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Systematic Review

Different machine learning language models for cardiovascular disease risk prediction: a systematic review

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ABSTRACT

Cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide, prompting the urgent need for accurate and efficient predictive tools. This systematic review evaluates the efficacy of various machine learning algorithms in predicting cardiovascular disease risk by analyzing multiple studies that employed diverse techniques, including support vector machines, decision trees, and neural networks. The results consistently demonstrate that machine learning algorithms outperform traditional risk assessment models in predicting critical outcomes such as myocardial infarction, heart failure, and stroke, with advanced methods like gradient boosting and deep learning models showing superior accuracy. The review highlights the potential of these technologies to enhance clinical decision-making and improve patient outcomes, while also recognizing challenges such as implementation barriers and the need for validation across broader populations. Furthermore, the review underscores the transformative potential of machine learning in cardiovascular risk assessment, emphasizing the necessity for continued validation and adaptation to diverse patient groups. These findings affirm the growing role of artificial intelligence in revolutionizing cardiovascular care through early diagnosis and precise risk stratification, while also addressing the strengths and limitations of AI-based tools.

Keywords: Cardiovascular diseases, Stroke, Myocardial infarction

INTRODUCTION

Cardiovascular diseases (CVDs) represent a major contributor to global mortality.[1] Despite significant advancements in diagnostic procedures over the past 50 years, cardiologists, primary care physicians, and other healthcare providers continue to face considerable challenges in the early detection and diagnosis of heart disease.[2] Current diagnostic practices for CVD rely primarily on patient medical history, clinical assessments, physical tests, and biomarkers, which are often interpreted based on the physician's experience. This reliance on individual judgment is becoming increasingly error-prone and inefficient.[3] Moreover, as cardiovascular diagnostic technologies improve and generate large volumes of data, the complexity of clinical decision-making increases. Consequently, there is a growing need for medical treatments and diagnostic tools that are not only highly accurate but also simple to use, fast, and automated to enhance patient care, reduce healthcare costs, and lower mortality from CVDs.

Artificial intelligence (AI)-based predictive modeling has emerged as a potential solution to these challenges. However, constructive collaboration between data scientists and medical professionals are essential to ensure the clinical efficacy of automated diagnostic systems using AI.[4] Traditional predictive scoring systems, alongside newer machine learning (ML) and deep learning (DL) algorithms, are now available for the early diagnosis of CVD, predictive risk assessment, and prognostic evaluation following the onset of CVD.

A recent meta-analysis by Krittanawong et al assessed the ability of various ML models to predict stroke, heart failure, cardiac arrhythmias, and coronary artery disease. The analysis concluded that boosting algorithms and support vector machines (SVM) demonstrated promising predictive capabilities in the field of CVD.[5] Similarly, Damen et al, conducted a systematic review that examined the construction and external validation of multivariable models for predicting CVD risk in the general population. Damen's review highlighted the proliferation of CVD prediction models but raised concerns about the methodological shortcomings and lack of external validation studies. The review concluded that, instead of developing new models, future research should focus on validating and improving existing models.[6]

Baashar et al, explored factors related to treatment outcomes in patients with heart failure, stroke, diabetes, and hypertension. The study identified a key gap in the research, noting that most studies had not incorporated both ML and DL techniques. Baashar concluded that DL models outperformed ML models and suggested that both approaches should be applied in future research.[7]

A review of the current literature reveals that very few studies have conducted internal or external validation to assess the efficacy and performance of predictive models. Moreover, few studies have compared AI-based models with traditional methods. To our knowledge, no meta-analysis or systematic review has incorporated internal or external validation to establish the efficacy and performance of these models across diverse populations while also comparing traditional predictive tools with AI-based models. To address these gaps, the current analysis has three primary aims: (A) to assess the accuracy and performance of different machine learning algorithms in predicting the risk of cardiovascular disease, (B) to compare the predictive capabilities of machine learning algorithms with traditional cardiovascular disease risk assessment methods, and (C) to identify the strengths and limitations of various machine learning approaches in cardiovascular disease risk prediction. This manuscript seeks to answer the following question: "What is the effectiveness of various machine learning algorithms in predicting the risk of cardiovascular disease, and how do they compare to traditional risk assessment methods?"

A comprehensive understanding of the accuracy and performance of different CVD risk predictive ML algorithms, as well as a comparison of these algorithms with traditional methods, can enhance the development of more robust ML models. These models could be applied in clinical practice for early diagnosis and accurate risk assessment, ultimately reducing the burden on healthcare systems. Furthermore, such models could be integrated with other screening programs, such as lung cancer screening via CT scans, to predict coronary artery calcium and assess CAD risk without additional radiation exposure or placing extra strain on radiology departments.

METHODS

This review examines clinical research related to the effectiveness of various machine learning algorithms in predicting the risk of cardiovascular disease in predicting the risk of cardiovascular disease compared to traditional means. The methodology uses data from peer-reviewed articles and clearly shows how relevant studies were selected, following PRISMA guidelines. (Figure 1).

Systematic literature search and study selection

A comprehensive search for relevant studies was carried out using PubMed and Google Scholar, including references from review articles and editorials. An initial list of abstracts was created and evaluated by two independent reviewers based on specific criteria focused on cardiovascular diseases and machine learning. Any disagreements during the review were resolved through discussion.

Inclusion criteria

Studies published in peer-reviewed journals from 2003 up to the year 2023, Studies that evaluate the performance of machine learning algorithms in predicting cardiovascular disease risk & that compare machine learning-based risk prediction with traditional methods.

Exclusion criteria

We excluded studies involving animals, those focusing only on machine learning methods without clinical data, and reviews of animal model studies. After searching PubMed, Medline, and Google Scholar, we found 6,027 articles, excluding 5,971 due to duplicates or unsuitable titles and abstracts. We then reviewed the remaining 56 papers, excluding 38 that did not meet our criteria. Finally, we conducted a quality check on the 18 papers that met our inclusion criteria.

Data extraction

We extracted data regarding study design, participant characteristics, machine learning algorithms used, dataset details, model performance metrics (e.g., accuracy, sensitivity, specificity), and comparisons with traditional methods.

Data analysis

The extracted data was analyzed to calculate summary statistics, including effect sizes, confidence intervals, and p values where applicable. An analysis was conducted to synthesize the results across studies and assess the overall effectiveness of machine learning algorithms in cardiovascular disease risk prediction. Later, an analysis of subgroups was performed to explore variations in performance based on different algorithms, dataset characteristics, and study designs. The quality and risk of bias was also evaluated in the included studies using appropriate assessment tools. At last, gaps were identified in the existing literature and areas for future research were recommended.

RESULTS

A total of 18 studies were included in this systematic review. The result writing section was divided into 7 sections with three years each. A total of 6027 articles were screened out of which

5594 articles were excluded based on title, 377 articles were excluded based on abstract and 38 articles were excluded based on non-availability of full texts for retrieval or the articles being preprints.

A total of eighteen studies were included in this review, categorized by publication year. From 2023 to 2021, 5,086 studies were screened, yielding 10 included studies. In the period from 2020 to 2018, 243 studies were screened, resulting in 3 included studies. For the years 2017 to 2015, 39 studies were screened, with 4 included. Between 2014 and 2012, 312 studies were screened, and 1 study was included. In the years 2011 to 2009, 261 studies were screened, but none were included. Similarly, for the years 2008 to 2006, 22 studies were screened with no inclusions, and from 2005 to 2003, 64 studies were screened, again resulting in no included studies.

\Some studies were included at earlier screening processes but was later excluded as the study did not investigate cardiovascular disease (CVD) and its risk assessment or prediction as the primary outcome. Some studies were also excluded as they did not employ a machine learning (ML) or deep learning (DL) approach for risk assessment or prediction. Some studies solely compared+ different ML/DL models without comparing them against traditional risk scores were also excluded. (Table 1).

A total of 18 studies published between 2012 and 2023 are summarized, showcasing the growing interest in utilizing machine learning for cardiovascular risk prediction. These studies employed various designs, including cross-sectional, retrospective cohort, prospective cohort, and case-control studies, with participant numbers ranging from as few as 263 to as many as 1,883,068. This diversity in study scope and scale underscores the increasing relevance and applicability of machine learning techniques in the healthcare domain.

A wide array of machine learning algorithms was utilized across the studies, including Random Forest (RF), Support Vector Machines (SVM), Deep Learning (CNN), Gradient Boosting (GBDT), and Neural Networks (NN). This variety of methodologies reflects the different strategies researchers employed to optimize prediction accuracy and reliability. The use of these algorithms demonstrates a shift from traditional statistical methods toward more sophisticated techniques that can analyze complex, multidimensional data more effectively.

Many studies leveraged large, established datasets, such as the UK Biobank, West China Hospital, and Alberta’s Tomorrow Project, enhancing the credibility of the findings and supporting the robustness of the algorithms tested. Performance metrics such as AUC-ROC, sensitivity, specificity, C-index, and F1 score were commonly reported, illustrating the effectiveness of machine learning algorithms compared to traditional risk assessment methods. In most cases, machine learning models demonstrated superior predictive power, as reflected in higher AUC scores and better accuracy metrics.

The comparison with traditional methods revealed that machine learning algorithms either matched or outperformed conventional risk scores, such as the Framingham Risk Score (FRS) and ASCVD risk score. For instance, the study titled "cardiovascular disease risk assessment using a deep-learning-based retinal biomarker" achieved notable results using deep learning, indicating a significant advancement in predictive capabilities compared to traditional risk assessments like PCE and QRISK3. This consistent pattern across studies highlights the transformative potential of machine learning in improving clinical decision-making and patient outcomes.

Overall, the trend indicated by these studies is the increasing recognition of machine learning as a powerful tool in predicting cardiovascular risk. The findings suggest that machine learning algorithms provide enhanced accuracy and predictive power compared to traditional methods, ultimately leading to improved clinical decision-making and better patient outcomes. However, the review emphasizes the need for further validation across diverse populations to ensure effective integration of these tools into routine clinical practice. This body of research underscores the potential of machine learning to revolutionize cardiovascular care, contributing significantly to early diagnosis and precise risk stratification.

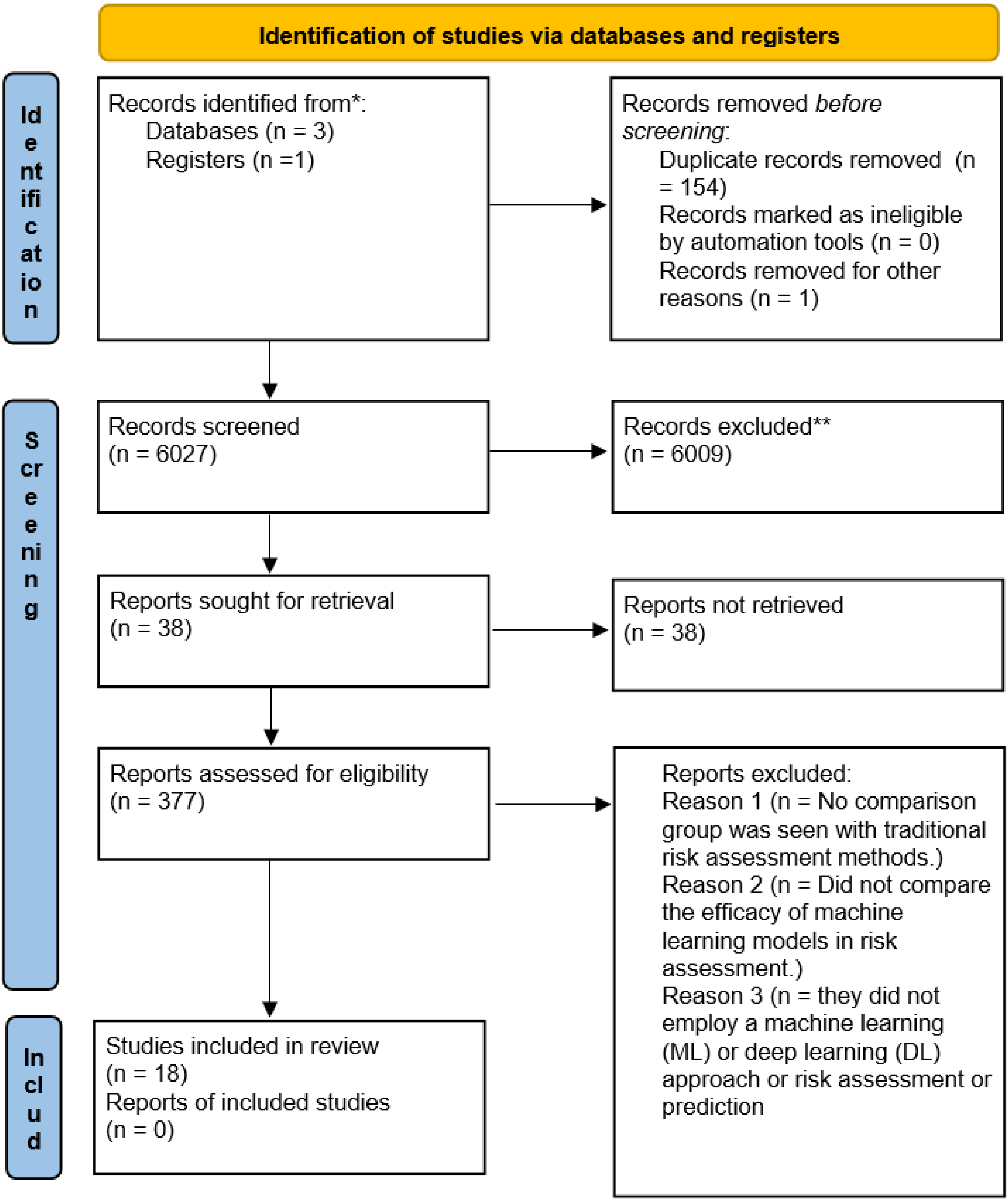

Figure 1: PRISMA chart.

Table 1: Results: study characteristics & comparison.

Year	Study name	Study design	Participants	Algorithms used	Dataset details	Performance metrics	Comparison with traditional Methods
2023	Cardiovascular disease risk assessment using a deep-learning-based retinal biomarker	Crosssectional study	55,070 (UK Biobank+SEED)	Reti-CVD (Deep learning), Convents	UK Biobank and SEED study	Prevalence, Sensitivity, Specificity, PPV, NPV	PCE, QRISK3, modified FRS
2023	A comparison of machine learning algorithms and traditional regression for predicting Hypertension	Retrospective cohort	18,322	Lasso, Ridge, EN, Cox model, RSF	Alberta's Tomorrow Project	C-index, p-value, Unpaired t-test	Traditional logistic regression
2022	An evolutionary machine learning algorithm for cardiovascular disease risk prediction	Prospective cohort	6,504 (ages 35-84)	CNN, XPARS	Isfahan Cohort Study	AUC-ROC	WHO and PARS risk scores
2022	An AI-based risk prediction model of myocardial infarction	Case-control	1,883,068 (MI + control)	RFE, RF, GBDT, LR, SVM	West China Hospital	F1 score, AUC-ROC	Not specified
2021	Machine learning enhances mortality prediction in non-ST-elevation myocardial infarction	Retrospective cohort	15,247	RF, SVM, XGBoost, Lasso, Ridge, Elastic Net	KRAMI-R CC	Sensitivity, Specificity, Accuracy, F1-score, AUC-ROC	TIMI, GRACE, ACTION-G WTG
2021	Short- and long-term mortality prediction after acute STEMI in Asians	Cohort	6,299 (in-hospital), 3,130 (30 days), 2,939 (1-year)	RF, SVM, LR	Malaysian National Cardiovascular Database	AUC-ROC, Accuracy, Sensitivity, Specificity, PPV, NPV	TIMI score
2021	Stroke risk prediction using machine learning in Chinese adults	Prospective study	503,842	RSF, LR, SVM, GBT, MLP	China Kadoorie Biobank	Sensitivity, Specificity, PPV, NPV, Accuracy, Cohen's kappa	Conventional Cox model
2021	Machine Learning Adds to Clinical Assessments in Predicting CHD and CVD Deaths	Retrospective study	66,636	LogitBoost	CAC Consortium	AUC-ROC, Accuracy, Sensitivity, Specificity, PPV, NPV	ASCVD risk score, CAC score, logistic regression
2021	Predicting 30-day mortality after STEMI using random forest	Retrospective, supervised	ACSIS (2,782) and MINAP (22,693)	Random Forest	ACSIS and MINAP cohort	AUC-ROC	GRACE score
2021	Automatic coronary calcium scoring using deep learning in chest CT	Prospective observational	263	CNN (ResNet architecture)	Not applicable	Correlation coefficient, Sensitivity, Specificity, Agreement analysis	DL vs manual measurements

Continued.

Year	Study name	Study design	Participants	Algorithms used	Dataset details	Performance metrics	Comparison with traditional Methods
2020	Cardiovascular risk prediction in Ankylosing Spondylitis	Retrospective cohort	AS patients	SVM, RF, KNN	Six Italian Rheumatology Units	AUC	FRS, CUORE, SCORE
2019	Predicting atrial fibrillation in primary care using machine learning	Retrospective cohort	Adults ≥30 years	Neural network, LASSO, RF, SVM	Clinical Practice Research Datalink	AUROC, PPV, NNS, Sensitivities	Existing AF risk models (Framingham, ARIC, CHARGE-AF)
2018	Machine learning methodologies vs cardiovascular risk scores	Cohort studies	2,020 adults	NN, RF, Decision Tree	ATTICA prospective study	Sensitivity, Specificity, NPV, PPV	Hellenic-SCORE
2017	Cardiovascular event prediction by machine learning	Randomized Control Trial	6,814 participants	Random Survival Forests	MESA	C-index, Brier Score	Traditional risk scores
2017	Can machine-learning improve cardiovascular risk prediction using routine clinical data	Prospective cohort study	378,256	RF, Logistic Regression, Gradient Boosting, Neural Networks	UK family practices	AUC, CI, PPV, NPV, Sensitivity, Specificity	American College of Cardiology guidelines
2016	Cardiovascular risk prediction: comparative study of Framingham and quantum neural network	Retrospective study	689 patients with CVD symptoms	Quantum Neural Network (QNN)	Framingham study	Accuracy	FRS, European Heart Score
2016	Development of health parameter model for risk prediction of CVD using SVM	Retrospective study	3,654 (CVD follow-up)	Support Vector Machines (SVM)	Blue Mountain Eye Study	Ranking of logistic regression coefficients	Framingham Risk Score
2012	Prediction of cardiac arrest using a machine learning score vs modified early warning score	Observational cohort	Critically ill patients ≥18	ML-based prediction model	ECG data from LIFEPAK 12	More accurate than MEWS in predicting cardiac arrest	Not specified

AUC: Area Under the Curve, AUROC: Area Under the Receiver Operating Characteristic Curve, CAC: Coronary Artery Calcium, CI: Confidence Interval, CVD: Cardiovascular Disease, DL: Deep Learning, EN: Elastic Net, F1: F1 Score, FRS: Framingham Risk Score GBDT: Gradient Boosting Decision Tree, GBT: Gradient Boosted Tree, KNN: K-Nearest Neighbors, LR: Logistic Regression, MI: Myocardial Infarction, ML: Machine Learning, NPV: Negative Predictive Value, PPV: Positive Predictive Value, RF: Random Forest, RSF: Random Survival Forest, SVM: Support Vector Machine, TIMI: Thrombolysis In Myocardial Infarction, XGBoost: Extreme Gradient Boosting.

DISCUSSION

This review evaluated the efficacy of various AI-based predictive tools for cardiovascular disease (CVD) outcomes compared to traditional models across multiple studies. A total of nine studies focused on asymptomatic patients, investigating future ischemic CVD events such as myocardial infarction (MI), heart failure, transient ischemic attack, and ischemic stroke. Notably, one study specifically examined AI-based models for predicting ischemic CVD events in patients with ankylosing spondylitis, a population at elevated risk for atherosclerotic CVD. Additionally, three studies assessed AI tools against traditional models for predicting mortality prior to discharge and within 30 days, three months, and one year following STEMI or NSTEMI. Further analyses explored predictive models for a range of outcomes, including stroke, atrial fibrillation, MI in hospitalized patients, cardiac arrest in critically ill patients within 72 hours of admission, and hypertension.

The application of AI-based machine learning (ML) models in predicting myocardial infarction among hospitalized patients demonstrated notable superiority over traditional guidelines such as the ITF and IAS. Similarly, for stroke prediction over a nine-year period, the Gradient Boosting Tree (GBT) model exhibited enhanced discrimination and calibration, outpacing both the Cox model and the 2017 Framingham Stroke Risk Profile.[26] Moreover, a neural network-based ML tool significantly outperformed established models such as Framingham, ARIC, and CHARGE-AF in identifying atrial fibrillation.[27] In critically ill patients, ML-based scores surpassed the traditional Modified Early Warning Score (MEWS) in accuracy for predicting cardiac arrest within 72 hours of emergency department admission.25 Additionally, machine learning algorithms showed comparable accuracy to the regression-based Cox proportional hazards model in predicting hypertension.[9]

In the context of asymptomatic patients, a study assessed Reti-CVD, an AI-based deep learning tool, against traditional risk models including PCE, QRISK3, and Modified FRS. The results indicated that Reti-CVD effectively identified intermediate and high-risk groups, achieving high sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV).

Specifically, Reti-CVD demonstrated results for PCE (82.7% sensitivity, 87.6% specificity), QRISK3 (82.6% sensitivity, 85.5% specificity), and Modified FRS (82.1% sensitivity, 80.6% specificity), aligning well with existing risk assessment tools.[28]

Similarly, research compared Reti-CVD with QRISK3 and found that individuals identified as high-risk by Reti-CVD had an increased risk of CVD (adjusted hazard ratio (HR) 1.41; 95% confidence interval (CI) 1.30-1.52). Furthermore, Reti-CVD was validated against established metrics such as coronary artery calcium scores (CAC), carotid intima-media thickness (CIMT), and brachial-ankle pulse wave velocity (baPWV). Their findings indicated that Reti-CVD risk stratification was significantly associated with increased CVD risk, yielding HRs of 2.40 for moderate risk and 3.56 for high risk, with low risk as the reference. This validation led to the Korean regulatory body authorizing Reti-CVD as a substitute for CAC due to its comparable efficacy in predicting future CVD events without radiation exposure.[29,30] In the area of coronary artery calcification, one study demonstrated that AI-based automated calcium quantification on non-ECG-triggered chest CT scans correlated strongly with manual quantification and Agatston scores derived from cardiac CTs, with high correlation coefficients ranging from 0.93 to 0.98.[31-34] This suggests significant potential for integrating lung cancer screening with cardiovascular risk evaluation, thereby minimizing additional costs or radiation exposure.[35-39]

For ischemic CVD prediction among rheumatic patients, it was reported that a deep belief network outperformed traditional CVD predictive tools, achieving 73.3% specificity, 87.6% sensitivity, and 83.9% accuracy.[18] Another study highlighted a quantum neural network approach that attained an impressive accuracy of 98.57%, emphasizing the effectiveness of ML methods in this patient population.[23]

In terms of post-MI mortality prediction, one study compared traditional tools such as TIMI, GRACE, and ACTION-GWTG with ML models for predicting in-hospital, 30-day, and one-year mortality following STEMI and NSTEMI. While traditional and ML tools performed similarly for STEMI patients, ML models outperformed traditional methods in NSTEMI cases. Supporting this, another study found that ML models offered superior predictive accuracy for in-hospital, 30-day, and one-year mortality post-STEMI, with area under the curve (AUC) values of 0.88 vs. 0.81, 0.90 vs. 0.80, and 0.84 vs. 0.76, respectively.[12,13]

Another study developed ML-based risk scores using a cohort of 0.5 million Chinese adults for stroke prediction, demonstrating that the GBT technique provided better discrimination and calibration compared to traditional Cox models. Their proposed ensemble approach further enhanced prediction accuracy for high-risk individuals.[14] Lastly, regarding atrial fibrillation prediction, it was noted that ML tools reduced the number needed to screen (NNS) by 31%, enhancing the area under the receiver operating characteristic curve (AUROC) from 0.725 (for CHARGE-AF) to 0.827. This improvement highlights a significant advancement in the cost-effectiveness of atrial fibrillation detection within clinical practice.[19]

In summary, the studies reviewed collectively illustrate that AI-based predictive tools provide substantial advantages over traditional models across various aspects of cardiovascular risk assessment. These innovations facilitate timely interventions and contribute to improved patient outcomes, underscoring the potential for AI to transform cardiovascular care.

CONCLUSION

This review highlights the transformative potential of AI-based predictive tools in assessing cardiovascular disease (CVD) risk, demonstrating that machine learning and deep learning algorithms consistently outperform traditional risk models across various outcomes, including myocardial infarction, stroke, and atrial fibrillation. Notably, tools like Reti-CVD and gradient boosting trees exhibit superior accuracy and robustness in diverse patient populations, enhancing early detection and precise risk stratification while minimizing radiation exposure.

Despite these promising results, further validation in larger, more varied populations is essential to establish the generalizability and reliability of AI-based models. Ongoing research should focus on integrating these technologies into existing healthcare frameworks, equipping clinicians to effectively utilize AI in routine practice. Embracing these innovations could significantly reduce the global burden of cardiovascular diseases and improve outcomes for at-risk patients.

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