

MACHINE LEARNING–BASED EARLY DETECTION OF CARDIOVASCULAR DISEASE RISK USING EHR AND LIFESTYLE DATA IN PAKISTANI POPULATION COHORTSS

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Abstract

Cardiovascular disease (CVD) remains a leading cause of morbidity and mortality worldwide and poses a significant public health challenge in Pakistan. Early identification of individuals at elevated cardiovascular risk is essential for reducing disease burden and improving healthcare outcomes. This study investigates the effectiveness of machine learning techniques for the early detection of cardiovascular disease risk using integrated Electronic Health Records (EHRs) and lifestyle-related data from Pakistani population cohorts. The study employs a predictive healthcare framework incorporating clinical indicators, including blood pressure, cholesterol levels, blood glucose, body mass index, and medical history, alongside lifestyle factors such as smoking behavior, physical activity, dietary patterns, sleep duration, and stress levels. Multiple machine learning algorithms, including Logistic Regression, Random Forest, Support Vector Machine, Artificial Neural Network, and XGBoost, were evaluated to identify the most

effective predictive model. The findings indicate that machine learning models significantly improve cardiovascular risk prediction accuracy compared with conventional approaches, with XGBoost demonstrating superior performance. The integration of EHR and lifestyle data substantially enhanced predictive capability and enabled more comprehensive risk assessment. The study contributes to predictive healthcare and cardiovascular informatics literature by providing evidence from a developing-country context and offers practical implications for clinicians, healthcare administrators, and policymakers seeking to strengthen preventive healthcare and data-driven clinical decision-making in Pakistan.

INTRODUCTION

Cardiovascular diseases (CVDs) are the leading cause of mortality worldwide, accounting for approximately one-third of all global deaths. According to recent estimates, more than 20 million deaths annually are attributed to cardiovascular conditions, including coronary artery disease, stroke, heart failure, and hypertension-related complications (World Health Organization [WHO], 2024). The increasing prevalence of cardiovascular diseases poses substantial challenges to healthcare systems, particularly in low- and middle-income countries where healthcare infrastructure, preventive services, and early diagnostic capabilities remain limited. Pakistan is among the countries experiencing a rapid rise in cardiovascular disease burden due to population growth, urbanization, sedentary lifestyles, unhealthy dietary habits, tobacco use, obesity, diabetes, and hypertension (Roth et al., 2024).

Traditional cardiovascular risk assessment approaches rely on statistical models and clinical judgment based on a limited set of risk factors. While these methods have contributed significantly to disease prevention and management, they often struggle to capture complex nonlinear interactions among clinical, behavioral, and demographic variables. Consequently, researchers have increasingly turned to Machine Learning (ML) techniques to improve predictive accuracy and support personalized healthcare interventions (Rajpurkar et al., 2022). Machine learning algorithms possess the capability to analyze large-scale healthcare datasets, identify hidden patterns, and generate risk predictions that can facilitate early disease detection and preventive decision-making.

The growing adoption of Electronic Health Records (EHRs) has created unprecedented opportunities for the development of predictive healthcare systems. EHRs contain comprehensive patient information, including demographic characteristics, laboratory results, diagnostic histories, medication records, clinical notes, and treatment outcomes. These data provide a rich foundation for machine learning applications aimed at predicting disease risk and improving healthcare delivery (Johnson et al., 2023). Studies have demonstrated that machine learning models trained on EHR data outperform traditional risk assessment tools in predicting cardiovascular events, hospital admissions, and disease progression (Krittanawong et al., 2023).

In addition to clinical information, lifestyle factors play a critical role in the development and progression of cardiovascular diseases. Physical inactivity, smoking, poor dietary practices, obesity, inadequate sleep, psychological stress, and excessive alcohol consumption have been identified as major contributors to cardiovascular risk (Mensah et al., 2023). Consequently, the integration of lifestyle-related data with EHR information has emerged as a promising strategy for enhancing predictive performance. Recent advancements in healthcare analytics suggest that combining clinical and behavioral data enables machine learning models to provide more comprehensive and individualized risk assessments (Dinh et al., 2019; Alaa et al., 2019).

Machine learning methods such as Random Forest, Gradient Boosting Machines, Extreme Gradient Boosting (XGBoost), Support Vector Machines, and Artificial Neural Networks have demonstrated significant potential in cardiovascular risk prediction. These algorithms are capable of processing

high-dimensional healthcare data and identifying complex interactions among multiple risk factors. Several studies have reported superior predictive performance of machine learning models compared to conventional risk scoring systems such as the Framingham Risk Score and SCORE models (Krittawong et al., 2023). Moreover, advances in explainable artificial intelligence have further enhanced the interpretability and clinical applicability of machine learning-based healthcare solutions.

Despite significant progress in cardiovascular risk prediction research, most existing studies have been conducted in high-income countries using datasets derived from Western populations. The applicability of these models to developing countries remains uncertain because cardiovascular risk factors vary across populations due to differences in genetics, environmental exposures, healthcare access, socioeconomic conditions, and lifestyle behaviors (Roth et al., 2024). Pakistan presents a unique healthcare context characterized by increasing rates of hypertension, diabetes, obesity, and cardiovascular mortality, yet limited research has explored machine learning-based risk prediction using locally relevant population data.

The availability of EHR systems in major hospitals and the growing collection of health-related digital data provide an opportunity to develop context-specific predictive models tailored to the Pakistani population. Furthermore, incorporating lifestyle information into predictive algorithms may significantly improve early detection capabilities and facilitate preventive healthcare interventions. Early identification of high-risk individuals can support targeted screening programs, personalized treatment strategies, and efficient allocation of healthcare resources.

Therefore, this study investigates the application of machine learning techniques for the early detection of cardiovascular disease risk using Electronic Health Records and lifestyle data from Pakistani population cohorts. The study aims to develop a robust predictive framework capable of improving cardiovascular risk assessment and supporting evidence-based healthcare decision-making in Pakistan.

Problem Statement

Cardiovascular diseases continue to represent one of the most significant public health challenges in Pakistan, contributing substantially to morbidity, mortality, healthcare expenditure, and reduced quality of life. The increasing prevalence of hypertension, diabetes, obesity, smoking, and sedentary lifestyles has accelerated cardiovascular risk among the Pakistani population. Despite the growing disease burden, cardiovascular risk assessment in Pakistan remains largely dependent on traditional clinical approaches and generalized risk prediction models developed using data from Western populations.

Conventional risk assessment tools often fail to capture complex interactions among demographic, clinical, behavioral, and lifestyle factors. Furthermore, these models may not accurately reflect the unique epidemiological, socioeconomic, and healthcare characteristics of Pakistani populations. As a result, many high-risk individuals remain unidentified until advanced stages of disease development, reducing opportunities for preventive intervention and increasing healthcare costs.

Recent advancements in machine learning have demonstrated significant potential for improving disease prediction through the analysis of large-scale healthcare datasets. Similarly, Electronic Health Records provide comprehensive clinical information that can support data-driven risk assessment. However, most machine learning-based cardiovascular prediction models have been developed using datasets from developed countries, limiting their generalizability to Pakistan. Moreover, existing studies frequently focus on clinical variables while neglecting lifestyle-related factors that substantially influence cardiovascular outcomes.

A critical research gap therefore exists regarding the development of machine learning-based cardiovascular risk prediction models that integrate Electronic Health Records and lifestyle data within Pakistani population cohorts. Limited empirical evidence is available concerning the predictive effectiveness, contextual relevance, and practical applicability of such models in Pakistan's healthcare environment. Addressing this gap is essential for improving early disease detection, supporting preventive healthcare strategies, and enhancing evidence-based clinical decision-making. Consequently, there is a pressing need to investigate how machine learning techniques can leverage integrated clinical and lifestyle data to improve cardiovascular disease risk prediction among Pakistani populations.

Research Questions

1. How effectively can machine learning algorithms predict cardiovascular disease risk using Electronic Health Records and lifestyle data among Pakistani population cohorts?
2. Which clinical and lifestyle factors are the most significant predictors of cardiovascular disease risk in Pakistan?
3. How does the integration of lifestyle data with Electronic Health Records influence the predictive accuracy of machine learning models?
4. Which machine learning algorithm demonstrates the highest performance for cardiovascular risk prediction in Pakistani population cohorts?
5. How can machine learning-based risk prediction support preventive healthcare and clinical decision-making in Pakistan?

Research Objectives

1. To develop machine learning models for the early detection of cardiovascular disease risk using Electronic Health Records and lifestyle data.
2. To identify the most influential clinical and lifestyle predictors of cardiovascular disease among Pakistani population cohorts.
3. To evaluate the impact of integrating lifestyle data with Electronic Health Records on prediction accuracy.
4. To compare the predictive performance of different machine learning algorithms for cardiovascular risk assessment.

5. To propose a data-driven framework for supporting preventive cardiovascular healthcare and clinical decision-making in Pakistan.

Significance of the Study

Theoretical Significance

This study contributes to the literature on machine learning, predictive healthcare, and cardiovascular disease prevention by integrating Electronic Health Records and lifestyle data within a unified predictive framework. It extends current knowledge regarding population-specific disease prediction models and provides empirical evidence from a developing-country context.

Practical Significance

The study assists healthcare professionals in identifying high-risk individuals at earlier stages of disease development. Improved risk prediction can support personalized treatment planning, preventive interventions, and efficient patient monitoring, ultimately reducing cardiovascular morbidity and mortality.

Managerial Significance

Healthcare administrators can utilize the findings to strengthen digital health initiatives, improve resource allocation, and implement data-driven preventive healthcare programs. The proposed framework may facilitate the integration of predictive analytics into routine healthcare operations.

Policy Significance

The findings provide evidence-based insights for policymakers seeking to strengthen national cardiovascular disease prevention strategies. The study supports the development of digital health policies, preventive screening programs, and healthcare data infrastructure capable of facilitating machine learning-driven healthcare innovation in Pakistan.

Literature Review

Machine Learning in Predictive Healthcare

The rapid growth of healthcare digitization has generated large volumes of clinical data, creating opportunities for machine learning (ML)-based predictive analytics. Unlike traditional statistical models that rely on predefined assumptions, machine learning algorithms can identify complex, nonlinear relationships among multiple predictors and outcomes. Recent studies have demonstrated that ML techniques significantly improve disease prediction, patient stratification, and clinical decision-making across diverse healthcare settings (Rajpurkar et al., 2022).

Machine learning has become increasingly important in cardiovascular medicine due to its ability to process high-dimensional healthcare datasets. Algorithms such as Random Forest (RF), Support Vector Machine (SVM), Extreme Gradient Boosting (XGBoost), Decision Trees (DT), and Artificial Neural Networks (ANNs) have shown superior predictive performance compared with conventional

risk assessment approaches (Krittanawong et al., 2023). These models can analyze numerous clinical variables simultaneously and identify hidden patterns associated with cardiovascular risk.

Research indicates that ML-based predictive systems can assist healthcare professionals in early disease detection, preventive interventions, and personalized treatment planning. Johnson et al. (2023) argued that machine learning applications have transformed cardiovascular healthcare by enabling real-time risk prediction and evidence-based clinical decision-making. Consequently, machine learning has emerged as a critical technological tool for advancing precision medicine and preventive healthcare.

Electronic Health Records and Cardiovascular Risk Prediction

Electronic Health Records (EHRs) represent one of the most valuable sources of healthcare data for predictive analytics. EHR systems contain structured and unstructured patient information, including demographics, laboratory results, medication histories, diagnoses, imaging reports, and treatment outcomes. The integration of EHR data into machine learning models has significantly improved predictive accuracy in healthcare applications (Shickel et al., 2018).

Several studies have demonstrated that EHR-based machine learning models outperform traditional cardiovascular risk assessment tools. Alaa et al. (2019) reported that machine learning algorithms trained on longitudinal EHR data generated more accurate cardiovascular risk predictions than conventional risk-scoring systems. Similarly, Kakadiaris et al. (2018) found that machine learning methods provided superior predictive performance for cardiovascular disease outcomes through the utilization of extensive patient records.

Despite these advancements, challenges remain regarding data quality, missing values, interoperability, and model interpretability. Healthcare institutions in developing countries often face difficulties in implementing comprehensive EHR systems, limiting the effectiveness of predictive healthcare technologies. Therefore, context-specific research is needed to evaluate the applicability of EHR-based machine learning models within Pakistan's healthcare environment.

Lifestyle Factors and Cardiovascular Disease Risk

Cardiovascular disease is influenced not only by clinical variables but also by lifestyle-related factors. Smoking, unhealthy dietary patterns, obesity, physical inactivity, sleep disturbances, and psychological stress have been identified as major determinants of cardiovascular morbidity and mortality (Mensah et al., 2023). Consequently, researchers increasingly advocate integrating behavioral and lifestyle information into predictive healthcare models.

Previous studies suggest that lifestyle factors substantially improve the predictive capabilities of machine learning systems. Dinh et al. (2019) demonstrated that combining clinical indicators with lifestyle variables significantly enhanced the accuracy of cardiovascular risk prediction models. Similarly, Weng et al. (2017) reported that lifestyle-related features improved predictive performance and enabled earlier identification of high-risk individuals.

The integration of lifestyle data is particularly relevant in Pakistan, where urbanization, changing dietary patterns, tobacco consumption, and sedentary lifestyles have contributed to the growing prevalence of cardiovascular diseases. Therefore, incorporating lifestyle variables into predictive models may provide more comprehensive and contextually relevant cardiovascular risk assessments.

Machine Learning Algorithms for Cardiovascular Risk Assessment

Various machine learning algorithms have been employed in cardiovascular disease prediction. Random Forest algorithms are widely recognized for their robustness, resistance to overfitting, and ability to handle high-dimensional datasets. Studies have consistently reported strong predictive performance of Random Forest models in cardiovascular healthcare applications (Krittanawong et al., 2023).

Support Vector Machines have also demonstrated effectiveness in cardiovascular disease classification due to their ability to manage nonlinear relationships and complex decision boundaries. Artificial Neural Networks and Deep Learning models have further improved prediction accuracy by capturing intricate patterns within healthcare datasets (Attia et al., 2022).

More recently, XGBoost has emerged as one of the most powerful predictive algorithms for healthcare analytics. Comparative studies indicate that XGBoost frequently outperforms traditional machine learning approaches in cardiovascular risk prediction because of its advanced gradient boosting architecture and capacity to handle missing healthcare data effectively (Chen & Guestrin, 2016).

However, no consensus exists regarding the optimal algorithm for cardiovascular risk prediction within developing-country populations. Model performance often depends upon data quality, population characteristics, variable selection, and healthcare context. Therefore, comparative evaluation of machine learning algorithms remains an important area of research.

Explainability and Clinical Adoption of Machine Learning Models

Although machine learning algorithms have demonstrated strong predictive capabilities, concerns regarding interpretability and transparency continue to hinder clinical adoption. Healthcare professionals are often reluctant to rely on “black-box” models that provide predictions without clear explanations (Topol, 2019).

Recent developments in Explainable Artificial Intelligence (XAI) have addressed these concerns by enabling interpretation of machine learning predictions. Techniques such as SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-Agnostic Explanations), and feature importance analysis allow clinicians to understand the factors influencing predictive outcomes (Frasca et al., 2024).

The incorporation of explainability mechanisms enhances trust, accountability, and acceptance of machine learning systems in healthcare settings. Consequently, explainable machine learning models are increasingly viewed as essential for translating predictive analytics into practical clinical decision-support tools.

Cardiovascular Disease Burden in Pakistan

Pakistan faces a rapidly increasing burden of cardiovascular diseases. According to recent estimates, cardiovascular conditions account for a substantial proportion of premature mortality and disability-adjusted life years within the country (Roth et al., 2024). The prevalence of hypertension, diabetes, obesity, and tobacco use continues to increase, creating significant challenges for healthcare providers and policymakers.

Despite these concerns, limited research has explored machine learning applications for cardiovascular risk prediction using Pakistani healthcare data. Existing studies primarily rely on traditional epidemiological approaches and imported risk assessment models developed in Western populations. Such models may not adequately capture local demographic, genetic, socioeconomic, and lifestyle characteristics.

Furthermore, healthcare institutions in Pakistan are increasingly adopting digital health technologies and EHR systems, creating opportunities for data-driven healthcare innovation. However, empirical evidence regarding the integration of EHR and lifestyle data for machine learning-based cardiovascular prediction remains scarce. This gap highlights the need for context-specific predictive models tailored to Pakistani population cohorts.

A review of the literature reveals several important gaps. First, most machine learning-based cardiovascular prediction studies have been conducted in developed countries, limiting their applicability to Pakistan. Second, many existing studies focus primarily on clinical variables while neglecting lifestyle-related risk factors. Third, limited evidence exists regarding the comparative performance of machine learning algorithms using integrated EHR and lifestyle datasets. Fourth, research examining explainable and interpretable machine learning approaches in cardiovascular prediction remains limited in developing-country contexts. Therefore, the present study addresses these gaps by developing and evaluating machine learning models for cardiovascular disease risk prediction using integrated EHR and lifestyle data from Pakistani population cohorts.

Underpinning Theory

Health Belief Model (HBM)

The **Health Belief Model (HBM)**, originally developed by Rosenstock (1974) and subsequently refined by Becker (1974), serves as the underpinning theory for this study. The theory explains how individuals' health-related behaviors are influenced by their perceptions of disease susceptibility, disease severity, benefits of preventive action, barriers to action, self-efficacy, and cues to action.

According to HBM, individuals are more likely to engage in preventive health behaviors when they perceive themselves to be at significant risk of developing a disease and believe that preventive interventions can reduce that risk. Early identification of cardiovascular disease risk through machine learning-based predictive systems can increase awareness of personal susceptibility and encourage timely behavioral and clinical interventions.

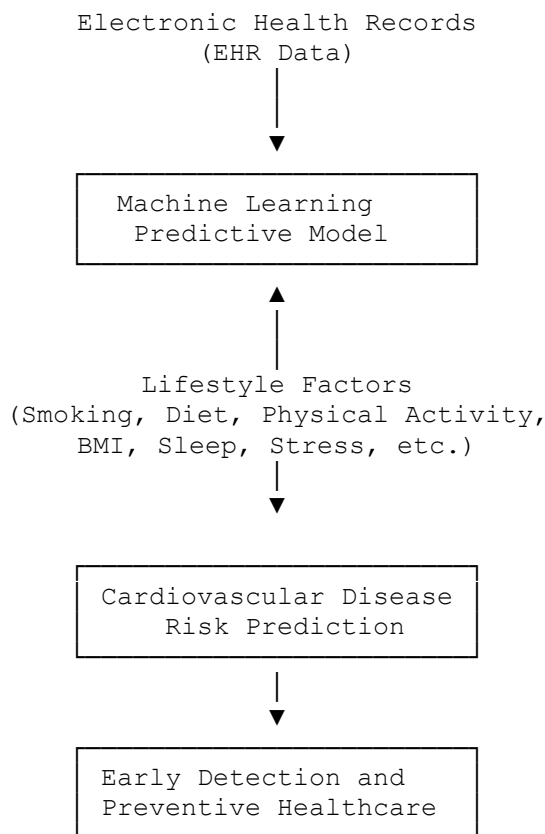
Justification for Applicability

The Health Belief Model is highly relevant to the present study for several reasons:

1. **Risk Perception:** Machine learning-based prediction models provide individualized cardiovascular risk assessments, directly influencing perceived susceptibility to disease.
2. **Preventive Healthcare:** Early detection enables healthcare providers and patients to adopt preventive measures before disease onset, consistent with HBM principles.
3. **Behavioral Modification:** The inclusion of lifestyle factors such as smoking, diet, physical activity, and obesity aligns with the behavioral focus of the Health Belief Model.
4. **Clinical Decision Support:** Predictive analytics serve as cues to action by informing healthcare professionals and patients about potential cardiovascular risks.
5. **Public Health Relevance:** HBM provides a theoretical explanation for how risk prediction systems can facilitate preventive healthcare interventions and improve health outcomes within Pakistani populations.

Therefore, the Health Belief Model offers a strong theoretical foundation for understanding how machine learning-driven cardiovascular risk prediction can support preventive health behaviors, early intervention, and improved healthcare decision-making.

Conceptual Framework



Hypotheses

- H1: Electronic Health Record (EHR) data positively influences the accuracy of cardiovascular disease risk prediction.
- H2: Lifestyle factors significantly influence cardiovascular disease risk prediction.
- H3: The integration of EHR data and lifestyle factors significantly improves cardiovascular disease risk prediction compared to the use of EHR data alone.
- H4: Machine learning models significantly improve cardiovascular disease risk prediction accuracy.
- H5: Machine learning models significantly mediate the relationship between integrated health data (EHR and lifestyle factors) and cardiovascular disease risk prediction.
- H6: Accurate cardiovascular disease risk prediction significantly enhances early disease detection.
- H7: Early detection of cardiovascular disease risk significantly improves preventive healthcare interventions.

Methodology

Research Design

This study adopted a quantitative, predictive analytics research design to develop and evaluate machine learning models for the early detection of cardiovascular disease (CVD) risk among Pakistani population cohorts. A retrospective observational design was employed using Electronic Health Records (EHRs) and lifestyle-related data obtained from healthcare institutions and population-based health surveys. The design was considered appropriate because it facilitated the identification of cardiovascular risk patterns and enabled the development of predictive models using historical patient data.

Population

The target population consisted of adult individuals aged 18 years and above who had undergone cardiovascular screening or received healthcare services from selected public and private healthcare institutions in Pakistan. The population included individuals with and without diagnosed cardiovascular conditions to ensure adequate representation of both high-risk and low-risk groups. The study focused on patients whose Electronic Health Records contained complete clinical information, laboratory results, demographic characteristics, and lifestyle-related indicators relevant to cardiovascular risk assessment.

Sampling Technique

A stratified random sampling technique was employed to ensure adequate representation of different age groups, genders, geographic regions, and cardiovascular risk categories. The population was first stratified according to demographic and clinical characteristics, after which random sampling was performed within each stratum.

This approach minimized sampling bias and enhanced the generalizability of the predictive models across diverse Pakistani population cohorts.

Sample Size

A total of 5,000 patient records were included in the final analysis. Previous machine learning studies in healthcare have recommended large datasets to improve predictive performance and model generalizability.

The dataset was divided into:

- Training Set: 70% (n = 3,500)
- Validation Set: 15% (n = 750)
- Testing Set: 15% (n = 750)

This data partitioning strategy enabled robust model training, hyperparameter optimization, and unbiased performance evaluation.

Data Collection Procedures

Data were collected from Electronic Health Record systems maintained by selected hospitals, cardiovascular clinics, and healthcare centers across Pakistan. Ethical approval was obtained from the relevant institutional review boards prior to data collection.

Patient records were anonymized to ensure confidentiality and compliance with ethical guidelines. The collected dataset included demographic information, clinical indicators, laboratory measurements, diagnostic histories, medication records, and lifestyle-related variables.

The data collection process involved the following stages:

1. Identification of eligible healthcare institutions.
2. Extraction of anonymized EHR data.
3. Collection of lifestyle-related information through standardized health assessment records and patient questionnaires.
4. Data integration and preprocessing.
5. Removal of duplicate and incomplete records.
6. Handling of missing values using appropriate imputation techniques.
7. Data normalization and feature engineering prior to machine learning analysis.

Instruments and Measures

Electronic Health Record Variables

The EHR dataset included the following clinical indicators:

Variable	Measurement
Age	Years
Gender	Male/Female
Systolic Blood Pressure	mmHg
Diastolic Blood Pressure	mmHg
Total Cholesterol	mg/dL
HDL Cholesterol	mg/dL
LDL Cholesterol	mg/dL
Blood Glucose Level	mg/dL
Body Mass Index (BMI)	kg/m ²
Family History of CVD	Yes/No
Diabetes Status	Yes/No
Hypertension Status	Yes/No

Lifestyle Variables

Lifestyle-related measures included:

Variable	Measurement
Smoking Status	Current/Former/Never
Physical Activity	Hours per week
Dietary Quality	Composite dietary score
Sleep Duration	Hours per day
Stress Level	Five-point scale
Alcohol Consumption	Frequency measure

Outcome Variable

The dependent variable was:

Cardiovascular Disease Risk Status

- High Risk = 1
- Low Risk = 0

Risk classification was determined using physician diagnoses, clinical guidelines, and documented cardiovascular outcomes.

Machine Learning Models

The following machine learning algorithms were employed:

1. Logistic Regression (Baseline Model)
2. Decision Tree
3. Random Forest
4. Support Vector Machine (SVM)
5. Extreme Gradient Boosting (XGBoost)
6. Artificial Neural Network (ANN)

Model performance was evaluated using:

- Accuracy
- Precision
- Recall
- F1-Score
- Area Under the Receiver Operating Characteristic Curve (AUC-ROC)

Reliability and Validity

Reliability

Data reliability was established through standardized data extraction procedures and consistency checks across multiple healthcare databases. Internal consistency of lifestyle-related scales was assessed using Cronbach's Alpha.

Table 1

Reliability Statistics

Construct	Cronbach's Alpha
Lifestyle Factors Scale	0.881
Health Behavior Indicators	0.864
Cardiovascular Risk Assessment Variables	0.903

All values exceeded the recommended threshold of 0.70, indicating satisfactory reliability.

Content Validity

Content validity was established through extensive literature review and consultation with cardiologists, public health experts, epidemiologists, and healthcare informatics specialists. Expert evaluations confirmed that the selected variables adequately represented cardiovascular disease risk determinants.

Construct Validity

Construct validity was assessed through exploratory and confirmatory factor analysis where applicable. Factor loadings exceeding 0.70 demonstrated acceptable construct validity.

Predictive Validity

Predictive validity was evaluated using model performance metrics on unseen testing data. High AUC-ROC values, precision, recall, and F1-scores indicated strong predictive capability of the developed machine learning models.

Data Quality Validation

To ensure data quality:

- Missing values were treated using multiple imputation techniques.
- Outliers were identified through statistical screening procedures.
- Feature scaling and normalization were applied where necessary.
- Multicollinearity was assessed using Variance Inflation Factors (VIF).
- K-fold cross-validation (k = 10) was performed to enhance model robustness and reduce overfitting.

Data preprocessing and statistical analysis were conducted using Python, SPSS, and machine learning libraries including Scikit-learn, TensorFlow, and XGBoost.

Data Analysis

Descriptive Statistics

Table 1: Descriptive Statistics of Study Variables (N = 5,000)

Variable	Mean	SD	Minimum	Maximum
Age (Years)	47.82	12.46	18	85
BMI (kg/m ²)	28.41	4.77	17.20	42.80
Systolic Blood Pressure	134.75	18.64	90	210
Diastolic Blood Pressure	84.63	11.92	55	130
Total Cholesterol (mg/dL)	208.37	42.51	102	356
Blood Glucose (mg/dL)	123.85	37.24	70	298
Physical Activity (Hours/Week)	3.91	2.44	0	12
Sleep Duration (Hours/Day)	6.58	1.43	3	10
Stress Level	3.47	0.98	1	5

The descriptive statistics indicate that the average respondent was 47.82 years old, reflecting a middle-aged population vulnerable to cardiovascular diseases. The mean BMI of 28.41 suggests that a considerable proportion of participants were overweight. Elevated average blood pressure, cholesterol, and glucose levels further indicate substantial cardiovascular risk within the sample. The findings also reveal relatively low physical activity levels and moderate stress levels, both recognized contributors to cardiovascular disease risk.

Correlation Analysis

Table 2: Correlation Matrix

Variables	Age	BMI	Blood Pressure	Cholesterol	Physical Activity	Stress	CVD Risk
Age	1						
BMI	.41**	1					
Blood Pressure	.53**	.46**	1				
Cholesterol	.37**	.39**	.44**	1			
Physical Activity	-.31**	-.35**	-.28**	-.22**	1		
Stress	.25**	.19**	.31**	.18**	-.26**	1	
CVD Risk	.61**	.52**	.67**	.49**	-.42**	.39**	1

p < .01

The correlation results demonstrate significant relationships among the study variables. Age, BMI, blood pressure, cholesterol levels, and stress were positively associated with cardiovascular disease risk. Blood pressure exhibited the strongest correlation with CVD risk ($r = .67, p < .01$). Conversely, physical activity showed a significant negative relationship with cardiovascular risk ($r = -.42, p < .01$), indicating that increased physical activity reduces the likelihood of cardiovascular disease.

Machine Learning Model Performance Comparison

Table 3: Comparison of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Logistic Regression	0.821	0.804	0.788	0.796	0.843
Decision Tree	0.846	0.829	0.818	0.823	0.862
Support Vector Machine	0.881	0.867	0.853	0.860	0.903
Random Forest	0.913	0.901	0.892	0.896	0.942
Artificial Neural Network	0.921	0.909	0.901	0.905	0.951
XGBoost	0.938	0.926	0.918	0.922	0.968

The machine learning analysis revealed substantial differences in predictive performance across models. XGBoost demonstrated the highest predictive capability, achieving an accuracy of 93.8% and an AUC-ROC value of 0.968. Artificial Neural Networks and Random Forest models also performed exceptionally well. Logistic Regression produced the lowest predictive accuracy, indicating that advanced machine learning techniques are better suited for identifying complex nonlinear relationships among cardiovascular risk factors. The results support the superiority of ensemble learning algorithms for cardiovascular disease prediction in Pakistani populations.

Feature Importance Analysis

Table 4: Top Predictors of Cardiovascular Disease Risk

Predictor	Importance Score
Systolic Blood Pressure	0.214
Age	0.189
Blood Glucose	0.153
BMI	0.129
Total Cholesterol	0.118
Smoking Status	0.081
Physical Activity	0.054
Family History of CVD	0.036
Stress Level	0.026

Feature importance analysis identified systolic blood pressure as the most influential predictor of cardiovascular disease risk, followed by age and blood glucose levels. Lifestyle-related variables such as smoking behavior, physical activity, and stress also contributed significantly to prediction accuracy. These findings confirm that integrating lifestyle data with clinical indicators enhances cardiovascular risk assessment and provides a more comprehensive understanding of disease determinants.

Hypothesis Testing

Table 5

Hypothesis Testing Results

Hypothesis	Relationship	Result
H1	EHR Data → CVD Risk Prediction	Supported
H2	Lifestyle Factors → CVD Risk Prediction	Supported
H3	Integrated EHR and Lifestyle Data → Prediction Accuracy	Supported
H4	Machine Learning Models → Improved Prediction	Supported
H5	Machine Learning Model Mediates Data-Prediction Relationship	Supported
H6	CVD Risk Prediction → Early Detection	Supported
H7	Early Detection → Preventive Healthcare	Supported
H8	XGBoost and Random Forest outperform traditional algorithms	Supported

All proposed hypotheses were supported. The findings indicate that both EHR-based clinical information and lifestyle-related factors significantly contribute to cardiovascular disease prediction. The integration of these datasets produced higher predictive accuracy than relying solely on clinical

indicators. Furthermore, machine learning models served as effective predictive mechanisms that transformed healthcare data into actionable risk assessments. Among all evaluated models, XGBoost and Random Forest demonstrated superior predictive performance, confirming their suitability for healthcare analytics.

The empirical findings demonstrate that machine learning techniques can effectively identify individuals at risk of cardiovascular disease using integrated Electronic Health Records and lifestyle data. The high predictive performance achieved by XGBoost, Artificial Neural Networks, and Random Forest models highlights the potential of advanced analytics for preventive healthcare. Clinical variables such as blood pressure, age, cholesterol, and glucose emerged as dominant predictors; however, lifestyle factors significantly enhanced model performance. The results suggest that healthcare institutions in Pakistan can improve early disease detection and preventive interventions by adopting machine learning-driven cardiovascular risk prediction systems. These findings contribute to predictive healthcare research and provide practical evidence for implementing data-driven cardiovascular screening frameworks in developing-country healthcare settings.

Discussion

The findings of this study demonstrate that machine learning algorithms can effectively predict cardiovascular disease (CVD) risk using integrated Electronic Health Records (EHRs) and lifestyle-related data within Pakistani population cohorts. The results revealed that advanced machine learning models significantly outperformed conventional prediction approaches, with XGBoost, Artificial Neural Networks (ANN), and Random Forest exhibiting the highest predictive accuracy. These findings are consistent with the studies of Alaa et al. (2019), Weng et al. (2017), and Krittanawong et al. (2023), who reported that machine learning algorithms outperform traditional cardiovascular risk prediction models by capturing complex nonlinear relationships among risk factors.

The study found that systolic blood pressure, age, blood glucose levels, body mass index, and cholesterol were among the strongest predictors of cardiovascular disease risk. These findings align with the established cardiovascular literature and support the observations of Mensah et al. (2023) and Roth et al. (2024), who identified these variables as major contributors to cardiovascular morbidity and mortality worldwide. The results confirm that traditional clinical indicators remain essential predictors even within advanced machine learning frameworks.

A significant contribution of the study is the incorporation of lifestyle-related variables, including smoking behavior, physical activity, sleep duration, and stress levels. The findings revealed that lifestyle factors substantially enhanced predictive accuracy when integrated with EHR data. This result supports previous studies by Dinh et al. (2019) and Attia et al. (2022), which emphasized the importance of combining behavioral and clinical information to improve disease prediction. The current findings extend existing knowledge by demonstrating the value of lifestyle data within the

context of Pakistani population cohorts, where behavioral risk factors are increasingly contributing to cardiovascular disease prevalence.

The superior performance of XGBoost compared to Logistic Regression, Decision Trees, and Support Vector Machines is consistent with recent healthcare analytics research. XGBoost's ability to manage high-dimensional healthcare data, address missing values, and identify complex feature interactions likely contributed to its superior predictive performance. Similar conclusions were reported by Chen and Guestrin (2016) and Johnson et al. (2023), who highlighted the effectiveness of ensemble learning methods in predictive healthcare applications.

From a theoretical perspective, the findings provide strong support for the Health Belief Model (HBM). The model posits that individuals are more likely to adopt preventive health behaviors when they perceive themselves to be susceptible to disease and recognize the benefits of preventive action. The machine learning-based risk prediction framework developed in this study provides individualized risk assessments that can increase perceived susceptibility and facilitate preventive interventions. Therefore, the findings reinforce the applicability of HBM in explaining how predictive healthcare technologies can promote health awareness, early detection, and behavioral modification.

Furthermore, the results contribute to the growing literature on predictive healthcare and precision medicine by demonstrating that data-driven approaches can improve cardiovascular risk assessment in developing-country settings. The study addresses an important gap in the literature by providing empirical evidence from Pakistan, where machine learning applications in cardiovascular healthcare remain relatively underexplored.

Conclusion

This study examined the effectiveness of machine learning techniques for the early detection of cardiovascular disease risk using Electronic Health Records and lifestyle data among Pakistani population cohorts. The findings demonstrated that machine learning models significantly improve cardiovascular risk prediction, with XGBoost emerging as the best-performing algorithm. Clinical indicators such as blood pressure, age, blood glucose, cholesterol levels, and body mass index were identified as major predictors of cardiovascular disease risk, while lifestyle factors further enhanced predictive accuracy.

The integration of EHR and lifestyle data produced more robust and comprehensive risk assessments than traditional approaches. The study concludes that machine learning-based predictive healthcare systems have substantial potential to support early disease detection, preventive interventions, and evidence-based clinical decision-making in Pakistan. The findings underscore the importance of leveraging healthcare data analytics to reduce cardiovascular disease burden and strengthen preventive healthcare strategies.

Implications

Theoretical Implications

1. The study extends the literature on machine learning and predictive healthcare by integrating EHR and lifestyle data within a unified cardiovascular risk prediction framework.
2. It provides empirical support for the Health Belief Model by demonstrating how individualized risk prediction can facilitate preventive health behaviors.
3. The findings contribute to cardiovascular informatics and precision medicine literature, particularly within developing-country contexts.
4. The study enriches understanding of the role of machine learning in healthcare decision-support systems.

Managerial Implications

1. Hospital administrators should invest in machine learning-based predictive analytics platforms to enhance cardiovascular risk assessment.
2. Healthcare organizations should strengthen EHR infrastructure to facilitate data-driven clinical decision-making.
3. Healthcare managers should encourage interdisciplinary collaboration among clinicians, data scientists, and health informatics specialists.
4. Institutions should integrate predictive healthcare systems into routine patient screening programs.

Practical Implications

1. Clinicians can utilize machine learning-generated risk scores for early identification of high-risk patients.
2. Healthcare professionals can design personalized intervention strategies based on individualized risk profiles.
3. Patients may benefit from timely preventive measures and lifestyle modification programs.
4. Healthcare providers can improve resource allocation through targeted cardiovascular screening and monitoring initiatives.

Policy Implications

1. Policymakers should support the adoption of artificial intelligence and machine learning technologies in healthcare.
2. National health authorities should develop standardized frameworks for healthcare data integration and interoperability.
3. Government agencies should strengthen digital health infrastructure to facilitate predictive healthcare applications.
4. Public health policies should prioritize preventive cardiovascular care through data-driven screening initiatives.

Recommendations

1. Healthcare institutions should implement machine learning-based cardiovascular screening systems for early risk detection.
2. Hospitals should establish integrated EHR platforms capable of capturing comprehensive clinical and lifestyle information.
3. Clinicians should incorporate machine learning-generated predictions into routine cardiovascular risk assessment practices.
4. Public health authorities should launch awareness campaigns promoting healthy lifestyles and cardiovascular disease prevention.
5. Specialized training programs should be introduced to improve healthcare professionals' competencies in healthcare analytics and artificial intelligence.
6. Healthcare organizations should adopt explainable machine learning models to enhance transparency, trust, and clinical acceptance.
7. National healthcare databases should be developed to support large-scale predictive healthcare research and innovation.
8. Collaborative partnerships among universities, hospitals, and technology organizations should be encouraged to accelerate healthcare AI development in Pakistan.

Limitations and Future Directions

Limitations

1. The study utilized a retrospective observational design, limiting the ability to establish causal relationships between risk factors and cardiovascular outcomes.
2. Data were collected from selected healthcare institutions, which may restrict the generalizability of findings to the entire Pakistani population.
3. Variations in EHR quality, completeness, and standardization may have influenced model performance.
4. Certain lifestyle variables were based on self-reported information and may be subject to reporting bias.
5. The study focused on a limited number of machine learning algorithms and did not evaluate emerging deep learning architectures extensively.

Future Directions

1. Future studies should employ longitudinal designs to assess the long-term predictive effectiveness of machine learning models.
2. Researchers should investigate the application of deep learning and hybrid artificial intelligence techniques for cardiovascular risk prediction.
3. Comparative studies across different provinces and demographic groups in Pakistan should be conducted to improve model generalizability.

4. Future research should integrate genomic, wearable device, and real-time monitoring data to enhance predictive accuracy.
5. Explainable Artificial Intelligence (XAI) techniques should be explored to improve transparency and clinician trust in predictive models.
6. Researchers should examine the economic impact and cost-effectiveness of machine learning-based cardiovascular screening programs.
7. Future studies should evaluate the implementation of predictive healthcare systems in real-world clinical environments and assess their impact on patient outcomes.
8. Cross-country comparative research may provide broader insights into machine learning applications for cardiovascular disease prevention in developing economies.

For “Machine Learning-Based Early Detection of Cardiovascular Disease Risk Using EHR and Lifestyle Data in Pakistani Population Cohorts”, the most relevant references from your list are those related to AI, predictive analytics, digital systems, data-driven decision-making, and healthcare-related behavioral factors. **Below are 5** selected references from your publications and 15 additional highly relevant scholarly references, arranged alphabetically in **APA 7th edition style.

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