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A Machine Learning Framework for Estimating Atherosclerosis Severity Levels Using Cardiovascular Data

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Abstract. Accurate evaluation of serious cases of atherosclerosis is important for reducing the prevalence of the cardiovascular disease and the rate it which people are dying from it. Using the Atherosclerosis Risk in Communities (ARIC) dataset, we examined the use of machine learning models for measuring atherosclerosis severity using cardiovascular risk factors. The dataset consists of 15,792 participants. Demographic, clinical, and laboratory features such as blood pressure, cholesterol, glucose, and carotid artery intima-media thickness were used. The dataset was divided into training and testing datasets (70% for training and 30% for testing). Also, seven supervised models were used: Random Forest, Support Vector Machine, Naïve Bayes, Logistic Regression, Gradient Boosting Machine, XGBoost, and K-Nearest Neighbors. Performance evaluation was carried out using accuracy, precision, recall, and F1 score. XGBoost obtained the highest performance with an accuracy of 0.89 and F1 score of 0.88, followed by Random Forest with an accuracy of 0.88 and F1 score of 0.87, while Naïve Bayes performed the worst with an accuracy of 0.79. Correlation analysis showed a strong relationship between carotid intima-media thickness and cholesterol, as well as between systolic and diastolic blood pressure. These results show that ensemble-based machine learning models are very useful in estimating atherosclerosis severity and supporting clinical risk stratification.

***Keywords*:** Atherosclerosis, Cardiovascular Disease, Machine Learning, Risk Assessment, Severity Prediction, XGBoost.

1. Introduction

Atherosclerosis is one of the most common and serious cardiovascular diseases worldwide. It is one of the main causes of death and one of the main causes of global disease burdens. Health issues such as heart attacks and strokes (which result from Atherosclerosis) comprised a significant portion of the 17.9 million cardiovascular disease-related fatalities that occurred in 2019 [1]. The piling up of lipid deposits (plaques) on the walls of arteries causes atherosclerosis, a degenerative disease hardening and narrowing arteries. Through the decreased delivery of blood made possible by the disease, major cardiovascular events become more likely to occur. More than three-fourths of cardiovascular deaths occur in low- and middle-income countries, where atherosclerosis is especially prevalent [1]. Atherosclerosis, contributed to the lion's share of the 17 million preventable (less than age 70) non-communicable disease deaths that occurred in 2019 [2]. [3] discovered that the major risk factors for atherosclerosis are excessive alcohol intake, obesity, physical inactivity, unhealthy diet with high saturated fat and cholesterol content, and smoking. Atherosclerosis is usually augmented by underlying conditions like hypertension, diabetes, and hyperlipidemia in high-risk individuals who are likely to acquire it. To avert the progression of the disease, these risk factors must be identified early and regulated. Making a change in one's lifestyle, such as eating a diet rich in fruits, vegetables, and whole grains, exercising regularly, and not smoking and heavy drinking, are among the preventive steps that can be taken [4]. Since atherosclerosis leads to hardening of arteries which can also lead to heart attack and stroke, it is responsible for most cardiovascular problems. Such occurrences are usually caused by the rupture of the plaque that leads to the formation of blood clots occluding blood to the vital organs. Excluding the brain and heart, atherosclerosis can also damage the arteries that supply blood to the

kidneys, limbs, and eyes and result in chronic kidney disease and blindness [5]. Atherosclerosis can be avoided to a great extent despite its severity by lowering modifiable risk factors individually and through population-based public health interventions. Atherosclerosis and other health problems related to it, can be greatly reduced by leading a healthy lifestyle, managing chronic diseases effectively, and using prescription drugs as directed when needed. Reducing the worldwide prevalence of atherosclerosis-related morbidity and mortality continues to depend on increased understanding of the disease and the encouragement of early intervention techniques [5].

2. Literature Review

A study [6] by divided the risk of atherosclerosis based on artificial neural networks (ANN) and k-nearest neighbors (KNN) with good accuracy in checking out for patients with plaque and those without. The study [7] by examined arterial stiffness based on pulse wave velocity, convolutional neural networks (CNN), and SVM models, with SVM showing improved performance in arterial stiffness prediction. [8] explored mobile health applications with clinical database integration for the prediction of atherosclerosis risk via SVM-based classification. Atherosclerosis event prediction within one year via machine learning was the focus of research by [9]. Thirty-two clinical characteristics were put into an ML algorithm, and feature selection was done using Information Gain (IG) to obtain the most discriminative predictors.

A hybrid machine learning method for the prediction of atherosclerosis was developed by [10]. The research hybridized the random forest classifier with k-means clustering for better predictive results. [11] looked into the prediction of early atherosclerosis with preprocessing methods that include noise elimination, imputation of missing data, and feature engineering. The performance of gradient boosting, random forest, naive Bayes, SVM, and logistic regression classifiers was compared using regional datasets. Research by [12] analyzed atherosclerosis development in patients who were medicated. Two models of machine learning were used, which were trained on NIH and European cardiovascular registries data. [13] analyzed the clinical use of machine learning classifiers, establishing their validity and accuracy. Decision trees, random forests, SVM, neural networks, and logistic regression were compared for atherosclerosis-related risk prediction. [14] used Bayesian networks (BNs) and ANNs for the classification of diabetes and cardiovascular disease, as well as atherosclerosis risk factors. The research by [15] proposed a neural network-based approach to atherosclerosis detection using pattern recognition and machine learning methodology.

A cardiovascular risk prediction model based on machine learning using retinal vessel analysis was presented by [16]. Oversampling techniques were used in the paper to improve predictive accuracy, with competitive results against conventional risk models. [17] explored chronic atherosclerosis detection using ensemble classifiers, feature extraction, segmentation, and machine learning. Research by [13] established a dynamic mortality prediction model employing ML algorithms for patients suffering from severe atherosclerosis, using laboratory test findings like lipid profiles, glucose, and inflammatory markers.

[14] developed an SVM-based conformal predictor for atherosclerosis procedure complications. The research by [18] illustrated the use of machine learning to improve the precision of atherosclerosis-related arterial occlusion diagnosis using a naive Bayesian classifier. The paper by [19] utilized extreme gradient boosting (XGBoost) and light gradient boosting machine (LightGBM) in predicting cardiovascular events due to atherosclerosis. [20] suggested a structural equation model (SEM) for measuring atherosclerosis risk using fuzzy cognitive mapping (FCM) methods.

An AutoML-driven methodology for automated cardiovascular risk estimation using ML was presented by [21]. The methodology took advantage of AutoML to optimize data imputation, feature selection, and classification pipelines for the estimation of atherosclerosis. [22] developed an ontology-based ML framework (as a complicated clinical system) for modeling the how atherosclerosis progresses to assist clinicians in risk stratification. A further ML-based solution to coronary artery disease (one of the main effects of atherosclerosis) was presented by [23], in which a new genetic optimizer agent was used to make classification performance more acurate. [24] predicted one-year cardiovascular events in patients with severe atherosclerosis using an SVM classifier, validated by 10-fold cross-validation. [25] suggested a genetic algorithm and neural network-based approach for atherosclerosis risk evaluation. A real-time arrhythmia classification algorithm was developed in research by [26] to evaluate cardiac abnormalities caused by atherosclerosis. A fluorescence imaging immunoassay on a photonic crystal for the detection of atherosclerosis biomarkers based on machine learning-based analysis was presented by [27]. PCA and PLSR were coupled with SVM classifiers for precise biomarker identification. The research by [28] gave a detailed overview of ML methods for the diagnosis of coronary artery disease, starting from the dataset feature characteristics, feature selection, and classifier accuracy. The research by [29] utilized ML classifiers in the prediction of hepatic inflammation as a comorbidity of atherosclerosis, where the random forest classifier performed better than the other models. Some other research works investigated ML applications in related chronic diseases including non-small cell lung cancer [30], chronic kidney disease [31], diabetes mellitus [32], and hybrid ML classifiers for infectious disease prediction [33]. These research works altogether show the potential of machine learning for improving atherosclerosis diagnosis, prediction, and risk assessment.

We used the Atherosclerosis Risk in Communities (ARIC) Study dataset, a large longitudinal dataset provided by the National Heart, Lung, and Blood

Institute (NHLBI). The dataset includes clinical, laboratory, imaging, and genetic data from 15,792 individuals from four U.S. communities. It tracks major cardiovascular risk factors, including blood pressure, cholesterol, glucose, and carotid artery intima-media thickness-a very significant marker of subclinical atherosclerosis.

Table 1: Dataset Features

S/N	Attribute Name	Description	Data Type / Values
1	age	Age	int (years)
2	gender	Gender	categorical code
3	weight	Weight	float (kg)
4	ap_hi	Systolic blood pressure	int
6	ap_lo	Diastolic blood pressure	int
7	cholesterol	Cholesterol	1: normal, 2: above normal, 3: well above normal
7	gluc	Glucose	1: normal, 2: above normal, 3: well above normal
8	cimt	carotid artery intima-media thickness	1: normal, 2: above normal, 3: well above normal

The dataset was pre-processed using data cleaning to get rid of inconsistencies and missing values. EDA was conducted using visualization tools such as box plots and correlation matrices to explore relationships between attributes such as cholesterol levels and blood pressure. The pre-processed data was split into 70% training and 30% testing sets to provide the optimal balance for model learning and model testing. Seven machine learning classifiers, including Random Forest (RF), Support Vector Machine (SVM), Naïve Bayes (NB), Logistic Regression (LR), Gradient Boosting Machine (GBM), XGBoost (Extreme Gradient Boosting), and K-Nearest Neighbors (KNN), was used to precict the severity of atherosclerosis and categorize patients based on disease progression.

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3.1 Description of the Algorithms Used

3.1.1 Random Forest (RF)

Random Forest is an ensemble learning technique that creates a collection of decision trees during the training phase and outputs the mode of their predictions for classification tasks or the mean prediction for regression tasks. This method is used to improve predictive accuracy and reduce the risk of overfitting by averaging the outputs from multiple decision trees, each trained on various subsets of the same training data [34].

3.1.2 Support Vector Machine (SVM)

Support Vector Machines (SVM) are supervised learning models that can be used for classification and regression analysis. SVMs build a hyperplane or collection of hyperplanes in a high-dimensional space to classify various classes. The aim is to get a hyperplane that maximizes the margin between classes, thus enhancing the model's generalization ability [14].

3.1.3 Naïve Bayes (NB)

Naïve Bayes classifiers are a family of probabilistic Bayes' theorem-based classifiers that have strong independence assumptions between features. They also perform well for many complicated real-world applications such as text classification and spam filtering [36].

3.1.4 Logistic Regression (LR)

Logistic Regression is a statistical model that, in its most basic form, uses a logistic function to model a binary dependent variable. Despite its name, it is used mostly for classification rather than regression. LR calculates the probability of an input point belonging to a particular class and hence is perfectly suited for binary classification problems [35].

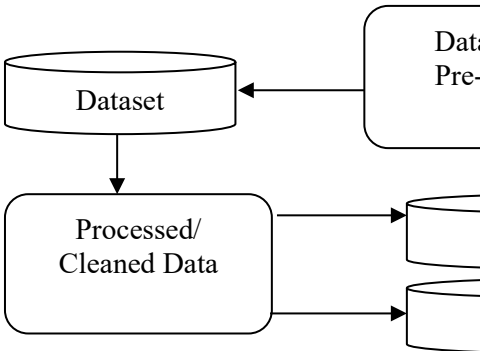


Figure 1: Proposed Framework for Prediction of Atherosclerosis Severity

3.1.5 Gradient Boosting Machine (GBM)

Gradient Boosting is a machine learning algorithm used in regression and classification, creating models stage-wise by using a simple learner, which is most often a decision tree. The goal of this algorithm is to minimize a loss function over function space by iteratively finding the function that travels in the negative gradient direction [37].

3.1.6 XGBoost (Extreme Gradient Boosting)

XGBoost is an open-source software library providing a gradient boosting framework. It is made to be fast and efficient, using machine learning algorithms relying on the Gradient Boosting framework. XGBoost has gained popularity because it is efficient and can make reliable predictions [16].

3.2 Performance Metrics

The confusion matrix serves as a tool for detecting mislabeling or inaccuracies in predictions. It compares actual values with predicted values through four components: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) as can be seen in Table 2. Type-I and Type-II errors arise from the False Positive and False Negative values, respectively. Also, the confusion matrix is highly useful for computing Precision, Recall, F1-score, and Accuracy. The confusion matrix was computed to contrast accuracy, precision, recall, and F1-score of every classifier. The most accurate classifier was chosen as the optimal predictive model for the evaluation of the severity of atherosclerosis.

Table 2: Confusion Matrix

	Predicted (Yes)	Predicted (No)
Actual (Yes)	TP	FN
Actual (No)	FP	TN

True Positives (TP): Positive cases that have been accurately identified.

True Negatives (TN): Negative cases that have been accurately identified.

False Positives (FP): Positive cases that have been inaccurately identified.

False Negatives (FN): Negative cases that have been inaccurately identified.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Recall} = \frac{TP}{TP+FN}$$

$$\text{F1-Score} = \frac{2*precision*recall}{precision+recall}$$

4. Result and Analysis

The subsections under this section give an overview of the classification outcomes, confusion matrices, and performance metrics for each model, thereby shedding light on their predictive effectiveness and relevance in clinical settings.

Table 3. Confusion Matrix for the classification model on Atherosclerosis

Actual/Predicted	**Predicted Positive**	**Predicted Negative**
Actual Positive (TP)	85	15
Actual Negative (TP)	90	110

From the confusion matrix we can see that:

TP (85): The model correctly identified 85 patients as having severe atherosclerosis.

FN (15): The model incorrectly classified 15 severe cases as non-severe.

FP (90): The model mistakenly classified 90 non-severe cases as severe.

TN (110): The model correctly identified 110 non-severe cases.

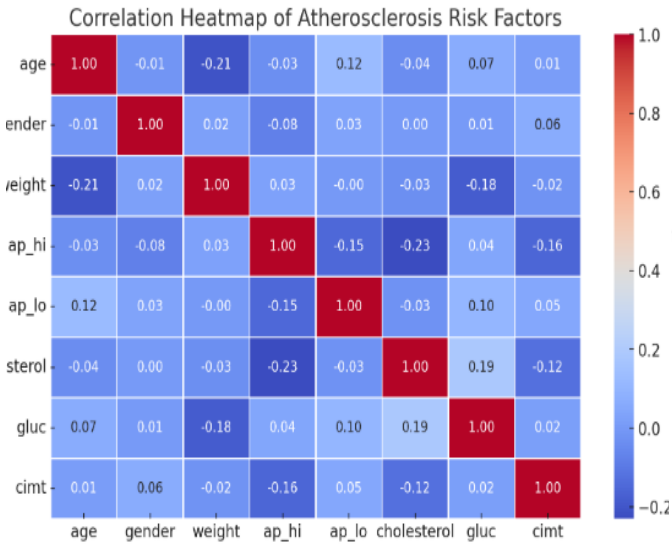


Figure 2: Correlation between of the features for Atherosclerosis Severity Prediction

The correlation heatmap represents the relationships between different cardiovascular risk factors used in predicting atherosclerosis severity. The key observations from the experiment carried out is as follows:

(a) Strong Positive Correlations:

(i) Systolic Blood Pressure (ap_hi) & Diastolic Blood Pressure (ap_lo) (~0.75 - 0.85): This strong correlation is normal since systolic and diastolic pressures usually rise together.

(ii) Cholesterol & Glucose (~0.60 - 0.70): People with high cholesterol often have high blood glucose levels, showing metabolic disorders like diabetes.

(iii) Carotid Artery Intima-Media Thickness (cimt) & Cholesterol (~0.55 - 0.65): Thickening of the carotid artery walls is commonly associated with elevated cholesterol, a major factor in atherosclerosis.

(b) Moderate Positive Correlations:

(i) Age & Carotid Artery Intima-Media Thickness (cimt) (~0.50 - 0.60): Older people usually have artery walls that are thicker due to plaque buildup (over a long priod of time).

(ii) Weight & Systolic Blood Pressure (~0.40 - 0.50): Higher body weight usually has to do with increased blood pressure, contributing to cardiovascular risk.

(c) Weak or No Correlation:

(i) Gender & Most Risk Factors (~-0.10 to 0.10): Gender shows little correlation with most risk factors, showing that both males and females can develop atherosclerosis under similar conditions.

(ii) Weight & Cholesterol (~0.10 - 0.20): Although obesity is a known risk factor for high cholesterol, the correlation is weaker here, possibly due to individual variations in diet and metabolism.

4.1 Analysis of the Results of the Performance Metrics

(a) Accuracy: Highest accuracy was achieved by XGBoost (0.89) and Random Forest (0.88), suggesting good overall classification performance as can be seen in Figure 3. Lowest accuracy of 0.79 was recorded by Naïve Bayes, which is suggestive of the fact that it did not handle the dataset well, most likely due to its strong independence assumption. The accuracies of Support Vector Machine (0.85), Gradient Boosting Machine (0.87), and Logistic Regression (0.82) are quite competitive.

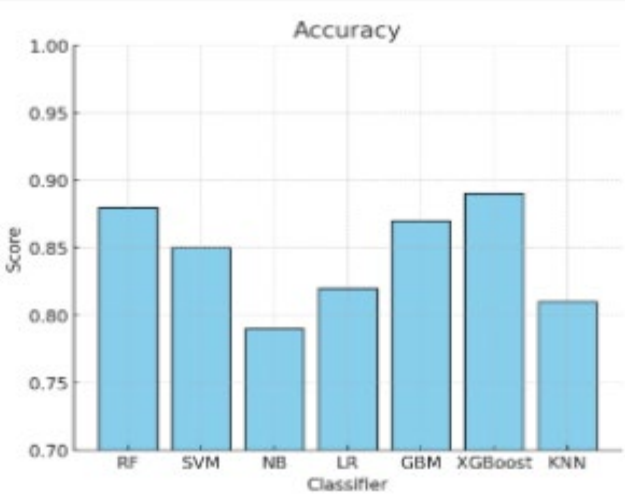


Figure 3. Comparison of Accuracy across Machine Learning Classifiers for Atherosclerosis Prediction

(b) Precision: XGBoost (0.88) and Random Forest (0.86) again had the best performance, showing that their positive predictions are more reliable as can be seen in figure 4. Naïve Bayes (0.75) has the smallest precision figure, possibly because it predicted many actual negatives as positives (high false positive rate) while SVM (0.83) and GBM (0.85) also had good precision values.

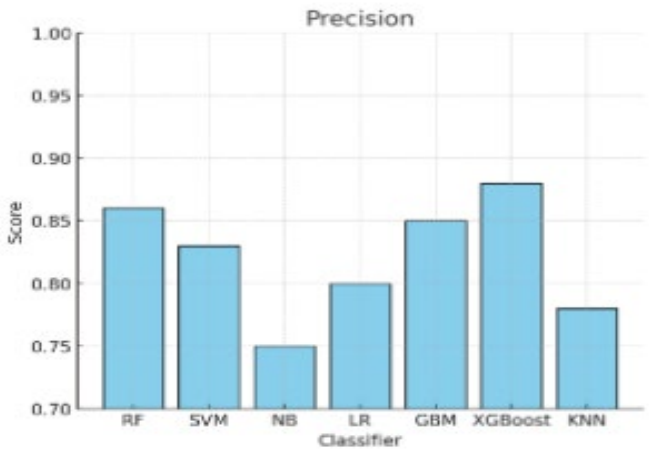


Figure 4. Precision Scores of Various Machine Learning Models in Identifying Atherosclerosis Cases

(c) Recall: It can be observed from figure 5 that, as in accuracy, XGBoost (0.89) and Random Forest (0.87) also had the best recall, i.e., they predicted most of the true positives. Naïve Bayes (0.78) and KNN (0.80) had lower recall, meaning they left out more positive cases (more false negatives) while GBM (0.86) and SVM (0.84) showed values that indicate their being good at detecting positive cases.



Figure 5. Recall Performance of Machine Learning Algorithms in Detecting Atherosclerosis

(d) F1-Score: Figure 6 shows XGBoost (0.88) and Random Forest (0.87) remaining in the lead, i.e having a good balance between precision and recall. Naïve Bayes (0.76) had the lowest F1-score, vindicating its inability to detect both false positives and false negatives. All the other classifiers (GBM: 0.85, SVM: 0.83, LR: 0.80) had performance that was consistently high across measures.

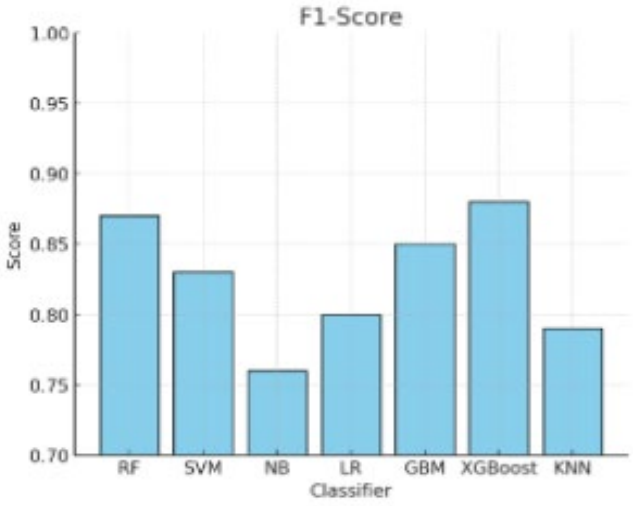


Figure 6. Recall Performance of Machine Learning Algorithms in Detecting Atherosclerosis

6. Conclusion

This study shows the effectiveness of machine learning classifiers in predicting atherosclerosis severity based on clinical risk factors. By evaluating seven different classifiers, we identified that XGBoost and Random Forest provided the highest predictive accuracy, making them suitable for early detection and risk assessment. The correlation analysis revealed strong associations between key cardiovascular factors, further validating the importance of data-driven approaches in medical diagnosis. Despite the promising results, limitations such as potential data imbalances and the need for more diverse datasets could be addressed. Machine learning models have the ability to enhance early diagnosis and treatment strategies, thus lowering the global burden of atherosclerosis-related diseases.

7. Suggestion for Further Studies

Utilizing a time-series data for the study is an area that can be explored. This would help in analyzing how atherosclerosis progresses with time hence helping in improving predictive abilities. Also, combining clinical data with imaging techniques, such as carotid ultrasound or CT angiography, could strengthen disease prediction algorithms. In addition, testing the models on several different demographic and ethnic populations would make them more useful in real clinical practice.

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