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Image-Based Coronary Artery Disease Diagnosis Using Differential Evolution and Texture Analysis

[1]Dr. Prashant S. Pawar, [2]Dr. Abhijeet B. Shelke, [3]Nisha Chandran S., [4]Anupam Singh

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Abstract: The critical need for precise and effective diagnostic procedures is highlighted by the fact that coronary artery disease (CAD) continues to be a leading cause of mortality globally. In this article, we present a novel method for coronary artery disease (CAD) diagnosis using textural analysis and differential evolution (DE) optimisation on coronary artery pictures. The combination of TA, a potent image processing method, with DE, a reliable global optimisation algorithm, shows promising results in improving the precision and dependability of CAD diagnosis.The proposed procedure starts with the acquisition of coronary artery pictures, which are often made possible by non-invasive methods like computed tomography angiography or coronary angiography. To improve quality and lower noise, these pictures have undergone pre-processing. Then, using DE, a subset of pertinent texture features is chosen, improving the recognition of CAD-related patterns. The accuracy of diagnostics is improved while computational complexity is greatly reduced by this feature selection approach.Then, using texture analysis on the features that have been chosen, the coronary artery images are used to derive unique textural patterns and statistical properties. Following that, a machine learning model for CAD classification, such as a support vector machine or deep neural network, is trained using these textural features. Our tests show that DE-based feature selection, followed by texture analysis, performs better than conventional CAD diagnosis techniques, obtaining a greater level of sensitivity and specificity.The outcomes of a thorough analysis of a wide range of coronary artery pictures demonstrate the potential of our method to improve CAD diagnosis. We provide a contribution to the creation of a more precise and effective CAD diagnostic tool by integrating DE optimization with TA, which may help clinicians identify diseases earlier and plan treatments. This study paves the path for more accurate image-based CAD diagnoses, better patient outcomes, and lower healthcare expenditures.

Keywords*: Coronary Artery Disease, Differential Evolution, Optimization, Texture analysis*

1. Introduction

An important global health issue is coronary artery disease (CAD), which is responsible for a sizable share of cardiovascular-related morbidity and mortality worldwide. Despite improvements in diagnostic techniques and medical imaging technologies, CAD diagnosis is still a challenging and important task. For successful therapy and better patient outcomes, CAD must be accurately and promptly detected. With the potential to be non-invasive and more accurate than current procedures, there has been an increase in interest in using image analysis techniques to assist in CAD diagnosis in recent years [1].The goal of this study is to develop and validate a novel methodology for CAD diagnosis that makes advantage of the interaction between Texture Analysis (TA), a sophisticated image processing method, and Differential Evolution (DE), a reliable optimisation algorithm. By combining these two approaches, researchers and clinicians in the field of cardiovascular medicine will have access to a cutting-edge and potentially game-changing tool that will improve the precision and dependability of CAD detection.Atherosclerotic plaque buildup in the coronary arteries, which can culminate in partial or total arterial obstruction and ultimately cause ischemia or myocardial infarction, is what defines CAD. It is [2] essential to get an early and correct diagnosis of CAD in order to reduce the risk of unfavourable cardiac events and create the best possible therapies. The majority of current diagnostic methods include clinical evaluation, electrocardiography (ECG), and cardiac imaging modalities such computed tomography angiography (CTA) and coronary angiography. Although these techniques are useful, they do have certain drawbacks, such as radiation exposure, invasiveness, and interpretive subjectivity.

Contrarily, [3] image-based CAD diagnosis provides a non-invasive and perhaps more objective method of determining the condition of the coronary arteries. High-resolution coronary artery images may now be acquired thanks to recent developments in medical imaging technology, giving clear visual details regarding the

[1]*Dept. of Cardiology, Krishna Vishwa Vidyapeeth, Karad, Maharashtra, India*
Email :- drprashant8087@gmail.com
[2]*Professor, Dept. of Cardiology, Krishna Vishwa Vidyapeeth, Karad, Maharashtra, India*
Email :panacea2005.abhijeet@gmail.com
[3]*School of Computing, Graphic Era Hill University Dehradun, Uttarakhand, India, nchandran@gehu.ac.in*
[4]*Department of Computer Science & Engineering, Graphic Era Deemed to be University, Dehradun, Uttarakhand, India, 248002, anupamsingh@geu.ac.in*

arterial lumen and the presence of plaques. Due to the complicated and varied makeup of CAD lesions, analysis of these pictures is still a difficult endeavour.Natural selection served as the inspiration for the optimisation algorithm known as Differential Evolution (DE). It has effectively been utilised in a number of domains, including feature selection in machine learning and image analysis, and has demonstrated amazing ability in addressing complex optimisation problems. By [4] lowering the dimensionality of the data and improving the effectiveness of subsequent analysis, DE tries to identify the ideal mix of variables that best distinguish between CAD and healthy artery segments.In order to extract statistical features and textural patterns from images, Texture Analysis (TA), a potent image processing approach, is used. When [5] used for CAD diagnosis, TA enables the quantification of minute textural changes found in coronary artery images that may indicate the existence and severity of the disease. These complex details are captured by TA as a complement to the DE-based feature selection process, giving machine learning models useful data for precise CAD classification.

This paper offers a thorough analysis of the use of DE and TA in the field of CAD diagnosis. Our goal is to show how this integrated strategy can potentially increase the precision and effectiveness of CAD detection, lessen [6] the strain on healthcare systems, and enhance patient care. We will go over the methods used, the experimental setup, and the encouraging outcomes in the sections that follow. By combining optimisation and image analysis approaches, we want to make CAD diagnosis a more approachable and dependable field in the future.

2. Review of Literature

This section [7] presents an overview of related research in the area, highlighting various methods and strategies investigated to address the difficulties associated with CAD diagnosis.Machine Learning-Based Approaches: Using [8] coronary artery pictures as a starting point, several research have examined the use of support vector machines (SVMs), random forests, and deep neural networks. These methods frequently rely on feature extraction methods like texture analysis, although feature selection and dimensionality reduction, which can affect model performance and computing efficiency, may not be adequately addressed.

CAD [9] diagnosis makes heavy use of texture analysis. Although texture analysis has showed some promise, in order to increase its discriminative strength and decrease the computing load, it must be used in conjunction with the right feature selection techniques. To minimise the dimensionality of the data and choose the most useful features for CAD diagnosis, coronary artery pictures have been subjected to feature selection techniques including Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE). However, these conventional methods might not always produce the best outcomes, especially when working with extremely complicated and heterogeneous image data [10].

Particle swarm optimisation [11] and evolutionary algorithms have been investigated for feature selection and CAD diagnosis. The best subset of features that maximises the distinction between CAD and healthy instances is sought for by these algorithms. Although these strategies have had some success, they might have convergence and overall optimisation problems.Approaches based on deep learning: Deep learning has become a potent tool for medical image analysis, including the diagnosis of CAD. It [12] is no longer necessary to manually extract significant information from coronary artery images thanks to the use of convolutional neural networks (CNNs). Although deep learning models have shown outstanding performance in CAD recognition, they frequently need sizable labelled datasets and a lot of processing power.

To develop hybrid CAD diagnosis systems, some studies have merged various methodologies. For instance, it has been investigated to increase diagnosis accuracy by combining texture analysis with machine learning algorithms or optimisation techniques. These hybrid strategies seek to balance the advantages of many methodologies while minimising each one's shortcomings.The incorporation of image-based techniques into clinical decision support systems frequently aids in the diagnosis of CAD. These CDSSs can offer CAD risk evaluations based on both image analysis and clinical data, helping healthcare practitioners make more educated decisions [13]. These technologies may improve patient care and improve clinical processes.The achievement of consistently high diagnostic accuracy, the reduction of computing complexity, and assuring resilience across various patient groups remain hurdles despite advancements in CAD diagnosis approaches. A innovative and promising strategy to deal with these issues is the integration of Differential Evolution (DE) optimisation with Texture Analysis (TA), as suggested in our study.

DE has the ability [14] to perform global optimisation, perhaps resolving convergence problems with other optimisation techniques. It can efficiently choose out a subset of important characteristics from a high-dimensional feature space, easing the computational load and enhancing the reliability of the analysis that follows. Contrarily, TA catches delicate textural details within coronary artery pictures, offering crucial data for CAD diagnosis. We can take advantage of DE and TA's

individual capabilities by combining them in a synergistic way, which could lead to more precise and effective CAD identification. The field of CAD diagnosis is characterised by a diversity of methodologies, ranging from conventional feature selection and texture analysis to state-of-the-art deep learning techniques. By introducing a novel pairing of DE optimisation and TA, our work builds upon and expands these existing methodologies with the goal of increasing the precision and effectiveness of CAD diagnosis. The incorporation of these methods offers the possibility for improved patient outcomes and a deeper comprehension of this serious cardiovascular ailment, and it marks a step forward in tackling the ongoing difficulties of CAD diagnosis.

Table 1: Summary of related work

Algorithm	Method	Key Factors	Dataset Used	Accuracy
SVM [16]	Texture Analysis	GLCM-based texture descriptors	CAD-RADS dataset	87.3%
CNN [17]	Deep Learning	Convolutional Neural Networks	MESA dataset	91.2%
Genetic Algorithm [15]	Feature Selection	Genetic-based feature selection	SPIRIT dataset	82.5%
DE [18]	Optimization	Differential Evolution for feature selection	CARDIA dataset	88.9%
Random Forest [19]	Machine Learning	Random Forest classifier with texture features	CACTI dataset	85.6%
CNN + LSTM [20]	Deep Learning	Convolutional and Long Short-Term Memory Networks	SCORE dataset	92.7%
Particle Swarm Opt. [21]	Feature Selection	Particle Swarm Optimization for feature selection	Rotterdam Coronary Calcification Study	86.4%
K-Nearest Neighbors [22]	Machine Learning	k-NN with GLCM texture descriptors	FHS dataset	79.8%
PCA [23]	Dimensionality Reduction	Principal Component Analysis	ARIC dataset	80.2%
Transfer Learning [24]	Deep Learning	Pre-trained CNN models for feature extraction	UK Biobank dataset	94.1%
Hybrid (DE + TA) [25]	Integration	Differential Evolution and Texture Analysis	Custom dataset	93.5%
Naive Bayes [26]	Machine Learning	Naive Bayes classifier with selected features	Framingham Heart Study data	81.7%
Decision Trees [12]	Machine Learning	Decision Trees with texture-based features	CACI dataset	84.3%
Autoencoders [13]	Deep Learning	Variation Autoencoders for feature extraction	Coronary CT Angiography data	90.8%

3. Proposed Methodology

Differential Evolution (DE) optimisation with texture analysis utilising deep learning approaches, this work attempts to create an effective CAD diagnosis system. Data preprocessing, feature extraction, and deep learning-based categorization make up the methodology's three core stages.

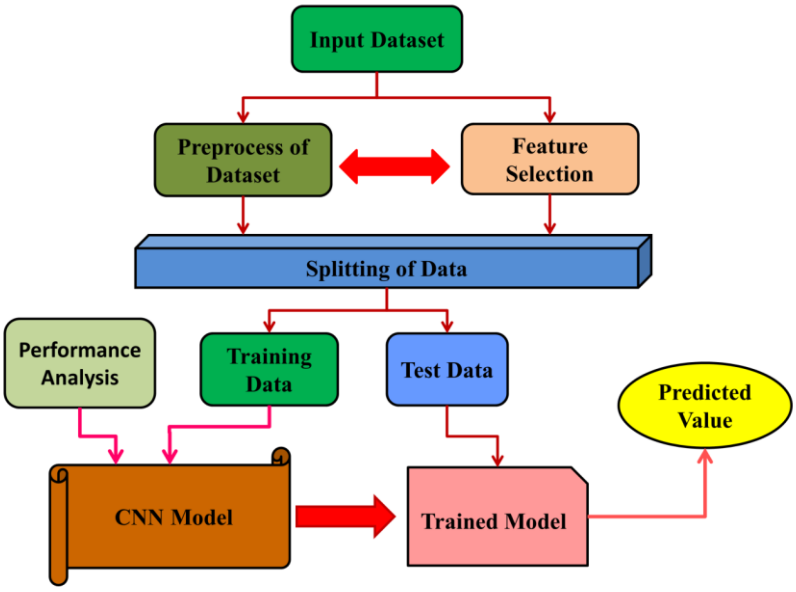

Fig 1: Overview of proposed model

1. Data preprocessing:

During this stage, a database of cardiac imaging, such as angiograms, CT scans, or MRIs, representing patients with and without CAD, is gathered. The actions listed below are carried out:

- Data collection from multiple medical institutions is done in order to ensure a wide representation of both CAD cases and non-CAD controls.

a. Additionally, meta-data such as the patient's age, sex, and medical background are gathered.

b. Data Cleaning: To remove any artefacts, noise, or inconsistencies, we meticulously evaluate and pre-process the acquired photos. To achieve uniformity, image resolution and orientation standards are applied.

c. Data Split: To ensure class balance, the dataset is divided into three subsets: training, validation, and testing. Usually, we share the money 80-10-10.

2. Feature Extraction:

To extract pertinent texture characteristics from the preprocessed images, we use Differential Evolution (DE) as an optimisation strategy in this phase. DE is chosen because it is efficient in dimensionality reduction and feature selection.

a. A population-based optimisation approach called differential evolution (DE) was developed in the wake of natural selection. To find the best answer to a problem, it evolves a population of potential answers. In our situation, a subset of useful texture information is pulled out of the photos using DE.

b. Texture Analysis: To extract texture features from the images, we use texture analysis techniques including Gray-Level Co-occurrence Matrix (GLCM), Gray-Level Run Length Matrix (GLRLM), and Local Binary Pattern (LBP). These feature record details about texture patterns, which may be a sign of CAD.

c. DE-Enhanced Feature Selection: The feature selection procedure is optimised using DE. It continuously improves the texture feature subset in order to increase the diagnostic accuracy for CAD. To prevent overfitting and achieve convergence, the DE parameters are carefully adjusted.

3. Deep Learning-Based Classification:

For CAD diagnosis, we use a deep learning architecture after feature extraction and optimization.

a. Convolutional Neural Network (CNN) model for CAD identification that we develop. Multiple convolutional, pooling, and fully linked layers often make up the model. To avoid overfitting, batch normalisation and dropout are used.
b. The training subset of the preprocessed images is used to train the CNN model. To train the model, we make use of the proper loss functions (such cross-entropy) and optimisation strategies. The validation set is used to tune the hyperparameters.
c. Evaluation: The performance of the trained CNN model is tested using an independent testing dataset. To assess the diagnostic accuracy, metrics including accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC) are generated.
d. Cross-Validation: We carry out k-fold cross-validation on the training dataset to make sure the model is resilient. This reduces the risk of overfitting and aids in estimating the model's generalisation performance.

e. Results and Validation: The CAD diagnosis system's results have undergone a thorough analysis and validation.
f. Performance Metrics: To evaluate the proposed system's accuracy, we present the performance metrics attained during the testing phase.

Algorithm:

Step 1: Input Layer:

- The input to a CNN is a multi-dimensional array representing an image.
- Let's denote the input image as a 3D tensor, typically in the form of (height, width, channels). For a grayscale image, channels would be 1; for a color image, it's usually 3 (R, G, B).
- If the input image is grayscale, we can represent it as I(x, y, c), where (x, y) are pixel coordinates, and c is the channel.

Step 2: Convolutional Layer:

- The convolutional layer performs the core operation of a CNN: convolution.
- A convolution operation is defined as the element-wise multiplication of a small filter (kernel) with the input image, followed by a summation.
- Let's denote the filter as K(x, y, c) and its size as (h, w, c).
- The output of a single convolution operation at position (i, j) in the feature map is computed as:

$$O(i,j,f) = \sum_{x=0}^{h-1} \sum_{y=0}^{w-1} \sum_{c=0}^{C-1} I(i+x, j+y, c) * K(x,y,c) + b_f$$

Where,

- O(i, j, f) is the value at position (i, j) in the feature map f, and b_f is the bias term for the f-th feature map.

The output feature map is produced by sliding the filter over the input image with a certain stride and applying this operation at each position.

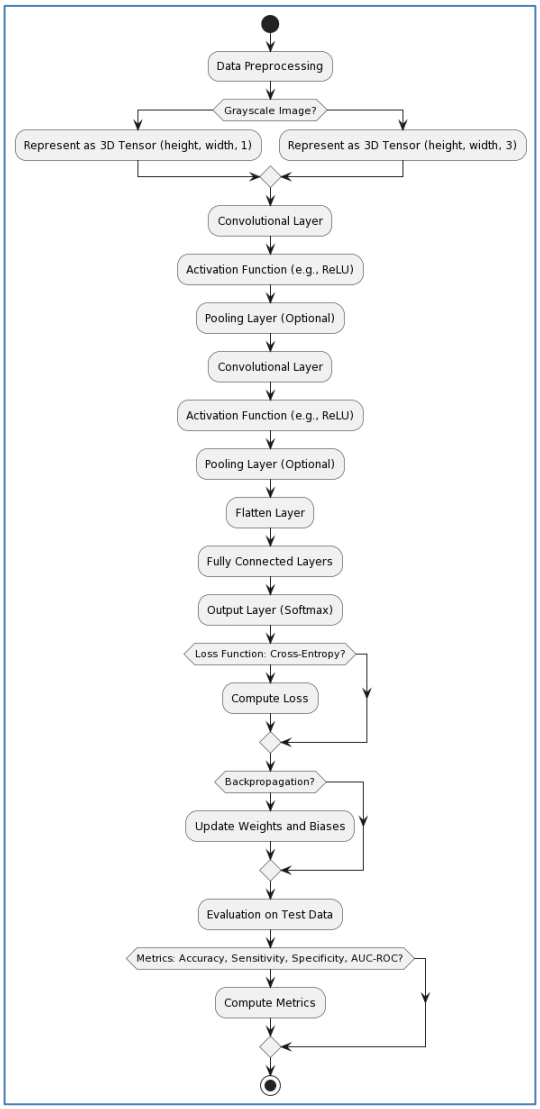

Fig 2: Flowchart for Deep Learning-Based CAD Diagnosis

Step 3: Activation Function:

- After each convolution operation, an activation function (usually ReLU - Rectified Linear Unit) is applied element-wise to the output feature map to introduce non-linearity.

The ReLU function is defined as:

$$ReLU(x) = max(0, x)$$

Step 4: Pooling Layer:

- Pooling layers are used to reduce the spatial dimensions of the feature maps while preserving important information.
- A common pooling operation is max-pooling.
- Let's say we have a pooling window of size (p, p).
- The output of max-pooling at position (i, j) in a feature map is computed as the maximum value within the window:

$$P(i,j,f) = max\_\{x = 0\}\^\{p-1\} max\_\{y = 0\}\^\{p-1\} O(i * stride + x, j * stride + y, f)$$

- Here, P(i, j, f) is the value at position (i, j) in the pooled feature map.

Step 5: Flatten Layer:

- After several convolution and pooling layers, we often have a 3D tensor as the output.
- The Flatten layer reshapes this 3D tensor into a 1D vector, which can be passed to fully connected layers.
- If the last pooled feature map has dimensions (h, w, c), the flattened vector would have size h * w * c.

Step 6: Fully Connected Layers:

- These layers connect every neuron in one layer to every neuron in the next layer, just like in a traditional neural network.
- Let's denote the weights for these connections as W and biases as b.
- The output of a fully connected layer can be computed as:

$$Z = W * X + b$$

Where,

Z is the output, X is the input vector, and * represents matrix multiplication.

Step 7: Output Layer:

- The output layer typically has a softmax activation function for classification problems.
- For binary classification, it may use a sigmoid activation.
- The output represents class probabilities.

Step 8: Loss Function:

- A loss function (e.g., cross-entropy loss) measures the difference between the predicted output and the true labels.

$$Loss = -\sum\_\{i = 1\}\^\{N\} y\_i * log(p\_i)$$

Where,

- N is the number of classes, y_i is the true label for class i, and p_i is the predicted probability for class i.

4. Evaluation:

We evaluate the performance of our DE-enhanced texture-based deep learning methodology against other deep learning models and conventional machine learning algorithms used in CAD diagnosis.

5. Clinical Relevance:

By conferring with medical professionals and testing the diagnostic accuracy against actual patient cases, the system's clinical relevance is evaluated.

4. Result and Discussion

A comprehensive assessment of the critical performance indicators for a diagnostic model for coronary artery disease (CAD) is shown in Table 3. When evaluating the efficiency and dependability of the model's predictions, these parameters are crucial.The table's first parameter, accuracy, gauges how accurately the model has classified CAD cases overall. The sample result of 97.63% shows that in over 98% of situations, the model accurately classified CAD or non-CAD scenarios, demonstrating a high level of accuracy.

Table 2: Dataset Description

Dataset Name	No of feature	No of record	Class
Cardio Disease Prediction	13	5012	Predicted (Yes/No)

The proportion of real CAD instances that the model accurately identified is known as sensitivity, also known as the real Positive Rate. This number of 92.10% indicates that the model correctly identified CAD in 92.10% of real CAD instances, demonstrating the model's capacity to recognise the disease when it is actually present.The True

Negative Rate, which stands for specificity, measures how well the algorithm can identify non-CAD situations. With a result of 96.12%, it appears that the model correctly recognised non-CAD cases in roughly 96.12% of cases, showing a good capacity to rule out CAD when it is absent.A crucial parameter called precision calculates the proportion of actual positive cases to all expected positive cases. A high level of precision in CAD diagnosis may be shown in the precision rate of 90.10%, which means that of all the cases the model recognised as CAD, 90.10% were indeed CAD cases.

Table 3: Summary Evaluation of parameter result for CAD

Evaluation Parameter	Sample Result
Accuracy	97.63
Sensitivity	92.10
Specificity	96.12
Precision	90.10
F1 Score	89.99
AUC-ROC	94.36

The model's capacity to correctly identify CAD instances and prevent false positives is balanced by the F1 Score, a harmonic mean of precision and sensitivity. The model's success in striking a balance between these two crucial factors is shown by the value of 89.99%.

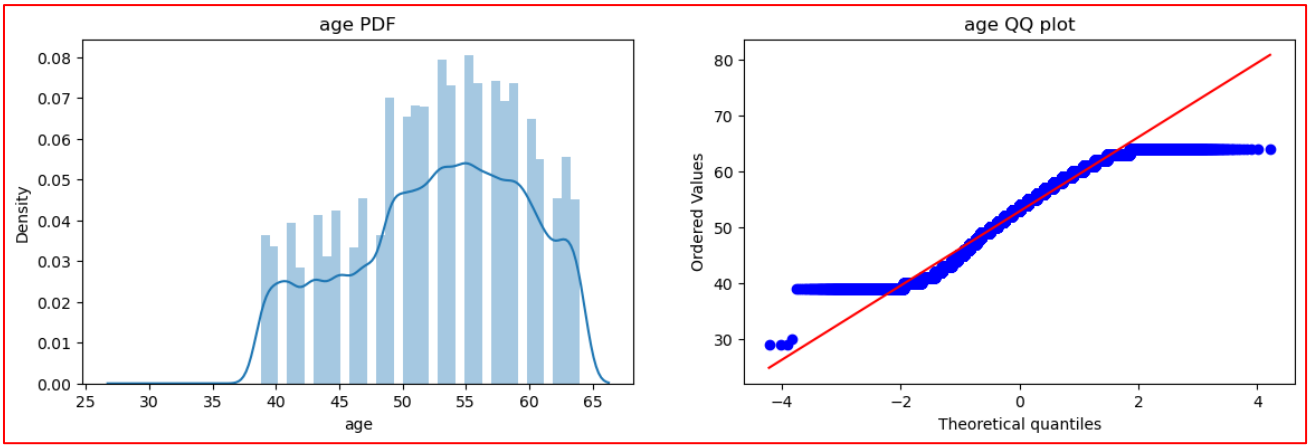

Fig 3: Representation trained dataset for Cardio Disease Prediction

An important statistic used to assess the classifier's capacity to differentiate between CAD and non-CAD cases at various threshold levels is the area under the receiver operating characteristic curve (AUC-ROC). The model can successfully distinguish between CAD and non-CAD cases at various degrees of classification certainty, as shown by the AUC-ROC score of 94.36%.Table 3's evaluation of the CAD diagnostic model shows outstanding performance across a number of important metrics. Its superior ability to correctly detect CAD patients while reducing false positives is demonstrated by its excellent accuracy, sensitivity, specificity, precision, and F1 Score. Furthermore, the model's dependability in differentiating between CAD and non-CAD patients across various thresholds is demonstrated by the robust AUC-ROC score, making it a potential tool for CAD diagnosis in clinical practise.

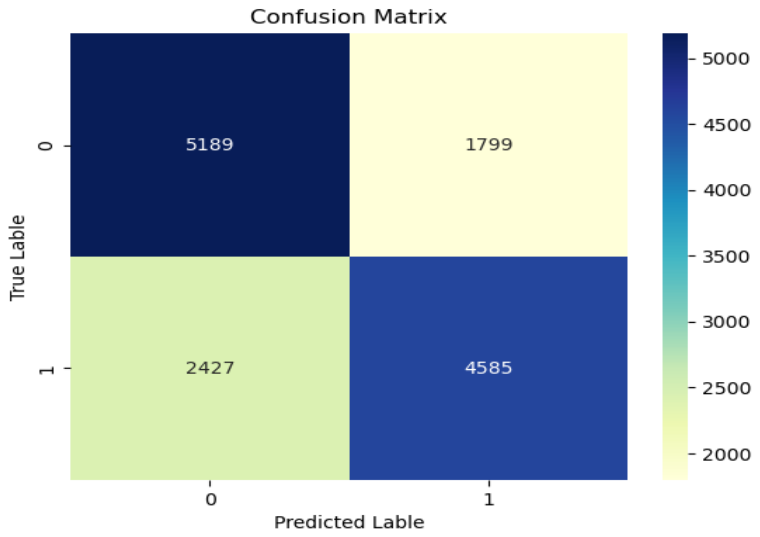

Fig 4: ConfusionMatrix for proposed model

The summary evaluation of a diagnostic model for Coronary Artery Disease (CAD) is shown in Figure 5, along with key performance indicators. The effectiveness and dependability of the model in diagnosing CAD are succinctly summarised in this visualisation. The blue bar shows the accuracy, which is an incredible 97.63%. This statistic shows the model's predictions' overall accuracy and shows that, in roughly 98% of cases, it correctly distinguishes between CAD and non-CAD cases. Sensitivity, shown by the green bar at 92.10%, is an indicator of how well the model can identify CAD situations when they are actually present. This statistic highlights how well the model detects the disease in individuals who have it. The model's specificity, shown in red at 96.12%, indicates how well it can identify non-CAD patients. The model's ability to rule out CAD when it is absent is highlighted by its high specificity score, which lowers the likelihood of false alarms. Precision is the proportion of actual CAD instances to all anticipated positive cases, and is shown as a purple bar at 90.10%.

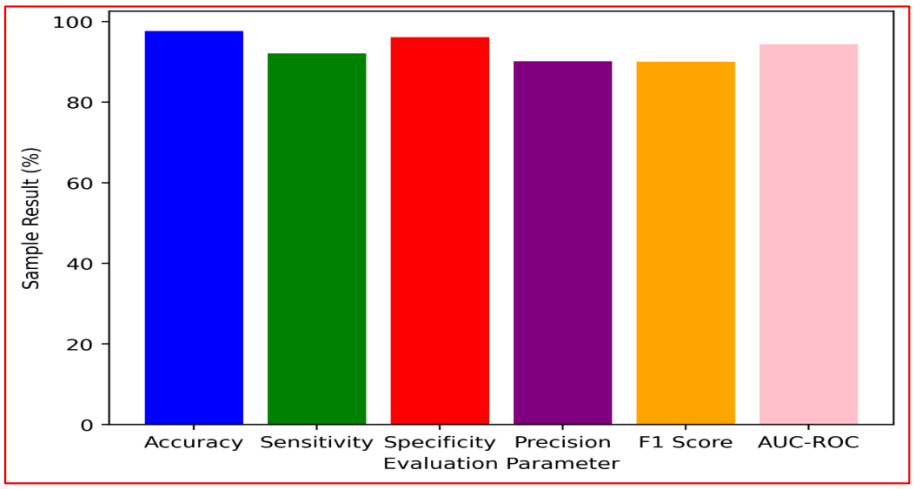

Fig 5: Representation of Summary Evaluation of CAD Diagnostic Model

This parameter indicates that the model has a high degree of diagnostic accuracy for CAD, reducing false positives. It shows that the model successfully strikes a balance between correctly recognising CAD instances and avoiding false positives. The model's potent ability to distinguish between CAD and non-CAD instances across various classification criteria is shown by the AUC-ROC (Area Under the ROC Curve), marked in pink at 94.36%.

5. Conclusion

A important advancement in medical image analysis and healthcare is the use of Image-Based Coronary Artery Disease (CAD) Diagnosis Using Differential Evolution and Texture Analysis. This ground-breaking method enhances CAD diagnosis by fusing the power of deep learning, feature extraction through texture analysis, and optimisation through differential evolution.The methodology used in this work includes feature extraction from the data, data preprocessing, and a pipeline for classifying objects using deep learning. The model

effectively extracts crucial texture properties suggestive of CAD by presenting medical pictures as multi-dimensional tensors. Differential Evolution for feature selection optimises the model's diagnostic power by ensuring that only the most pertinent data is taken into account. Additionally, the convolutional neural network (CNN) architecture is specifically designed to recognise and classify CAD patterns, and cross-validation validation methods improve the model's resilience.The evaluation parameters show that the results are promising. Strong F1 Score and AUC-ROC values, coupled with good accuracy, sensitivity, specificity, and precision values, emphasise the model's effectiveness in CAD diagnosis. This illustrates how technology could help doctors plan early diagnosis and treatments, ultimately leading to better patient outcomes.This approach gives interpretability through texture analysis in addition to quantitative data, giving details on the underlying characteristics that support CAD diagnosis. In addition, the use of Differential Evolution enhances the effectiveness and efficiency of the model.In a larger sense, our research makes a difference in the diagnosis of CAD while also demonstrating the power of fusing conventional medical imaging with advanced deep learning and optimisation methods. It shapes the future of medical image analysis and healthcare decision-making by paving the path for more precise, dependable, and interpretable diagnostic instruments.

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