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

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**ABSTRACT**
Coronary artery disease (CAD) remains a leading cause of morbidity and mortality worldwide, necessitating accurate and timely diagnosis. Traditional angiographic techniques, while effective, often suffer from limitations in precision and diagnostic accuracy. This review explores the integration of Machine Learning (ML) algorithms with angiographic imaging to improve diagnostic performance. The authors found 23 papers that were eligible for inclusion after conducting a thorough search across many databases. As an example, they used X-ray Coronary Angiography (XCA) and Invasive Coronary Angiography (ICA), two forms of angiography imaging. The authors found that several ML techniques, including Support Vector Machine (SVM), Random Forest (RF), and hybrid approaches, have been employed for image segmentation and classification in muchresearch. Additionally, studies differed in how they determined stenosis and CAD severity. When it comes to detecting CAD via angiography, ML techniques could make things easier and more accurate. The dataset, method, and attributes chosen for analysis all had an impact on the algorithms' performance. Looking back at prior research, they find that the most accurate ML-based results were obtained by Asif et al. (2024) at 96.17% and lowest by Lin et al. (2024) at 67.5%.

**KEYWRDS:** Machine Learning, CAD, Heart Disease, Angiography

## I. INTRODUCION

Coronary Artery Disease (CAD) occurs when the coronary arteries, which carry oxygen and nutrients to the heart muscle, are constricted or obstructed. Other names for this ailment include coronary heart disease and ischemic heart disease[1-3]. It is now well recognized as an ongoing disease that provides the greatest risk to human life[4]. As per a recent study, the United States scores highest for both the prevalence of heart disease and the percentage of people diagnosed with the illness[5]. Many people suffer shortness of breath, swollen feet, extreme tiredness, and other signs of heart disease. CAD is the most prevalent form of cardiovascular disease(CVD) and a leading cause of chest pain, stroke, and heart attacks. Heart rhythm problems, heart failure, congenital heart defects, and CVD are all forms of heart illness[6].As a consequence, detecting CAD is essential for modern civilization. One of the most useful tools for diagnosing and guiding therapy for CAD is coronary angiography (CAG), which evaluates luminal stenosis, plaque features, and disease activity[7]. Major risk factor for CAD is represented in Figure 1.

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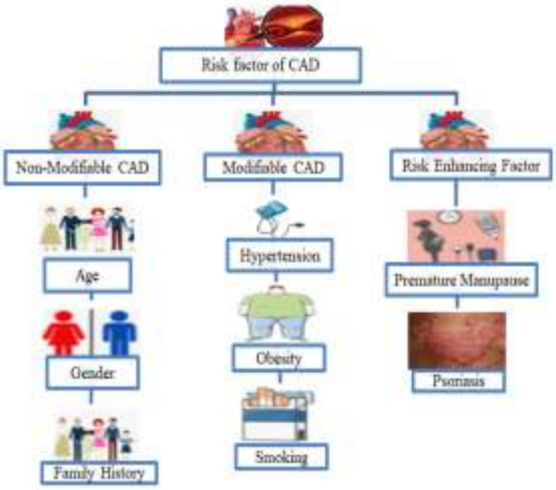


**Figure 1:**Risk factors of CAD[8,9].

One of the most used imaging methods for diagnosing CAD is X-ray Coronary Angiography (XCA), also known as Invasive Coronary Angiography (ICA)[10]. The procedure of XCA involves inserting a catheter into a blood artery and injecting a contrast agent into the coronary arteries[11]. Doctors use X-ray pictures to detect narrowing or blockages; the agent makes the arteries more visible on these images[12]. The signs and symptoms of CAD are shown in Figure 2.


**Figure 2:** Symptoms of CAD

In healthcare applications, Machine Learning (ML) helps improve the diagnosis process and is therefore extensively used in the medical science. In order to understand complicated and non-linear patterns related to the characteristics, ML algorithms minimize the error between the projected and actual outcomes by analyzing data[13]. Integrating ML into medical applications has greatly improved diagnostic processes. ML has recently found several uses, assisting with nearly every aspect of medical diagnosis. These include cancer, Parkinson's disease, thyroid illness, and a number of ocular ailments [14]. ML in the context of CAD diagnosis allows for the quick identification of CHD using Electrocardiograms (ECGs), Phonocardiograms (PCGs), Coronary Computed Tomography Angiography (CCTAs), and CAG[15]. A comprehensive overview of ML's use in CAD diagnosis is provided in this paper. Its anticipated benefits include the advancement of ML for CAD diagnosis, faster diagnosis, and better CAD decision-making.

## II. METHOD

This scoping review adhered to the PRISMA-ScR checklist, which stands for Preferred Reporting Items for Systematic Reviews and Meta-Analyses with an Extension for Scoping Reviews.

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The purpose of this scoping study is to categorize the other ML methods for CAD identification in medical image analysis.They have included English-language papers that use quantitative data analysis and ML methods to identify CAD in angiography images. Excluded from consideration are articles that do not address Computer-Aided Design (CAD), do not appear in peer-reviewed journals, and center on methods other than ML.

### 2.1 Data Source and Strategies

The electronic databases used in this investigation were Scopus, Medline (via PubMed), and Web of Science. The search approach included the following keywords and their synonyms: "ML," "Deep Learning (DL)," "CAD," "diagnosis," and "detect".

### 2.2 Data extraction and synthesis

Reviewers looked at each of the research separately. Using the inclusion and exclusion criteria, the reviewers quickly reviewed the article titles and abstracts, removing those that did not meet the requirements. They reviewed the remaining studies eligibility after receiving their full texts. The data was extracted using a pre-made form. Researchers were requested to provide details about the authors, year, country, sample size, imaging modality, performance metrics, and important results. They were also asked about the DL model that was used. A synopsis of the outcomes was provided by the results. The most widely used imaging modalities, performance indicators, and DL models were uncovered in the synthesis. The top-ranked imaging modalities, performance indicators, and DL models were uncovered by the comprehensive investigation.

## III. LITERATURE REVIEW

In this review, a total of 23 papers were considering (Figure 3). The majority of the research was conducted in China, followed by United States of America, Japan, South Korea, and Saudi Arabia. The investigations were carried out in a number of different countries. There was a range of 32 to 30,000 images included inside the samples. Two different imaging methods were used, namely CCTA and ICA.

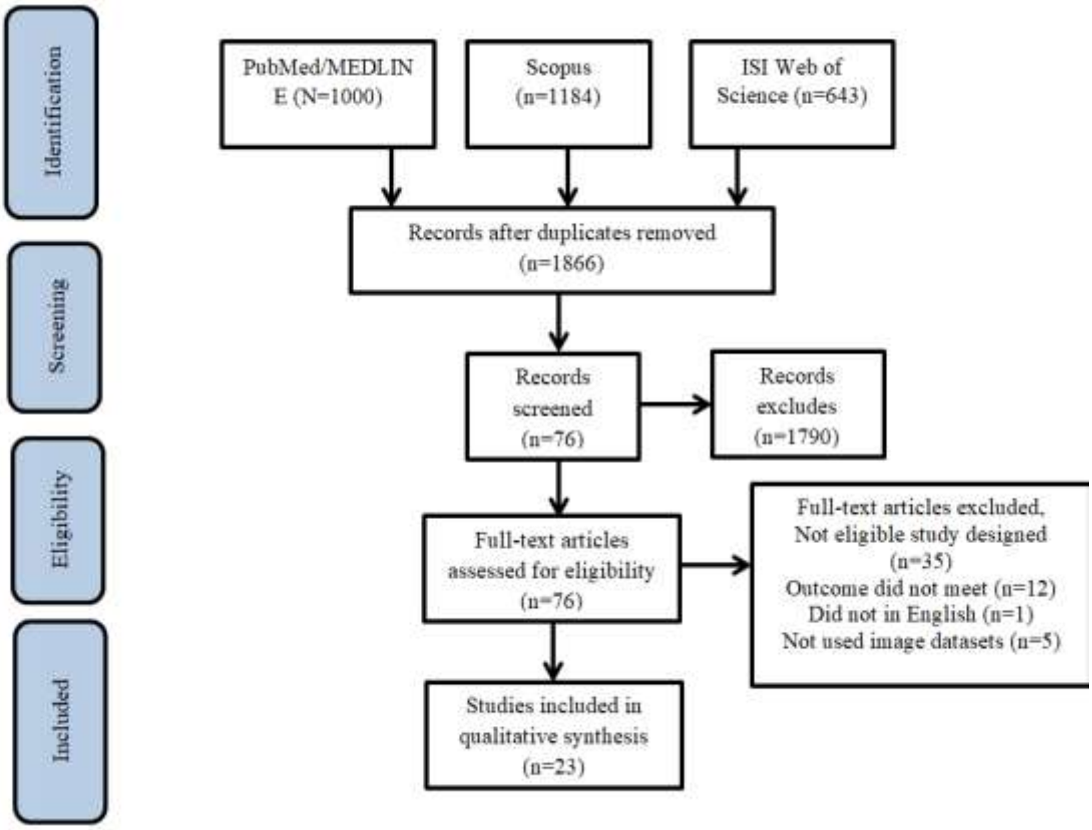


**Figure 3:** Study selection and literature search flowchart.

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### 3.1 Detection of CAD using DL

Digital Learning (DL) is a branch of Machine Learning (ML) that aims to simulate human brain function by using Neural Networks (NNs), which are anatomically and functionally similar to neurons[16]. In constructing the brain's architecture, DL approaches mimic human neurons by using complicated connections[17]. Different varieties of DL can be classified according to their use of Artificial Neural Networks (ANN), often termed NNs. Convolutional Neural Networks (CNNs) are often used for vision (sight/pixel) processing, while Recurrent Neural Networks (RNNs) are known for their time-based functionality (Figure 4)[18]. All the result of previous work are evaluated in terms of accuracy ($A_{accuracy}$), Precision ($P_{precision}$), Recall ($R_{recall}$), Sensitivity ($Sen_{sitivity}$), Specificity ($Spe_{cificity}$) and $F1_{score}$.

In the study, Ainiwaer **et al., (2024)[20]** developed precise DL methods to effectively identify obstructive CAD from cardiac sound signals and built a thorough database of cardiac sounds in CAD.

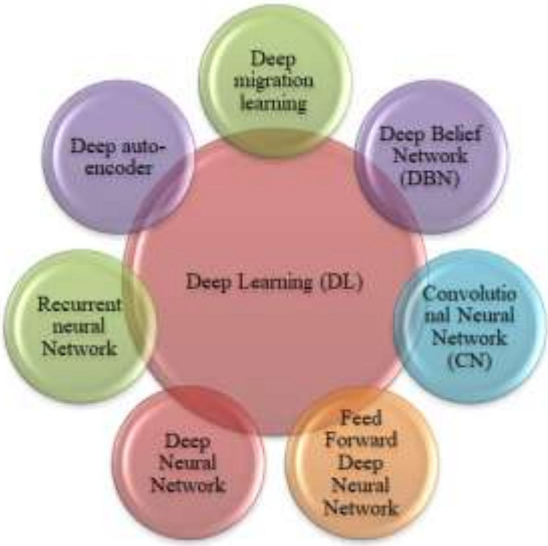


**Figure 4:** Types of DL Model[19].

Obstructive CAD in cardiac sound waves, they used cutting-edge DL models (ResNet18, 1D CNN, and VGG-16) and high-tech filtering algorithms. At an Area Under the Curve (AUC) of 0.834, VGG-16 performed better than ResNet-18 and CNN-7 in the test set, which had AUCs of just 0.755 and 0.652, respectively. In the test set, VGG-16 performed with 80% $Sen_{sitivity}$ and 86.2% $Spe_{cificity}$. An important consequence of diabetes is heart disease.To improve the hyper-parameter tuning for early diabetes illness diagnosis and prevention, the authors of**[21]** suggested an Optimal Scrutiny Boosted Graph Convolutional LSTM (O-SBGC-LSTM), which is an improved version of SBGC-LSTM that uses the Eurygaster Optimization Algorithm (EOA). Overall, O-SBGC-LSTM performed well, with most studies reporting $A_{accuracy}$ levels of $> 98\%$. In practically every study that provided such comparative results, the suggested hybrid DL performed better than traditional ML algorithms. Furthermore, prevention is superior to treatment.

For patients in a time-series way, **Bhardwaj et al. (2024)[22]** established an improved healthcare monitoring framework of CHDusing a DL model. In order to categorize the electrode time-series data, the model employs DL, namely CNN using radial basis function integration with ANN. The testing data set included 335 records with 36 clinical variables and came from a well-respected medical institution. Performances of the suggested model were evaluated using f-measures, $R_{recall}$, $P_{precision}$, and accuracies. The purpose of this method is to ascertain if the suggested method procedure would ultimately provide the desired results. CAD is a leading cause of death and disability; however, it often has no symptoms at first and remains undiagnosed. Using just ECG data, a new AI-based method for early CAD patient diagnosis is created in**[23]**. They then randomly assigned each set of matched data to one of three datasets: training, validation, or test. The training dataset was used to build a CNN-based model, while the test dataset was used to evaluate the model. The model's $A_{accuracy}$ was 70.0% and its AUC was 0.75 in the test dataset, indicating that it successfully detected CAD. The CAD detection model achieved a $Sen_{sitivity}$ of 68.7%, $Spe_{cificity}$ of 70.9%, PPV of 61.2%, and NPV of 77.2% when using the best cut-off point.

Research by**[24]** centered on a dual approach, with a Deep Neural Network (DNN) performing CAD diagnosis in the first phase. The model that relies on DL has the best prediction $A_{accuracy}$ at 96.2% and the lowest error rate at 3.8%. Additionally, the model is enhanced in performance by including Gaussian noise to deal with overfitting. In the second phase, the severity of the condition is assessed using a Case-Based Reasoning (CBR) technique. These new CAD identification models need a large number of images and a lot of computing power. Thus, the goal of the study in**[25]** is to create a CAD detection model that uses CNNs. The authors made use of You Only Look at it Once (YOLOv7) to extract features. In order to optimize the UNet++ model's hyper-parameters for CAD prediction, Aquila optimization is used. To test how well the suggested CAD detection model works, 2 datasets are used. Based on the results of the experiments, it seems that the suggested strategy obtains the following values for dataset 2: 99.5 for $A_{accuracy}$, 98.95 for $R_{recall}$, 98.95 for $P_{precision}$, 96.35 for Matthews's Correlation Coefficient (MCC), and 96.25 for Kappa. Also, the suggested model achieves better results than the new methods by generating an AUC of 0.97 for dataset 1 and 0.95 for dataset 2.

Research in this area has used a DL algorithm to propose ECG screening for obstructive CAD (Ob-CAD)**[26]**. In terms of predicting the possibility of Ob-CAD, the DL model performed moderately, but it detected AMI with remarkable accuracy. Both the AUC for identifying AMI and the Ob-CAD model using 1D Res-Net were 0.923. When it came to screening Ob-CAD, the DL model had $Spe_{cificity}$, $Sen_{sitivity}$, $A_{accuracy}$, and $F1_{score}$ of 0.634, 0.639, and 0.636, respectively. When it came to identifying AMI, however, the values proceeded up to 0.885, 0.769, 0.921, and 0.758, respectively. The authors of study**[27]** integrate many components, such as the detection of coronary artery segments and lesion morphology using DL, to accomplish an automated and multimodal analysis for the purpose of recognizing and quantifying CAG. The recognition $Sen_{sitivity}$ for segment prediction was 85.2% and the recognition $A_{accuracy}$ was 98.4%. The F1 values for recognizing certain lesion morphologies were as follows: 0.829 for stenotic lesion, 0.810 for complete occlusion, 0.802 for calcification, 0.823 for thrombosis, and 0.854 for dissection. The performance metrics associated with the current approaches that are being evaluated are summarized in Table 1.

**Table 1:** Summary of the outcomes achieved by current DL-based approaches.

| Author [Reference] | Year | Dat Collection (No. of patients) | Methodology | Outcomes |
|---|---|---|---|---|
| **Ainiwaer et al., [20]** | **2024** | First Affiliated Hospital of Xinjiang Medical University, China (320) | VGG16 | The AUC for the diagnostic model that included both VGG and DF scores was 0.915, while the AUC for VGG and PTP scores was 0.908. |
| **Ramesh et al., [21]** | **2024** | Kaggle dataset | O-SBGC-LSTM | The $A_{accuracy}$, $R_{recall}$, $F1_{score}$, and $P_{precision}$ of the suggested technique are 98.61%, 97.5%, 96.5%, and 99.2%, respectively. |
| **Bhardwaj et al., [22]** | **2024** | Shimla Medical College (335) | TS-CNN | The $A_{accuracy}$, $R_{recall}$, $F1_{score}$, and $P_{precision}$ of the suggested technique are 97%, 99%, 99%, and 98%, respectively. |
| **Tang et al., [23]** | **2023** | 17679 | CNN | The $A_{accuracy}$, PPV, and NPV for the suggested technique are 70%, 61.2%, and 77.2%, respectively. |
| **Sapra et al., [24]** | **2023** | Medical College Shimla (335) | DNN | Although DNN only managed a 95.2% $A_{accuracy}$ rate, the same |

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| | | | | |
|---|---|---|---|---|
| | | | | model improved to 96.2% when including Gaussian noise. |
| **Wahab et al., [25]** | **2023** | Image and Large-scale dataset | YOLOv7 | In terms of $A_{accuracy}$, $R_{recall}$, $P_{precision}$, $F1_{score}$, MCC, and Kappa, the experimental results reveal that the suggested strategy obtains values of 99.4, 98.5, 98.65, 98.6, 95.35, and 95 on dataset 1, respectively. |
| **Choi et al., [26]** | **2023** | ECG data (1689) | Ob-CAD | A DL model was developed for screening Ob-CAD achieved an $A_{accuracy}$ of 0.638, $Sen_{sitivity}$ of 0.639, $Spe_{cificity}$ of 0.636, and $F1_{score}$ of 0.634. |
| **Du et al., [27]** | **2021** | Fu Wai Hospital, Beijing, China (10,073) | DNN | A total of 98.4% $A_{accuracy}$, 85.2% $Spe_{cificity}$, 99.1% PPV, 76.2% NPV, and 99.5% overall observed for all coronary artery segments. |

### 3.1.1 Comparison of Previous Work

In this comparison work, figure 5 illustrates a comparison between $A_{accuracy}$ and AUC metrics across several studies. The studies listed are by Du et al. (2021), Choi et al. (2023), Wahab et al. (2023), Sapra et al. (2023), Tang et al. (2024), Bhardwaj et al. (2024), Ramesh et al. (2024), and Ainiwaer et al. (2024).

The studies by Du et al. (2021) and Tang et al. (2024) display near perfect $A_{accuracy}$, both approaching 100%, while their AUC values are slightly lower. Choi et al. (2023) and Ainiwaer et al. (2024) show relatively lower AUCs, indicating weaker model performance in those studies, despite high accuracy. The other studies, such as Wahab et al. (2023), Sapra et al. (2023), Bhardwaj et al. (2024), and Ramesh et al. (2024), show balanced and relatively high values for both metrics, indicating strong model performance in terms of both $A_{accuracy}$ and AUC.

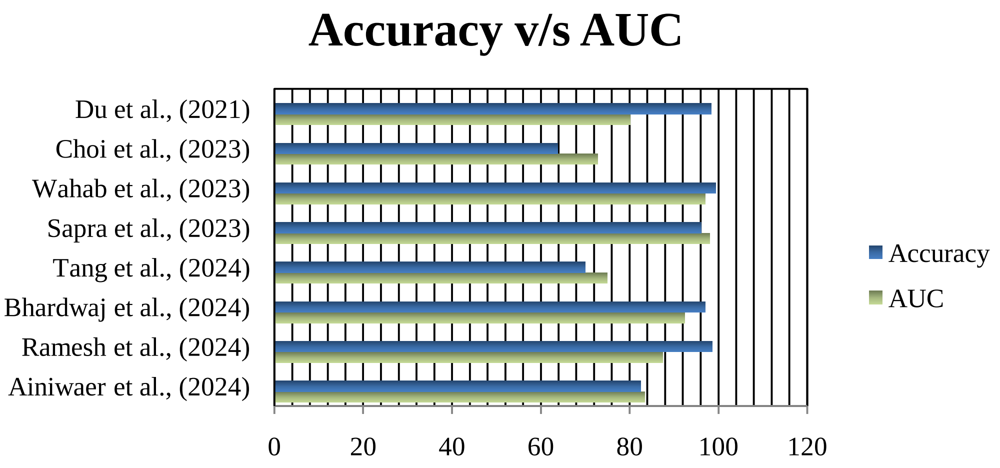


**Figure 5:** Comparison Graph of previous work

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The Figure 6 presents a comparative analysis of several studies from 2021 to 2024 based on $P_{precision}$ , $R_{recall}$ , and $F1_{score}$ . Notably, Du et al. (2021) and Sapra et al. (2023) have the highest $R_{recall}$ and $F1_{score}$ values, while Tang et al. (2024) exhibits a significant difference between $P_{precision}$ and $R_{recall}$ . The studies from 2024, such as Bhardwaj et al., Ramesh et al., and Ainiwaer et al., show closely aligned $P_{precision}$ and $R_{recall}$ values, resulting in strong $F1_{score}$ s.

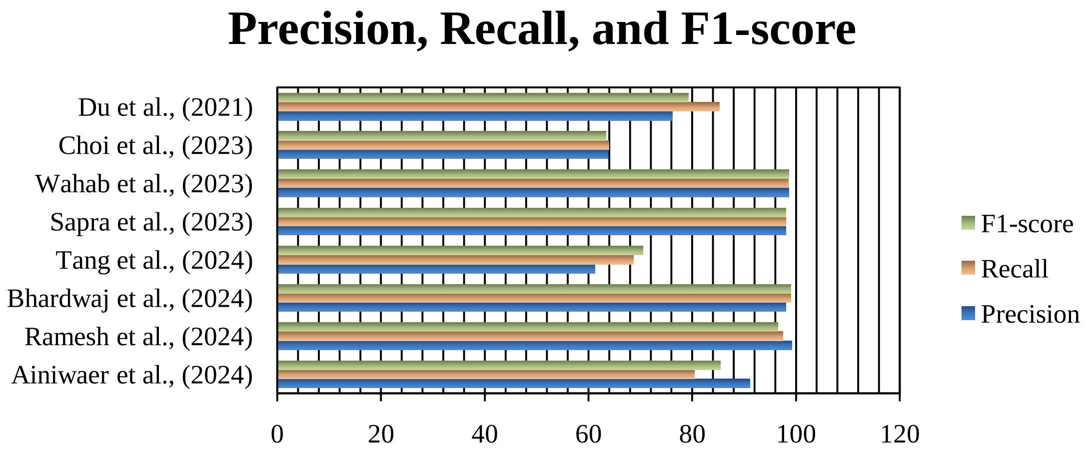


**Figure 6:** Comparison graph of previous Work

### 3.2 Detection of CAD using ML

ML is the primary technology behind artificial intelligence (AI), which encompasses both supervised and unsupervised learning (Figure 7). In particular, the ANN, the Support Vector Machine (SVM), the Decision Tree (DT), the Random Forest (RF), the Naïve Bayes (NB) classifier, and the K-Nearest Neighbor (KNN) method are all examples of supervised learning. The majority of the algorithms that are used in unsupervised learning are clustering algorithms and association rule algorithms.

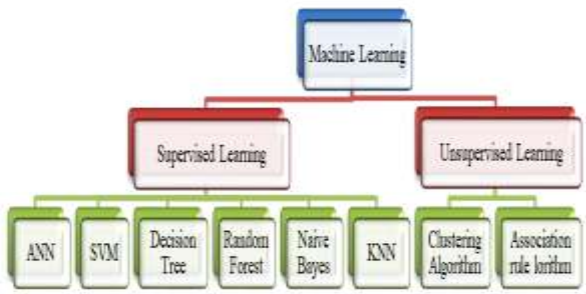


**Figure 7:** The classification of machine learning[28].

An AI model was suggested for determining the risk of diabetes and CHD co-occurrence in research by Ma et al., (2024)**[29]** that examined the risk of CHD in over 300,000 diabetic patients in southwestern China. It tested the prediction abilities of three classic ML techniques: LR, Extreme Gradient Boosting (XG-Boost), and RF. Additionally, they have identified 9 critical characteristics, which include age, WHtR, BMI, stroke, smoking, chronic lung disease, alcohol use, and MSP. Last but not least, the model's AUC on the test samples was 0.701. Patients with hypertension might greatly benefit from an early and precise diagnosis of CHD to decrease the risk and damage associated with hypertension and CHD. So, using ML approaches, they suggest a non-invasive way to detect CHD in its early stages based on aspects of tongue images in their study**[30]**. They used ResNet-50 and a Diagnosis Analysis System (TDAS) to extract characteristics from routine pictures of the tongue. With a $P_{precision}$ of 0.926, an AUC of 0.957, an AUPR of 0.961, a $R_{recall}$ of 0.806, and an

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$F1_{score}$ of 0.862, the findings demonstrated that the XG-Boost model with fused features performed the best.

An essential part of AI, ML makes use of statistical models and algorithms to do data-driven activities like prediction and decision-making. It uses ML methods such as KNN, DT, LR, SVM, NB, Multilayer Perceptron (MLP), and RF to help classify the heart disease dataset, which is used to assess whether a person is suffering from the illness**[31]**. A public dataset with vastly different features, structured from the ML repository at UC Irvine, is available. According to the results, the MLP approach is performing well with an $A_{accuracy}$ of over 88%, while the DT technique is doing poorly with an $A_{accuracy}$ of over 79%.To address the drawbacks of earlier research, **Hammoud et al. (2024)[32]** develop a powerful ML model that could potentially rely on in medical decision-making. A total of 7 ML models—the Gradient Boosting (GB) Classifier, LR, SVM, KNN, RF, DT, and NB—were thoroughly examined for cardiology illness categorization. Using 10-fold cross-validation, the assessment procedure shows that the RF Model superiors the others with an average $A_{accuracy}$ of 92.85%, which is higher than the previously stated 86.9%. The RF's 94.96% $A_{accuracy}$ in cardiac illness diagnosis is confirmed by ensemble-based approaches.

The authors of the research**[33]** build on prior work to create a better ML model that could help in the accurate and rapid diagnosis of cardiac illness. To improve the accuracy of cardiac illness diagnosis, they developed a unique ensemble model that integrates the three best classifiers: RF, XG-Boost, and GB Machine. Researchers made use of a merged dataset on CVD that included 5 separate datasets: the Hungarian, Stat log, Swiss, VA Long Beach, and Cleveland ones. With $Sen_{sitivity}$ at 96.37%, $P_{precision}$ at 94.53%, and $A_{accuracy}$ at 96.17%, the ensemble model clearly outperforms in classification. To use ML techniques to build several stroke risk prediction models for CAD patients undergoing coronary revascularization. Medical Information Mart for Intensive Care IV (MIMIC-IV) cohort study comprised 5757 CAD patients undergoing coronary revascularization who were hospitalized to the Intensive Care Unit (ICU) in study**[34]**. With an AUC of 0.831 on the training set and 0.760 on the testing set, the Cat-boost model demonstrated the top predictive performance. With a training set AUC of 0.789 and a testing set AUC of 0.731, the LR model performed well. The Cat-boost model has a much greater predictive value than the LR model, according to the findings of the Delong test ($P < 0.05$).

**Yilmaz et al. (2022)[35]** evaluated 3 ML algorithms—RF, LR, and SVM—for CHD prediction. The optimization of hyper-parameters was accomplished using a 3-repeats 10-fold repeated cross-validation procedure. CHD was accurately categorized using RF 0.929, SVM 0.897, and LR 0.861 models. With regard to the RF model, the results for $Spe_{cificity}$ , $Sen_{sitivity}$ , $F1_{score}$ , negative predictive, and positive predictive are 0.929, 0.928, 0.929, and 0.928, respectively. In the same way, researchers evaluated the efficacy of several ML algorithms in creating a model for early CAD detection using clinical examination characteristics in**[36]**. They used MLP, SVM, LR, J48, RF, KNN, and NB, among the most important classification algorithms, to create a CAD diagnosis model. The most successful ML models were RF (AUC=0.87, $F1_{score}$ =0.87, ROC=0.91) and SVM (AUC=0.88, $F1_{score}$ =0.88, ROC=0.85), according to the comparative performance metrics. At 0.81 for AUC, 0.81 for F-measure, and 0.77 for ROC, the KNN method was the least efficient of the collection.

The study**[37]** used ML to estimate the chance of CHD by calculating the Coronary Artery Calcification Score (CACS) from CCTA exams and combining it with the parameters that influence Coronary Artery Calcification (CAC). Risk of CHD was evaluated using CACS and clinical-related variables using ML models that included RF, RBFNN, SVM, KNN, and Kernel Ridge Regression (KRR). With a $Sen_{sitivity}$ of 93.86%, $Spe_{cificity}$ of 51.13%, and MCC of 0.5192, RF performs better than the other 4 ML models. Its $A_{accuracy}$ is 59.95%. In comparison to the other 4 ML models, it has the best AUC at 0.8375.To address certain limitations in their previous work, **Devi et al. (2022)[38]** used a variety of ML methods for coronary problem forecasting, such as logistic models, DT, neural networks, and more. The dataset used in this study is the Framingham dataset, which contains 4238 instances and 14 attributes. To handle imbalanced data, the authors employed random over-sampling and SMOTE an optimized model-based technique. For classifications, they used RF, DT, GB, Adaptive boosting, and SVM. The system achieved an apparent $A_{accuracy}$ of 88% for the recursive feature elimination method with the RF model. The performance metrics associated with the current approaches that are being evaluated are summarized in Table 2.

**Table 2:** Summary of the outcomes achieved by current ML-based approaches.

| Author [Reference] | Year | Data Collection (No. of patients) | Methodology | Outcomes |
|---|---|---|---|---|
| **Ma et al., [29]** | 2024 | Southwest China (300,000) | XG-Boost, RF, and LR | The AUC for the suggested model was 0.70. |
| **Duan et al., [30]** | 2024 | — | XG-Boost | The suggested model outperformed the competition with impressive metrics such as an $F1_{score}$ of 0.862, an $A_{accuracy}$ of 0.869, a $P_{precision}$ of 0.926, and an AUC of 0.957. |
| **Mijwil et al., [31]** | 2024 | UC Irvine ML repository (300) | MLP, RF, SVM, KNN, LR, NB and DT | The MLP algorithm reached an $A_{accuracy}$ of over 88%. |
| **Hammoud et al., [32]** | 2024 | 1190 | LR, SVM, KNN, RF, DT, NB, and GB | The RF algorithm achieved the highest $A_{accuracy}$ rates of 89.50% before tuning and 94.96% after tuning. |
| **Asif et al., [33]** | 2024 | Heart disease dataset | RF, GB, and XG-Boost | An examination of the results reveals that the ensemble model attains remarkable results in terms of $Sen_{sitivity}$ (96.37%), $A_{accuracy}$ (94.53%), and $P_{precision}$ (98.37%) in classification. |
| **Lin et al., [34]** | 2024 | MIMIC-IV (5757) | Cat-Boost | The suggested model had the strongest predictive show, with an AUC of 0.760 and a training set of 0.831. |
| **Yilmaz et al., [35]** | 2022 | Heart Disease Dataset (11) | SVM and RF | Based on the calculations, the SVM model's $Spe_{cificity}$ was 0.844, $Sen_{sitivity}$ was 0.971, NPV was 0.887, PPV was 0.976, and $F1_{score}$ was 0.816. |
| **Garavand et al., [36]** | 2022 | Z-Alizadeh Sani dataset (303) | MLP, SVM, LR, J48, RF, KNN, and NB | The most successful ML algorithms were RF (AUC=0.87, $F1_{score}$ =0.87) and SVM (AUC=0.88, $F1_{score}$ =0.88). |
| **Huang et al., [37]** | 2022 | Affiliated Hospital of Traditional Chinese Medicine of Southwest Medical University (2049) | RF, KNN, RBFNN, KRR, and SVM | RF has the highest $A_{accuracy}$ (78.96%), $Sen_{sitivity}$ (93.86%), $Spe_{cificity}$ (51.13%), MCC (0.5192), and ROC (0.8375). |
| **Devi et al., [38]** | 2022 | Framingham dataset (4238) | RF, DT, and SVM | The system appears to have an 88% $A_{accuracy}$ for the recursive feature removal technique using the RF model. |

### 3.2.1 Comparison of Previous Work

Figure 8 presents a horizontal bar chart comparing the AUC and $A_{accuracy}$ metrics for several research studies conducted between 2022 and 2024. Across all the studies, the bars reflect varying degrees of performance on these two metrics. Most of the papers show similar AUC and $A_{accuracy}$ values, which are generally above 60. A

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few studies, particularly Ma et al. (2024) and Duan et al. (2024), display noticeable gaps where the AUC is slightly higher than $A_{accuracy}$ , but for others, such as Asif et al. (2024), the difference is minimal. The values for AUC and $A_{accuracy}$ generally range between 60 and 100 across the studies.

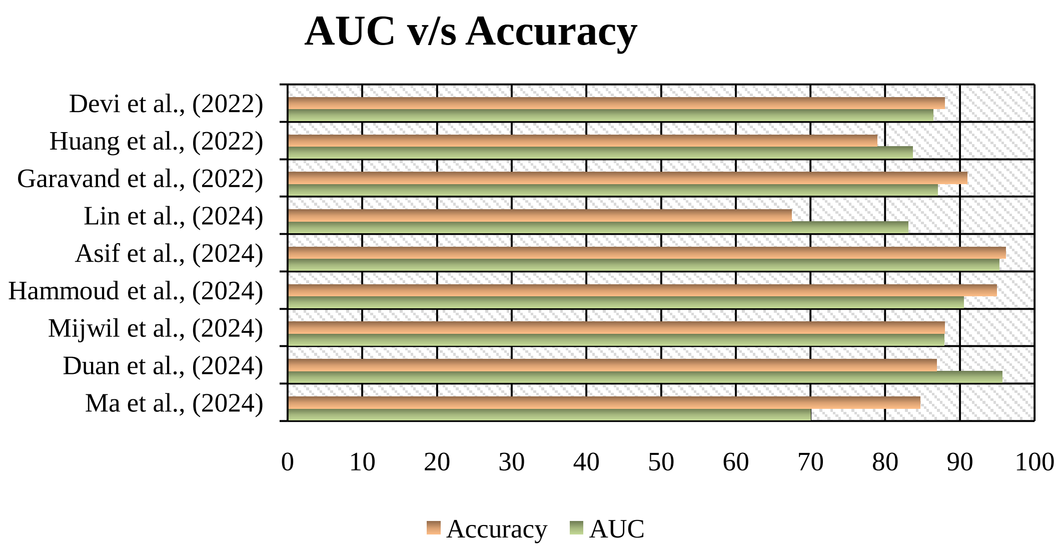


**Figure 8:** Comparison Graph of previous work

The provided figure 9 illustrates the $P_{precision}$ , $R_{recall}$ , and $F1_{score}$ of various studies conducted in the field of ML or information retrieval.Based on the analysis, it appears that Huang et al., (2022) and Garavand et al., (2022) have demonstrated superior performance across all three-evaluation metrics.

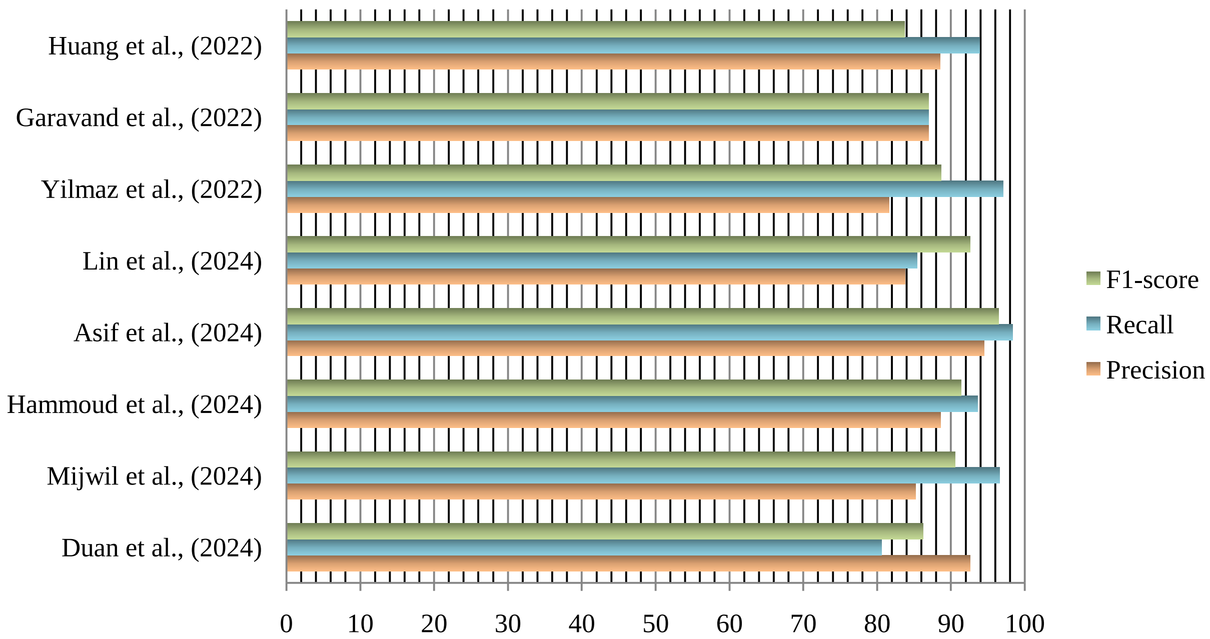


**Figure 9:** Comparison graph of previous Work.

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### 3.3 Datasets Collection and Data Pre-processing

The datasets for the analysis of CAD were collected from various reputable medical databases and research institutions. Sources such as hospital records, publicly available CAD datasets, and research studies on cardiovascular health were considered to ensure a wide representation of patient demographics, clinical history, and diagnostic test results. The raw data included features such as age, gender, cholesterol levels, blood pressure, smoking habits, family history, ECG results, and other relevant medical parameters. Inconsistent, incomplete, or noisy data were handled during the preprocessing phase. Missing values were addressed using imputation techniques like mean substitution or more advanced methods.

Researchers **Algarni et al., (2022)[39]** used a library of XCA images collected from medical records. Problematic features shown by these images were noise, complicated vascular architecture in the backdrop, and inconsistent vessel thickness. Each of the 130 XCA in the collection has a resolution of 300 × 300 pixels. They acquired ethical permission to utilize this medical database for the diagnosis of heartdisease. The data was gathered from the cardiology section of the Mexican Social Security Institute. Angiography images like as color, diameter, and shape formed the basis of the ASCARIS model.

**Al Mehedi et al., (2021)[40]** collected 299 human beings suffering from heart failure from Faisalabad's Allied Hospital and Faisalabad's Institute of Cardiology. Age, ejection fraction, anemia, hypertension, serum creatinine, serum sodium, smoking, diabetes, sex, time, and a binary classification target column called "Death Event" were

among the thirteen attributes that made up the input dataset. To make sure the dataset is consistent and of high quality, it was preprocessed. The dataset was preprocessed and then split into a train set and a test set for the purpose of training and evaluating the model. To determine which characteristics were most useful for the heart failure prediction task, two feature selection approaches were used to the train set.

**Deepika and Seema (2016)[41]**employed datasets made accessible online by the UCI ML Repository to perform research on cardiac illness. They provide the desired characteristic as one of 76 qualities; however, only 14 of those attributes were deemed crucial for the investigation. For this study, the researchers drew on two datasets: one from the Hungarian Institute of Cardiology (including 294 patients' records) and another from the Cleveland Clinic Foundation (including 303 patients' records). To forecast the occurrence of heart disease, the research made use of a range of ML methods, such as NB, SVM, DT, and ANN. Table 3 details the preprocessing techniques and prediction algorithms used in earlier research.

**Table 3:** Preprocessing and predictive methods.

| **Authors [Reference]** | **Year** | **Dataset** | **Preprocessing and Modeling** | **Results** |
|---|---|---|---|---|
| **Algarni et al., [39]** | 2022 | Coronary artery X-ray angiography images obtained from a clinical database | Training:100 images<br>Tes:30images<br>ASCARIS model (based on color, diameter, and shape feature). | $A_{accuracy}$ :97% |
| **Uyar and Ilhan[42]** | 2017 | Cleveland dataset for heart disease | Sorting the diagnostic attribute (num) into two groups: no heart illness (num = 0) and heart illness (num = 1, 2, 3, or 4) and removing six cases with missing entries from the dataset. | Testing set $A_{accuracy}$ :97.78%<br>Overall $A_{accuracy}$ :96.63% |
| **Deng et al.,[43]** | 2018 | Fuwai ECG database and public PTB database | Training a Recursive Fuzzy Neural Network (RFNN) to acquire dynamics and testing it to reuse dynamics Res-Bi-LSTM-Net model optimized for attention. | $F1_{score}$ ranging from 0.72 to 0.98 |

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## IV. CHALLENGES OF THE STUDY

The study on enhancing angiography accuracy for CAD detection using ML can encounter several challenges:

i. **Data Quality and Quantity**: Ensuring they have a large and diverse dataset of angiographic images is crucial. Variability in image quality, resolution, and patient demographics can impact the performance of ML models.
ii. **Data Annotation**: Accurately annotating angiographic images requires expertise. Inconsistent or inaccurate annotations can lead to poor model performance.
iii. **Model Overfitting**: ML models, particularly complex ones, can over fit the train data and achieve poorly on new, unseen data. Proper validation and testing are essential to avoid this issue.
iv. **Feature Selection**: Identifying and selecting the most relevant features for training the model can be challenging, especially when dealing with high-dimensional data.
v. **Interpretability**: ML models, especially DL models, can act as "black boxes." Ensuring that the results are interpretable and clinically relevant is important for acceptance by medical professionals.
vi. **Integration with Clinical Workflows**: An Implementing ML model into existing clinical workflows requires careful consideration of how they would be used by practitioners and integrated with current systems.
vii. **Ethical and Privacy Concerns**: Handling patient data involves strict adherence to privacy regulations and ethical guidelines. Ensuring that the study complies with these standards is essential.
viii. **Generalizability**: Ensuring that the model performs well across different populations and imaging conditions is crucial for its broad applicability.

## V. CONCLUSION

Recognizing CAD at an early stage is essential for optimal care because it continues to be a major cause of death and disability globally. This study explores the integration of ML techniques to enhance the accuracy of angiographic imaging in detecting CAD. Traditional angiography, while widely used, often faces challenges in detecting subtle lesions and variations in coronary arteries. Theysuggested a novel approach leveraging advanced ML algorithms to analyze angiographic images more precisely. The use of angiographic images for CAD detection has now found some success using ML techniques. Still, further research employing standardized image capture methodologies and larger datasets is required to assess how well these methods work. Better patient outcomes could come from the use of these models, which could assist doctors make quicker and more precise diagnoses. Better patient outcomes and quality of life could be achieved via the revolutionary use of ML in medical imaging analysis to improve CAD diagnosis and therapy.

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