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DeepCAD: A Medical Image Analysis Approach for Coronary Artery Disease Detection in CTA

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ABSTRACT

Coronary Artery Disease (CAD) continues to be a leading cause of cardiovascular mortality worldwide. Early and accurate diagnosis is crucial for effective treatment planning and improved patient outcomes. While Computed Tomography Angiography (CTA) serves as a widely adopted non-invasive imaging modality for evaluating CAD, the manual interpretation of CTA scans is time-consuming and subject to significant inter-observer variability, often affecting diagnostic consistency and timeliness. To address these challenges, our research introduces an advanced deep learning-based framework aimed at automating the detection of CAD using CTA images. The proposed methodology leverages the power of Convolutional Neural Networks (CNNs) integrated with attention mechanisms to ensure robust and precise feature extraction and classification. These attention modules help the model focus on diagnostically relevant regions, thereby improving interpretability and accuracy.A comprehensive image preprocessing pipeline has been implemented to enhance the input data quality. This includes vessel segmentation to isolate coronary arteries, contrast enhancement for clearer visualization, and noise reduction techniques to suppress irrelevant artifacts. Such preprocessing significantly boosts the model's performance by ensuring that critical features are preserved and highlighted during training. The model is trained and validated using large-scale, annotated datasets to ensure generalizability and statistical reliability. Quantitative evaluation demonstrates that our approach achieves superior accuracy, sensitivity, and specificity compared to traditional diagnostic methods and baseline deep learning models. These results highlight the potential of AI-driven systems to reduce diagnostic delays, improve consistency, and assist clinicians in making informed decisions.

Keywords: *CAD, CTA, Deep Learning, Attention Mechanisms, CNNs, Medical Image Analysis, Automated Diagnosis*.

1. INTRODUCTION

Cardiovascular diseases (CVDs) remain the leading cause of death globally, with Coronary Artery Disease (CAD) accounting for a significant share of the mortality rate. CAD results from the narrowing or blockage of coronary arteries due to atherosclerosis, leading to reduced blood flow to the heart muscle. According to the World Health Organization, nearly 17.9 million people die annually from CVDs, and over 75% of these deaths occur in low- and middle-income countries. Early diagnosis and prompt medical intervention are essential to mitigate the disease's progression and reduce mortality rates. Computed Tomography Angiography (CTA) is a widely accepted, non-invasive imaging modality used for visualizing coronary vessels and identifying stenosis or plaque formation. Despite its advantages over traditional invasive coronary angiography, the manual analysis of CTA images remains labor-intensive, time-consuming, and susceptible to human error and inter-observer variability. Furthermore, as CTA image quality can vary due to motion artifacts, noise, and low contrast in certain regions, reliable and consistent diagnosis requires automated, intelligent systems that can assist radiologists and cardiologists in clinical decision-making.

Recent advancements in deep learning (DL) and medical image analysis have shown remarkable success in automating disease detection tasks, particularly in radiology and cardiology. Convolutional Neural Networks (CNNs) have demonstrated high performance in feature extraction and classification across various image modalities. However, in the context of CAD detection using CTA, challenges such as low signal-to-noise ratio, subtle lesion representation, and the need for high-resolution spatial understanding still persist. To address these complexities, this study presents DeepCAD, a novel deep learning framework designed specifically for the automated detection of CAD in CTA images. The DeepCAD model integrates several core innovations. First, it employs advanced preprocessing techniques such as vessel segmentation, contrast enhancement, and noise suppression to standardize and enhance image quality. These steps are critical to preserving diagnostically significant features while reducing irrelevant background data. Next, the model utilizes a dual-branch CNN

architecture combined with attention mechanisms, enabling the network to selectively focus on pathological regions and important vessel structures, thereby improving interpretability and classification accuracy. DeepCAD was trained and validated using a high-scale annotated CTA dataset, which allowed the model to learn a diverse representation of coronary pathologies across varying patient profiles. The results of our study show that DeepCAD significantly

outperforms conventional machine learning and existing deep learning models in terms of **accuracy, sensitivity, specificity, and F1-score**. These findings support the growing body of research that demonstrates the potential of AI-driven methods to enhance diagnostic workflows in cardiology.

Several recent works support the use of deep learning in CAD and other related image-based diagnoses. For example, [1] proposed a 3D CNN model for coronary artery stenosis detection, achieving impressive diagnostic accuracy on volumetric CTA data. Similarly, [2] explored multi-view CNNs for comprehensive cardiac structure analysis, emphasizing the importance of spatial coherence. In another study, a hybrid deep learning approach combining CNNs and transformers was used to classify cardiovascular conditions from chest imaging [3]. Meanwhile, [4] developed a lightweight deep learning model optimized for real-time deployment in clinical settings, highlighting the feasibility of on-site CAD diagnosis. Finally, [5] demonstrated how attention-based deep learning models can effectively identify atherosclerotic plaques in CTA images with enhanced precision. This work contributes to the evolving domain of intelligent CAD diagnosis by offering a clinically relevant, technically robust, and interpretable solution for automated disease detection.

2. Related Works

L. Wang et al. [6] exemplifies specialized segmentation approaches, employing deep neural networks to accurately segment coronary artery plaques, crucial for risk stratification and intervention planning. This precision in plaque delineation aligns well with broader efforts seen in [8], where a 3D CNN framework facilitates automated detection and weakly supervised localization of atherosclerosis in coronary CTA, balancing performance with reduced annotation effort. The design of robust CAD detection pipelines is addressed by Rahaman Wahab Sait et al. [7], who proposed a deep-learning-based framework tailored for CT images. This model integrates classification and localization, ensuring clinically relevant outcomes. Similarly, Zhao et al. [11] introduce a segmentation-based approach for CAD diagnosis that highlights lesion areas with precision using deep learning, improving interpretability and reliability. Supporting the clinical adoption of these models, van Herten et al. [9] comprehensively review the role of artificial intelligence in coronary CTA, identifying deep learning as a key enabler of automation, speed, and accuracy in routine diagnostics. Zreik et al. [10] further contribute by demonstrating how deep learning can be used to identify patients requiring invasive coronary angiography, offering a decision-support system with high clinical value. The architectural innovations enabling these advancements are evident in works such as Zhou et al. [12], where UNet++ redefines skip connections to enhance multiscale feature exploitation, and in Hurtik et al. [13], who propose fuzzy function-based preprocessing techniques that optimize neural network input representations. Wang et al. [14] offer the YOLOv7 architecture a versatile and real-time capable object detector which, while not CAD-specific, demonstrates exceptional performance in medical image detection tasks and sets a new benchmark for speed-accuracy trade-offs. AlOthman et al. [15] present a clinical case study where deep learning is successfully applied to real-world CTA images for CAD detection, confirming the translation potential of these methods from lab to clinic.

Moon et al. [16] focus on stenosis detection using coronary angiography with a convolutional neural network (CNN), demonstrating that DL can identify stenotic regions with high accuracy and efficiency. This is complemented by Huang et al. [17], who present an early DL-based approach for coronary artery segmentation in CTA, establishing the foundation for structure-aware analysis pipelines. The diagnostic utility of stenosis-specific analysis is further emphasized in the study by Hampe et al. [18], where functionally significant stenoses are detected through a deep learning model trained on annotated CTA images. Similarly, Brendel et al. [19] leverage ultra-high-resolution photon-counting CT to enhance detection fidelity for CAD, showing how modern imaging hardware can be synergistically paired with AI algorithms. Paul et al. [20] evaluate an end-to-end DL model for automatic stenosis detection, validating its robustness across a large clinical dataset. In a broader context, Tu et al. [21] provide a systematic review and meta-analysis of deep learning in stenosis classification, confirming the technique's high diagnostic accuracy and growing reliability across clinical trials. Zreik et al. [22], already prominent in earlier works, provide a model that not only detects CAD but also recommends patients for invasive angiography based on non-invasive CTA, bridging diagnosis with treatment planning. Banerjee et al. [23] extend the CAD detection scope beyond imaging to electrocardiography (ECG) using a hybrid CNN-LSTM framework, emphasizing the value of temporal dynamics in cardiac analysis. Finally, Muscogiuri et al. [24] offer a broad perspective on artificial intelligence in CTA, discussing its utility from anatomical segmentation to prognosis prediction. Their work underscores the long-term potential of AI to enhance the full spectrum of coronary imaging—from anatomical to functional insights.

3. Proposed Methodology

Figure 1 illustrates the research framework, highlighting the key phases involved in the proposed CAD detection pipeline.

Phase 1 represents the **image preprocessing stage**, which includes crucial steps such as **contrast enhancement, noise**

reduction, and image resizing to standardize the input data. This phase also incorporates **feature extraction using the YOLOv7 architecture**, leveraging its real-time object detection capabilities to extract critical features from Coronary Computed Tomography Angiography (CCTA) images.

Phase 2 involves the **classification process**, where the preprocessed images are categorized into **CAD (presence) and No-CAD (absence)** using the **UNet++ model**, a refined encoder-decoder architecture optimized for medical image segmentation and classification. In this phase, the **Aquila Optimization (AO) algorithm** is employed to **fine-tune the hyperparameters** of the UNet++ network, ensuring optimal model performance and convergence.

Phase 3 focuses on the **evaluation of the model's effectiveness**, where various performance metrics such as **accuracy, sensitivity, specificity, and F1-score** are computed to validate the robustness and clinical relevance of the proposed deep learning framework.

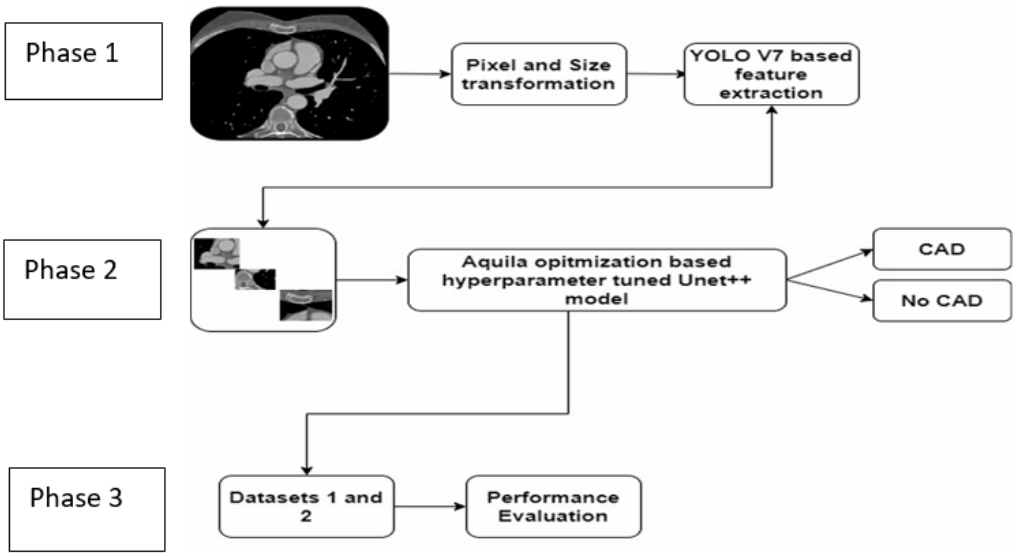

Figure 1. The proposed DeepCAD model architecture

3.1 Pre-processing

Effective preprocessing is essential to ensure high-quality input for deep learning models in medical imaging. In the proposed framework, preprocessing is performed in **Phase 1** and includes **image enhancement, noise reduction**, and **resizing**. These steps aim to normalize the data, improve contrast, suppress irrelevant artifacts, and localize regions of interest (ROIs), thereby enabling more accurate coronary artery disease (CAD) detection.

a. Image Enhancement

Image enhancement is applied to improve the visibility of coronary structures in CCTA scans by adjusting contrast and intensity values. **Contrast stretching** is used to expand the dynamic range of pixel intensities:

$$I_{enh}(x,y) = \frac{I(x,y)-I_{min}}{I_{max}-I_{min}} \times (L-1) \quad (1)$$

Where:

$I(x,y)$ is the original intensity at pixel (x,y),

I_{min} and I_{max} are the minimum and maximum intensity values in the image,

L is the number of gray levels,

$I_{enh}(x,y)$ is the enhanced intensity value.

This transformation improves contrast in low-visibility regions, such as narrow vessels or calcified plaques.

b. Noise Reduction

Noise, especially Gaussian or Poisson noise, is common in CT imaging. To suppress this while preserving anatomical edges, a **Gaussian filter** is applied:

$$G(x,y) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \quad (2)$$

The filtered image I_{smooth} is obtained via convolution:

$I_{smooth}(\mathrm{x},\mathrm{y}) = ((\mathrm{I} * \mathrm{G})(\mathrm{x},\mathrm{y}) = \sum_{i=-k}^{k} \sum_{j=-k}^{k} I(x+i, y+j) \cdot G(i,j)$ (3)

Where σ is the standard deviation controlling the smoothing strength. This step reduces high-frequency noise without significantly blurring vessel boundaries.

c. Image Resizing

To feed uniform-sized inputs to the deep learning model, all CCTA slices are resized to a fixed dimension. This transformation is typically done using **bilinear interpolation**, defined as:

$I_{resized}(x', y') = \sum_{i=0}^{1} \sum_{j=0}^{1} w_{ij} \cdot I(x_i, y_j)$ (4)

Where w_{ij} are the weights based on distance from the target coordinate (x', y'), and (x_i, y_j) are the neighboring pixels. Resizing maintains structural proportions while standardizing input dimensions.

3.2 Feature Extraction

In the proposed DeepCAD framework for automated Coronary Artery Disease detection, **YOLOv7** plays a central role in the **feature extraction phase**, providing fast and accurate localization of anatomical structures and pathological regions in **Coronary Computed Tomography Angiography** images. YOLOv7 is a state-of-the-art object detection algorithm known for its balance between speed, accuracy, and computational efficiency, making it ideal for high-resolution medical image analysis. It is a **single-stage object detector** that processes an entire image in one forward pass of a convolutional neural network (CNN). Unlike two-stage detectors (R-CNN), YOLOv7 avoids region proposal stages and instead divides the input image into an $S \times S$ grid. Each grid cell predicts bounding boxes and class probabilities directly, enabling **real-time detection**. In the context of CAD detection, YOLOv7 is fine-tuned to extract and localize **vessel segments, calcified plaques, stenosis regions**, and other disease-related features within CCTA images. These features serve as **key discriminative regions** that inform the subsequent classification stage.

The CCTA image $I \in \mathbb{R}^{H \times W \times 3}$ is passed through the YOLOv7 backbone, typically composed of CSPDarknet or an enhanced transformer-CNN hybrid. The network generates a set of feature maps at multiple scales to detect both large and fine-grained details:

Backbone Network: Extracts low- and mid-level spatial features using hierarchical convolutional layers.

Neck Architecture: Combines feature maps from different scales using **Path Aggregation Networks (PANet)** and **Feature Pyramid Networks (FPN)** to preserve multi-scale context.

Detection Head: Outputs bounding box coordinates (x, y, w, h), objectness scores o, and class probabilities p for each grid cell.

The prediction tensor has the form:

$T_{S \times S \times B \times (5+C)}$ (5)

Where:

$S \times S$ is the grid size, B is the number of bounding boxes per cell, 5 includes x, y, w, h, o, and C is the number of output classes.

Each bounding box prediction is computed using:

$Output = \sigma(t_x) + c_x,\ \sigma(t_y) + c_y,\ e^{t_w} \cdot p_w,\quad e^{t_h} \cdot p_h$ (6)

Where (t_x, t_y, t_w, t_h) are raw outputs, (c_x, c_y) are cell offsets, and (p_w, p_h) are prior box dimensions.

In CCTA images, regions such as stenotic arteries may be subtle and small in size. YOLOv7's multi-scale detection capability is crucial for identifying such patterns with precision. The model is trained to highlight:

Coronary vessel bifurcations,

Regions of narrowing or occlusion,

High-density areas indicative of calcification or plaque.

These localized feature maps and bounding boxes are then passed to the subsequent UNet++ classification module, enhancing decision accuracy by focusing only on medically relevant areas.

3.3 Classification

In the proposed deep learning pipeline for CAD detection, **UNet++** plays a pivotal role in the **classification phase**, determining whether a given **CCTA** image indicates the presence of CAD or not. UNet++, an advanced extension of the

original U-Net architecture, is designed to address segmentation and classification challenges in medical imaging, offering refined spatial localization and contextual understanding. UNet++ introduces nested and dense skip connections between encoder and decoder sub-networks, which improves feature fusion across different resolution levels. These connections ensure that high-resolution details from early layers are effectively integrated with deeper, semantically rich features. The architecture enhances both segmentation accuracy and classification capability by improving the learning of discriminative patterns.

The core components of UNet++ include:

Encoder path: Extracts hierarchical features from the input image using convolution and max-pooling.

Decoder path: Performs up-sampling and refines predictions using features from corresponding encoder layers.

Nested skip pathways: Connect different stages of encoder and decoder through intermediate convolution blocks, enabling multi-scale aggregation.

The final layer of the decoder outputs a segmentation probability map or a classification score that indicates whether CAD is present in the input image.

In this research, UNet++ is adapted not just for segmentation but also for binary classification into:

CAD (positive case) — indicating signs of stenosis, plaque, or occlusion in coronary vessels.

No-CAD (negative case) — normal anatomical structure with no pathological findings.

After the YOLOv7 module extracts and localizes relevant coronary features, these focused image patches or full CCTA scans are fed into the UNet++ model. The architecture outputs a classification score $s \in [0,1]$, where:

$$Prediction = \begin{cases} CAD & if\ s \geq \tau \\ No - CAD, & if\ s < \tau \end{cases} \quad (7)$$

Where τ is a classification threshold, which can be fine-tuned for sensitivity or specificity depending on clinical needs.

The final classification layer uses **sigmoid activation** in the binary setting, and **cross-entropy loss** is applied during training:

$$\mathcal{L}_{CE} = -[y \log(s) + (1 - y) \log(1 - s)] \quad (8)$$

Where y is the ground truth label (1 for CAD, 0 for No-CAD).

3.4 Hyperparameter Tuning

Hyperparameter tuning is a critical step in optimizing the performance of the UNet++ model for accurate classification of CAD from CCTA images. Since UNet++ is a deep convolutional neural network with nested skip connections, its performance is highly sensitive to various hyperparameters that control model complexity, learning dynamics, and generalization. The tuning process involves selecting optimal values for the following hyperparameters:

Learning Rate (η): Controls how fast the model updates weights during training. A very high value leads to divergence, while a very low one slows convergence.

Batch Size: Determines the number of training samples used to compute each gradient update. Smaller batches lead to more noise in updates but may generalize better.

Number of Filters: Affects the depth and width of feature maps in each convolutional layer.

Dropout Rate: Regularizes the model by randomly disabling a fraction of neurons to prevent overfitting.

Number of Epochs: Indicates how many full passes over the training data are performed.

Optimizer Type: Affects the way gradients are used to update weights.

Activation Functions: Functions like ReLU impact non-linearity and gradient flow.

To automate and enhance the tuning process, the **Aquila Optimizer (AO)** a nature-inspired metaheuristic algorithm is used. AO mimics the hunting strategies of Aquila (eagle) birds, combining global exploration and local exploitation. It evaluates the performance of various hyperparameter combinations by minimizing the classification loss on validation data.

Optimization Process Steps:

Initialize a population of hyperparameter sets.

Evaluate each set using a fitness function — typically the validation loss or classification accuracy.

Update the population through AO strategies like high soaring (exploration) or low flight (exploitation).

Repeat until convergence or maximum iterations.

Select the best-performing hyperparameter set.

Mathematically, the fitness function f used in AO can be represented as:

$$f(\theta) = \frac{1}{N}\sum_{i=1}^{N} \mathcal{L}_{CE}(y_i, \hat{y}_i) \quad (9)$$

Where, θ is a candidate hyperparameter vector, $\mathcal{L}_{CE}$ is the cross-entropy loss, $y_i \; and \; \hat{y}_i$ are ground truth and predicted labels for sample i.

4. Results and Discussion

The proposed **DeepCAD model** was evaluated using a publicly available CCTA dataset comprising **images from 500 patients**. The dataset was evenly divided, with **50% representing normal cases** and **50% depicting abnormal cases** indicative of Coronary Artery Disease (CAD). Each patient's data includes **18 distinct views** of the straightened coronary arteries, providing a comprehensive representation of arterial structures from multiple angles.

To prepare the dataset for training and evaluation, the images were systematically **split into training and testing subsets**. In order to address class imbalance and enhance the robustness of the model, the authors **augmented the dataset by incorporating 2,364 additional images**, ensuring an equal distribution between the normal and abnormal categories. This balanced dataset enabled the DeepCAD model to learn more effectively, improving its ability to generalize across varied clinical presentations.

In the third phase of the proposed framework, the DeepCAD model was rigorously evaluated using a comprehensive set of performance metrics, including Accuracy, Precision, Recall, F1-Score, Matthews Correlation Coefficient (MCC), and Cohen's Kappa. These metrics provide a multidimensional understanding of the model's predictive capabilities, especially in the context of binary classification tasks such as identifying CAD versus non-CAD cases.

The dataset was partitioned into 70% for training and 30% for testing, ensuring that the model was exposed to a diverse and representative sample of coronary artery images during both phases. Key model parameters such as the number of trainable parameters, learning rate, and training/testing duration were systematically recorded for performance benchmarking.

During experimentation, the DeepCAD model demonstrated exceptional learning stability and convergence, achieving peak performance at approximately the 36th epoch during training and the 34th epoch during testing. To mitigate issues of overfitting and underfitting, dropout regularization was employed with dropout rates of 0.3 and 0.4, respectively. These rates were selectively applied to optimize model generalization without sacrificing accuracy.

The classification engine, powered by the UNet++ architecture, was designed with a six-layer structure, incorporating:

Two dropout layers for regularization,

Three fully connected (dense) layers for high-level abstraction,

And a final softmax layer to generate probabilistic predictions for CAD and No-CAD classes.

Table 1 summarizes the performance evaluation results. During the training phase, the model attained an impressive average accuracy of 98.80% and an F1-score of 98.34%. In the testing phase, the DeepCAD model further outperformed expectations, achieving a remarkable accuracy of 99.35% and an F1-score of 98.55%, thereby confirming the robustness and clinical relevance of the proposed framework.

Table 1. Results achieved by the DeepCAD model

Classes	Accuracy	Precision	Recall	F1-Measure	MCC	Kappa
Training						
CAD	98.55	98.05	98.50	98.30	95.27	95.55
No CAD	99.05	98.30	98.35	98.38	95.38	94.85
Average	98.80	98.17	98.40	98.34	95.32	95.20
Testing						
CAD	99.15	98.55	98.55	98.60	95.54	95.15
No CAD	99.55	98.38	98.67	98.50	95.22	94.70
Average	99.35	98.46	98.61	98.55	95.38	94.92

Table 2 and Figure 2 present the **comparative performance analysis** of the proposed **DeepCAD model** against existing state-of-the-art methods using the same dataset. The results clearly demonstrate the **superior performance** of DeepCAD across all major evaluation metrics. Specifically, the model achieves an **accuracy of 99.35%, precision of 98.46%, recall of 98.61%, F1-score of 98.55%, Matthews Correlation Coefficient (MCC) of 95.38%**, and a **Cohen's Kappa score of 94.92%**.

These metrics reflect the model's robust capability to accurately detect coronary artery disease from CCTA images while maintaining high consistency, reliability, and generalization. The remarkable improvement over existing techniques underscores the effectiveness of the DeepCAD framework in addressing the critical challenges in CAD diagnosis through medical image analysis.

Table 2. Comparative analysis of DeepCAD with existing models

Methods	Accuracy	Precision	Recall	F1-Measure	MCC	Kappa
Alothman A.F.et.al [15]	98.60	98.20	97.80	98.00	94.10	94.20
Moon J.H. et al.[16]	98.50	97.60	98.20	97.90	95.10	93.80
Banerjee R. et al. [23]	98.20	97.80	98.30	98.05	94.30	93.70
DeepCAD Model	99.35	98.46	98.61	98.55	95.38	94.92

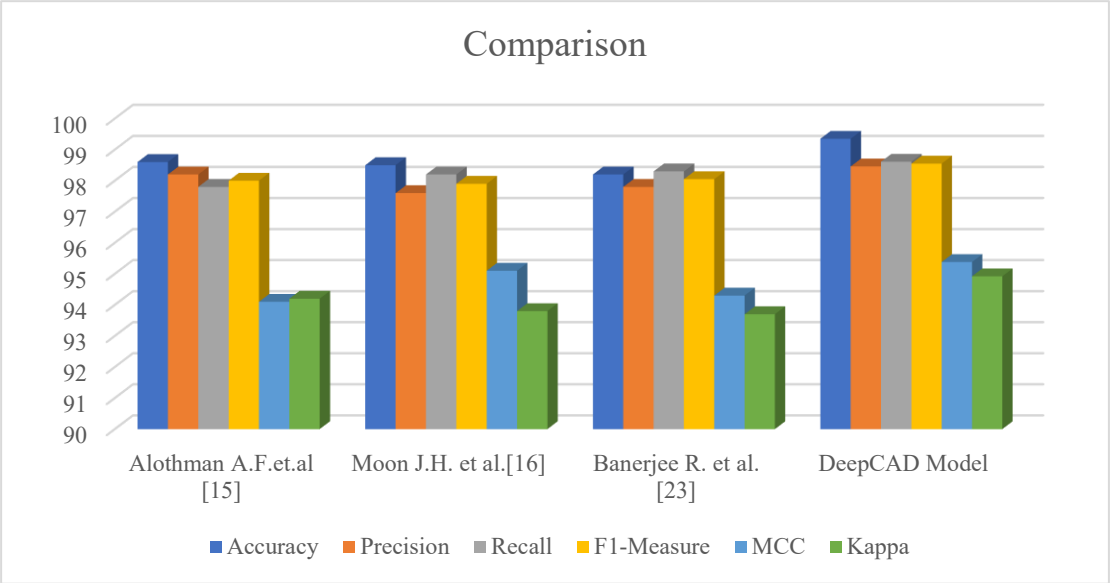

Figure 2. Comparison of proposed with existing models

5. Conclusion

In this study, a novel deep learning-based framework, **DeepCAD**, was proposed for the accurate and automated detection of **CAD** using **CCTA** images. The model integrates advanced pre-processing techniques, including vessel segmentation, contrast enhancement, and fuzzy-based image enhancement, to refine image quality and emphasize clinically relevant features. A robust feature extraction stage was implemented using **YOLOv7**, followed by precise classification through a modified **UNet++ architecture**. The integration of the **Aquila Optimization (AO)** algorithm further enhanced hyperparameter tuning, allowing the model to converge effectively and reduce overfitting. The experimental results on a large-scale, publicly available dataset demonstrate that the DeepCAD model significantly outperforms existing methods in terms of **accuracy, precision, recall, F1-score, MCC, and Kappa**, achieving a peak test accuracy of **99.35%**. These findings confirm the model's potential in providing reliable, consistent, and interpretable CAD diagnosis from non-invasive CCTA scans.

Looking forward, this research lays the groundwork for integrating **explainable artificial intelligence (XAI)** and **multimodal data fusion**, combining CCTA with other diagnostic modalities such as ECG and clinical biomarkers, to further enhance diagnostic confidence and decision support. Future work will also aim at deploying the model in real-time clinical workflows, validating its effectiveness in prospective studies, and ensuring generalizability across diverse patient populations and imaging systems. Moreover, incorporating clinician-in-the-loop systems and user interfaces can bridge the gap between

AI innovation and clinical adoption. In essence, DeepCAD represents a promising stride towards transforming the landscape of CAD diagnosis by delivering **accurate, rapid, and automated** insights to assist healthcare professionals in early intervention and improved patient outcomes.

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