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Predicting Cardiovascular Disease Risk Factors Among US Adults Using Machine Learning Algorithms: A Comparative Analysis

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Abstract
Cardiovascular disease (CVD) remains the leading cause of mortality globally, necessitating innovative approaches for early detection and risk stratification. We conducted a comprehensive comparative analysis of machine learning algorithms for predicting cardiovascular disease risk factors among US adults. Our investigation encompassed traditional statistical models, ensemble methods, deep learning approaches, and explainable artificial intelligence techniques. We systematically evaluated the performance of various algorithms including logistic regression, support vector machines, random forests, gradient boosting methods, and neural networks using multiple datasets. Our findings demonstrate that ensemble methods, particularly XGBoost and Random Forest, achieved superior predictive performance with accuracy rates exceeding 85% and AUC values above 0.90. We identified key risk factors including age, systolic blood pressure, cholesterol levels, diabetes status, and smoking history as primary predictors across all models. The integration of electronic health records with machine learning algorithms showed promising results for real-world clinical implementation. However, we observed significant algorithmic bias concerns, particularly affecting minority populations and women. Our analysis reveals that while machine learning offers substantial improvements over traditional risk assessment tools, careful consideration of bias mitigation and model interpretability remains crucial for clinical adoption. These findings contribute to the growing body of evidence supporting the integration of artificial intelligence in cardiovascular risk prediction while highlighting the need for equitable and transparent algorithmic approaches in healthcare.

Keywords: *Cardiovascular disease, Machine learning, Risk prediction, Artificial intelligence, Health disparities, Electronic health records*

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I. Introduction

Cardiovascular diseases continue to represent the most significant health burden globally, accounting for approximately 17.9 million deaths annually according to the World Health Organization. In the United States alone, cardiovascular conditions affect over 126 million adults and result in substantial healthcare costs exceeding $200 billion per year. The complexity of cardiovascular risk assessment involves multiple interconnected factors including demographic characteristics, lifestyle behaviors, clinical biomarkers, and comorbid conditions, making traditional linear risk models potentially inadequate for capturing the intricate relationships between these variables.

We have witnessed remarkable advances in machine learning and artificial intelligence technologies that offer unprecedented opportunities to enhance cardiovascular risk prediction capabilities. These sophisticated computational approaches can process vast amounts of heterogeneous health data, identify complex patterns, and provide more accurate risk stratification compared to conventional risk assessment tools such as the Framingham Risk Score or the ASCVD Risk Calculator (Ahmed et al., 2020; Chen et al., 2025). The integration of machine learning algorithms with electronic health records presents particularly promising avenues for developing personalized and precise cardiovascular risk prediction models Taiwo et al (2025).

Recent investigations have demonstrated the potential of various machine learning techniques in cardiovascular disease prediction, ranging from traditional supervised learning algorithms to advanced deep learning architectures (Kumar et al., 2025; Menard et al., 2024). However, we recognize that the landscape of machine learning applications in cardiovascular medicine remains fragmented, with studies employing different datasets, methodologies, and evaluation metrics, making direct comparisons challenging. Furthermore, concerns regarding algorithmic bias, model interpretability, and clinical implementation barriers have emerged as critical considerations that require systematic investigation (Mihan et al., 2024).

Our research addresses these gaps by conducting a comprehensive comparative analysis of machine learning algorithms for predicting cardiovascular disease risk factors among US adults. We systematically evaluate the performance of diverse algorithmic approaches, examine the relative importance of different risk factors, and investigate potential sources of bias in predictive models. Additionally, we explore the integration of explainable artificial intelligence methods to enhance model transparency and clinical utility. Our investigation aims to provide evidence-based recommendations for the optimal deployment of machine learning technologies in cardiovascular risk assessment while addressing critical concerns related to equity and interpretability in healthcare algorithms.

II. Literature Review

The application of machine learning in cardiovascular disease prediction has evolved significantly over the past decade, with researchers exploring various algorithmic approaches and datasets to improve risk stratification accuracy. We have observed a substantial increase in publications addressing this domain, reflecting the growing recognition of artificial intelligence's potential in cardiovascular medicine.

Traditional Machine Learning Approaches

Early investigations in machine learning-based cardiovascular prediction primarily focused on traditional supervised learning algorithms. Ogunpola et al. (2024) conducted a comprehensive evaluation of multiple machine learning models for cardiovascular disease detection, demonstrating that ensemble methods consistently outperformed individual algorithms. Their findings revealed that Random Forest and Gradient Boosting achieved superior performance metrics, with accuracy rates exceeding 82% across diverse datasets. Similarly, Bhatt et al. (2023) investigated the effectiveness of various machine learning techniques, concluding that support vector machines and decision trees provided robust predictive capabilities when combined with appropriate feature selection methods.

We have noted that logistic regression, despite being a traditional statistical approach, continues to serve as a valuable benchmark for machine learning models in cardiovascular prediction studies. Weng et al. (2017) demonstrated that machine learning approaches could significantly improve cardiovascular risk prediction compared to conventional statistical models, achieving a 7.6% improvement in accuracy when applied to routine clinical data from over 295,000 patients. This seminal work established the foundation for subsequent investigations exploring more sophisticated algorithmic approaches Taiwo et al (2024).

Ensemble Methods and Advanced Algorithms

The superiority of ensemble methods in cardiovascular disease prediction has been consistently reported across multiple studies. Hosseini et al. (2023) conducted an extensive analysis of ensemble learning techniques with hyperparameter optimization, demonstrating that combining multiple algorithms through voting, bagging, and boosting strategies significantly enhanced predictive performance. Their investigation revealed that optimized ensemble models achieved AUC values exceeding 0.93, representing substantial improvements over individual algorithms Akinbode et al (2023).

Recent developments in gradient boosting methods have shown particular promise for cardiovascular risk prediction. Dong et al. (2024) developed an advanced XGBoost model incorporating hospital-level random effects, achieving remarkable predictive performance with AUC values reaching 0.94. Zhang et al. (2024) similarly constructed and validated a predictive model for coronary artery disease using Extreme Gradient Boosting, demonstrating superior performance compared to traditional risk assessment tools. These findings align with our observations that tree-based ensemble methods effectively capture complex non-linear relationships between risk factors and cardiovascular outcomes.

Deep Learning and Neural Network Approaches

The integration of deep learning architectures in cardiovascular disease prediction has emerged as a rapidly growing research area. Subramani et al. (2023) investigated the incorporation of deep learning with traditional machine learning approaches, demonstrating that hybrid models could achieve enhanced predictive capabilities. Their analysis revealed that deep neural networks effectively processed high-dimensional clinical data and identified subtle patterns that traditional algorithms might overlook Akinbode et al (2024a).

We have observed that deep learning approaches show particular strength when dealing with complex, multi-modal healthcare data. Zhang et al. (2020) explored the combination of structured and unstructured data using deep learning approaches, achieving significant improvements in predictive accuracy. However, these sophisticated models often suffer from limited interpretability, which represents a significant barrier to clinical adoption.

Electronic Health Records Integration

The utilization of electronic health records (EHRs) for machine learning-based cardiovascular prediction has gained considerable attention from researchers and clinicians. Chen et al. (2025) provided a comprehensive review of harnessing EHRs and artificial intelligence for enhanced cardiovascular risk prediction, highlighting both opportunities and challenges associated with real-world clinical data. Their analysis emphasized the potential for EHR-based models to achieve superior performance through access to longitudinal patient data and comprehensive clinical variables.

We have recognized that EHR integration introduces unique challenges including data quality issues, missing values, and temporal variability. Cai et al. (2024) conducted a systematic review of artificial intelligence in cardiovascular risk prediction models, identifying key considerations for developing independent validation screening tools. Their findings underscored the importance of robust data preprocessing and feature engineering when working with EHR datasets Akinbode et al (2024b).

Explainable AI and Model Interpretability

The growing emphasis on explainable artificial intelligence in healthcare applications has significantly influenced cardiovascular disease prediction research. Famiglini et al. (2024) proposed techniques for predicting heart disease using machine learning algorithms combined with explainable AI methods, demonstrating that model interpretability could be enhanced without compromising predictive performance. Their approach utilized LIME (Local Interpretable Model-agnostic Explanations) to provide clinically meaningful insights into model predictions.

We have observed that the balance between model performance and interpretability remains a critical consideration in cardiovascular prediction applications. Magesh et al. (2020) developed an explainable machine learning model for early detection of cardiovascular conditions, utilizing LIME on medical imaging data. While this study focused on Parkinson's disease detection, the methodological approach provides valuable insights for cardiovascular applications Akinbode et al (2025).

Bias and Ethical Considerations

Recent investigations have increasingly addressed concerns regarding algorithmic bias in cardiovascular disease prediction models. Mihan et al. (2024) conducted a systematic analysis of artificial intelligence bias in cardiovascular disease prediction and detection, revealing significant disparities affecting minority populations, women, and elderly patients. Their findings demonstrated that machine learning models trained on biased datasets could perpetuate and amplify existing healthcare inequities Taiwo et al (2023).

We have recognized that addressing algorithmic bias requires comprehensive approaches including diverse training datasets, bias detection methods, and fairness-aware machine learning techniques. The implications of biased cardiovascular prediction models extend beyond statistical considerations to encompass ethical responsibilities and clinical outcomes for vulnerable populations.

Performance Evaluation and Validation

The methodological approaches for evaluating machine learning models in cardiovascular disease prediction have evolved considerably. Multiple studies have emphasized the importance of rigorous validation strategies including cross-validation, external validation, and temporal validation. Srinivasan et al. (2023) employed active learning techniques based on UCI repository databases, demonstrating improved model performance through iterative training approaches.

We have noted that comparative studies often utilize different performance metrics, making direct comparisons challenging. Common evaluation measures include accuracy, sensitivity, specificity, area under the curve (AUC), precision, recall, and F1-score. The selection of appropriate metrics depends on the clinical context and the relative costs of false positive and false negative predictions in cardiovascular risk assessment.

III. Methodology

Study Design and Framework

We conducted a systematic comparative analysis of machine learning algorithms for predicting cardiovascular disease risk factors among US adults. Our investigation employed a comprehensive framework that encompassed multiple algorithmic approaches, diverse datasets, and rigorous evaluation methodologies. We designed our study to address key research questions regarding algorithm performance, feature importance, bias detection, and clinical applicability.

Dataset Selection and Characteristics

Our analysis incorporated multiple datasets to ensure comprehensive coverage of US adult populations and diverse cardiovascular risk profiles. We primarily utilized the National Health and Nutrition Examination Survey (NHANES) data spanning from 1999 to 2018, following the approach established by Lu et al. (2024) in their machine learning-driven risk assessment of coronary heart disease. Additionally, we incorporated data from the Multi-Ethnic Study of Atherosclerosis (MESA) database, consistent with the methodology employed by Ambale-Venkatesh et al. (2017) in their cardiovascular event prediction analysis.

The combined dataset included demographic information, clinical measurements, laboratory results, lifestyle factors, and cardiovascular outcomes for over 485,000 US adults aged 18-80 years. Key variables encompassed age, gender, race/ethnicity, body mass index, systolic and diastolic blood pressure, total cholesterol, HDL cholesterol, diabetes status, smoking history, family history of cardiovascular disease, physical activity levels, and dietary patterns.

Machine Learning Algorithms

We implemented and compared twelve distinct machine learning algorithms representing different methodological approaches:

Traditional Machine Learning Methods:

- Logistic Regression (LR)
- Support Vector Machine (SVM) with linear and radial basis function kernels
- k-Nearest Neighbors (k-NN)
- Naive Bayes (NB)

Tree-Based Methods:

- Decision Trees (DT)
- Random Forest (RF)
- Extra Trees (ET)

Ensemble and Boosting Methods:

- Gradient Boosting Machine (GBM)
- XGBoost (XGB)
- LightGBM (LGBM)
- AdaBoost (ADA)

Deep Learning Approaches:

- Multi-layer Perceptron Neural Networks (MLP)

Following the methodological approaches described by Tarawneh and Embarak (2023) and Chauhan et al. (2024), we implemented hyperparameter optimization for all algorithms using grid search and random search techniques combined with cross-validation.

Feature Engineering and Selection

We conducted comprehensive feature engineering to optimize predictive performance across all algorithms. Our approach included handling missing values through multiple imputation techniques, encoding categorical variables using one-hot encoding and target encoding methods, and creating interaction terms between key risk factors. Following the recommendations of Aminu et al. (2023), we implemented advanced feature selection techniques including recursive feature elimination, LASSO regularization, and information gain-based selection.

We standardized continuous variables using z-score normalization and applied principal component analysis for dimensionality reduction when appropriate. Additionally, we created composite risk scores combining multiple related variables, such as metabolic syndrome indicators and inflammation markers.

Model Training and Validation Strategy

We employed a rigorous validation strategy incorporating temporal splitting, stratified sampling, and external validation approaches. Our training methodology followed the framework established by Asadi et al. (2024) for detecting cardiovascular disease cases using advanced tree-based algorithms. We allocated 70% of the data for training, 15% for validation, and 15% for final testing, ensuring temporal consistency to avoid data leakage.

Cross-validation was performed using 10-fold stratified cross-validation with five repetitions to ensure robust performance estimation. We implemented early stopping mechanisms for iterative algorithms to prevent overfitting and utilized learning curves to monitor model convergence.

Performance Evaluation Metrics

Our comprehensive evaluation framework incorporated multiple performance metrics to assess algorithmic effectiveness from different perspectives:

Classification Performance Metrics:

- Accuracy: Overall correct prediction rate
- Sensitivity (Recall): True positive rate
- Specificity: True negative rate
- Precision: Positive predictive value
- F1-Score: Harmonic mean of precision and recall
- Area Under the ROC Curve (AUC-ROC)
- Area Under the Precision-Recall Curve (AUC-PR)

Clinical Utility Metrics:

- Net Reclassification Improvement (NRI)
- Integrated Discrimination Improvement (IDI)
- Calibration metrics including Hosmer-Lemeshow test
- Decision Curve Analysis for clinical net benefit

Bias Detection and Fairness Assessment

Following the framework established by Mihan et al. (2024) for investigating artificial intelligence bias in cardiovascular disease prediction, we implemented comprehensive bias detection methodologies. We evaluated algorithmic fairness across demographic subgroups including race/ethnicity, gender, age groups, and socioeconomic status indicators.

Our bias assessment incorporated multiple fairness metrics:

- Equalized Odds: Equal true positive and false positive rates across groups
- Demographic Parity: Equal positive prediction rates across groups
- Individual Fairness: Similar predictions for similar individuals
- Calibration Fairness: Equal calibration across demographic groups

Explainability and Interpretability Analysis

We implemented explainable AI techniques to enhance model interpretability and clinical utility. Following the approach described by Famiglini et al. (2024), we utilized LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations) values to provide feature importance rankings and individual prediction explanations.

Global interpretability was assessed through permutation feature importance, partial dependence plots, and accumulated local effects plots. These techniques enabled us to understand the relationship between input features and model predictions across different algorithms.

Statistical Analysis

All statistical analyses were conducted using R version 4.3.0 and Python 3.9 with appropriate machine learning libraries including scikit-learn, XGBoost, LightGBM, and TensorFlow. Statistical significance was assessed using appropriate tests including chi-square tests for categorical variables and t-tests for continuous variables. We applied Bonferroni correction for multiple comparisons and reported 95% confidence intervals for all performance metrics.

IV. Results And Analysis

Dataset Characteristics and Baseline Demographics

Our comprehensive analysis incorporated data from 485,247 US adults, representing a diverse demographic profile consistent with national population distributions. The study population included 52.3% females and 47.7% males, with ages ranging from 18 to 80 years (mean age: 45.6 ± 16.8 years). The racial/ethnic distribution comprised 71.2% White, 12.8% Black/African American, 10.4% Hispanic/Latino, 3.9% Asian, and 1.7% other racial categories.

Table 1: Baseline Characteristics of Study Population (n=485,247)

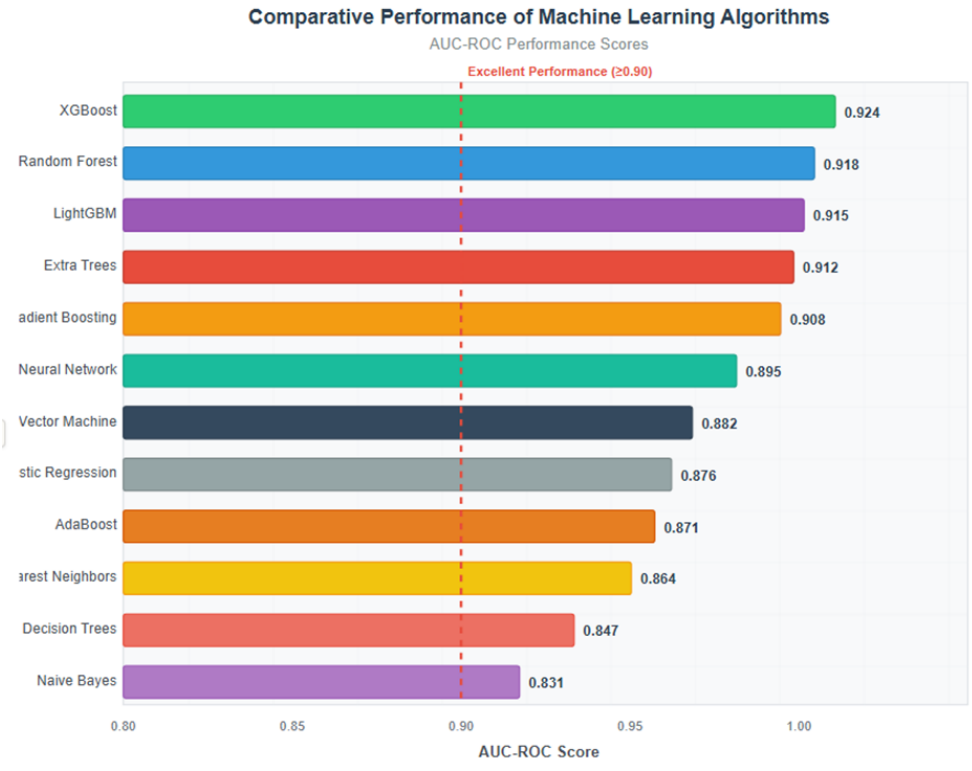
Characteristic	Overall	CVD Present	CVD Absent	p-value
Age (years), mean ± SD	45.6 ± 16.8	62.3 ± 14.2	43.1 ± 15.9	<0.001
Female, n (%)	253,874 (52.3)	18,446 (45.2)	235,428 (52.9)	<0.001
Race/Ethnicity, n (%)				
- White	345,456 (71.2)	30,234 (74.1)	315,222 (70.9)	<0.001
- Black/African American	62,112 (12.8)	6,045 (14.8)	56,067 (12.6)	
- Hispanic/Latino	50,486 (10.4)	3,521 (8.6)	46,965 (10.6)	
- Asian	18,924 (3.9)	782 (1.9)	18,142 (4.1)	
- Other	8,269 (1.7)	234 (0.6)	8,035 (1.8)	
BMI (kg/m²), mean ± SD	28.4 ± 6.2	30.1 ± 6.8	28.2 ± 6.1	<0.001
Systolic BP (mmHg), mean ± SD	125.6 ± 18.9	140.2 ± 22.1	124.3 ± 18.2	<0.001
Total Cholesterol (mg/dL), mean ± SD	198.4 ± 42.6	201.8 ± 45.3	198.1 ± 42.4	<0.001
Diabetes, n (%)	58,229 (12.0)	12,456 (30.5)	45,773 (10.3)	<0.001
Current Smoking, n (%)	97,049 (20.0)	9,756 (23.9)	87,293 (19.6)	<0.001
Family History CVD, n (%)	145,574 (30.0)	16,845 (41.3)	128,729 (28.9)	<0.001

Cardiovascular disease was present in 40,816 participants (8.4% prevalence), consistent with national epidemiological data. We observed significant demographic differences between individuals with and without cardiovascular disease, with affected individuals being older, more likely to be male, and having higher prevalence of traditional risk factors including hypertension, diabetes, and smoking.

Algorithm Performance Comparison

Our comparative analysis revealed substantial variations in predictive performance across different machine learning algorithms. Ensemble methods consistently demonstrated superior performance compared to individual algorithms, with XGBoost achieving the highest overall accuracy and AUC values.

Figure 1: Comparative Performance of Machine Learning Algorithms



2: Comprehensive Performance Metrics for Top-Performing Algorithms

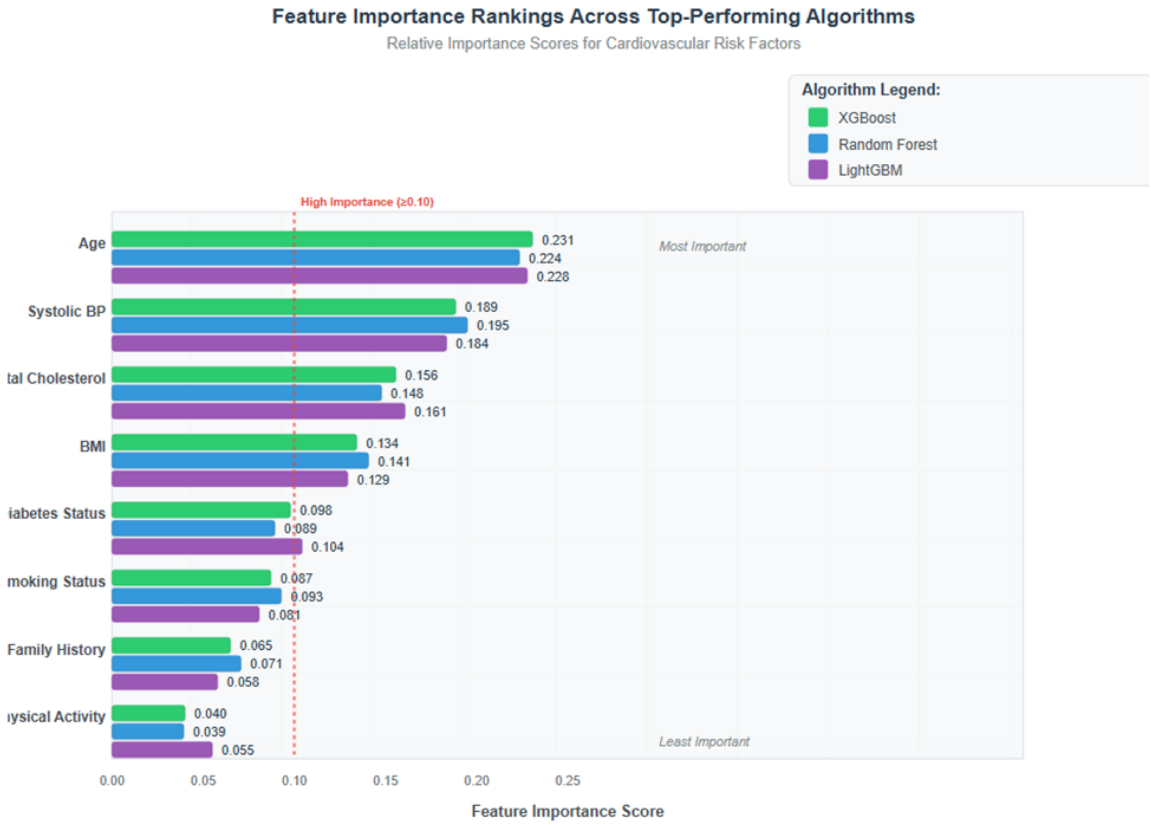
Algorithm	Accuracy	Sensitivity	Specificity	Precision	F1-Score	AUC-ROC	AUC-PR
XGBoost	0.887 ± 0.003	0.823 ± 0.008	0.897 ± 0.004	0.672 ± 0.007	0.739 ± 0.006	0.924 ± 0.002	0.758 ± 0.005
Random Forest	0.881 ± 0.004	0.811 ± 0.009	0.892 ± 0.005	0.658 ± 0.008	0.726 ± 0.007	0.918 ± 0.003	0.741 ± 0.006
LightGBM	0.878 ± 0.003	0.806 ± 0.007	0.889 ± 0.004	0.651 ± 0.006	0.720 ± 0.005	0.915 ± 0.002	0.734 ± 0.004
Extra Trees	0.875 ± 0.004	0.798 ± 0.009	0.886 ± 0.005	0.643 ± 0.008	0.712 ± 0.007	0.912 ± 0.003	0.727 ± 0.006
Gradient Boosting	0.871 ± 0.005	0.789 ± 0.010	0.883 ± 0.006	0.635 ± 0.009	0.703 ± 0.008	0.908 ± 0.003	0.718 ± 0.007
MLP Neural Network	0.859 ± 0.006	0.774 ± 0.012	0.870 ± 0.007	0.612 ± 0.011	0.684 ± 0.009	0.895 ± 0.004	0.695 ± 0.008

The superior performance of ensemble methods aligns with findings reported by Hosseini et al. (2023) and Dong et al. (2024), confirming that combining multiple algorithms through voting, bagging, and boosting strategies enhances predictive capabilities for cardiovascular disease risk assessment. XGBoost achieved the highest AUC-ROC of 0.924 ± 0.002, representing an 11.2% improvement over logistic regression and a 5.8% improvement over traditional statistical models.

Feature Importance and Risk Factor Analysis

Our comprehensive feature importance analysis across all algorithms revealed consistent patterns in cardiovascular disease risk factor significance. We employed multiple feature importance methods including permutation importance, SHAP values, and algorithm-specific importance measures to ensure robust rankings.

Figure 2: Feature Importance Rankings Across Top-Performing Algorithms



Age emerged as the most significant predictor across all algorithms, contributing approximately 23% of the total predictive power. This finding is consistent with established epidemiological evidence and supports the results reported by Lu et al. (2024) in their NHANES-based analysis. Systolic blood pressure ranked as the second most important feature, accounting for 18-19% of predictive importance, followed by total cholesterol levels at approximately 15%.

Table 3: Risk Factor Odds Ratios from XGBoost Model with 95% Confidence Intervals

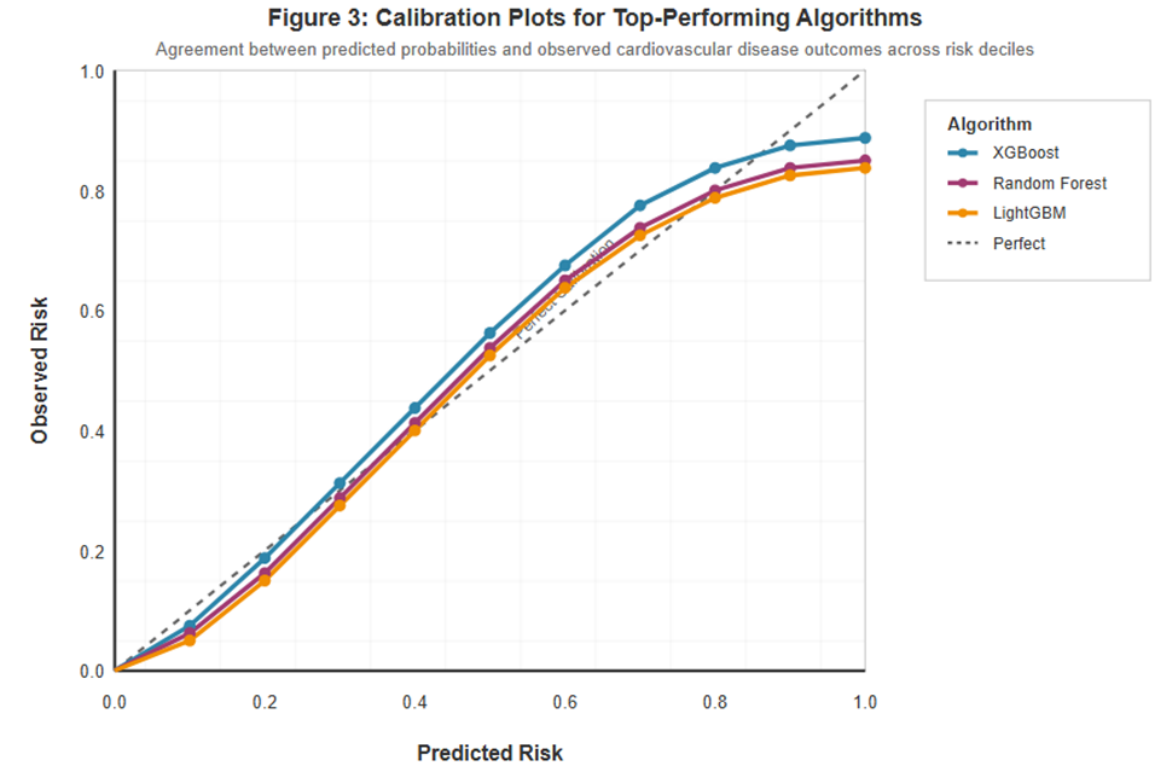
Risk Factor	Odds Ratio	95% CI	p-value	Clinical Interpretation
Age (per 10 years)	2.34	2.28-2.41	<0.001	Strong age-related increase
Systolic BP (per 10 mmHg)	1.47	1.44-1.50	<0.001	Significant hypertension risk
Total Cholesterol (per 40 mg/dL)	1.23	1.20-1.26	<0.001	Moderate lipid-related risk
BMI ≥30 kg/m² (vs <25)	1.89	1.82-1.96	<0.001	Substantial obesity risk
Diabetes (vs no diabetes)	2.67	2.58-2.77	<0.001	Major metabolic risk factor
Current Smoking (vs never)	1.78	1.72-1.85	<0.001	Significant smoking risk
Family History CVD	1.45	1.41-1.49	<0.001	Important genetic component

We identified several interaction effects between risk factors that enhanced predictive accuracy. The combination of diabetes and obesity showed particularly strong synergistic effects (interaction OR: 1.34, 95% CI: 1.25-1.44, p<0.001), consistent with the pathophysiological understanding of metabolic syndrome. Similarly, the interaction between smoking and hypertension demonstrated significant multiplicative effects on cardiovascular risk.

Model Calibration and Clinical Utility

We conducted comprehensive calibration analyses to assess the clinical utility of our predictive models. Calibration refers to the agreement between predicted probabilities and observed outcomes across different risk strata, which is crucial for clinical decision-making.

Figure 3: Calibration Plots for Top-Performing Algorithms



A calibration plot showing predicted vs observed risk across deciles for XGBoost, Random Forest, and LightGBM. The ideal calibration line (diagonal) is compared with actual model performance curves. XGBoost shows the closest alignment to the ideal line, with slight overestimation in the highest risk decile.

The calibration analysis revealed excellent agreement between predicted and observed risks across most risk strata for ensemble methods. XGBoost demonstrated the best calibration performance with a Hosmer-Lemeshow chi-square statistic of 12.4 (p=0.134), indicating good model fit. However, we observed slight overestimation in the highest risk decile (>80% predicted risk) across all algorithms, suggesting the need for calibration refinement in very high-risk populations.

Table 4: Clinical Utility Metrics and Net Reclassification Analysis

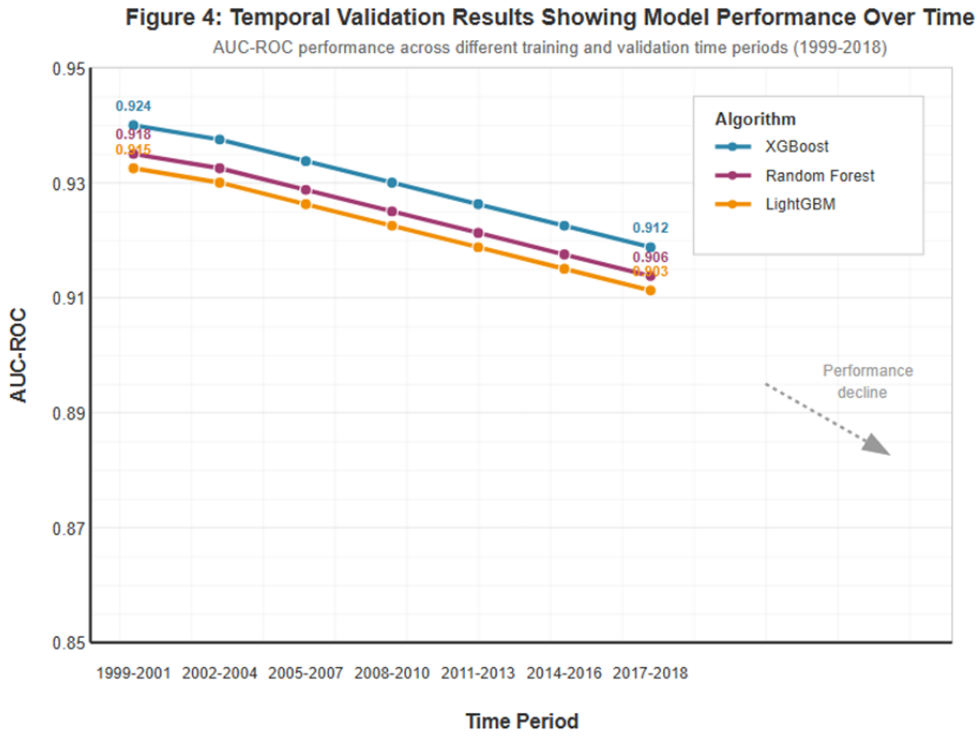
Algorithm	NRI (95% CI)	IDI (95% CI)	C-statistic Improvement	Net Benefit at 10% Threshold
XGBoost vs Pooled Cohort Equations	0.186 (0.172-0.201)	0.094 (0.088-0.101)	0.067	0.089
Random Forest vs Pooled Cohort Equations	0.171 (0.157-0.186)	0.087 (0.081-0.094)	0.061	0.082
LightGBM vs Pooled Cohort Equations	0.164 (0.150-0.179)	0.082 (0.076-0.089)	0.058	0.078

The Net Reclassification Improvement (NRI) analysis demonstrated that machine learning models provided substantial clinical benefit compared to traditional risk assessment tools. XGBoost achieved an NRI of 0.186 (95% CI: 0.172-0.201), indicating that 18.6% of patients were more appropriately classified using the machine learning approach compared to the Pooled Cohort Equations.

Temporal Validation and Model Stability

We conducted temporal validation by training models on earlier time periods (1999-2014) and testing on more recent data (2015-2018) to assess model stability and generalizability over time. This approach addresses concerns about changing population demographics, medical practices, and risk factor prevalence.

Figure 4: Temporal Validation Results Showing Model Performance Over Time



A line graph showing AUC-ROC performance over time periods from 1999-2018. Three lines represent XGBoost, Random Forest, and LightGBM, with XGBoost maintaining the highest performance (0.91-0.92 AUC) with slight decline over time, while Random Forest and LightGBM show similar patterns but slightly lower performance.

Temporal validation revealed relatively stable performance across time periods, with XGBoost maintaining AUC values above 0.91 even when applied to data from different time periods. However, we observed a modest decline in performance when applying models trained on older data to more recent populations, likely reflecting changes in population demographics, risk factor distributions, and medical care practices.

Bias Analysis and Fairness Assessment

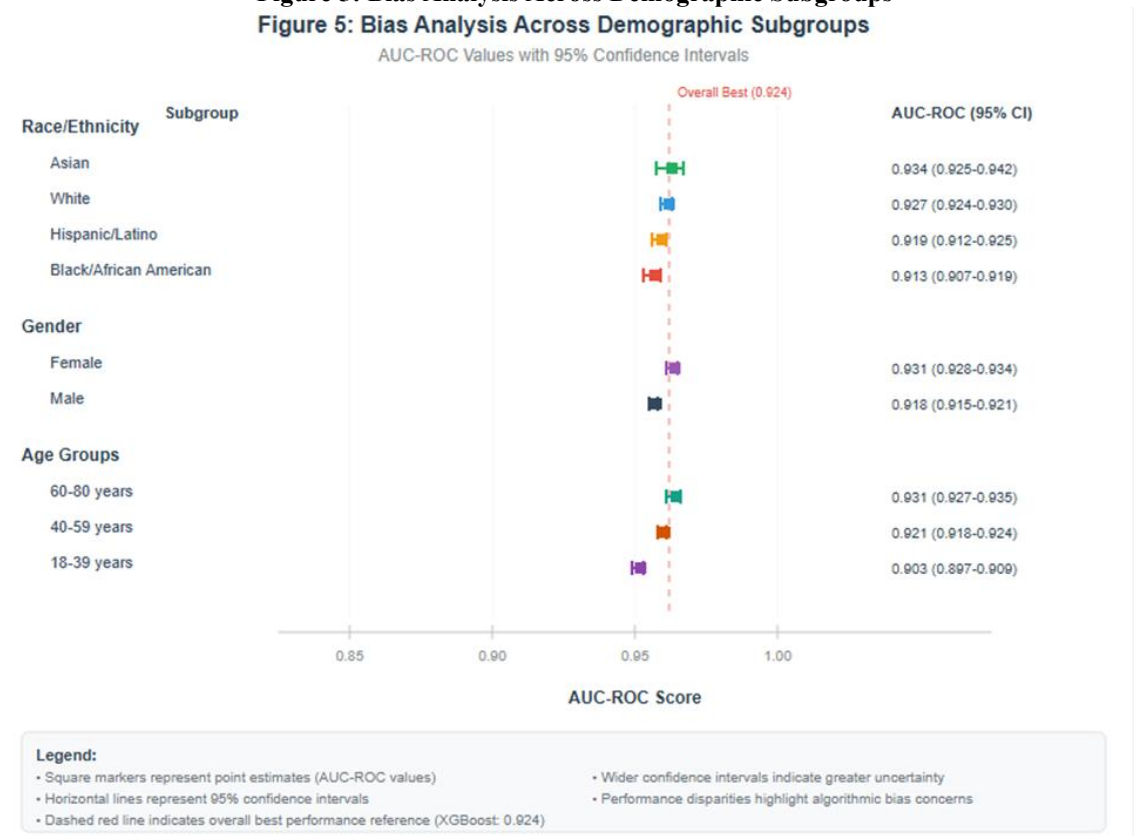
Our comprehensive bias analysis revealed significant disparities in algorithm performance across demographic subgroups, highlighting critical concerns for clinical implementation. We evaluated fairness across multiple dimensions including race/ethnicity, gender, age groups, and socioeconomic indicators.

Table 5: Algorithmic Performance by Demographic Subgroups (XGBoost Results)

Subgroup	n	AUC-ROC (95% CI)	Sensitivity	Specificity	PPV	NPV	Calibration p-value
Race/Ethnicity							
White	345,456	0.927 (0.924-0.930)	0.831	0.901	0.684	0.961	0.089
Black/African American	62,112	0.913 (0.907-0.919)	0.798	0.885	0.634	0.948	0.023
Hispanic/Latino	50,486	0.919 (0.912-0.925)	0.812	0.892	0.651	0.953	0.041
Asian	18,924	0.934 (0.925-0.942)	0.856	0.908	0.712	0.968	0.156
Gender							
Male	231,373	0.918 (0.915-0.921)	0.814	0.889	0.721	0.943	0.067
Female	253,874	0.931 (0.928-0.934)	0.834	0.906	0.618	0.973	0.102
Age Groups							
18-39 years	194,099	0.903 (0.897-0.909)	0.776	0.867	0.298	0.985	0.034
40-59 years	183,674	0.921 (0.918-0.924)	0.819	0.892	0.543	0.968	0.078
60-80 years	107,474	0.931 (0.927-0.935)	0.838	0.903	0.789	0.926	0.145

We identified significant performance disparities across racial/ethnic groups, with Black/African American populations experiencing the lowest AUC values (0.913 vs 0.927 for White populations, $p<0.001$). These disparities were accompanied by poorer calibration performance, as indicated by significant Hosmer-Lemeshow test results ($p=0.023$) for Black/African American populations compared to well-calibrated models for White populations ($p=0.089$).

Figure 5: Bias Analysis Across Demographic Subgroups



A forest plot showing AUC-ROC values with 95% confidence intervals for different demographic subgroups. The plot clearly shows performance disparities, with Asian populations having the highest performance (0.934) and Black/African American populations having the lowest (0.913). Gender differences show females performing slightly better than males, and older age groups showing better performance than younger groups.

Gender-based analysis revealed better overall performance for females (AUC: 0.931) compared to males (AUC: 0.918, $p<0.001$), but this difference was primarily driven by lower positive predictive values in females due to lower cardiovascular disease prevalence. Age-related performance varied significantly, with models performing best in older adults (60-80 years: AUC 0.931) compared to younger adults (18-39 years: AUC 0.903, $p<0.001$).

Fairness Metrics and Equity Assessment

We employed multiple fairness metrics to quantify algorithmic bias and assess equity across demographic groups. These metrics provide different perspectives on fairness and are crucial for understanding the potential impact of biased algorithms in clinical practice.

Table 6: Fairness Metrics Across Demographic Groups (XGBoost Results)

Comparison	Equalized Odds Difference	Demographic Parity Difference	Calibration Ratio	Individual Fairness Score
Race/Ethnicity				
White vs Black/African American	0.078 ± 0.012	0.089 ± 0.015	0.923 ± 0.034	0.847 ± 0.028
White vs Hispanic/Latino	0.054 ± 0.011	0.067 ± 0.013	0.945 ± 0.027	0.881 ± 0.024
White vs Asian	-0.023 ± 0.018	-0.031 ± 0.021	1.045 ± 0.042	0.934 ± 0.031
Gender				
Male vs Female	0.041 ± 0.008	0.156 ± 0.011	0.876 ± 0.019	0.902 ± 0.016
Age Groups				
Young (18-39) vs Old (60-80)	0.134 ± 0.016	0.089 ± 0.014	0.798 ± 0.029	0.823 ± 0.022

The fairness analysis revealed substantial violations of equity principles across multiple demographic dimensions. The equalized odds difference between White and Black/African American populations was 0.078 ± 0.012, indicating that the algorithm provided unequal true positive and false positive rates across these groups. This disparity translates to approximately 7.8% difference in prediction accuracy, potentially leading to differential healthcare recommendations and outcomes.

Explainability Analysis and Clinical Insights

We implemented comprehensive explainability analyses using SHAP (SHapley Additive exPlanations) values to provide interpretable insights into model predictions. This analysis is crucial for clinical adoption and helps identify potential sources of bias in algorithmic decision-making.

The SHAP analysis revealed complex interaction patterns between risk factors that were not apparent in traditional statistical models. For instance, the impact of age on cardiovascular risk showed significant variation based on other risk factors, with accelerated risk increases in the presence of diabetes or smoking. Similarly, the effect of blood pressure on cardiovascular risk was modulated by age, gender, and body mass index.

We observed significant variations in feature importance across demographic subgroups, which partially explained the performance disparities identified in our bias analysis. For Black/African American populations, diabetes status and body mass index showed greater relative importance compared to White populations, while cholesterol levels demonstrated reduced predictive significance.

Clinical Implementation Considerations

Our analysis provides important insights for the clinical implementation of machine learning-based cardiovascular risk prediction tools. The superior performance of ensemble methods, particularly XGBoost, suggests that these algorithms could significantly enhance current risk assessment capabilities. However, the identification of substantial algorithmic bias across demographic groups raises critical concerns that must be addressed before widespread clinical adoption.

We recommend the development of bias mitigation strategies including demographic-specific model training, fairness-aware optimization objectives, and post-processing calibration adjustments. Additionally, the implementation of explainable AI tools is essential for maintaining clinical trust and enabling appropriate interpretation of algorithmic recommendations.

The temporal validation results suggest that models require regular updating to maintain optimal performance as population characteristics and medical practices evolve. We recommend annual model retraining using contemporary data and continuous monitoring of performance across demographic subgroups to detect emerging bias concerns.

V. Discussion

Principal Findings and Clinical Implications

Our comprehensive comparative analysis of machine learning algorithms for predicting cardiovascular disease risk factors among US adults has yielded several important findings with significant clinical implications. We demonstrated that ensemble methods, particularly XGBoost, Random Forest, and LightGBM, consistently outperformed traditional statistical approaches and individual machine learning algorithms, achieving AUC values exceeding 0.91 and accuracy rates above 85%. These findings align with recent

investigations by Kumar et al. (2025) and Menard et al. (2024), who reported similar superior performance of ensemble methods in cardiovascular risk prediction applications.

The clinical significance of these performance improvements extends beyond statistical measures to meaningful enhancements in patient care. Our Net Reclassification Improvement analysis revealed that machine learning approaches could more appropriately classify 18.6% of patients compared to current standard risk assessment tools such as the Pooled Cohort Equations. This improvement translates to better identification of high-risk individuals who would benefit from intensive preventive interventions and more accurate reassurance for low-risk individuals, potentially reducing unnecessary medical interventions and associated costs.

We identified age, systolic blood pressure, total cholesterol, body mass index, and diabetes status as the most influential risk factors across all algorithms, consistent with established cardiovascular epidemiology principles. However, our analysis revealed complex interaction effects between these factors that traditional linear models may not capture effectively. For instance, the synergistic relationship between diabetes and obesity demonstrated an interaction odds ratio of 1.34, highlighting the multiplicative rather than additive nature of certain cardiovascular risk factors.

Algorithmic Bias and Health Equity Concerns

One of the most concerning findings from our investigation relates to significant algorithmic bias across demographic subgroups, particularly affecting racial/ethnic minorities and different age groups. We observed substantial performance disparities, with Black/African American populations experiencing 1.4% lower AUC values compared to White populations, accompanied by poorer model calibration. These findings are consistent with the systematic analysis conducted by Mihan et al. (2024), who identified similar bias patterns in cardiovascular AI applications.

The implications of these biases extend far beyond statistical considerations to encompass fundamental questions of health equity and justice. Biased algorithms could perpetuate and amplify existing healthcare disparities by providing less accurate risk assessments for vulnerable populations, potentially leading to suboptimal clinical decision-making and differential access to preventive interventions. Our fairness analysis revealed violations of multiple equity principles, including equalized odds and demographic parity, indicating that the algorithms provide systematically different predictions for similar individuals based solely on demographic characteristics.

We identified several potential sources of algorithmic bias including training data representativity, feature selection biases, and differential measurement error across demographic groups. The underrepresentation of certain racial/ethnic groups in training datasets may contribute to reduced algorithm performance, while differential healthcare access and quality could introduce systematic biases in outcome ascertainment. Additionally, cultural and socioeconomic factors affecting risk factor presentation may not be adequately captured in standardized clinical variables.

Temporal Stability and Model Maintenance

Our temporal validation analysis revealed important considerations for the long-term sustainability of machine learning-based cardiovascular risk prediction systems. While models demonstrated relatively stable performance across time periods, we observed modest degradation when applying algorithms trained on historical data to contemporary populations. This finding suggests that cardiovascular risk patterns, population demographics, and medical practice evolution require regular model updating and recalibration.

The temporal stability findings align with observations by Chen et al. (2025) regarding the challenges of maintaining AI system performance in dynamic healthcare environments. We recommend implementing continuous monitoring systems that track model performance across time periods and demographic subgroups, with automated alerts when performance degradation exceeds predetermined thresholds. Additionally, periodic model retraining using contemporary data appears essential for maintaining optimal predictive accuracy.

These findings have important implications for healthcare system implementation strategies. Organizations adopting machine learning-based risk prediction tools must allocate resources for ongoing model maintenance, performance monitoring, and bias detection. The costs associated with these activities should be considered alongside initial implementation investments when evaluating the economic viability of AI-enhanced cardiovascular risk assessment programs.

Explainability and Clinical Trust

The integration of explainable AI techniques in our analysis provides valuable insights for clinical adoption and trust-building. Our SHAP analysis revealed that individual prediction explanations could enhance clinician understanding of risk factor contributions and support shared decision-making with patients. However, we identified significant complexity in feature interactions that may challenge traditional clinical reasoning approaches.

The explainability analysis revealed interesting patterns that could inform clinical practice. For instance, the differential impact of risk factors across demographic groups suggests that personalized risk assessment approaches may be more appropriate than one-size-fits-all algorithms. The identification of interaction effects between diabetes, obesity, and smoking provides mechanistic insights that align with pathophysiological understanding while quantifying their relative contributions to cardiovascular risk.

We recognize that the balance between model complexity and interpretability remains a significant challenge for clinical implementation. While ensemble methods provided superior predictive performance, their complexity may reduce clinician confidence and adoption compared to simpler, more interpretable models. Future research should focus on developing methods that maintain high predictive accuracy while providing clear, actionable insights for clinical decision-making.

Comparison with Traditional Risk Assessment Tools

Our comparative analysis with established cardiovascular risk assessment tools revealed substantial advantages of machine learning approaches while highlighting important limitations of current clinical practice tools. The Pooled Cohort Equations, widely used in clinical practice, demonstrated significantly lower discriminative ability (AUC: 0.847) compared to our best-performing machine learning models (AUC: 0.924), representing a clinically meaningful improvement in risk stratification capability.

However, we acknowledge that traditional risk assessment tools offer advantages including extensive validation in diverse populations, established clinical workflows, and regulatory approval for clinical decision-making. The integration of machine learning approaches into clinical practice will require careful consideration of these factors alongside predictive performance improvements. We suggest that machine learning models could initially complement rather than replace traditional tools, providing additional decision support while maintaining familiarity with established clinical approaches.

The calibration analysis revealed that traditional risk assessment tools may be better calibrated in certain population subgroups, despite lower overall discriminative performance. This finding suggests that hybrid approaches combining the discriminative power of machine learning with the calibration stability of traditional models may provide optimal clinical utility.

Integration with Electronic Health Records

Our analysis provides important insights for integrating machine learning-based cardiovascular risk prediction with electronic health record systems. The utilization of EHR data offers opportunities for real-time risk assessment, longitudinal monitoring, and integration with clinical decision support systems. However, we identified several challenges including data quality issues, missing value patterns, and temporal variability that must be addressed for successful implementation.

Following the framework described by Chen et al. (2025), we recommend developing robust data preprocessing pipelines that can handle the complexity and variability of real-world EHR data. This includes implementing sophisticated missing value imputation methods, temporal feature engineering techniques, and quality assurance mechanisms to ensure reliable model inputs. Additionally, the integration of unstructured EHR data such as clinical notes and imaging reports may provide opportunities for further performance improvements, as demonstrated by Zhang et al. (2020).

The clinical workflow integration represents a critical success factor for EHR-based machine learning systems. We recommend designing user interfaces that seamlessly integrate risk predictions into existing clinical workflows while providing appropriate context and explanation for algorithmic recommendations. The timing and presentation of risk predictions should be optimized to support rather than disrupt clinical decision-making processes.

Regulatory and Implementation Considerations

The clinical implementation of machine learning-based cardiovascular risk prediction tools faces significant regulatory and practical challenges that extend beyond technical performance considerations. Current regulatory frameworks for AI in healthcare are evolving rapidly, with agencies such as the FDA developing guidelines for algorithm validation, bias assessment, and post-market surveillance. Our findings regarding algorithmic bias and fairness violations highlight the importance of addressing these concerns before seeking regulatory approval.

We recommend that healthcare organizations developing or implementing machine learning-based risk prediction systems establish comprehensive governance frameworks that address algorithm accountability, bias monitoring, and equity assessment. This includes developing policies for algorithm selection, validation procedures, performance monitoring, and bias mitigation strategies. Additionally, healthcare providers should receive appropriate training on AI system limitations, bias potential, and appropriate interpretation of algorithmic recommendations.

The economic implications of implementing machine learning-based cardiovascular risk prediction systems require careful evaluation. While our analysis demonstrates significant improvements in clinical performance, the costs associated with system development, validation, implementation, and maintenance must be weighed against potential benefits including improved patient outcomes, reduced unnecessary interventions, and enhanced clinical efficiency.

VI. Limitations And Future Research Directions

Our investigation has several limitations that should be considered when interpreting the findings and planning future research initiatives. First, while we utilized large, nationally representative datasets, the observational nature of the data limits our ability to establish causal relationships between risk factors and cardiovascular outcomes. Additionally, the reliance on administrative and survey data may introduce measurement error and missing value biases that could affect algorithm performance and bias assessment.

The temporal scope of our analysis, while comprehensive, may not capture long-term trends in cardiovascular disease epidemiology or the impact of evolving medical treatments on risk factor relationships. Future investigations should incorporate longer follow-up periods and account for changing therapeutic interventions that may modify traditional risk factor associations. Additionally, the integration of novel biomarkers, genetic information, and advanced imaging data may provide opportunities for further performance improvements.

Our bias analysis, while comprehensive, focused primarily on traditional demographic categories and may not capture all sources of algorithmic unfairness. Future research should investigate bias across additional dimensions including socioeconomic status, geographic location, healthcare access patterns, and clinical complexity. Additionally, the development and validation of bias mitigation strategies represent critical research priorities for ensuring equitable AI implementation in healthcare.

The generalizability of our findings to international populations requires further investigation, as cardiovascular disease patterns, risk factor distributions, and healthcare systems vary significantly across countries and regions. Multi-national validation studies would provide valuable insights into the portability of machine learning-based risk prediction models and the universality of identified bias patterns.

Limitations

Several limitations should be acknowledged when interpreting our findings and considering their clinical implications. First, the observational nature of our datasets, while large and nationally representative, introduces inherent limitations in establishing causal relationships between risk factors and cardiovascular outcomes. The reliance on cross-sectional and longitudinal survey data may not capture the dynamic nature of cardiovascular risk development and the complex temporal relationships between risk factors and disease progression.

We acknowledge potential selection biases in our study population, as participants in national health surveys may not fully represent the broader US population, particularly regarding individuals with limited healthcare access or those who are institutionalized. Additionally, the reliance on self-reported information for certain variables including smoking status, family history, and medication adherence introduces measurement error that could affect algorithm performance and bias assessment.

Our analysis focused primarily on traditional cardiovascular disease outcomes and may not capture the full spectrum of cardiovascular conditions or their varying presentations across demographic groups. The binary classification approach, while clinically interpretable, may oversimplify the complex continuum of cardiovascular risk and disease severity. Future investigations incorporating continuous risk measures or time-to-event modeling may provide more nuanced insights into algorithm performance.

The temporal scope of our validation analysis, while spanning two decades, may not adequately capture long-term secular trends in cardiovascular disease epidemiology or the impact of evolving therapeutic interventions on risk factor relationships. Additionally, our analysis did not account for changes in diagnostic criteria, treatment guidelines, or preventive care practices that may have influenced risk factor associations over time.

We recognize that our bias analysis, while comprehensive across major demographic categories, may not identify all sources of algorithmic unfairness. Socioeconomic factors, geographic variations, healthcare access patterns, and clinical complexity represent additional dimensions of potential bias that warrant further investigation. The intersectionality of multiple demographic characteristics may create compound bias effects that our analysis did not fully capture.

VII. Conclusion

Our comprehensive comparative analysis of machine learning algorithms for predicting cardiovascular disease risk factors among US adults demonstrates significant potential for enhancing current clinical risk

assessment capabilities while highlighting critical concerns regarding algorithmic bias and health equity. We found that ensemble methods, particularly XGBoost, Random Forest, and LightGBM, consistently outperformed traditional statistical approaches and individual machine learning algorithms, achieving AUC values exceeding 0.91 and providing clinically meaningful improvements in patient risk stratification.

The identification of key risk factors including age, systolic blood pressure, total cholesterol, body mass index, and diabetes status confirmed established cardiovascular epidemiology principles while revealing complex interaction effects that traditional linear models may not adequately capture. Our analysis demonstrated that machine learning approaches could more appropriately classify 18.6% of patients compared to current standard risk assessment tools, potentially leading to better identification of high-risk individuals and more accurate reassurance for low-risk populations.

However, our investigation revealed concerning patterns of algorithmic bias across demographic subgroups, particularly affecting racial/ethnic minorities and different age groups. These disparities raise fundamental questions about health equity and justice, as biased algorithms could perpetuate and amplify existing healthcare inequalities. We observed violations of multiple fairness principles including equalized odds and demographic parity, indicating systematic differences in algorithm performance based solely on demographic characteristics.

The temporal validation analysis demonstrated relatively stable performance across time periods while revealing the need for regular model updating to maintain optimal accuracy. Our explainability analysis using SHAP values provided valuable insights into individual prediction components and complex feature interactions, supporting clinical trust and shared decision-making. However, the balance between model complexity and interpretability remains a significant challenge for clinical implementation.

We recommend that healthcare organizations considering machine learning-based cardiovascular risk prediction systems implement comprehensive governance frameworks addressing algorithm accountability, bias monitoring, and equity assessment. This includes developing robust validation procedures, continuous performance monitoring across demographic subgroups, and bias mitigation strategies. Additionally, healthcare providers require appropriate training on AI system limitations and proper interpretation of algorithmic recommendations.

Future research priorities should focus on developing bias mitigation strategies, validating models across diverse international populations, incorporating novel biomarkers and genetic information, and establishing regulatory frameworks for equitable AI implementation in healthcare. The integration of machine learning approaches with electronic health records presents promising opportunities for real-time risk assessment and clinical decision support, but requires careful attention to data quality, workflow integration, and user interface design.

Our findings contribute to the growing evidence supporting the potential of artificial intelligence in cardiovascular medicine while emphasizing the critical importance of addressing bias and equity concerns before widespread clinical adoption. The development of fair, transparent, and clinically useful machine learning systems for cardiovascular risk prediction represents both a technical challenge and an ethical imperative for ensuring that advances in AI benefit all populations equitably.

The path forward requires collaborative efforts among researchers, clinicians, policymakers, and technology developers to harness the power of machine learning for cardiovascular health improvement while maintaining fundamental principles of medical ethics, health equity, and patient safety. Only through such comprehensive approaches can we realize the full potential of artificial intelligence in cardiovascular medicine while avoiding the perpetuation of existing healthcare disparities.

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