address imbalance distribution, ML classifiers.	Applied SMOTE for handling imbalance and used six ML classifiers with Hyperparameter Optimization (HPO)	HPO maximizes model performance whereas SMOTE increases accuracy on unbalanced datasets.	HPO may become computationally costly, while SMOTE can result in overfitting.
Oyeleye, et al., 2022	Applying data-driven models to evaluate accelerometer data to predict heart rate (HR).	ARIMA, Random Forest, SVR, KNN, Linear Regression, Decision Tree, and LSTM	The ability to handle various data kinds with flexibility is provided by many models.	Performance fluctuates across different periods and may not transfer well to other kinds of information.
Ogunpola, et al., 2024	To emphasize the use of machine learning methods for the early diagnosis of myocardial infarction.	Employed seven classifiers (XGBoost, KNN, SVM, CNN, LR, Gradient Boost, and RF)	Improves prediction accuracy and effectively manages unbalanced datasets.	Large datasets and processing power are needed to train several models.
Sharma and Parmar, et al., 2020	To discuss the application of deep learning models to the categorization and prediction of cardiac disease.	KNN, SVM, Naïve Bayes, and RF	Increases the quality and accuracy of classification by utilizing deep learning models.	It could need a lot of processing power and be sensitive to the quality of the data.
Pandey, et al., 2024	To generate a model for detecting heart disease by combining CNN with blockchain-BLSTM.	Modified Mixed Attention-Enabled Search Optimizer-based CNN-Bidirectional Long Short-Term Memory model.	Data security is improved via blockchain integration, and the model makes accurate forecasts in real-time.	Data management issues and system complexity could be exacerbated by the blockchain component.

Research Gap

Despite great advances in ML and DL techniques for heart disease diagnosis and prediction, many research gaps exist that have prevented the complete realization of their potential. The studies are mainly limited to a particular ML or DL technique, like CNN, SVM, and RF, but they fail to provide an integrated view of multiple methodologies for the overall exploitation of their combined strengths. Also, feature selection algorithms such as mutual information and SMOTE address data imbalance and improve the overall classification accuracy; however, they may tend to cause overfitting or inefficiency when these large datasets are used. The existing DL models showcase excellent accuracy in a certain perspective of real-world applications like ECG analysis or coronary artery disease, but there is very little exploration of end-to-end architectures that fuse diverse feature types including both conceptual, automatic and transformed features in the presence of EMG. Furthermore, the absence of strong frameworks for dealing with real-time, dynamic, and imbalanced datasets, especially for underrepresented populations and pediatric cases represents a critical challenge. Lastly, the integration of emerging technologies like blockchain and IoT with advanced DL architectures for secure and real-time cardiac data processing is in its infancy, leaving significant room for innovation in developing holistic, efficient, and scalable systems for heart disease prediction.

3. Proposed Methodology

The proposed methodology introduces a novel framework for cardiac arrest prediction by combining advanced preprocessing, feature extraction, optimization, and classification techniques. Initially, the raw data undergoes preprocessing steps, including replacing missing attributes, removing redundant data, and applying wavelet transform for noise reduction and feature enhancement. The pre-processed data is now passed through the two parallel channels. The first has Fuzzy C-Means-based feature aggregation integrated with an Information Gain-optimal Self-Adaptive Whale Optimization Algorithm and the second utilizes a multi-folded dynamic regularized dual-crossed CNN to conduct robust feature extraction. These features from both pathways are then concatenated to be fed into a fully connected layer followed by softmax for classification. This methodology also avoids overfitting, poor feature learning, and dataset imbalanced problems, therefore providing better predictive accuracy for detecting cardiac arrest. The framework of the proposed work is shown in Figure 1.

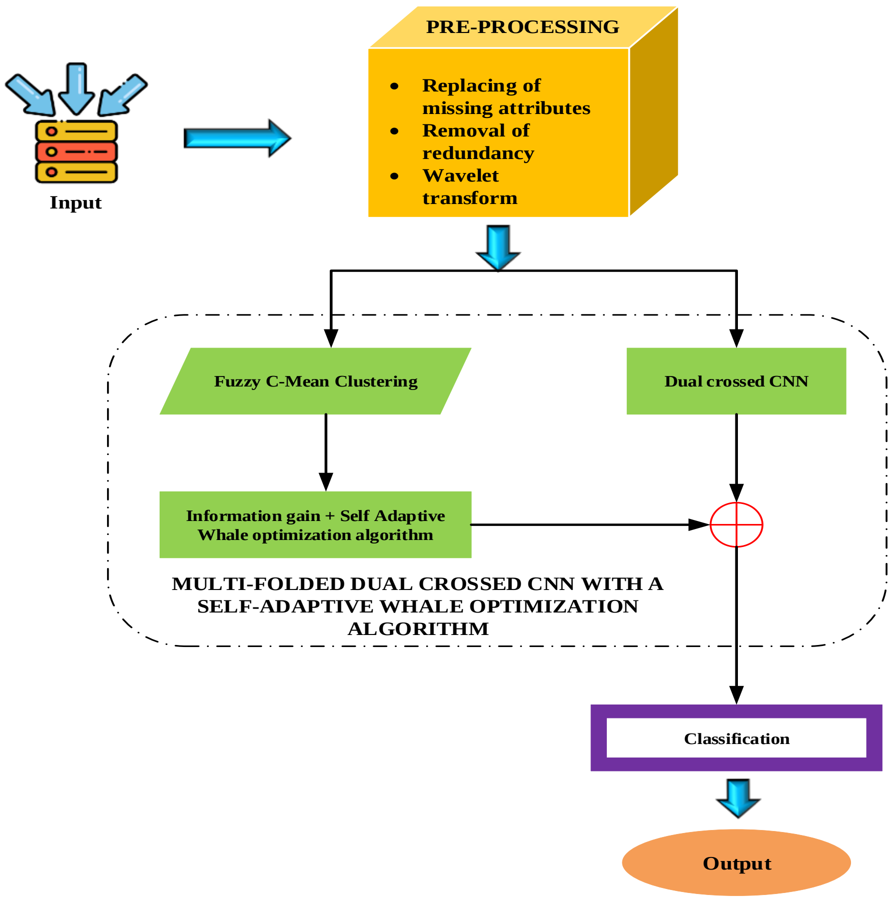


Figure 1 Proposed Architecture

3.1 Preprocessing techniques

Preprocessing is the most significant step in data analysis, where raw data are changed into clean, structured formats. It improves the quality and consistency of input data, thus reducing noise, missing values, and scale differences. In this study, various preprocessing techniques have been used to make the data clean for the accurate estimation of heart disease. These are the replacement of missing attributes, redundancy removal, and use of wavelet transform. The approaches prepare data well to be robust in analysis and efficient in learning so that the proposed model can accurately and reliably predict cardiac arrest.

3.1.1 Replacing of missing attributes

One can replace missing attribute values with the most frequently occurring attribute values in the preprocessing of heart disease datasets to avoid erroneous accuracy of the prediction model. For instance, the maximum frequency of the same kind of value of age, blood pressure, and cholesterol levels about the respective patient group is substituted for the patient. This way, it ensures that there is complete data without losing critical information in the dataset.

3.1.2 Removal of redundancy

Redundant and irrelevant attributes are identified and removed, making the dataset simpler. For heart disease prediction, redundant features may cause overfitting. Overfitting will degrade the ability of the model to generalize from the training dataset. Removing redundant features makes the dataset more compact, focused, and computationally efficient, making the overall performance of the predictor better.

3.1.3 Wavelet transform

Wavelet transform has a significant impact on heart disease prognosis with the decomposition of patient data into different frequency components, both the high and low-frequency patterns that are not visible in raw data can be captured. This transformation is done by wavelets, which are derived as basic functions by a prototype wavelet and adapted by scaling and shifting it. The definition of the Continuous Wavelet Transform can be given by

$$W_{a,b} = \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{|a|}} \varphi * \left(\frac{t-b}{a}\right) dt \qquad (1)$$

where a and b represent the scale and shift of the wavelet, respectively, and ϕ is the wavelet function. The wavelet function itself is defined as:

$$\varphi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \varphi \left(\frac{t-b}{a}\right) \qquad (2)$$

The use of DWT in the process of heart disease prediction is rather frequent. DWT is done through the inner product of a signal with wavelet basis, decomposing a signal into the discrete components reflecting the data under different scales, thereby improving the extraction of the features from the time-series data and making it more effective at the detection of slight patterns corresponding to heart diseases. The resolution can be enhanced on the data by applying wavelet transform, thus increasing the accuracy for predicting heart disease risks.

3.2 Dual Crossed CNN with A Self-Adaptive Whale Optimization with Optimized Information Gain

The Dual Crossed CNN enhances the model's capacity to recognize intricate patterns by employing two parallel networks that communicate to increase feature extraction. The CNN's hyperparameters are dynamically optimized by the SWOA, which modifies the search approach to improve accuracy. Optimized IG minimizes overfitting and eliminates extraneous data by choosing the most pertinent characteristics. These elements work together to produce a strong, effective model that predicts cardiac arrests with accuracy and improves performance on unbalanced datasets.

3.2.1 Fuzzy C-Mean clustering

Fuzzy C-Means (FCM) is a clustering technique that extends the k-means approach by allowing the use of fuzzy membership in the process. In contrast with k-means, where data points strictly belong to one of the clusters, FCM will allow each point to have degrees of membership in multiple clusters. The centroid or prototype of a cluster is a weighted mean of all points whose weights are derived from their degrees of membership. The definition for the calculation of the centroid is:

A fuzzy variation of the k-means partitional technique is the fuzzy c-means. The central point (also known as a prototype) of a group is calculated using fuzzy c-means as the average of all samples, adjusted by the degree (u_k) of affiliation within the cluster c_k.

$$\text{center}_k = \frac{\sum_t u_k'''(t) \cdot t}{\sum_t u_k(t)} \qquad (3)$$

The reverse of the distance from the cluster's center determines how much a person connects to a certain cluster:

$$u_k(t) \propto \frac{1}{d(\text{center}_k \cdot t)} \qquad (4)$$

To ensure that the total of the components equals 1, they're normalized and fuzzified using a real variable $m > 1$:

$$u_k(t) = \frac{1}{\sum_j \left(\frac{d(\text{contr } t,t)}{d(\text{con } t(r_j,t))}\right)^{(2/(m-1))}} \qquad (5)$$

This is essentially identical to linear adjusting the coefficients to generate the total 1 for $m = 2$. The algorithm most closely resembles k-means when m is near 1. The cluster center nearest to the instance is given a significantly higher weight than the others.

While FCM minimizes well the intra-cluster variance, however, it has similarities in some limits as k-means like it depends on the initial selection of the centers of the clusters and convergence might occur towards the local optimum. To mitigate these constraints, the performance of the obtained features from FCM is fine-tuned further with the aid of a Self-adaptive Whale Optimization Algorithm (SWOA) based on Optimized Information Gain (IG), thereby refining the feature aggregation with enhanced classification.

3.2.2 Optimized Information Gain

Optimized Information Gain (IG) measures the relevance of features by quantifying how much uncertainty is reduced when a feature is used. It selects the most informative features, improving model accuracy and efficiency. To improve prediction efficiency and accuracy, SWOA dynamically improves model parameters while Optimized IG chooses pertinent characteristics.

3.2.2.1 Information Gain

Information Gain (IG) is a key metric used to assess the significance of a characteristic in forecasting the result. It measures the reduction in entropy or uncertainty of the data when a feature is used for splitting. Higher information gain indicates that a feature is more informative and relevant for the prediction task. In this case, information gain is used to optimize feature selection, helping to enhance the model's functionality by concentrating on the most impactful features.

$$F_i = \delta_1 + \delta_2 \times \left(1 - \frac{N}{T}\right) \quad (6)$$

where T represents the overall number of attributes and N for the number of attributes that were chosen. Here, δ_1 and δ_2 have values of 1 and 0.001, respectively.

3.2.2.2 Self-adaptive Whale Optimization Algorithm (SWOA)

A novel optimization framework is proposed in this section as WOA cooperating with a cyclone weight coefficient of foraging, which finally leads to the implementation of the SWOA. This mechanism can adaptively balance exploration and exploitation and enhance the optimization process. The SWOA output is integrated into Information Gain. This information produces an Optimized Information Gain (IG) strategy used to help one select the most crucial characteristic for forecasting the outcome of heart illness. A more efficient feature selection hybrid improves efficiencies in robust accuracy classification.

The three tactics used by the WOA to mimic whale behavior include spiral bubble-net attack (exploitation phase), hunting for prey (exploration stage), and encircling the prey. At iteration t, the position of the ith whale is given by,$X_i^t = \left(x_{i,1}^t, x_{i,2}^t, \ldots\ldots x_{i,D}^t\right)$ where $i = 1, 2, \ldots, N$ and $N\ and\ D$. The following subsections provide a mathematical presentation of WOA techniques.

Step 1: Encircling Prey Strategy

Whales can locate and encircle their prey. Whales in WOA consider their intended victim or a place close to it inside the area of search to be the best option. Other whales attempt to approach the optimal agent during prey encirclement and use Equation (1) to update their location. This equation's t is the current iteration X_i^t is the location of the ith whale in the present iteration, and X^{*t} is the position vector of the greatest answer so far, which is modified in every iteration if a better solution is found.

$$X_i^{t+1} = X^{*t} - A.D \quad (7)$$

$$D = |C \times X^{*t} - X_i^t| \quad (8)$$

where D is the distance, as determined by Eq. (2), between the whale, X_i^t and the prey, X^{*t} where symbols $|.|$ represent the absolute value, and $A\ and\ C$ are coefficient matrices that are determined by Eqs. (9) and (10)

$$A = 2 \times a \times r - a \quad (9)$$

$$C = 2 \times r \tag{10}$$

$$a = 2 - t \times \frac{2}{\text{MaxIter}} \tag{11}$$

The parameter r in Eqs. (9) and (10) is a random value between 0 and 1, and Eq. (11) states that an in Eq. (9) decreases linearly from 2 to 0. The present iteration along with the total amount of repetitions are indicated by the variables t & $MaxIter$ in Eq. (11). The whales are gradually confined to the surrounding scope by the parameter a.

Step 2: Cyclone Spiral Bubble-Net Attacking Strategy

The bubble-net hunting mechanism in the Whale Optimization Algorithm (WOA) imitates the humpback whales' cooperative hunting strategy and is divided into two behaviors: the spiral updates positioning and the diminishing encircling technique. The spiral motion is mathematically modeled as:

$$X(t+1) = \overrightarrow{D'} \cdot e^{bl} \cos(2\pi l) + X^*(t) \tag{12}$$

$$\overrightarrow{D'} = |X^*(t) - X(t)| \tag{13}$$

The spiral updating position in WOA limits exploration lacks flexibility, and risks premature convergence. Adding the cyclone foraging weight coefficient β enhances adaptability, balances exploration and exploitation, and refines search accuracy over iterations.

$$X(t+1) = \beta.\left(\overrightarrow{D'}.\, e^{bl} \cos(2\pi l) + X^*(t)\right) \tag{14}$$

Final Position Update Equation Including β, the final equation becomes:

$$X(t+1) = \begin{cases} X^*(t) - A \cdot D \text{ if } p < 0.5 \\ \beta \cdot \left(\overrightarrow{D'} \cdot e^{bl} \cos(2\pi l)\right) + X^*(t) \text{ if } p \geq 0.5 \end{cases} \tag{15}$$

$$\beta = 2e^{r1\frac{T-t+1}{T}} \cdot \sin\,(2\pi r_1) \tag{16}$$

where β is the weight coefficient, the maximal quantity of iterations is T, and r_1 is the rand number in [0, 1]. This ensures adaptive and dynamic searching, enhancing performance in general. The coefficient of the cyclone foraging approach significantly improves abilities to explore an array of possible solutions and efficiently avoid getting stuck on local optima and convergence at the global optimum.

Step 3: Searching for Prey Strategy

In the search of a prey strategy, whales investigate the search space to enhance diversity by updating their positions relative to a randomly chosen whale using:

$$X(t+1) = X_{rand} - A \cdot D \tag{17}$$

$$D = |C \cdot X_{rand} - X(t)| \tag{18}$$

where X_{rand} is a random position, and A and C are control parameters. WOA alternates between the position of spiral update ($p \geq 0.5$), encircling prey ($p < 0.5, |\, A \,| < 1$), and searching for prey ($p < 0.5, |\, A \,| \geq 1$) strategies. The best solution is iteratively refined until maximum iterations are reached.

3.2.2.3 Optimal Information Gain with Self-Adaptive WOA

The proposed framework is a combination of SWOA and IG for achieving Optimized Information Gain (OIG). In this hybrid mechanism, it is guaranteed that the ideal subset of characteristics will be chosen to realize the maximum performance in terms of classification. All features are represented as binary strings of 1s and 0s to denote selection and exclusion, respectively, to finally determine the accuracy of the overall model. The fitness function is defined as:

$$F_i = \delta_1 \times X(t+1) + \delta_2 \times \left(1 - \frac{N}{T}\right) \tag{19}$$

Where, $X(t+1)$ is the updated position from SWOA, δ_1 and δ_2 are the weighting coefficients ensuring balanced optimization.

The framework utilizes dynamic position updates via cyclone foraging mechanisms for optimized exploration and exploitation balance along with optimal feature selection. By using OIG, the framework overcomes problems such as overfitting, inappropriate feature learning, and imbalance in the dataset. Heart disease can be predicted with efficiency and accuracy.

3.2.3 Multi-Folded Dual Crossed CNN

The pre-processed data in the proposed framework is put through a Multi-Folded CNN for feature extraction and reducing the dimension. The Multi-Folded CNN starts by preprocessing the input to extract critical patterns and lower-level features, which include edges and textures, in a series of convolutional layers. After that, pooling layers are used on each convolutional layer to decrease spatial dimensions and compress the data while retaining meaningful features. Figure 2 shows the architecture of Multi-Folded Dual crossed CNN.

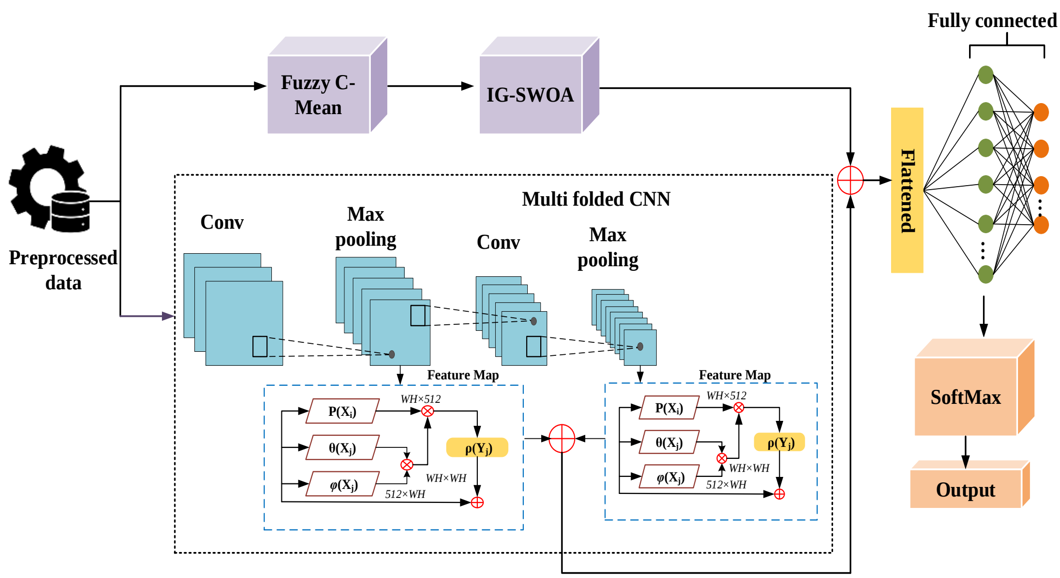


Figure 2 Architecture of Multi-Folded Dual crossed CNN

The process starts with input data, which undergoes preprocessing steps like normalization or noise reduction to be prepared for further processing. Then, the preprocessed data is used in the FCM algorithm, where membership probabilities are assigned to each data point so that overlapping clusters can deal with uncertainties very effectively. Optimization with an IG-SWOA was applied to the clustered data for improving parameters of features, weights, or hyperparameters in terms of model improvement and convergence. Optimized data was fed to a multi-folded CNN. The CNN features the convolution layers, which will extract key information from the input data, while the max-pooling layers reduce spatial dimensions of feature maps while maintaining the critical information that prevents overfitting. Feature maps obtained from these layers undergo further transformations to extract the refined features. It is then fed to a fully connected layer that combines all the features to do the final classification. The SoftMax activation function is finally used to calculate the probability of each class, and the framework outputs the predicted class label. This integration of clustering, optimization, and deep learning techniques makes the system robust and efficient for complex classification tasks.

3.2.3.1 Feature Map

A feature map is the output of a convolutional layer in the CNN, representing spatial and depth-wise information about detected features. It is defined as $W \times H \times D$ where W and H are the width and height, and D (depth) is the number of channels, set to 1024 in this architecture. Processes like 1×1 convolutions $(g(\cdot), \theta(\cdot)\theta, \varphi(\cdot))$, matrix multiplication $(\otimes)$, and element-wise summation $(\oplus)$ refine the feature representations. In addition, the $\rho(\cdot)$ convolution layer recovers the original shape of the features. These feature maps are important for encoding spatial patterns and are important for accurate classification in the proposed architecture. Figure 3 shows the architecture of the Feature Map.

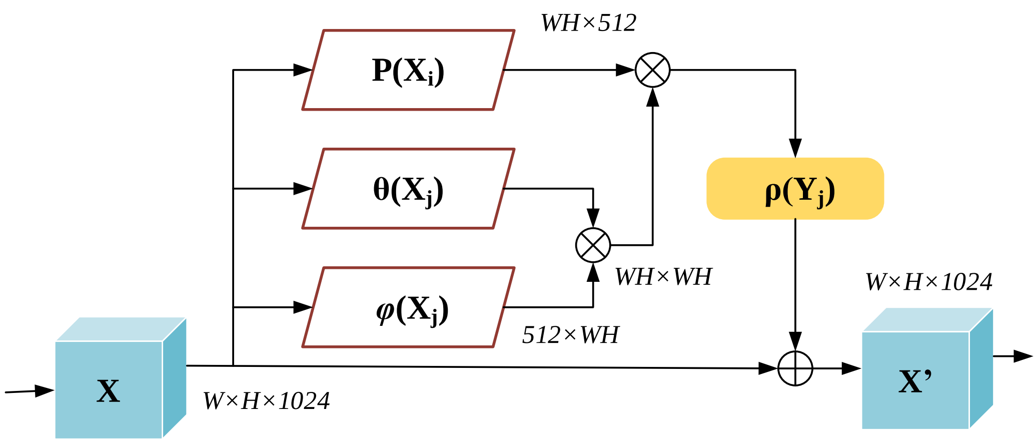


Figure 3 Feature Map

3.3 Classification

The output from the Multi-Folded CNN and the IG-SWOA is concatenated together and then classified. The feature set is passed on to the flattening layer that changes the feature maps in many dimensions into a one-dimensional vector to be fed into the fully connected layers. Fully connected layers make complex transformations over the flattened features to learn the high-level representations that are vital for classification.

The SoftMax activation function is applied at the output layer, which calculates the probabilities assigned to each class based on learned features. Therefore, the output of the framework corresponds to the predicted class label with the maximum probability, resulting in an accurate prediction of cardiac arrest. The combined features extracted using CNN and the optimized features derived from IG-SWOA lead to improved classification accuracy and the robustness of the overall proposed framework.

3.3.1 Flattened Layer

The flattening layer helps in transforming multi-dimensional feature maps created by convolution and pooling layers to one-dimensional vectors. This further transforms the input data into vectors, ready to be fed to fully connected layers of the proposed system. In this system, output from the concatenation of the CNN and IG-SWOA was fed to a flattening layer. It eliminates redundant features of the image by keeping the salient features to feed to subsequent classification layers for further processing in the classification system.

3.3.2 Fully Connected Layer

The fully connected layers form the backbone for all classification aspects due to deep, complex feature transforms of flattened features. Establish weighted connections from/to every neuron for learning, ensuring high-order abstract representations as inferred from feature collections of a combination of CNN-IG-SWOA. Based on these higher relationships between various aspects of extracted features, deep contributions are facilitated of the accuracy through the making precise predictions hence also improving cardiac arrest detection framework.

3.3.3 SoftMax

The SoftMax layer is the last step of classification. It takes the output of the fully connected layer and changes it into a distribution of chances. It assigns a value to every class so that the sum of all values will add up to one. In the proposed system, the SoftMax function determines the most probable class label and helps in cardiac arrest prediction using the extracted and optimized features. This ensures that the outputs provided are reliable and interpretable to the medical practitioner.

4. Results and Discussion

This section details the results and performance evaluation of the proposed Multi-Folded Dynamic Regularized Dual Crossed CNN framework in the context of cardiac arrest prediction. The goal is to counter overfitting, improper feature learning, and high error rates while detecting heart diseases. With the help of Precision, Sensitivity, Accuracy, F1-Score, MCC, Specificity, and NPV metrics, the efficacy of the framework is determined. The results are compared with current methods: KNN, ANN, CNN, and Long Short-Term Memory (LSTM). The evaluation demonstrates that the suggested framework significantly surpasses the traditional approaches in terms of reliability and accuracy regarding prediction for cardiac disease.

4.1 Evaluation Setup

The evaluation setup for the proposed cardiac arrest prediction framework was performed on a system with the following hardware configuration: an Intel Core i5 or i7 processor, ensuring efficient processing power to handle complex computations. The system is equipped with a minimum of 8GB RAM, while 16GB or more are recommended for the handling of large datasets and deep learning tasks. An Solid-State Drive (SSD) with free space of 100GB minimum was used in the storage. During the training and evaluation of models, this device ensured faster data access, increasing the overall speed and performance of the experiment. This helps in achieving perfect performance and dependability in the testing of the proposed framework.

4.2 Dataset description

The performance of the proposed method is evaluated on the four datasets and are as follows

Dataset 1

This dataset https://www.kaggle.com/datasets/shayanfazeli/heartbeat consists of two large collections of heartbeat signals, namely the MIT-BIH Arrhythmia Dataset and the PTB Diagnostic ECG Database, which are most commonly used in heartbeat classification studies. The dataset contains ECG signals that reflect normal heartbeats and heartbeats with various arrhythmias, such as myocardial infarction. Each signal is preprocessed and segmented; each segment represents an individual heartbeat. It is, therefore, very apt for training deep neural networks to classify various heartbeats. The dataset is valuable in that it explores the capacities of deep learning and transfer learning in the classification of ECG signals for developing models used in diagnostics for the identification of arrhythmias and other heart conditions.

Dataset 2

The Cleveland Heart Disease Dataset, https://www.kaggle.com/datasets/johnsmith88/heart-disease-dataset originally from 1988 is a very well-known dataset for heart disease presence prediction. The dataset consists of data from four different databases: Hungary, Cleveland, Long Beach V, and Switzerland, which contain 76 attributes, but experiments are generally performed on a subset of 14 key features. The main target variable is the condition of the disease or not with 0 means no disease, and 1 means the diseased. Included in the given dataset are medical attributes such as gender, age, cholesterol, blood pressure, electrocardiographic test findings, and even other variables on which the basis of risk depends. The applications are commonly employed in machine learning to develop prediction models that assist in identifying subjects at risk of heart disease; thus, supporting preventive care efforts and early diagnoses.

Dataset 3

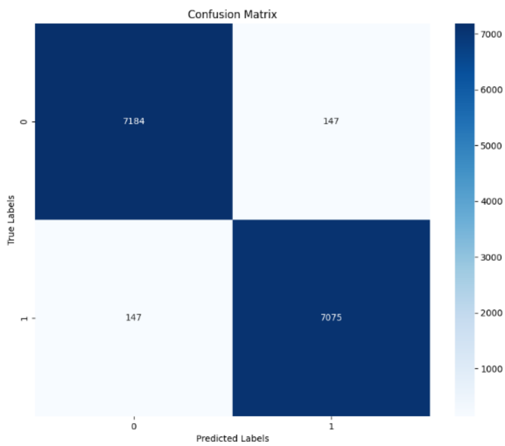
The dataset https://www.kaggle.com/datasets/devavratatripathy/ecg-dataset on electrocardiogram signals of patients can be considered as full data that may help classify cardiac diseases. Each row corresponds to an entire ECG reading consisting of 140 data points that cover different time segments. Some data were accompanied by a categorical attribute, namely if the ECG was normal or not (0 or 1). This is a binary classification problem focused on finding abnormal heartbeats in patients, which can lead to an overall diagnosis of most cardiovascular conditions. The availability of this dataset means that there are opportunities to utilize machine learning for the extraction of patterns from ECG signals to classify signals as normal or abnormal, which are crucial components in cardiac health research.

Dataset 4

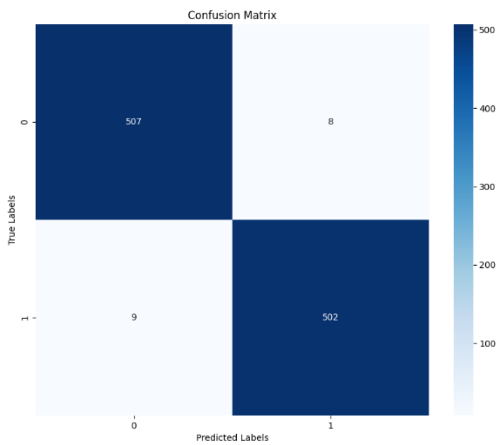
The Heart Attack Risk Prediction Dataset https://www.kaggle.com/datasets/iamsouravbanerjee/heart-attack-prediction-dataset is the aggregate set of all attributes, which might cause heart disease predictions. These involve attributes such as cholesterol level, age, heart rate, blood pressure, family history, obesity, diabetes, smoking, alcohol intake, hours exercising, dieting habits, stress level, sedentary, heart issues previously faced, medicines used, triglycerides levels, income, and geographical features. These characteristics are essential for determining the risk factors that may cause heart attack or myocardial infarction. There are 8,763 entries in this dataset, which is well sufficient for a binary classification task to predict the possibility of having a heart attack. By analyzing the relationship among these variables, models can be built by researchers as well as healthcare professionals for early prediction and preventive measures against cardiovascular diseases.

4.3 Performance Evaluation

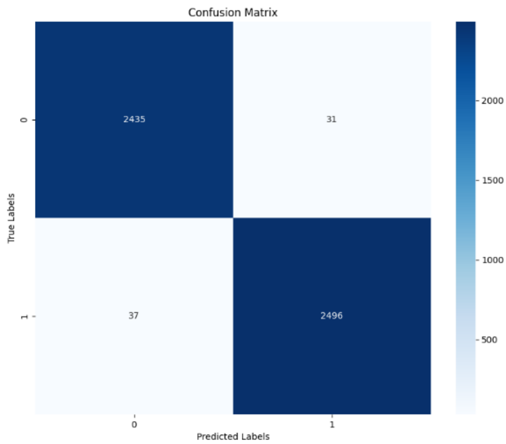
In this performance evaluation, we evaluate the KNN, ANN, CNN, and LSTM methods by comparing them to the proposed Multi-Folded Dynamic Regularized Dual Crossed CNN framework. The evaluation of the performance utilizes key metrics, such as Accuracy, Precision, Sensitivity, F1-Score, Specificity, Matthews Correlation Coefficient (MCC), and Negative Predictive Value (NPV). Furthermore, for datasets 1, 2, 3, and 4, we plot Receiver operating characteristics (ROC) curves to show the trade-off between each model's true positive and false positive rates. A confusion matrix for datasets 1, 2, 3, and 4 is also presented that depicts the classification results with the false negatives, true positives, true negatives, and false positives for each model. Figure 4 displays the confusion matrix for each dataset.



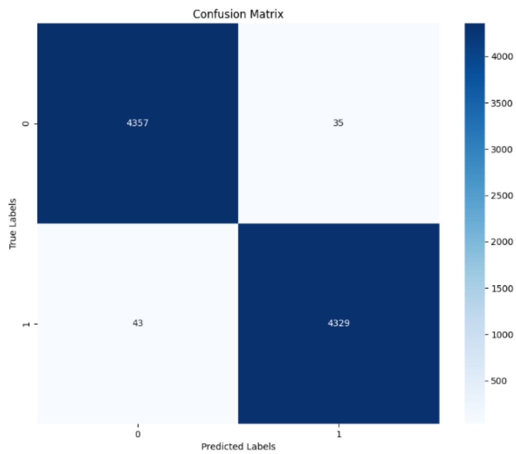
(a)



(b)



(c)



(d)

Figure 4 (a)-(d) Confusion matrix visualization for Datasets 1, 2, 3, and 4

The comparison among the existing methods and the proposed method using the specified metrics for different datasets is presented in Tables 2, 3, 4, and 5.

Table 2 Evaluation of performance for Dataset 1

Metrics	KNN	ANN	CNN	LSTM	Dual crossed CNN
Accuracy	89.8765	93.8765	88.5432	93.7654	97.9876
Precision	84.5432	88.4321	81.2345	90.4321	95.4321
Sensitivity	87.2345	89.5432	82.9876	89.8765	96.5432
Specificity	90.8765	92.9876	85.4321	91.6543	97.8765
F-Measure	88.6543	91.7654	84.3210	88.7654	96.4321
MCC	85.4321	89.8765	83.8765	89.9876	97.8765
NPV	89.7654	88.5432	86.5432	86.5432	96.9876
FPR	0.2327	0.1998	0.2338	0.1765	0.0854
FNR	0.2487	0.2054	0.2287	0.1809	0.0708

Table 2 evaluates the performance of various methods on dataset 1. The proposed Dual Crossed CNN outperforms all existing methods across key metrics. It achieves the highest accuracy (97.9876), precision (95.4321), sensitivity (96.5432), specificity (97.8765), F-measure (96.4321), MCC (97.8765), and NPV (96.9876), demonstrating its superior predictive capability. Furthermore, it minimizes false positive rates (FPR) and false negative rates (FNR) to 0.0854 and 0.0708, respectively, highlighting its reliability in reducing errors. Comparatively, while ANN performs well with an accuracy of 93.8765, it lags behind the Dual Crossed CNN in all metrics. KNN, CNN, and LSTM show relatively lower performance, with higher error rates and reduced sensitivity and specificity.

Table 3 Evaluation of performance of Dataset 2

Metrics	KNN	ANN	CNN	LSTM	Dual crossed CNN
Accuracy	92.2345	87.6543	94.9876	79.5432	98.4321
Precision	87.5432	79.8765	88.6543	74.9876	97.8765
Sensitivity	88.6543	81.5432	90.1234	70.4321	98.1234
Specificity	91.8765	84.7654	92.4321	81.7654	98.6543
F-Measure	90.9876	83.4321	91.9876	77.6543	97.9876
MCC	89.8765	82.9876	93.4321	75.1234	98.7654
NPV	87.5432	85.4321	89.8765	79.8765	98.4321
FPR	0.1987	0.2204	0.1997	0.3128	0.0812
FNR	0.2075	0.2143	0.1854	0.2956	0.0698

Table 3 presents the evaluation for dataset 2. The Dual Crossed CNN again exhibits the highest performance, with an accuracy (98.4321), precision of 97.8765, sensitivity of 98.1234, specificity (98.6543), F-measure (97.9876), MCC (98.7654), and NPV (98.4321). It achieves the lowest false positive rate (0.0812) and false negative rate (0.0698), ensuring robust detection and minimal errors. CNN also performs reasonably well, with metrics such as accuracy (94.9876) and precision (88.6543), but it is outperformed by the Dual Crossed CNN. KNN, ANN, and LSTM show significantly lower performance, particularly in sensitivity, F-measure, and MCC.

Table 4 Evaluation of performance of Dataset 3

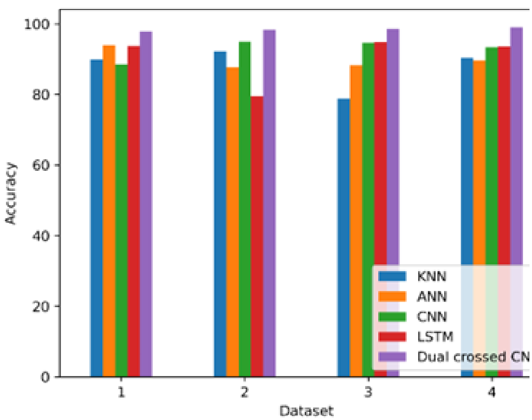
Metrics	KNN	ANN	CNN	LSTM	Dual crossed CNN
Accuracy	78.8765	88.4321	94.7654	94.8765	98.6543
Precision	72.9876	80.7654	89.4321	89.1234	96.1234
Sensitivity	75.5432	82.8765	90.7654	90.4321	97.7654
Specificity	80.6543	85.1234	92.8765	92.6543	98.4321
F-Measure	76.9876	84.4321	91.4321	91.9876	97.5432
MCC	74.4321	83.9876	93.7654	93.4321	98.7654
NPV	79.5432	86.2345	88.9876	89.1234	97.1234
FPR	0.31087	0.2287	0.2023	0.2017	0.0832
FNR	0.2965	0.2154	0.1798	0.1794	0.0719

Table 4 reveals the Dual Crossed CNN as the leading method, achieving an accuracy of 98.6543, precision (96.1234), sensitivity (97.7654), specificity (98.4321), F-measure of (97.5432), MCC (98.7654), and NPV (97.1234). The false positive and false negative rates are the lowest at 0.08321 and 0.071987, respectively, showcasing its efficiency in avoiding misclassifications. LSTM and CNN demonstrate competitive performance with metrics such as accuracy (94.8765 and 94.7654) and sensitivity (90.4321 and 90.7654), but their higher error rates make them less reliable. KNN and ANN trail further behind, particularly in specificity and NPV.

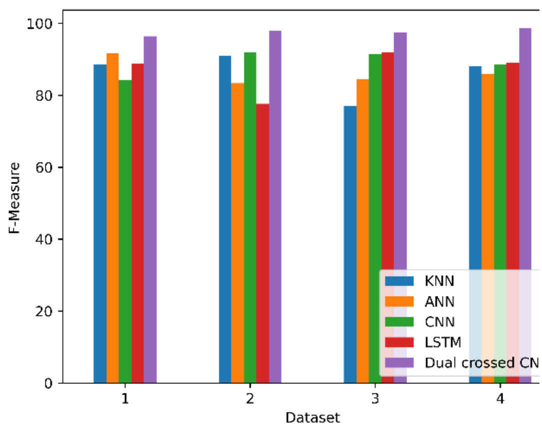
Table 5 Evaluation of performance of Dataset 4

Metrics	KNN	ANN	CNN	LSTM	Dual crossed CNN
Accuracy	90.4321	89.6543	93.4321	93.5432	99.1234
Precision	85.7654	82.1234	90.8765	90.6543	97.5432
Sensitivity	86.9876	83.9876	89.6543	89.4321	98.9876
Specificity	89.8765	86.7654	91.9876	91.8765	99.4321
F-Measure	88.12345	85.8765	88.5432	88.9876	98.7654
MCC	86.4321	84.6543	89.4321	89.7654	99.8765
NPV	87.98765	87.5432	86.7654	87.4321	98.6543
FPR	0.238765	0.2428	0.1698	0.1689	0.0823
FNR	0.250321	0.2304	0.1787	0.1776	0.0705

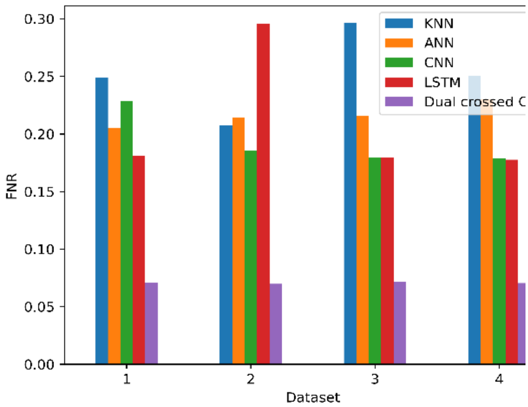
Table 5 evaluates dataset 4, where the Dual Crossed CNN significantly outshines other methods with an accuracy (99.1234), precision (97.5432), sensitivity (98.9876), specificity (99.4321), F-measure (98.7654), MCC (99.8765), and NPV (98.6543). It achieves the lowest false positive rate (0.0823) and false negative rate (0.0705), making it highly effective and reliable. CNN and LSTM follow, with comparable but lower metrics such as accuracy (93.4321 and 93.5432) and MCC (89.4321 and 89.7654). KNN and ANN remain less effective, with reduced specificity, sensitivity, and higher false positive and false negative rates.



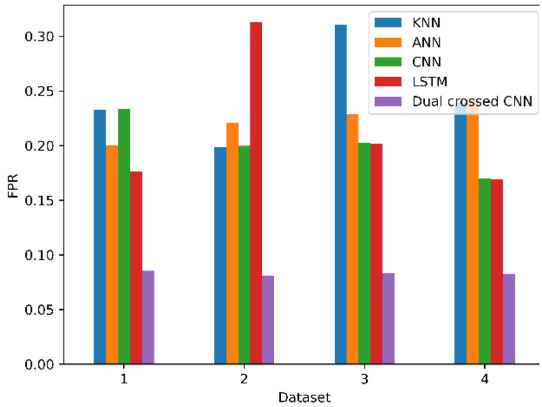
(a) Accuracy



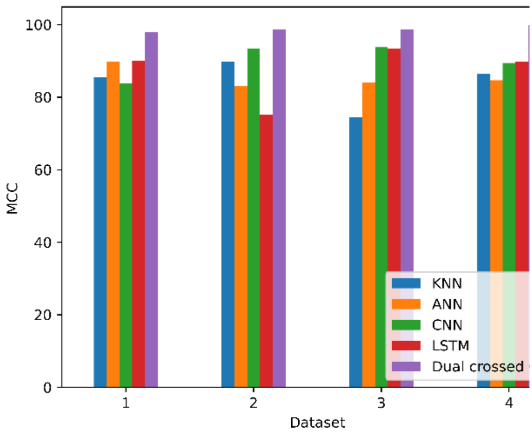
(b) F-Measure



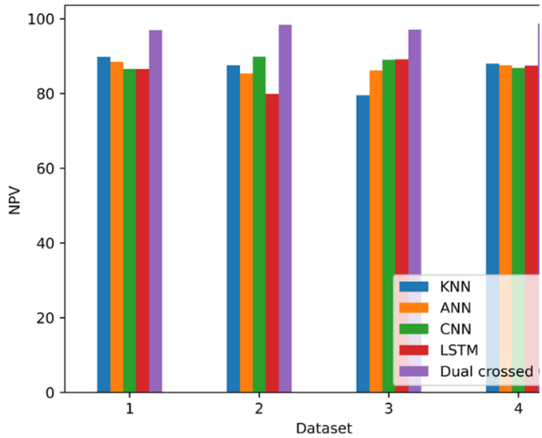
(c) FNR



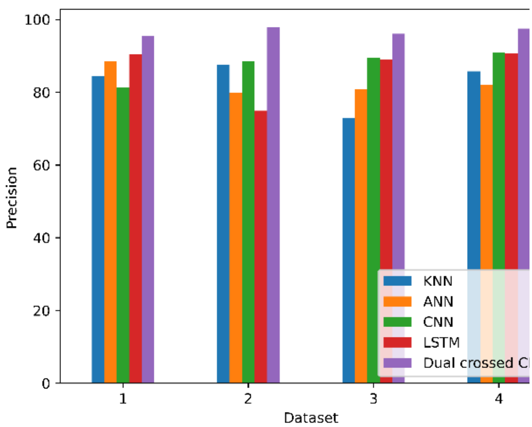
(d) FPR



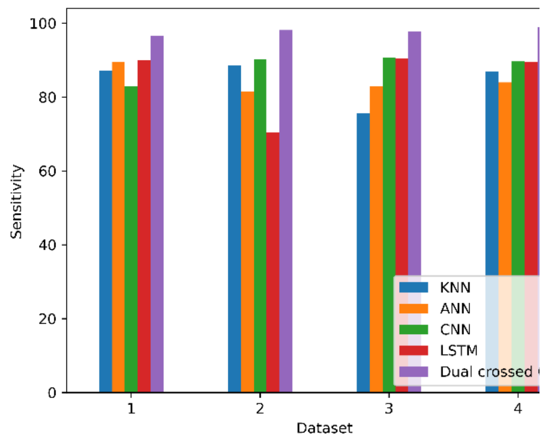
(d) MCC



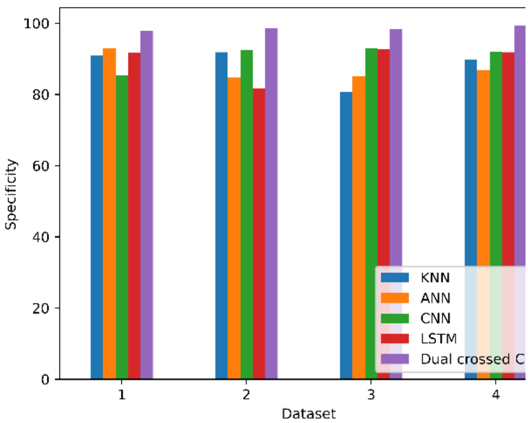
(e) NPV



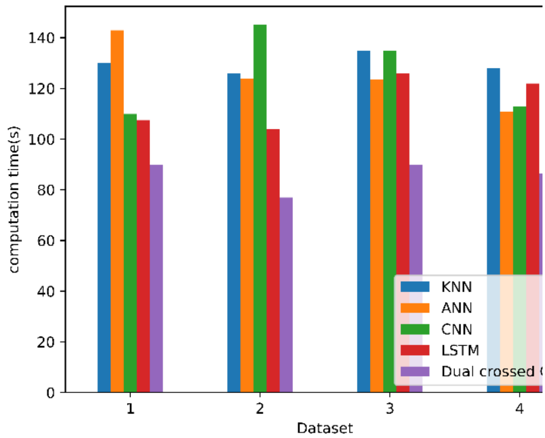
(f) Precision



(g) Sensitivity



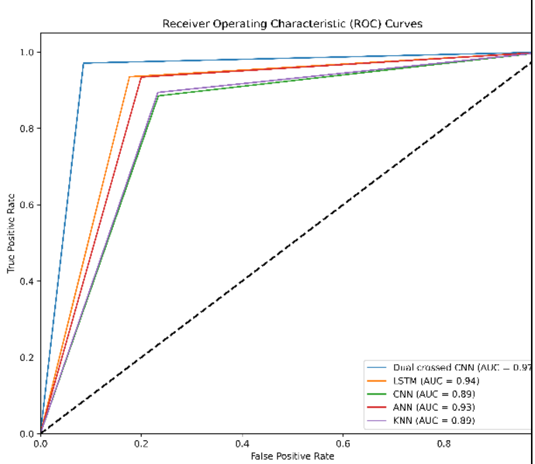
(h) Specificity



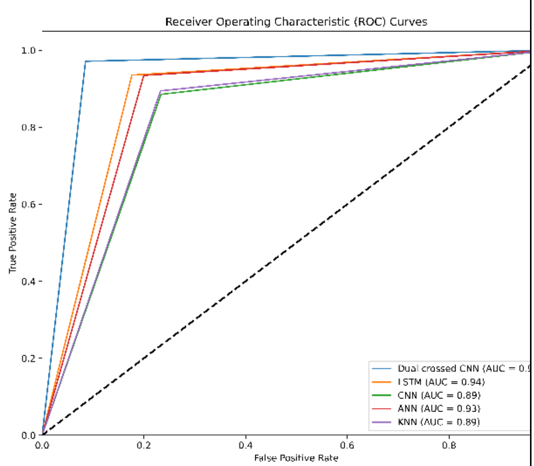
(i) Computation time (s)

Figure 5 (a)-(i) Visual representation of several performance metrics with proposed and existing works

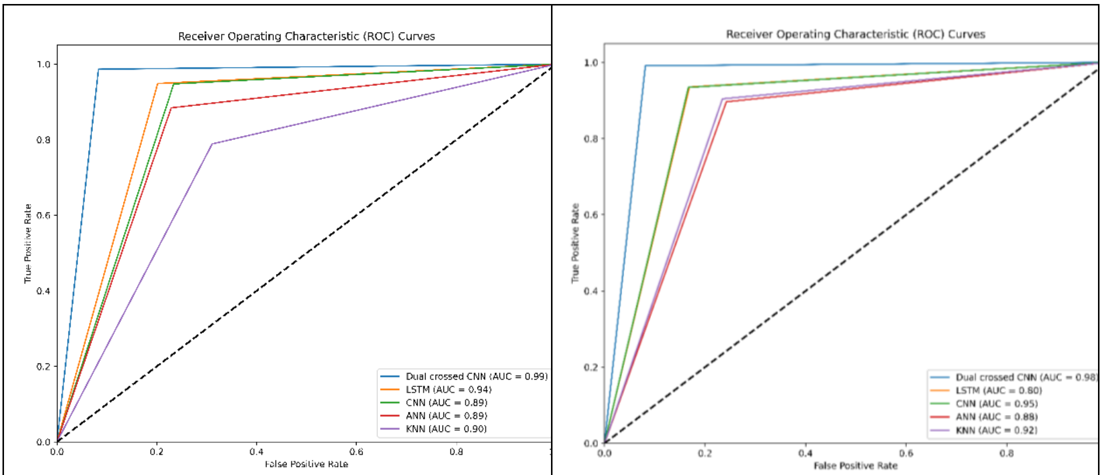
The performance metrics, which include sensitivity, accuracy, specificity, NPV, precision, FNR, FPR, MCC, F-Measure, Computation Time (s), and Specificity are represented graphically in Figures 5 (a) to (i). These metrics are compared with several approaches, including Proposed, ANN, KNN, CNN, and LSTM. The visual representation of the ROC curve for different datasets is depicted in Figure 6 (a)-(d)



(i) Dataset 1



(ii) Dataset 2



(iii) Dataset 3 | (iv) Dataset 4

Figure 6 (i)-(iv) Visual representation of ROC for Datasets 1, 2, 3, and 4

4.4 Ablation Study

In this ablation study, we explore the impact of key components on the performance of the suggested Multi-Folded Dynamic Regularized Dual Crossed CNN framework for cardiac arrest prediction. The ablation experiments are conducted on Datasets 1, 2, 3, and 4, where we systematically remove components like fuzzy C-means, optimized Information Gain (IG), Self-Adaptive Whale Optimization Algorithm (SWOA), and CNN. The evaluation highlights the contributions of each component in improving model accuracy and performance. Table 6 shows the ablation without dataset 1.

Table 6 Performance ablation without Dataset 1

Model Configuration	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F-Measure (%)
without fuzzy c means	87.654	85.45	83.67	80.87	81.76
with fuzzy c means	97.98	95.43	96.54	97.87	96.43
without optimized IG	83.55	82.767	80.867	82.76	80.76
with optimized IG	97.98	95.43	96.54	97.87	96.43
without SWOA	81.45	79.64	78.54	82.53	83.65
with SWOA	97.98	95.43	96.54	97.87	96.43
without CNN	80.53	83.53	82.42	83.23	79.56
with CNN	97.98	95.43	96.54	97.87	96.43

Table 6 highlights the performance on Dataset 1. The full model configuration achieves 97.99% accuracy, 95.43% precision, 96.54% sensitivity, 97.88% specificity, and 96.43% F-measure, which are the highest among all variations. When the fuzzy C-means, optimized IG, SWOA, or CNN are omitted, there is a clear decline in performance, particularly in accuracy and sensitivity. The absence of CNN shows the most significant drop, underlining its importance in feature extraction and model effectiveness. Overall, the results emphasize that all components work synergistically to enhance performance, and the inclusion of all parts is essential for optimal prediction accuracy in cardiac disease detection. Table 7 shows the ablation without dataset 2.

Table 7 Performance ablation without Dataset 2

Model Configuration	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F-Measure (%)
without fuzzy c means	87.64	86.45	85.2	82.645	80.54
with fuzzy c means	98.43	97.87	98.12	98.65	97.98
without optimized IG	86.53	84.34	83.54	82.65	81.64
with optimized IG	98.43	97.87	98.12	98.65	97.98
without SWOA	88.43	85.56	84.54	82.564	84.64
with SWOA	98.43	97.87	98.12	98.65	97.98
without CNN	80.64	79.36	82.54	81.65	82.53
with CNN	98.43	97.87	98.12	98.65	97.98

Table 7 examines the model’s performance on Dataset 2. The full model configuration, including fuzzy C-means, optimized IG, SWOA, and CNN, achieves 98.43% accuracy, 97.88% precision, 98.12% sensitivity, 98.65% specificity, and 97.99% F-measure. As with the other datasets, omitting any of the key components leads to a noticeable reduction in performance, with the accuracy and sensitivity showing significant declines. The absence of CNN results in a drop in both precision and sensitivity, highlighting the necessity of CNN for feature learning and accurate classification. The results reinforce the idea that the proposed framework's robust performance is largely because of the cumulative impact of the several elements.

Table 8 Performance ablation without Dataset 3

Model Configuration	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F-Measure (%)
without fuzzy c means	90.64	90.675	89.54	91.54	88.645
with fuzzy c means	98.65	96.12	97.76	98.43	97.54
without optimized IG	89.65	88.54	87.54	88.58	85.56
with optimized IG	98.65	96.12	97.76	98.43	97.54
without SWOA	90.54	89.564	88.44	86.43	84.99
with SWOA	98.65	96.12	97.76	98.43	97.54
without CNN	87.54	84.54	81.654	83.65	85.32
with CNN	98.65	96.12	97.76	98.43	97.54

In Table 8, The suggested model's performance is evaluated through various ablations, focusing on different components and their contributions to the overall performance on Dataset 3. The model with fuzzy C-means, Optimized Information Gain (IG), Self-Adaptive Whale

Optimization Algorithm (SWOA), and Convolutional Neural Network (CNN) shows superior performance across all metrics. The precision, accuracy, specificity, sensitivity, and F-measure reach 96.12, 98.65, 98.43, 97.77, and 97.54, respectively, when all components are included. The ablation experiments reveal that removing any of the components results in significant drops in performance. Notably, omitting fuzzy C-means, optimized IG, SWOA, or CNN causes a decrease in accuracy and sensitivity, confirming the importance of each component in boosting the model's efficiency for cardiac arrest prediction. Table 7 shows the ablation without dataset 4.

Table 9 Performance ablation without Dataset 4

Model Configuration	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F-Measure (%)
without fuzzy c means	93.54	92.43	91.65	90.65	88.65
with fuzzy c means	99.12	97.54	98.98	99.43	98.76
without optimized IG	91.54	90.65	89.33	90.343	88.754
with optimized IG	99.12	97.54	98.98	99.43	98.76
without SWOA	90.34	92.53	92.43	90.64	87.43
with SWOA	99.12	97.54	98.987	99.43	98.76
without CNN	89.65	88.53	87.32	90.54	89.54
with CNN	99.12	97.54	98.98	99.43	98.76

Table 9 presents the ablation study for Dataset 4. The model's performance is again evaluated with and without critical components. The full configuration (with fuzzy C-means, optimized IG, SWOA, and CNN) outperforms all other variations, achieving 99.12% accuracy, 97.54% precision, 98.99% sensitivity, 99.43% specificity, and 98.77% F-measure. When each component is removed, the model's performance declines, especially in precision and sensitivity. For instance, without fuzzy C-means or optimized IG, there is a notable reduction in accuracy and sensitivity, demonstrating that these components are crucial for the model's robustness. The results validate that each part of the model contributes to its ability to predict cardiac arrest reliably. Table 8 shows the ablation without dataset 4.

5. Conclusion

In conclusion, the proposed approach for cardiovascular disease prediction integrates more advanced pre-processing, feature extraction, optimization, and classification techniques that have effectively overcome some of the most significant problems concerning the detectivity of heart disease. This is improved significantly by feature learning by the combination of Fuzzy C-Means-based aggregation of features and the Self-Adaptive Whale Optimization Algorithm with IG along with a multi-folded dynamic regularized dual-crossed CNN. The proposed method is evaluated, which shows excellent results with an accuracy (99.1234), precision (97.5432), sensitivity (98.9876), specificity (99.4321), F-measure (98.7654), MCC

(99.8765), and NPV (98.6543) while minimizing FPR (0.0823) and FNR (0.0705). These metrics show that the framework outperforms existing methods like KNN, ANN, CNN, and LSTM. This approach ensures robustness in handling imbalances in the dataset and overfitting, which improves prediction accuracy. The innovative framework presented here has the potential to be a reliable tool for early cardiac arrest detection, thus contributing to better clinical decision-making and saving lives.

References

1. Abdellatif, A., Abdellatef, H., Kanesan, J., Chow, C. O., Chuah, J. H., & Gheni, H. M. (2022). An effective heart disease detection and severity level classification model using machine learning and hyperparameter optimization methods. ieee access, 10, 79974-79985.
2. Ali, F., El-Sappagh, S., Islam, S. R., Kwak, D., Ali, A., Imran, M., & Kwak, K. S. (2020). A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion. Information Fusion, 63, 208-222.
3. Ali, F., El-Sappagh, S., Islam, S. R., Kwak, D., Ali, A., Imran, M., & Kwak, K. S. (2020). A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion. Information Fusion, 63, 208-222.
4. Alqahtani, A., Alsubai, S., Sha, M., Vilcekova, L., & Javed, T. (2022). Cardiovascular disease detection using ensemble learning. Computational Intelligence and Neuroscience, 2022(1), 5267498.
5. Bharti, R., Khamparia, A., Shabaz, M., Dhiman, G., Pande, S., & Singh, P. (2021). Prediction of heart disease using a combination of machine learning and deep learning. Computational intelligence and neuroscience, 2021(1), 8387680.
6. Ghosh, P., Azam, S., Jonkman, M., Karim, A., Shamrat, F. J. M., Ignatious, E., ... & De Boer, F. (2021). Efficient prediction of cardiovascular disease using machine learning algorithms with relief and LASSO feature selection techniques. IEEE Access, 9, 19304-19326.
7. Khan, M. A., & Algarni, F. (2020). A healthcare monitoring system for the diagnosis of heart disease in the IoMT cloud environment using MSSO-ANFIS. IEEE access, 8, 122259-122269.
8. Li, J. P., Haq, A. U., Din, S. U., Khan, J., Khan, A., & Saboor, A. (2020). Heart disease identification method using machine learning classification in e-healthcare. IEEE access, 8, 107562-107582.
9. Mehmood, A., Iqbal, M., Mehmood, Z., Irtaza, A., Nawaz, M., Nazir, T., & Masood, M. (2021). Prediction of heart disease using deep convolutional neural networks. Arabian Journal for Science and Engineering, 46(4), 3409-3422.
10. Muhammad, Y., Tahir, M., Hayat, M., & Chong, K. T. (2020). Early and accurate detection and diagnosis of heart disease using intelligent computational model. Scientific reports, 10(1), 19747.
11. Nadeem, M. W., Goh, H. G., Khan, M. A., Hussain, M., & Mushtaq, M. F. (2021). Fusion-Based Machine Learning Architecture for Heart Disease Prediction. Computers, Materials & Continua, 67(2).
12. Nallamothu, B. K., Greif, R., Anderson, T., Atiq, H., Couto, T. B., Considine, J., ... & International Liaison Committee on Resuscitation. (2023). Ten steps toward improving in-hospital cardiac arrest quality of care and outcomes. Circulation: Cardiovascular Quality and Outcomes, 16(11), e010491.
13. Ogunpola, A., Saeed, F., Basurra, S., Albarrak, A. M., & Qasem, S. N. (2024). Machine learning-based predictive models for detection of cardiovascular diseases. Diagnostics, 14(2), 144.
14. Oyeleye, M., Chen, T., Titarenko, S., & Antoniou, G. (2022). A predictive analysis of heart rates using machine learning techniques. International Journal of Environmental Research and Public

Health, 19(4), 2417.
15. Pan, Y., Fu, M., Cheng, B., Tao, X., & Guo, J. (2020). Enhanced deep learning assisted convolutional neural network for heart disease prediction on the internet of medical things platform. Ieee Access, 8, 189503-189512.
16. Pandey, V., Lilhore, U. K., Walia, R., Alroobaea, R., Alsafyani, M., Baqasah, A. M., & Algarni, S. (2024). Enhancing heart disease classification with M2MASC and CNN-BiLSTM integration for improved accuracy. Scientific Reports, 14(1), 24221.
17. Pareek, N., Kordis, P., Beckley-Hoelscher, N., Pimenta, D., Kocjancic, S. T., Jazbec, A., ... & MacCarthy, P. (2020). A practical risk score for early prediction of neurological outcome after out-of-hospital cardiac arrest: MIRACLE2. European heart journal, 41(47), 4508-4517.
18. Pathan, M. S., Nag, A., Pathan, M. M., & Dev, S. (2022). Analyzing the impact of feature selection on the accuracy of heart disease prediction. Healthcare Analytics, 2, 100060.
19. Rahim, A., Rasheed, Y., Azam, F., Anwar, M. W., Rahim, M. A., & Muzaffar, A. W. (2021). An integrated machine learning framework for effective prediction of cardiovascular diseases. IEEE Access, 9, 106575-106588.
20. Sandroni, C., Nolan, J. P., Andersen, L. W., Böttiger, B. W., Cariou, A., Cronberg, T., ... & Soar, J. (2022). ERC-ESICM guidelines on temperature control after cardiac arrest in adults. Intensive care medicine, 48(3), 261-269.
21. Sharma, S., & Parmar, M. (2020). Heart diseases prediction using deep learning neural network model. International Journal of Innovative Technology and Exploring Engineering (IJITEE), 9(3), 2244-2248.
22. Thapa, S. B., Kakar, T. S., Mayer, C., & Khanal, D. (2021). Clinical outcomes of in-hospital cardiac arrest in COVID-19. JAMA Internal Medicine, 181(2), 279-281.
23. Wong, K. K., Fortino, G., & Abbott, D. (2020). Deep learning-based cardiovascular image diagnosis: a promising challenge. Future Generation Computer Systems, 110, 802-811.