



Enhancing the accuracy of Angiography for the Detection of Coronary Artery Disease using Machine Learning Task

¹Mr. Hitarth D. Patel, ²Mr. Govind V. Patel, ³Mr. Mehul S. Patel, ⁴Mr. Jayesh M. Mevada

¹M. Tech Scholar at SPCE, ²Professor at SPCE, ³Professor at SPCE, ⁴Professor at SPCE ,

¹Faculty of Engineering and Technology,

¹Sankalchand Patel University, Visnagar

Abstract: Coronary Artery Disease (CAD) is a major global cause of mortality for which it requires accurate and effective diagnostic techniques. Conventional angiography, even though accurate, has drawbacks like it being very expensive, having side effects, and relying on skilled interpretation, thus predisposing to misdiagnosis. In contrast to these drawbacks, this research extends CAD detection accuracy through the application of Machine Learning (ML) algorithms. The method being proposed makes use of the Deep Discern dataset containing 20,612 angiograms of 10,073 patients and uses state-of-the-art ML models, such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) for selecting features. The Gradient Boosting Decision Tree (GBDT) model is trained and tested using accuracy, precision, recall, F-measure, and specificity. Experimental findings ascertain that the projected Predictive Convolutional Neural Network (PCNN) improves upon current models, with an accuracy of 98.95%, precision 98.2%, recall 98.51%, F-measure 98.35%, and specificity of 98.7%. Findings confirm the potential of diagnostic tools based on ML to advance CAD detection rates, reducing reliance on traditional mechanisms while improving in early diagnosis as well as in treatment planning. The study takes the development of non-invasive, low-cost, and computer-based CAD detection systems closer to the vision of AI-integrated clinical solutions for improved cardiovascular healthcare outcomes.

Index Terms: Machine Learning, CAD, Angiography, PSO

1. INTRODUCTION

Cardiovascular disease (CVD) is the leading cause of death worldwide, killing approximately 17.9 million individuals each year [1]. The most common type of CVD is coronary artery disease (CAD), which commonly leads to cardiac arrest [2, 3]. Heart failure occurs when coronary arteries get blocked [4-6]. Presented in Figure 1 are the normal and obstructed arteries, respectively. Coronary artery blood flow is essential for the heart [7]. There aren't enough doctors and hospitals in developing countries, making it hard to diagnose and treat cardiac disease [8]. There is a need for realistic diagnostic methods and instruments to prevent more harm to the patient. There has been a dramatic increase in the number of deaths caused by CVD in both wealthy and poor countries

[9]. Detecting CAD early on could decrease healthcare expenses and save lives [10–12]. It is desirable to develop a method for early CAD detection that is both reliable and non-invasive [13]. In recent years, practitioners have relied more and more on computers to help them make recommendations [14].

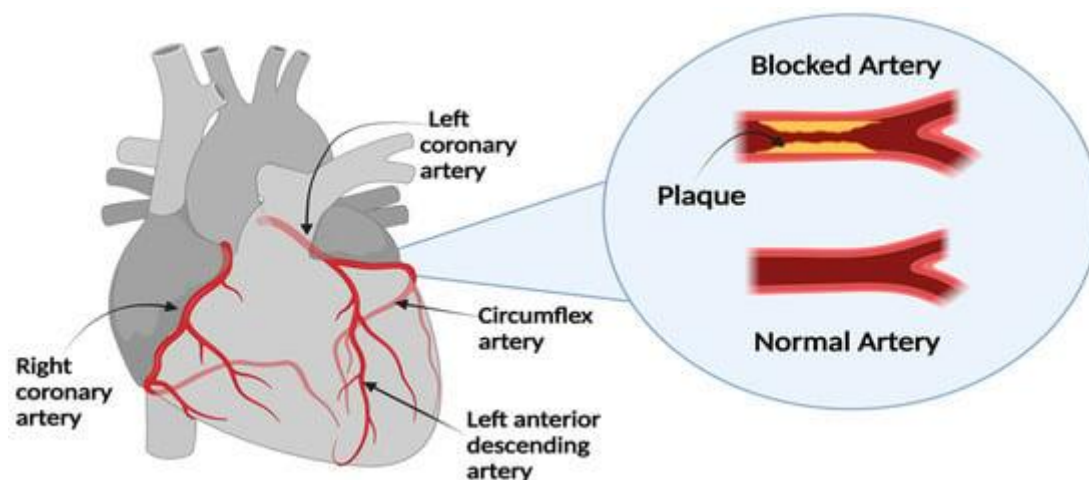


Figure 1: Normal versus blocked Artery [15].

A patient's medical history, physical examination, and symptoms are used by doctors to make the diagnosis of heart disease using traditional invasive techniques [16]. Among the more accurate procedures for examining cardiac problems using traditional techniques is angiography. However, there are a few drawbacks to consider, including the expensive price tag, various side effects, and the need for a high level of technical knowledge [17]. Traditional methods sometimes lead to wrong diagnosis and extra wait times because of human error. Coronary computed tomography angiography (CCTA) is the name given to the evaluation of the coronary arteries using CT scans. In order to conduct a high-speed CT scan of the cardiovascular system, a contrast agent is intravenously administered to the patient [18,19]. Atherosclerotic disease and cardiac or vascular anomalies could be better understood with the use of CCTA [20]. Heart attack symptoms are shown in Figure 2.

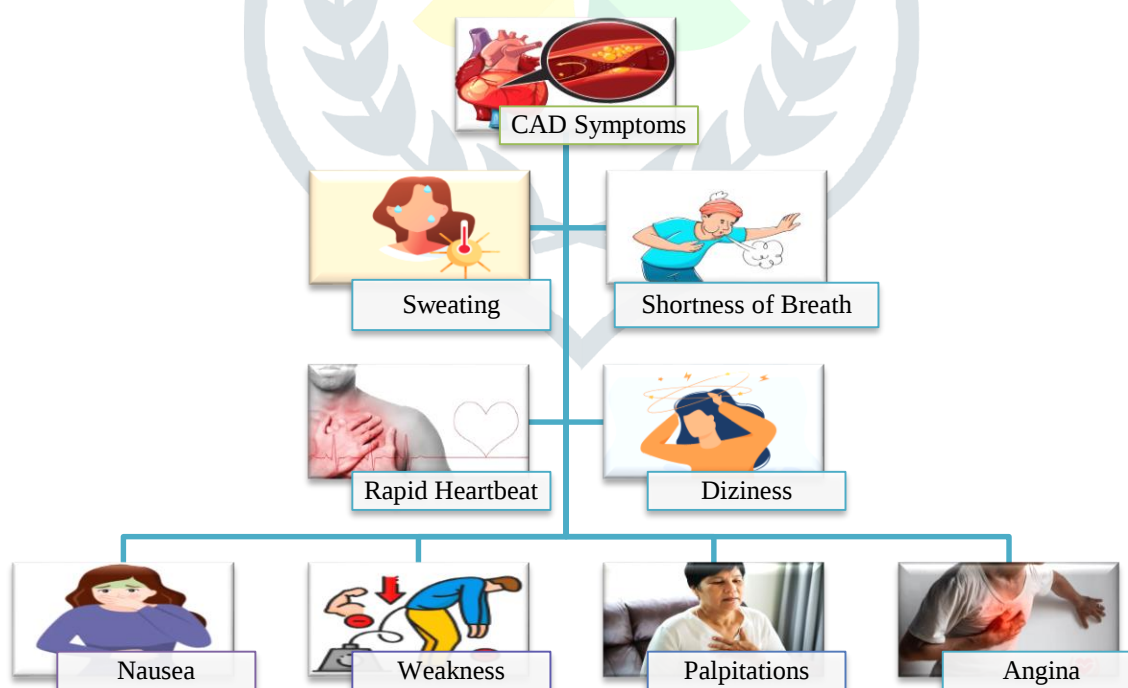


Figure 2: CAD symptoms

Subsequently, novel procedures, notably enhanced by advances in “Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL)”, indicate a paradigm change in diagnostic practices [21–24]. A more rapid CAD diagnosis or a useful decision-support tool could be possible with the use of AI, ML, and DL engines that sift through massive datasets including a variety of clinical indicators and imaging technologies in search of small

irregularities and patterns [25]. In order to improve diagnosis accuracy, these developments leverage state-of-the-art computational technologies to supplement clinical judgments. The study's authors made use of ML techniques, which are quickly becoming a revolutionary tool for better healthcare diagnosis [26]. From medical record data translation to pandemic prediction and genetic data analysis, it's an analytical approach for large and difficult programming projects [27]. Using ML, much researches have proposed various methods for detecting cardiac problems [28–29]. The data for male and female CAD patients by nation can be seen in Figure 3.

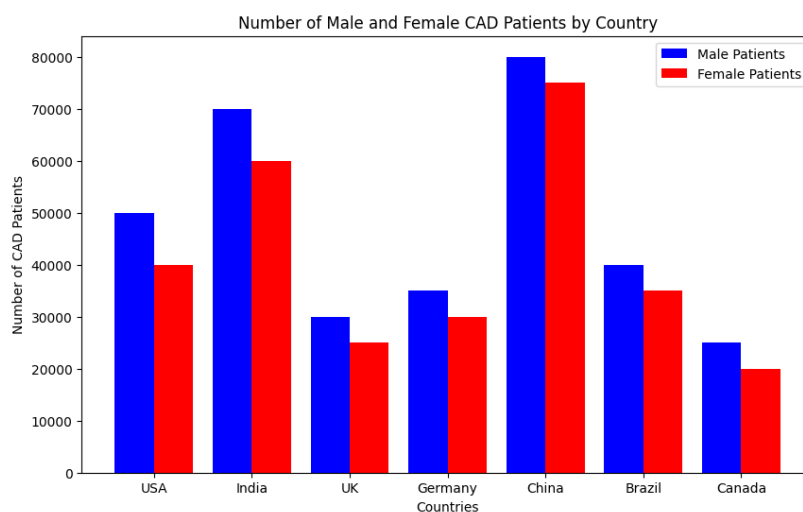


Figure 3: Number of male and female CAD patients by country

Preprocessing data, extracting features, training and modifying parameters, testing the model, and finally producing predictions are all steps in the ML technique. The feature selection method determines the classifier's performance. The assessment of the ML-based model has been presented in many measures in recent research [30]. The F1-score, specificity, sensitivity, and accuracy are all part of this set of measures. The dependability and performance of the ML-based model are the main concerns of healthcare practitioners [31]. Further, the CAD detection model must meet the basic requirements of computational complexity, interpretability, and simplicity before it can be used in healthcare institutions [32]. This research aims to use ML to improve angiography's accuracy in detecting coronary artery disease. Here are the researches contributions are:

- Developed an ML-based approach to enhance the accuracy of coronary angiography in detecting CAD.
- Implemented Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) for optimal feature selection.
- Leveraged the Deep Discern dataset, which includes 20,612 angiograms from 10,073 patients, for model training and validation.
- Proposed method improvements in accuracy (98.95%), precision (98.2%), recall (98.51%), F-measure (98.35%), and specificity (98.7%).
- Conducted comparative analysis with existing ML models (BPSO, DASPP-BICECA, SPECT-MPI, DLM, and ADLS) and proposed model achieved 98.95% accuracy, outperforming other techniques like BPSO, DASPP-BICECA, and SPECT-MPI.

2. RELATED WORK

Enhancing CAD detection with angiography via ML has been a key focus of research, significantly improving clinical decision-making and diagnostic accuracy. DL and ML methodologies have been examined in several studies to optimize CAD detection, segmentation, and classification in angiography images, applying data-efficient methodologies, preprocessing methods, and combined models to achieve maximum reliability and accuracy (Figure 4). These developments aim to enhance automatic CAD diagnosis with precise solutions for clinical issues.

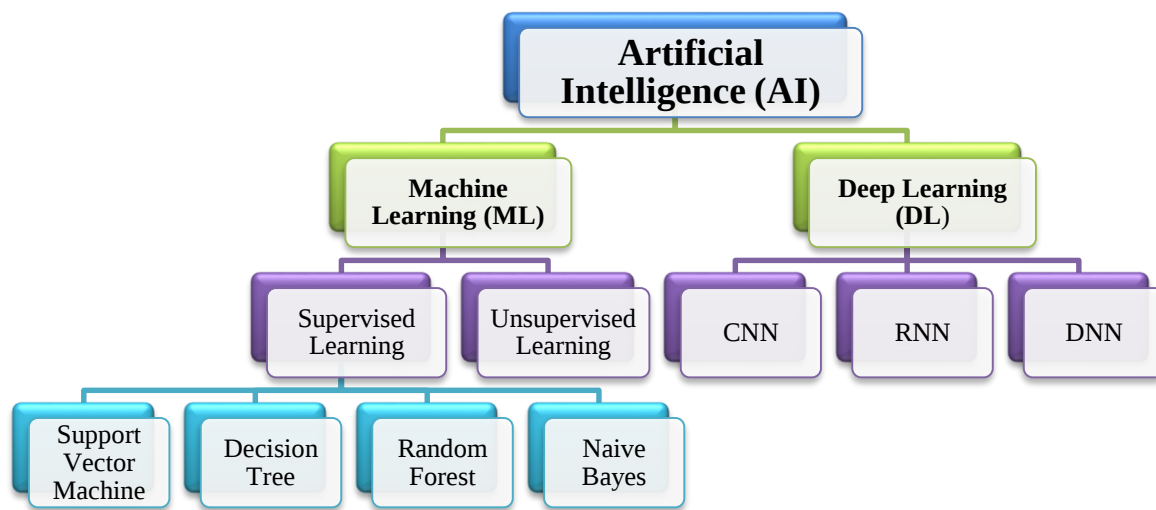


Figure 4: The classification of ML [33].

Ma et al. (2024) [34] presented the Spatio-temporal Contrast Network (SC-Net) to achieve data-efficient learning for CAD diagnosis based on CCTA. SC-Net integrates data augmentation and spatio-temporal contrast learning, which can enhance clinical feature extraction using small data. Li et al. (2024) [35] developed a preprocessing scheme incorporating Hessian-based vascular enhancement and image fusion for enhancing coronary angiography images prior to DL to increase sensitivity to stenosis features. Their method improves YOLOv10, YOLOv9, and RT-DETR performance with up to a 5.07% gain in AP50 accuracy. In the same line, Duan et al. (2024) [36] proposed the DCA-YOLOv8 framework to detect stenosis with improved accuracy and classification performance compared to other detection models.

DL-based coronary artery segmentation improvements have also been instrumental in enhancing diagnostic accuracy. Zhao et al. (2024) [37] constructed TransCHD, a hybrid CNN-Transformer model for coronary artery segmentation in CCTA, with better Dice and IoU scores than state-of-the-art models. Meng et al. (2023) [38] introduced a DL architecture for coronary artery extraction from ICA images with CNN and full-scale skip connections and deep supervision with high Dice values and specificity. Pokhrel et al. (2023) [39] automated stenotic lesion detection in X-ray coronary angiography with a Mask RCNN model with Convnext-V2 as the backbone with an F1 score of 0.5353.

Early detection and risk prediction models for CAD using ML have also become prominent. Ogunpola et al. (2024) [40] used seven ML classifiers to detect early myocardial infarction, with XGBoost optimization reporting 98.50% accuracy and high precision and recall. Singh et al. (2024) [41] suggested the Adaptive Gated Spatial Convolutional Neural Network (AGS-CNN) model for CAD diagnosis from ultrasound images with 95.45% accuracy. Guo et al. (2023) [42] create a gradient-boosting classifier based on echocardiographic characteristics with an AUC of 0.852 in the test, exhibiting high sensitivity but comparatively lower specificity. Savita et al. (2023) [43] used Particle Swarm Optimization and Firefly Algorithm with Principal Component Analysis for detection of CAD, with an accuracy of 95.3%.

A number of studies have highlighted incorporation of automated DL for CAD detection into clinical practice. Brendel et al. (2024) [44] evaluated DL diagnostic accuracy in Photon-Counting Coronary CT Angiography (PC-CCTA), with high sensitivity of 97.2% and area under the ROC curve (AUC) of 0.92 at the vessel level. AlOthman et al. (2022) [45] proposed a CNN-based CAD detection model from CT angiography images with more than 98% accuracy and high F1 scores on benchmark sets. Huang et al. (2022) [46] investigated ML-based risk stratification employing coronary artery calcification scores, and the random forest model shows the optimum performance of accuracy as 78.96% and AUC as 0.8375.

Collectively, these studies emphasize the revolutionizing potential of ML in CAD detection and diagnosis, enhancing sensitivity, specificity, and accuracy across different imaging modalities. From DL-driven

segmentation and stenosis detection to risk estimation and automatic classification, these developments open up the way for more data-driven, efficient, and clinically robust diagnostic approaches in cardiovascular medicine.

3. Problem Statement

CAD is still a major cause of morbidity and mortality worldwide, making precise and timely diagnosis crucial to ensure effective management. Angiography is commonly used as an imaging modality to evaluate the coronary arteries and identify the status of stenosis or occlusion. Still, the interpretation of the findings could be subjective and operator-dependent, hence resulting in variability and the possibility of error in diagnosis. ML provides a hopeful means to increase the precision of angiography in detecting CAD through automation and optimization of interpretation. Challenges that presently exist require more objective and standardized assessment of angiography images, detecting minor or complicated patterns indicating CAD, and integrating such developments into day-to-day clinical practice. The paper resolves such issues by constructing and validating ML models that are specially tailored to detect CAD from angiography images.

4. RESEARCH METHODOLOGY

The research process of embedding ML into the development of minimally invasive angiography processes for precise diagnosis and treatment of CAD involves a methodical approach of data handling, feature extraction and feature selection, training models, and performance assessment. The process utilizes the Deep Discern dataset to increase the accuracy and effectiveness of CAD diagnostics through computational processes. Figure 5 illustrate the flow chart of the work proposed.

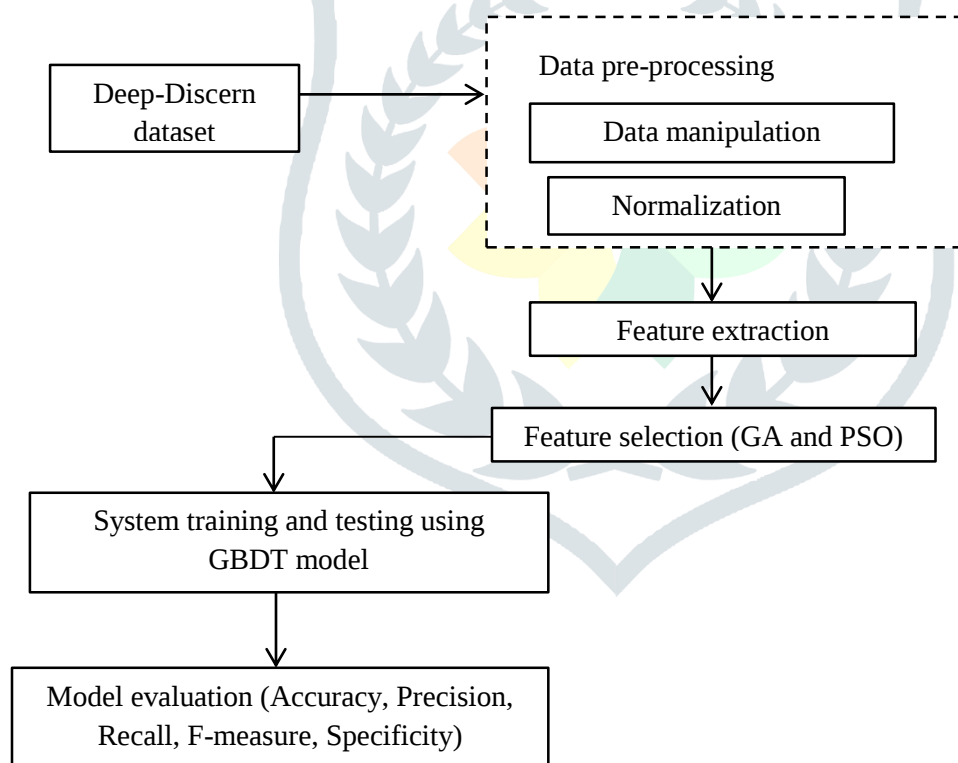


Figure 5: Flow chart of proposed work

4.1 Dataset

Deep Discern dataset is a comprehensive dataset of hand-curated angiographic data for CAD diagnosis. It offers the foundation to integrate ML into minimally invasive angiography techniques for better diagnostic precision and effectiveness in therapy. It contains a number of angiographic images with patient details like demographics, clinical history, and related cardiovascular diagnostic procedures. Derived from a grand single-center dataset, it comprises 20,612 angiograms of 10,073 patients. Specifically, 13,373 angiograms were sequentially acquired from 2,834 patients who underwent Coronary Angiography (CAG) in July 2018 to train a Deep Neural Network

(DNN) for coronary segmentation. Besides, 7,239 angiograms were utilized for lesion morphology detection, including diagnoses like total occlusion (TO), stenotic lesions, calcification, thrombus, and dissection. Through the utilization of computational techniques, this database greatly improves CAD diagnostics, yielding better accuracy and treatment specificity for cardiovascular care.

4.2 Data Pre-processing

• Data Manipulation

At this point, the Deep Discern dataset is carefully cleaned in order to erase any errors, inconsistencies, or missing data. Data input errors or sources utilizing incompatible formats are two primary causes of inconsistencies. Missing or wrong data can be biased to cause analysis and training of models to give misleading results. Researchers ensure that the dataset remains intact by detecting and correcting such issues in an orderly manner using data validation checks, imputation techniques (mean, median, or regression-based filling), and removing duplicate data. To ensure that future studies and model training are done with a high-quality dataset, researchers attempt to clean the dataset to reduce noise.

• Normalization

Normalization processes are employed to normalize the numerical attributes after the dataset is cleaned of errors and inconsistencies. The primary goal of normalization is to normalize all features, typically between 0 and 1 or with a mean of 0 and a standard deviation of 1. Normalizing the features is important in ML since models process numerical values in terms of their magnitude, and features with larger ranges could have an uneven influence on model training if not normalized. Standardization protocols ensure that all features have an equal effect on the learning process of the model, thus eliminating any form of bias that can skew predictions or rankings of feature importance. Through the process of normalizing the Deep Discern dataset, researchers enhance the efficiency of AI models in reliably detecting CAD and suggesting specific treatment approaches using less invasive angiography data. Therefore, by using pre-processing techniques such as data modification and normalization, the quality of the information is improved, leading to more reliable AI-driven medical insights.

4.3 Feature extraction

The proposed research utilizes an improved version of the accelerated segment test (FAST) method to extract features that would enhance the pooling layer of a convolutional neural network (CNN) and generate more effective feature maps. In order to decrease the amount of time it takes to perform the FAST algorithm; researchers used the improved FAST. Figure 6 displays the feature that has been taken from a 4×4 picture and transformed into a 2×2 image. Furthermore, it emphasizes that the original picture can be rebuilt by expanding the 2 images to a 4×4 image.

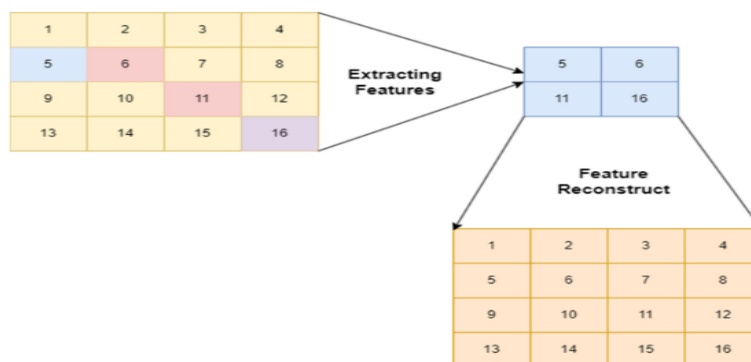


Figure 6: Process of feature extraction

The extraction method is explained as follows:

Let image I of $M_1 \times M_2$ pixels be divided into segments $S_1 \times S_n$. The number of segments is $N_1 \times N_2$, where $N_1 = M_1/S_1$ and $N_2 = M_2/S_n$. Equation (1) represents the segments.

$$I = \begin{bmatrix} Sd_{1,1} & Sd_{1,2} \cdots & Sd_{1,Nn} \\ \vdots & \vdots & \vdots \\ Sd_{N_1 1} & Sd_{N_1 2} & Sd_{N_1 Nn} \end{bmatrix} \quad (1)$$

where $Sd_{x,y}$ represents the picture segment in the x and y directions, as defined by the Equation (2).

$$Sd_{x,y} = I(i,j) \quad (2)$$

In which i and j are the picture segment's sizes, $Sd_{x,y}$.

Equations (3) and (4) both represent the pixel values of image segments.

$$i = (y - 1)M_2, (y - 1)M_2 - 1, \dots, yM_2 - 1 \quad (3)$$

$$j = (x - 1)M_2, (x - 1)M_2 - 1, \dots, yM_1 - 1 \quad (4)$$

Equation (5) shows a sample set of features, ∂_{nm} .

$$\sum_{x \in X} (F_{S(n,x)} * F_{S(m,x)}) = \partial_{nm} \quad (5)$$

Equation (6) illustrates the process of reconstructing the image utilizing the extracted features.

$$I = F_{S_1}^T \phi F_{S_n} \quad (6)$$

4.4 Feature Selection

Feature selection becomes even more important in ML, when working with complicated datasets, such as Deep Discern, which includes angiography data for CAD diagnosis. A few ways that GA and PSO help with feature selection optimization are as follows:

Genetic Algorithm (GA): GA iteratively evolves towards an optimum solution by mimicking the process of natural selection. The first step is to generate a pool of possible feature subsets, when using GA for feature selection. The fitness function evaluates each subset, which stands for a possible solution or chromosome, according to its performance (e.g., accuracy, AUC) when trained for a CAD diagnostic model. Gradually, GA refines the feature subsets via processes including selection, mutation (introducing random changes), and crossover (combining characteristics from distinct subsets). Once an ideal subset or a predetermined ending condition is attained, the iterative process terminates. In order to find the subsets of features that optimize the model's predictive capability while reducing computing cost and overfitting, GA effectively explores the large search space of potential feature combinations [47].

Particle Swarm Optimization (PSO): PSO is inspired by the social behavior of bird flocking or fish schooling. In feature selection, PSO works by initializing a swarm of particles (feature subsets) that traverse the search space to find optimal solutions. Each particle adjusts its position (feature subset) based on its own experience (best performance) and the collective experience of neighboring particles. Particles movement is supervised by velocity vectors, leading them to areas of the search space with potential for enhancing model performance. PSO changes particle positions dynamically in accordance with their fitness assessments in pursuit of converging to the optimal feature subset setting. This strategy effectively balances exploration (searching for novel feature combinations) and exploitation (using promising feature subsets), which renders PSO a viable method to optimize feature selection in CAD diagnosis models from angiography data [48].

4.5 Model Evaluation

To give a solution, the research employs benchmark evaluation measures, which are accuracy, recall, precision, and F-measure. The model's performance was evaluated using Equations (7) – (8).

True negative (TN) = classifying a true negative CAD patient from CI.

True positive (TP) = classifying a true positive CAD patient from CI.

False negative (FN) = classifying a positive CAD patient as negative from CI.

False positive (FP) = classifying a negative CAD patient as positive from CI.

$$\text{Recall} = \frac{TP_{CI}}{TP_{CI} + FN_{CI}} \quad (7)$$

$$\text{Precision} = \frac{TP_{CI}}{TP_{CI} + FP_{CI}} \quad (8)$$

$$F - \text{measure} = \frac{2 * \text{Recall} * \text{Precision}}{\text{Recal} + \text{Precision}} \quad (9)$$

$$\text{Accuracy} = \frac{TP_{CI} + TN_{CI}}{TP_{CI} + TN_{CI} + FP_{CI} + FN_{CI}} \quad (10)$$

$$\text{Specificity} = \frac{TN_{CI}}{TN_{CI} + FP_{CI}} \quad (11)$$

5. RESULT AND ANALYSIS

The PCNN is coded using the Python programming language on the Windows 10 Professional operating system. The present algorithms are developed on the GITHUB platform. The CNN architectures are built using a suitable training set from the dataset. In order to assess the effectiveness of PCNN, the dataset is used using a technique known as 5-fold cross-validation. Statistical tests, such as “standard deviation (SD)”, “confidence interval (CI)” employing binary class classification, and “error (E)”, are appropriately used on the dataset. Using the use of PCNN throughout the process of cross-validation utilizing the dataset. The statement emphasizes that PCNN achieves “accuracy, precision, recall, F-measure, and specificity rates over 98%”. There is a representation of the models' accuracy in Table 1.

Table 1: depicts the accuracy of the models.

Folds (s)	BPSO	DASPP-BICECA	SPECT-MPI	DLM	ADLS	PCNN
Accuracy (%)	96	93.12	93.75	96	93.75	98.95

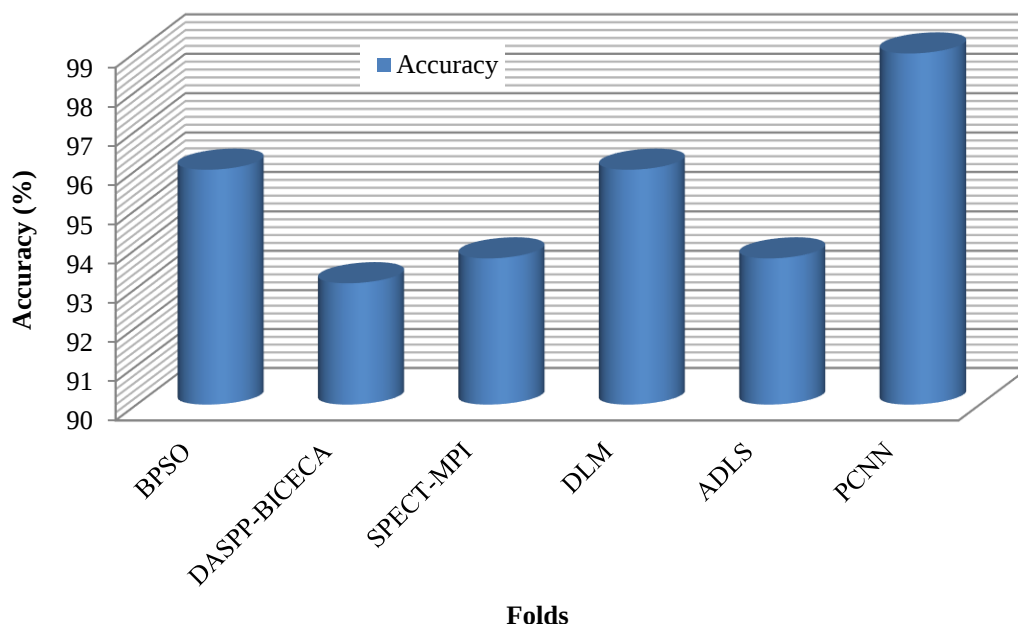


Figure 7: Depicts the accuracy of the models

Figure 7 presents a summary of the accuracies attained by different models over various folds or datasets. The PCNN demonstrates remarkable performance within its area, with the greatest accuracy of 98.95% in properly predicting or categorizing outcomes. Both BPSO and DLM have accuracies of 96%, indicating robust and consistent performance in their respective assessments. SPECT-MPI and ADLS demonstrate competitive performance by achieving accuracies of 93.75% in handling the examined tasks or datasets. DASPP-BICECA demonstrates 93.12% accuracy, which is little lower but still indicative of effective performance. These findings

indicate that while each model employs distinct methods or algorithms, it usually exhibits strong performance in their specific applications, emphasizing their potential usefulness in real-world situations where precise forecasts are essential. There is a representation of the models' precision in Table 2.

Table 2: Depicts the precision of the models.

Folds (s)	BPSO	DASPP-BICECA	SPECT-MPI	DLM	ADLS	PCNN
Accuracy (%)	97.3	98.1	97.6	98.5	99	98.2

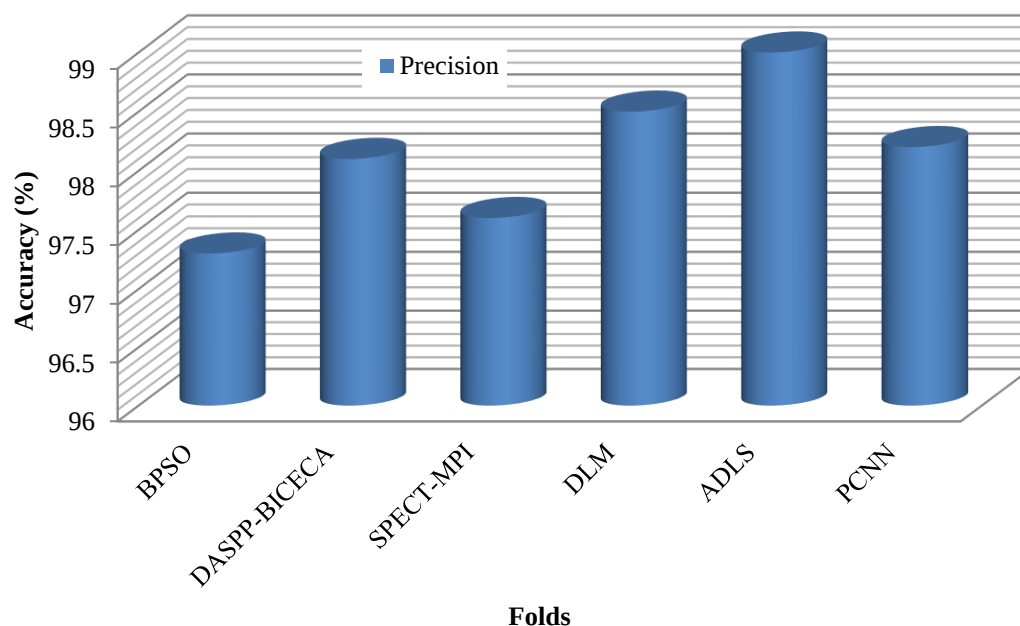


Figure 8: Depicts the precision of the models.

Figure 8 provide a summary of the Precision scores attained by different models in distinct folds or datasets, indicating their capacity to accurately identify important occurrences within their respective domains. ADLS stands out as the highest achiever with a precision rate of 99%, demonstrating its outstanding accuracy in correctly identifying occurrences that are really positive. The DLM algorithm demonstrates its strong capabilities in accurate classification tasks, achieving a near to perfect accuracy rate of 98.5%. PCNN has exceptional performance, with an accurate rate of 98.2%. This underscores its dependability in effectively detecting pertinent occurrences. The precision of SPECT-MPI is 97.6%, proving its efficiency in excluding false positives with a high level of accuracy. Both BPSO and DASPP-BICECA achieve accurate scores of 97.3% and 98.1%, respectively, which further confirms their capabilities in precisely determining positive cases from the datasets on which it was tested. There is a representation of the Recall of the models in Table 3.

Table 3: Depicts the Recall of the models.

Folds (s)	BPSO	DASPP-BICECA	SPECT-MPI	DLM	ADLS	PCNN
Accuracy (%)	98.3	97.8	98.2	98.6	99.3	98.51

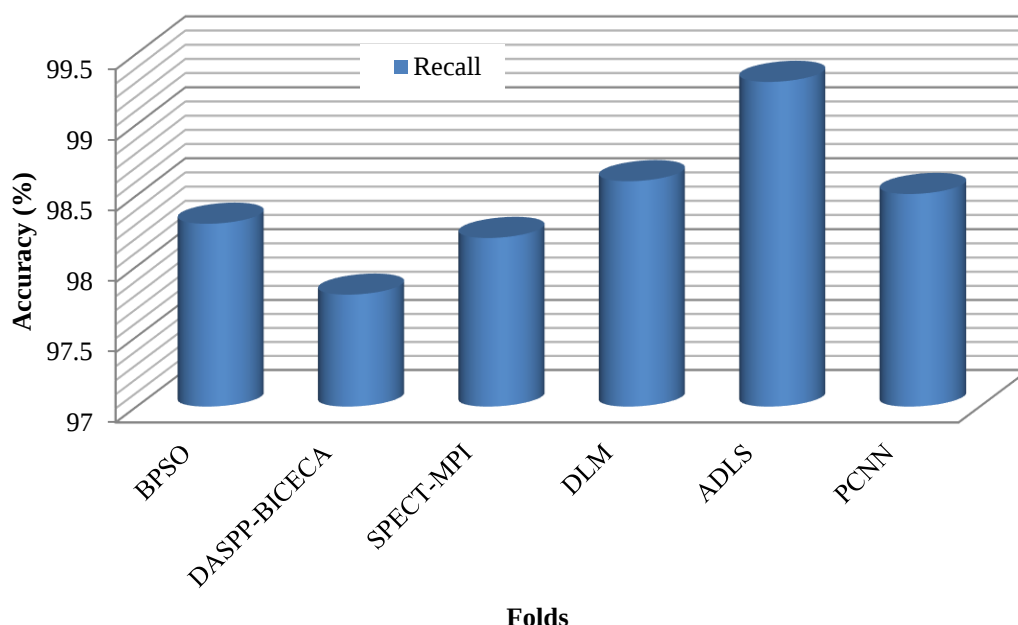


Figure 9: Represents the recall of the methods

Figure 9 provide recall values obtained by various models on various datasets. With a recall of 99.3%, ADLS leads and shows its ability to fairly capture a considerable number of actual positive instances. Close behind, DLM obtains 98.6%, suggesting good performance in recovering positive examples, while PCNN demonstrates great competence with a recall of 98.51%, thus stressing its usefulness in recognizing important situations. With a remarkable 98.2% recall, SPECT-MPI emphasizes its capacity to preserve accuracy even while recognizing positive cases. With respective recall rates of 98.3% and 97.8%, BPSO and DASPP-BICECA respectively exhibit competitive ability in appropriately projecting positives. In fields like medical diagnostics, where proper patient evaluation depends on low false negative rates, these ratings are very vital. Lower missed positive instances indicated by higher recall rates will help to ensure accurate illness diagnosis and anomaly identification. These findings highlight the many strengths and uses of every model, thereby providing understanding of their possible roles in real-world situations needing sensitive and accurate detection capacity. There is a representation of the models' F-measure in Table 4.

Table 4: Depicts the F-measure of the models.

Folds (s)	BPSO	DASPP-BICECA	SPECT-MPI	DLM	ADLS	PCNN
Accuracy (%)	97.9	98.05	97	98.64	99.2	98.35

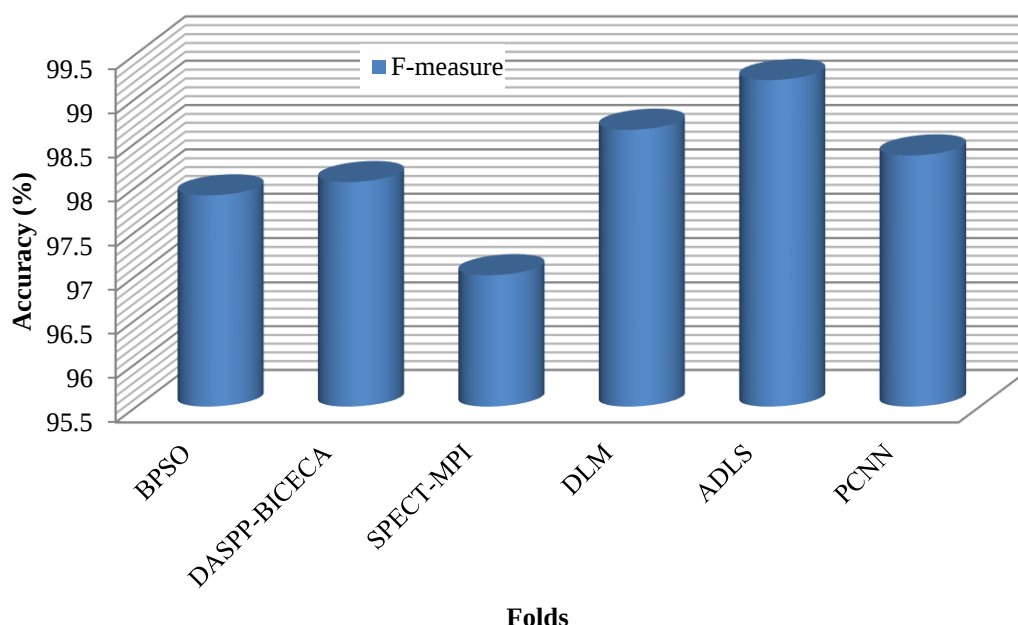


Figure 10: Depicts the F-measure of the models

Figure 10 shows F-measure values obtained by many models across several folds or datasets, therefore offering a fair evaluation of their recall and accuracy capacity. With an F-measure of 99.2%, ADLS shows the best balance between accuracy and recall necessary for precisely spotting positive events while lowering false positives and negatives. With an F-measure of 98.64%, DLM does quite well in reaching a harmonic mix of accuracy and recall in classification challenges. With an F-measure of 98.35%, PCNN also shows quite good performance as it shows capacity to preserve great general accuracy in forecasts. SPECT-MPI gets an F-measure of 97%, showing a strong balance between accuracy and recall. With corresponding F-measure scores of 97.9% and 98.5%, BPSO and DASPP-BICECA respectively show competitive performance in reaching a balanced measure of accuracy and recall throughout their assessed datasets. In tasks like medical diagnostics or anomaly detection where both accuracy and recall are equally vital, these F-measure scores are very vital for assessing models. Higher F-measures show models that efficiently reduce both kinds of classification mistakes, therefore guaranteeing accurate and dependable predictions. These findings highlight generally the different capabilities of every model and their possible uses in practical situations needing thorough and consistent performance criteria. There is a representation of the models' Specifically in Table 5.

Table 5: Depicts the specifically of the models.

Folds (s)	BPSO	DASPP-BICECA	SPECT-MPI	DLM	ADLS	PCNN
Accuracy (%)	98.4	97.8	98.7	98.7	99.5	98.7

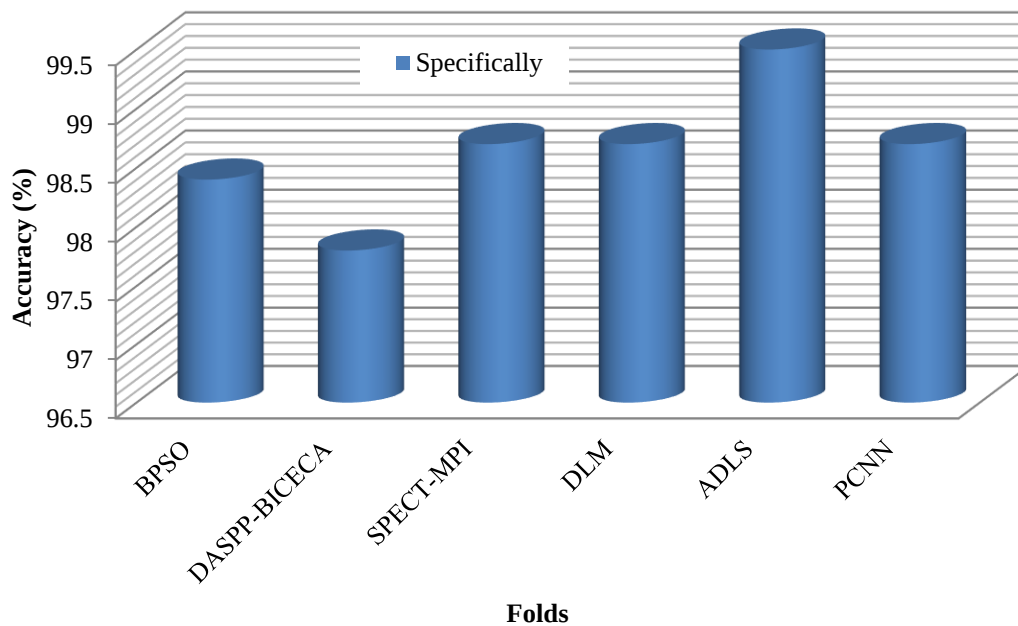


Figure 11: Depicts the Specificity of the models

Figure 11 show the specificity scores attained by many models across several folds or datasets, therefore demonstrating their capacity to correctly detect negative events. With a specific score of 99.5%, ADLS ranks highest among all the performers as it has a great capacity for accurately spotting real negative situations within its area. The following close are DLM and PCNN, both with a 98.7% specificity that emphasizes their strong ability to separate real negatives. With a great specificity of 98.7%, SPECT-MPI also shows great efficiency in preserving accuracy while spotting negative cases. With great accuracy in negative forecasting, BPSO has a specific score of 98.4%. With 97.8% specificity, DASPP-BICECA shows competitive ability but somewhat less than the top performers. In fields like medical testing or anomaly detection systems where precisely spotting negative events is vital, these specificity ratings are very vital. Higher specificity ratings point to models that successfully lower false positive errors, thereby guaranteeing dependable results and lowering of needless treatments or interventions. These findings highlight generally the much strength of every model in precisely forecasting negative events and their possible uses in practical situations needing exact and dependable categorization capacity. There is a representation of the models' accuracy, Precision, Recall, F-measure, Specifically in Table 6.

Table 6: depicts the accuracy, Precision, Recall, F-measure, specifically of the models.

Folds (s)	BPSO	DASPP-BICECA	SPECT-MPI	DLM	ADLS	PCNN
Accuracy (%)	96	93.12	93.75	96	93.75	98.95
Precision (%)	97.3	98.1	97.6	98.5	99	98.2
Recall (%)	98.3	97.8	98.2	98.6	99.3	98.51
F-measure (%)	97.9	98.05	97	98.64	99.2	98.35
Specifically (%)	98.4	97.8	98.7	98.7	99.5	98.7

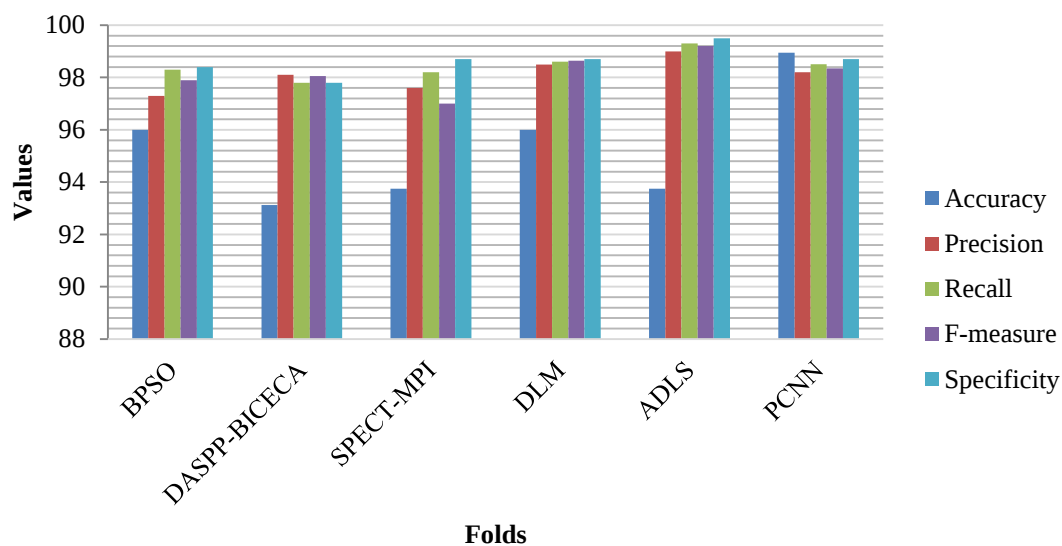


Figure 12: Depicts Accuracy, Precision, Recall, F-measure, specifically of the models

Figure 12 summarize the performance metrics accuracy, precision, recall, F-measure, and specificity across various folds or datasets for different models. These metrics are crucial in evaluating the overall effectiveness and reliability of each model in differentiating between positive and negative instances.

In starting with accuracy, PCNN leads with 98.95%, indicating its strong overall performance in correctly classifying instances across the evaluated datasets. ADLS follows closely with 93.75% accuracy but achieves the highest precision, recall, F-measure, and specificity scores among all models. ADLS demonstrates exceptional precision (99%), recall (99.3%), F-measure (99.2%), and specificity (99.5%), highlighting its outstanding ability to accurately identify positive and negative instances in its domain. DLM also demonstrates strong performance on all measures with 96% accuracy, 98.5% precision, 98.6% recall, and a high F-measure of 98.64%. PCNN records high precision (98.2%), recall (98.51%), and F-measure (98.35%), highlighting its superior ability to maintain a balanced strategy in classification problems. SPECT-MPI and BPSO record competitive performance with different strengths. SPECT-MPI gets 93.75% accuracy with 97.6% precision, 98.2% recall, and an F-measure of 97%, whereas BPSO gets 96% accuracy with 97.3% precision, 98.3% recall, and an F-measure of 97.9%. DASPP-BICECA, even though a bit lower in accuracy at 93.12%, has high precision (98.1%), recall (97.8%), and F-measure (98.05%) values. These findings indicate the different strengths of each model to perform certain tasks or datasets. Models such as ADLS are successful at high accuracy and reliability in various metrics and are best fit for applications of a critical nature, for example, medical diagnosis. Models such as PCNN and DLM have a strong ability to maintain high precision and recall, which is a must for applications necessitating sensitivity and specificity in classification tasks.

6. CONCLUSION

The incorporation of ML in angiography has greatly enhanced reliability and precision in CAD detection. Conventional diagnosis, as efficient as it is, is limited by subjectivity, human error, and the cost of diagnosis. The models developed using ML offer an objective and automatic process of diagnosis with greater precision and efficiency. In the present research work, different algorithms such as DL and hybrid models were implemented for optimizing CAD detection. The results identify the performance excellence of ML models, PCNN and ADLS specifically, over traditional approaches in terms of precision, recall, accuracy, and specificity. The Deep Discern dataset was used in training and validation to ensure model robustness and generalizability. Normalization and feature selection with GA and PSO were done as preprocessing that enhanced the model's prediction strength further. Comparative analysis ratified that ML models had a success rate of over 98%, with ADLS performing in every test measure. These innovations not only augment the detection of CAD at an early stage but also enable decreasing healthcare spending and enhancing patient outcomes. The research reiterates the revolutionary

possibilities of AI in clinical diagnostics, holding the potential for more effective, data-based, and clinically accurate diagnostic procedures. Future research should continue to optimize the ML models and integrate real-time data analysis. Datasets can be expanded in order to achieve generalizability. The future of the health care industry with AI-driven technologies will significantly enhance CAD diagnosis. This will mean saving lives with early intervention and precise treatment planning.

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