AI-Powered Predictive Analytics for Early Detection of Cardiovascular Diseases

Dr. Manoj Sakharam Ishi[1], Harshal Hemane[2], Ashutosh Gaurav[3], Dr. M. I. GLAD MOHESH, MSc, PhD[4]

[1]Assistant Professor, Computer Engineering R C Patel Institute of Technology Shirpur DBATU, Lonere
[2]Assistant Professor-Bharati Vidyapeeth (Deemed to be University) College of Engineering, Pune
[3]Department of statistics, Central University of South Bihar
[4]PROFESSOR, Department of Physiology, Shri Sathya Sai Medical College and RI, (SBV Chennai campus) Tiruporur-Gudvanchery Main road, Ammapettai, Nellikuppam Post, Chengalpattu District

ABSTRACT

Cardiovascular diseases (CVDs) remain the foremost cause of morbidity and mortality worldwide, accounting for an estimated 18 million deaths annually. Early identification of individuals at high cardiovascular risk is crucial for reducing disease burden and improving clinical outcomes. Traditional statistical models such as the Framingham Risk Score and ASCVD calculator, while useful for population-level screening, often fail to capture the complex, nonlinear relationships and temporal patterns underlying disease progression. In recent years, artificial intelligence (AI) and machine learning (ML) have transformed cardiovascular risk prediction by enabling large-scale integration of multimodal data—including electronic health records, imaging modalities, genomic signatures, proteomics, wearable sensors, and behavioral indicators.

This review explores the evolving landscape of AI-powered predictive analytics for early CVD detection. It discusses the types of data used, model architectures, performance metrics, validation approaches, and translational challenges. Emphasis is placed on deep learning methods such as convolutional, recurrent, and transformer networks, as well as ensemble and explainable AI (XAI) frameworks that enhance model transparency and trustworthiness. The paper further examines key applications across coronary artery disease, heart failure, atrial fibrillation, and hypertension, demonstrating how multimodal fusion can improve diagnostic precision and clinical decision-making.

Despite rapid advances, substantial challenges persist—data heterogeneity, privacy concerns, limited external validation, algorithmic bias, and the lack of regulatory clarity impede clinical deployment. Moving forward, collaborative frameworks incorporating federated learning, equity auditing, and regulatory-standard validation will be critical to transforming AI-driven prediction into real-world preventive cardiology. Ultimately, integrating interpretable AI into clinical workflows could redefine how cardiovascular disease is anticipated, managed, and prevented in the era of precision medicine.

KEYWORDS: Cardiovascular disease; early detection; artificial intelligence; predictive modeling; machine learning; risk stratification; explainable AI

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INTRODUCTION

Cardiovascular diseases (CVDs) continue to represent the foremost cause of mortality worldwide, accounting for nearly 18 million deaths annually according to the World Health Organization (WHO, 2023). The global burden of CVDs is not only a medical challenge but also an economic and societal concern, with increasing prevalence in low- and middle-income countries due to lifestyle transitions, urbanization, and aging populations. Despite advances in diagnostic imaging and biomarker development, early detection and risk stratification remain key gaps in preventive cardiology. Traditional statistical tools such as the Framingham Risk Score (FRS), the European SCORE system, and the Atherosclerotic Cardiovascular Disease (ASCVD) risk estimator rely on limited sets of variables including age, blood pressure, cholesterol levels, and smoking habits. While useful for population-level predictions, these models fail to capture the complexity and heterogeneity of individual patient profiles, leading to over- or under-estimation of cardiovascular risk.

Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has revolutionized predictive analytics by allowing systems to learn patterns from vast, multidimensional data. AI-based predictive analytics models can integrate heterogeneous inputs—ranging from electronic health records (EHRs), imaging modalities, and genomic data to wearable sensor outputs—thereby generating individualized risk assessments that are more dynamic and precise. For instance, ML algorithms can uncover subtle nonlinear relationships between variables, identify temporal changes in physiological data, and continuously refine predictions based on longitudinal monitoring.

Moreover, the rise of precision medicine has further emphasized the importance of personalized cardiovascular risk prediction. AI systems can process massive data streams from continuous monitoring devices such as smartwatches and fitness trackers to detect early signs of arrhythmias, myocardial strain, or ischemic patterns before clinical symptoms appear. Deep learning-based electrocardiogram (ECG) classifiers, for instance, have demonstrated performance comparable to expert cardiologists in detecting early atrial fibrillation or left ventricular hypertrophy.

However, despite impressive advancements, several challenges hinder clinical adoption. These include data heterogeneity, algorithmic bias, interpretability issues, and regulatory uncertainties. The transition from experimental algorithms to validated clinical tools requires standardized evaluation protocols, explainable AI frameworks, and regulatory compliance with bodies like the FDA or EMA. This review critically examines current progress in AI-powered predictive analytics for early detection of CVDs, exploring data sources, modeling strategies, validation approaches, and emerging challenges, while proposing future directions for ethical and scalable implementation in clinical environments.

2. Data Inputs for Predictive Models

The success of AI-powered predictive analytics depends largely on the diversity, quality, and integration of data inputs. Cardiovascular prediction models draw from multiple modalities, including clinical, imaging, molecular, and behavioral datasets, each contributing unique insights into disease pathophysiology and progression.

2.1 Clinical and Laboratory Data

Clinical data remain the backbone of most predictive models. Parameters such as age, gender, blood pressure, lipid profile, glucose tolerance, and smoking history are routinely collected in medical settings. When augmented by longitudinal laboratory data and medication records, AI models can identify subtle trends—such as rising cholesterol trajectories or fluctuating blood pressure—that precede overt CVD events. Machine learning techniques like penalized regression, random forests, and gradient boosting allow identification of nonlinear interactions among these variables. Importantly, EHR-based models can continuously update predictions, supporting dynamic risk stratification in real time.

2.2 Imaging Data

Medical imaging offers a rich source of phenotypic information for AI analysis.

Echocardiography provides structural and functional metrics like wall motion, ejection fraction, and myocardial strain patterns. **CT angiography (CTA)** and **MRI** supply detailed anatomical and tissue-level data, including plaque burden, myocardial fibrosis, and perfusion deficits.

Retinal fundus imaging has recently gained interest as a non-invasive surrogate for vascular health, with convolutional neural networks (CNNs) detecting microvascular anomalies predictive of CVD risk.
AI models, particularly deep learning networks, can automatically extract latent features from these images without manual annotation, outperforming traditional handcrafted approaches. For instance, CNN-based plaque characterization has achieved diagnostic accuracies above 90% in differentiating stable from vulnerable atherosclerotic lesions.

2.3 Genomic, Proteomic, and Omics Data

Genomic and multi-omics datasets reveal the molecular underpinnings of cardiovascular risk. Genome-wide association studies (GWAS) have identified polygenic risk scores (PRS) linked to coronary artery disease, hypertension, and dyslipidemia. Machine learning facilitates the integration of these scores with clinical and imaging data, improving predictive accuracy. Moreover, proteomics and metabolomics provide dynamic biomarkers reflecting systemic inflammation, oxidative stress, and lipid metabolism, further refining personalized risk assessment.

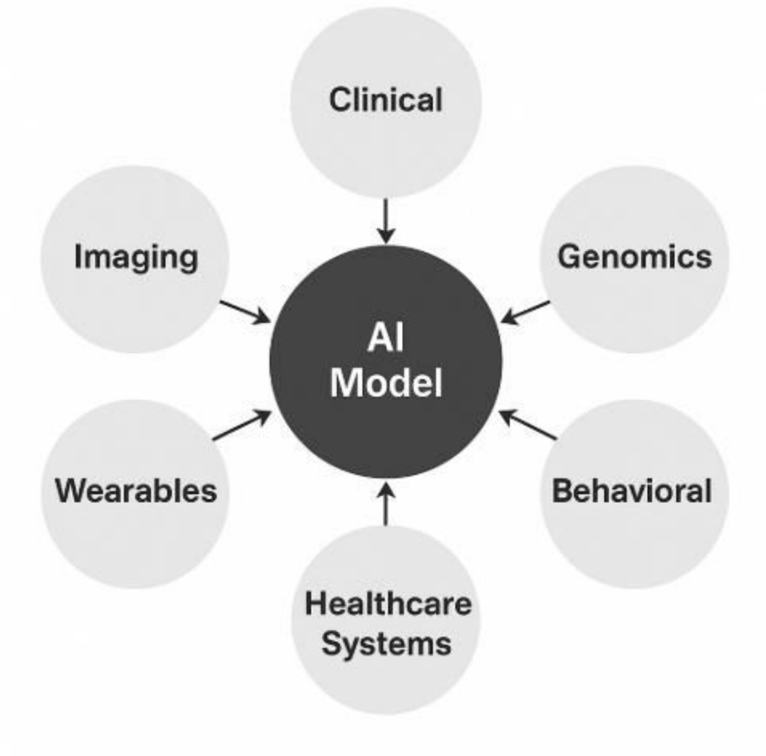
2.4 Wearables, Environmental, and Behavioral Data

Advancements in wearable technology enable continuous physiological monitoring via ECG, photoplethysmography, and accelerometry. These devices record heart rate variability, sleep patterns, and physical activity levels—factors closely tied to cardiovascular health. Additionally, AI models incorporating environmental and behavioral parameters such as air pollution exposure, diet, stress, and socioeconomic status offer a holistic view of risk determinants. Temporal data from wearables are often modeled using Long Short-Term Memory (LSTM) or Transformer architectures capable of capturing sequential dependencies and early deviations from baseline trends.

Table 1. Representative Data Types and AI Methods for Cardiovascular Prediction

Data Type	Examples	AI/ML Methods	Key Insights
Clinical/Lab	BP, lipids, glucose	Logistic Regression, XGBoost	Traditional variables refined with nonlinear patterns
Imaging	CT, MRI, Echo, Retinal Fundus	CNN, Autoencoders	Detect structural and microvascular features
Genomics/Proteomics	SNPs, gene expression, metabolites	Random Forests, Deep Neural Nets	Genetic risk integration
Wearables	ECG, HRV, activity, sleep	LSTM, Transformers	Continuous early detection
Environmental/Behavioral	Air quality, stress, SES	Gradient Boosting, Clustering	Population-level determinants

Figure 1. Multimodal Data Integration Framework



Description: A circular hub diagram showing five data streams (Clinical, Imaging, Genomics, Wearables, Behavioral) converging into a *central AI model* (hybrid ML/DL core), with bidirectional arrows for feedback to healthcare systems.

MODELING APPROACHES

Modeling lies at the heart of AI-driven cardiovascular prediction, where different algorithms are selected based on data type, dimensionality, and clinical interpretability requirements.

3.1 Traditional Machine Learning Models

Classical ML algorithms like logistic regression, random forests, support vector machines (SVM), and gradient boosting (XGBoost, LightGBM) have long been applied to cardiovascular prediction tasks. These models are favored for smaller datasets due to their transparency and interpretability. Logistic regression, for instance, remains useful for identifying independent risk factors, while ensemble models such as random forests can capture nonlinear interactions among variables. Gradient boosting methods, with built-in feature importance metrics, have shown strong performance in predicting adverse cardiac events from tabular EHR data.

3.2 Deep Learning Models

Deep learning (DL) techniques have revolutionized the processing of high-dimensional, unstructured data such as imaging, ECG waveforms, and continuous sensor inputs. Convolutional Neural Networks (CNNs) excel in feature extraction from images like CT scans or retinal photographs, identifying subtle morphological changes associated with atherosclerosis. Recurrent Neural Networks (RNNs) and their advanced variants (LSTMs, GRUs) effectively model temporal dependencies in physiological signals such as ECG or blood pressure series. Recently, transformer-based architectures have emerged as powerful alternatives, offering superior long-range temporal modeling in multimodal cardiovascular datasets.

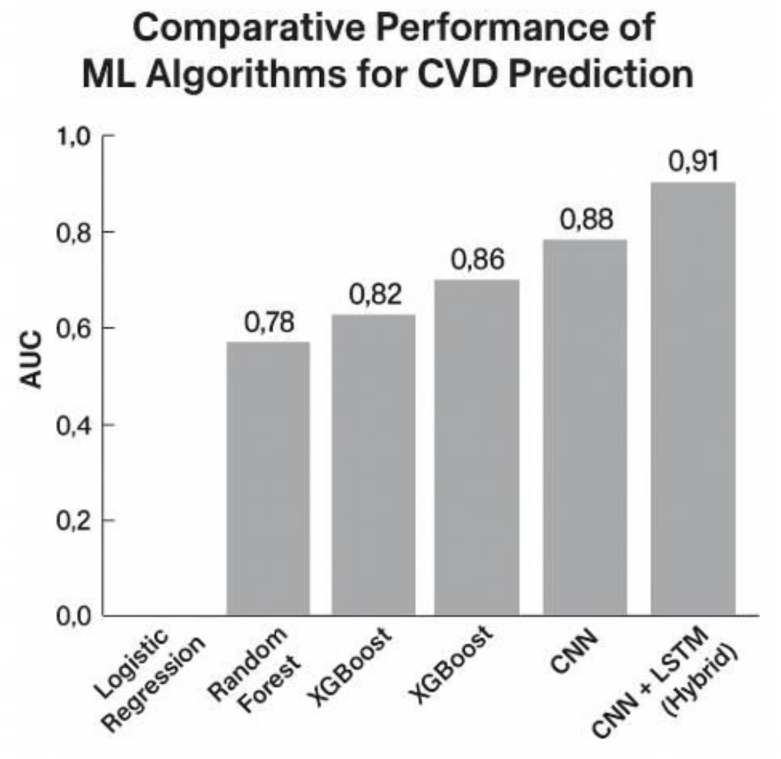
3.3 Hybrid and Ensemble Approaches

Hybrid models integrate the strengths of different algorithmic paradigms. For example, a CNN may first extract imaging features, which are then combined with clinical and genomic data in a gradient boosting classifier for holistic prediction. Ensemble techniques—bagging, boosting, and stacking—combine multiple base learners to reduce variance and bias. These approaches have consistently outperformed single-model architectures, especially when dealing with heterogeneous data sources.

3.4 Explainable and Interpretable AI

Interpretability remains a major bottleneck for clinical acceptance. Explainable AI (XAI) frameworks, such as SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-Agnostic Explanations), and attention heatmaps, are increasingly integrated to make AI outputs understandable to clinicians. Such visual and statistical interpretability tools allow the identification of critical features driving predictions, thereby enhancing trust and accountability in medical decision-making. Additionally, inherently interpretable architectures like Generalized Additive Models (GAMs) and symbolic regression are being revisited to balance transparency with predictive strength.

Graph 1. Comparative Performance of ML Algorithms for CVD Prediction Graph Type: Bar chart comparing AUC (Area Under Curve) across models: Logistic Regression = 0.78 Random Forest = 0.82 XGBoost = 0.86 CNN = 0.88 CNN + LSTM (Hybrid) = 0.91 Insight: Deep learning and hybrid architectures outperform traditional ML for large multimodal datasets.



VALIDATION, PERFORMANCE, AND BENCHMARKS

Rigorous validation is the cornerstone of reliable AI models for cardiovascular prediction. While many studies report impressive accuracy within training datasets, the true test lies in reproducibility and generalizability across populations and settings.

4.1 Internal Validation.

Internal validation typically employs *k*-fold cross-validation, bootstrapping, or stratified hold-out splits to estimate model stability. These methods ensure that predictive performance is not overly dependent on a particular data partition. However, internal validation alone may overstate real-world reliability, as it does not capture domain shift or external variability.

4.2 External Validation.

External validation—testing the model on a geographically or temporally distinct cohort—is indispensable. For instance, a deep learning model trained on European CT angiography data may underperform when applied to Asian or African cohorts due to demographic and genetic variability. Several multicenter initiatives, such as the UK Biobank and MESA (Multi-Ethnic Study of Atherosclerosis), provide diverse datasets for such benchmarking. Yet, fewer than 20 percent of AI-CVD studies perform full external validation, limiting clinical confidence.

4.3 Performance Metrics.

Model performance is commonly assessed using receiver operating characteristic (ROC) and area under the curve (AUC), precision-recall (PR) curves, sensitivity, specificity, and F-scores. However, in imbalanced datasets—where disease prevalence is low—metrics such as PR-AUC, calibration slope, Brier score, and decision-curve analysis offer more meaningful insights. The Net Reclassification Improvement (NRI) index quantifies whether an AI model improves patient risk categorization over standard tools like the FRS.

4.4 Prospective Evaluation and Clinical Trials.

Despite numerous retrospective validations, prospective trials remain scarce. Prospective testing in live clinical environments evaluates not only diagnostic accuracy but also impact on patient outcomes, physician workflow, and cost-effectiveness. The FDA's Software-as-a-Medical-Device (SaMD) framework now mandates real-world performance monitoring and continuous post-market evaluation.

4.5 Benchmarking Initiatives.

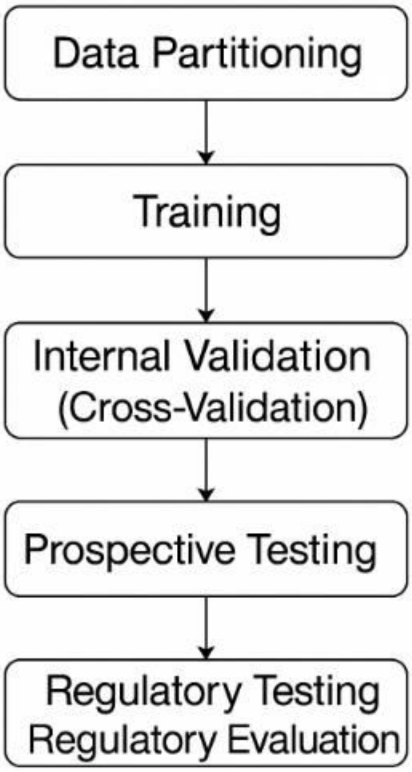
Open challenges such as PhysioNet Computing in Cardiology and NIH imaging datasets promote reproducibility by standardizing evaluation pipelines. Establishing shared benchmark repositories with standardized metrics will accelerate regulatory approval and translational uptake.

In sum, rigorous validation and transparent reporting are prerequisites for clinical adoption of AI-driven cardiovascular prediction. Without these, even the most accurate algorithms risk failure in real-world deployment.

Table 2. Common Performance Metrics in AI-CVD Studies

Metric	Definition	Clinical Relevance
ROC-AUC	Discrimination ability	Overall accuracy
PR-AUC	Precision in imbalanced data	Event prediction
Sensitivity / Specificity	True positive / negative rates	Clinical safety
Brier Score	Calibration measure	Model reliability
NRI	Improvement over standard models	Added clinical value

Figure 2. Model Validation Workflow Diagram



Purpose: Illustrates robust pipeline for real-world model deployment.

KEY APPLICATIONS AND CASE STUDIES

AI-based predictive analytics have demonstrated compelling applications across the spectrum of cardiovascular disorders, showcasing the power of multimodal data fusion.

5.1 Coronary Artery Disease (CAD).

Deep learning models applied to coronary CT angiography can quantify plaque burden, composition, and vessel stenosis. For example, a CNN model integrating CT and clinical data achieved AUC > 0.85 for predicting major adverse cardiac events (MACE), outperforming expert-graded plaque scores. Similarly, radiomic feature extraction from MRI and PET enables early identification of myocardial ischemia.

5.2 Heart Failure Prediction.

AI systems analyzing echocardiographic videos with recurrent networks can detect subtle myocardial strain patterns predictive of future heart failure, even before symptomatic decline. Integration of serum biomarkers such as NT-proBNP with imaging and EHR data has further enhanced sensitivity.

5.3 Atrial Fibrillation and Stroke.
Wearable ECG devices coupled with deep learning classifiers have shown >95 % accuracy in detecting paroxysmal atrial fibrillation episodes. Predictive modeling that fuses ECG-derived features with patient demographics can forecast stroke risk, improving upon CHADS-VASc scores.

5.4 Hypertension and Subclinical Vascular Disease.
Machine learning models trained on continuous blood-pressure monitoring and arterial stiffness parameters can identify early endothelial dysfunction—detecting vascular aging before clinical hypertension emerges.

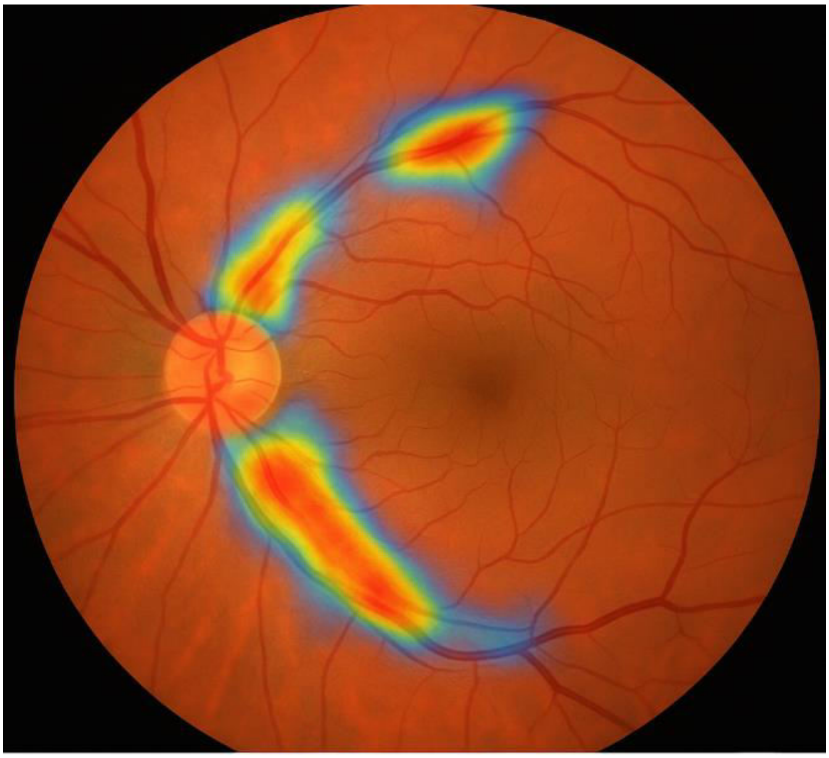
5.5 Multimorbidity Prediction.
Beyond single-disease forecasting, AI can predict composite cardiovascular endpoints such as myocardial infarction, heart failure hospitalization, and mortality. Multimodal fusion of EHRs, genomics, and wearable sensor data provides a holistic view of patient health trajectories.

5.6 Implementation Examples.
Notable case studies include Google Health's retinal-fundus AI model that infers cardiovascular risk factors non-invasively, and the Mayo Clinic's ECG-based neural network detecting asymptomatic left-ventricular dysfunction with AUC ≈ 0.93. These prototypes demonstrate clinical feasibility but require broader validation across ethnicities and hardware platforms.
Collectively, these applications highlight the transformative potential of AI to detect disease at pre-clinical stages, personalize therapy, and optimize resource allocation.

Table 3. Summary of AI Applications in Cardiovascular Disease Detection

CVD Type	Data Source	AI Model Used	Performance (AUC)	Key Outcome
Coronary Artery Disease	CT Angiography + Clinical	CNN + Gradient Boost	0.85–0.90	Detects vulnerable plaques
Heart Failure	Echo + Biomarkers	RNN / LSTM	0.83–0.88	Predicts preclinical heart failure
Atrial Fibrillation	Wearable ECG	CNN	0.95	Early arrhythmia detection
Stroke Risk	EHR + ECG + Clinical	Ensemble Model	0.86	Better than CHADS-VASc
Hypertension	Continuous BP + Lifestyle	Random Forest	0.80	Early vascular dysfunction

Figure 3. Case Study Illustration — AI-assisted Retinal Fundus Analysis



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features predictive of hypettensicon and CVD

Description: Retinal image with AI heatmap overlay highlighting microvascular features predictive of hypertension and CVD.

CHALLENGES AND LIMITATIONS

Despite significant progress, translating AI-driven cardiovascular prediction into routine clinical practice faces numerous obstacles.

6.1 Data Quality and Heterogeneity.
Clinical data are often incomplete, noisy, or inconsistently labeled. Variations in imaging protocols, equipment, and population demographics create biases that degrade model performance. Standardization initiatives such as FHIR (Fast Healthcare Interoperability Resources) aim to mitigate this, but adoption remains uneven.

6.2 Sample Size and Dimensionality Dilemma.
High-dimensional inputs from genomics and imaging require large sample sizes to avoid overfitting. Many current datasets comprise thousands rather than millions of records, limiting generalization. Data-augmentation, transfer-learning, and federated-learning frameworks are being explored to overcome this bottleneck.

6.3 Interpretability and Trust.
"Black-box" neural networks hinder clinician acceptance. Explainable-AI (XAI) methods—heatmaps, SHAP values, and attention visualizations—are being integrated to reveal which features influence predictions, but balancing accuracy with interpretability remains difficult.

6.4 Ethical and Regulatory Concerns.
Privacy, informed consent, and algorithmic fairness are major ethical issues. AI systems trained on homogeneous datasets may inadvertently reinforce health disparities. Regulatory agencies like the FDA and EMA are developing adaptive approval pathways, yet global harmonization is lacking.

6.5 Clinical Integration and Workflow.
Embedding AI models into electronic health record (EHR) systems poses technical and logistical challenges. Clinicians require user-friendly dashboards and alert systems that complement rather than complicate workflows. Continuous model updating, interoperability, and training are critical for sustained use.

6.6 Prospective Validation and Model Maintenance.
Few AI systems have undergone prospective randomized trials comparing AI-guided interventions versus standard care. Additionally, population drift and new clinical protocols necessitate periodic retraining. Without lifecycle management, model accuracy degrades over time.

6.7 Bias and Fairness.
Socioeconomic, gender, and ethnic imbalances in training data can skew predictions. Incorporating fairness auditing and bias-correction strategies—such as re-weighting or adversarial debiasing—is essential for equitable healthcare outcomes.
In essence, overcoming these limitations demands interdisciplinary collaboration among clinicians, data scientists, regulators, and ethicists. Sustainable deployment of AI-powered cardiovascular analytics will rely on transparent data governance, ongoing model monitoring, and equitable access across healthcare settings.

Figure 4. Summary of Key Challenges in AI-based CVD Prediction

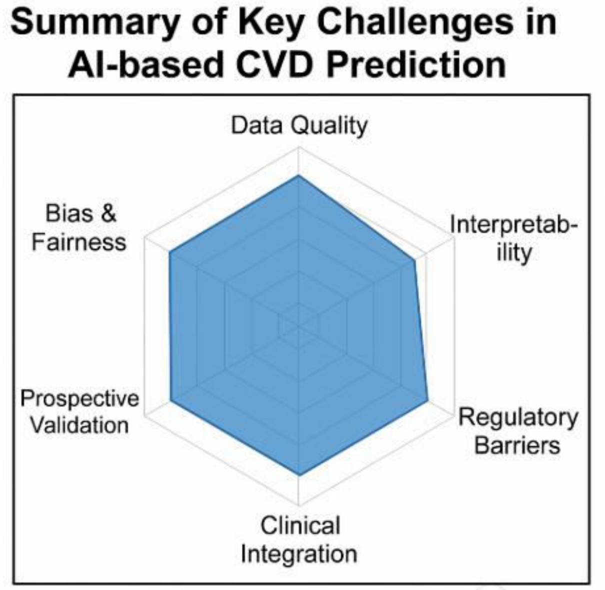

Diagram Type: Spider (radar) chart with six axes: *Data Quality*, *Bias & Fairness*, *Interpretability*, *Regulatory Barriers*, *Clinical Integration*, *Prospective Validation*.

Table 4. Ethical and Technical Challenges with Possible Mitigation Strategies

Challenge	Impact	Mitigation Strategy
Data bias	Misclassification across ethnicities	Fairness auditing, diverse datasets
Privacy concerns	Legal non-compliance	Federated learning, encryption
Model drift	Declining accuracy	Continuous retraining
Lack of interpretability	Low clinician trust	Explainable AI frameworks
Integration hurdles	Poor adoption	EHR-friendly interfaces

FUTURE DIRECTIONS & RECOMMENDATIONS

The coming decade promises transformative evolution in AI-based cardiovascular risk prediction, driven by advances in data integration, algorithmic transparency, and clinical translation. Yet, realizing this potential demands a coordinated, multidisciplinary approach bridging technology, clinical science, and regulatory policy.

7.1 Federated and Privacy-Preserving Learning

A key barrier to large-scale AI model development is data privacy. Federated learning enables multiple hospitals or institutions to collaboratively train models without sharing raw data. By exchanging only model parameters, it preserves patient confidentiality and overcomes institutional data silos. Techniques such as differential privacy and homomorphic encryption further safeguard sensitive health information. Global collaborations under this framework—such as the *Federated Tumor Segmentation* (FeTS) initiative—could be mirrored in cardiology to accelerate secure model training.

7.2 Multimodal Data Fusion

The next generation of predictive systems will integrate multimodal data—combining EHRs, imaging, genomics, and continuous wearable signals. Multimodal fusion improves prediction accuracy and interpretability by capturing inter-domain correlations. Graph neural networks (GNNs) and transformer-based architectures are particularly suited for such complex data fusion, enabling simultaneous analysis of heterogeneous inputs. Future research should focus on standardized pipelines that harmonize data preprocessing and synchronization across modalities.

7.3 Continual and Transfer Learning

CVD risk models must evolve with changing patient demographics, emerging biomarkers, and technological advances. Continual learning frameworks allow AI systems to update incrementally as new data arrive, avoiding catastrophic forgetting. Transfer learning—leveraging pretrained models on related datasets—reduces dependence on large annotated datasets and enhances adaptability across institutions.

7.4 Explainability-First Model Design

Trustworthy AI requires models that are explainable by design rather than retrospectively interpreted. Integrating attention mechanisms, interpretable surrogate layers, and rule-based hybrid architectures ensures clinical transparency. Research into causal inference and counterfactual explanations may further align AI reasoning with clinical logic, fostering clinician confidence.

7.5 Regulatory and Ethical Standardization

Global consensus on AI validation and certification is urgently needed. Frameworks like the FDA's *Good Machine Learning Practice (GMLP)* and the European Union's *AI Act* can provide templates for cardiovascular AI regulation. Ethical audits should accompany technical validation, emphasizing fairness, accountability, and patient autonomy. Standardized reporting checklists—such as TRIPOD-AI and CONSORT-AI—should be mandatory for publication and approval.

7.6 Clinical Implementation and Education

For effective deployment, AI tools must integrate seamlessly into existing clinical workflows. User-friendly dashboards, decision-support systems, and continuous feedback loops should be co-designed with clinicians. Parallel efforts in clinician education and digital literacy are essential to foster AI acceptance and reduce overreliance or misuse.

7.7 Open Science and Collaborative Benchmarking

Publicly accessible benchmark datasets and leaderboards (e.g., PhysioNet, UK Biobank, Kaggle CVD Challenges) will promote transparency and innovation. Open-source toolkits for model auditing and fairness testing can accelerate reproducibility. International consortiums linking academic, industry, and policy stakeholders should drive collaborative progress in AI-enabled preventive cardiology.

In summary, the future of AI in cardiovascular medicine will depend not only on algorithmic excellence but also on ethical governance, interoperability, and sustained collaboration among researchers, clinicians, and policymakers.

CONCLUSION

Artificial intelligence has emerged as a cornerstone of precision cardiovascular medicine, capable of transforming early disease detection and preventive care. Through machine-learning and deep-learning algorithms, clinicians can now analyze vast multimodal datasets—from genomics to imaging and wearables—to uncover patterns that were previously inaccessible to human cognition. Predictive analytics powered by AI have already demonstrated superior accuracy compared to traditional statistical models in identifying at-risk individuals, detecting subclinical pathologies, and forecasting adverse cardiac events.

Despite these advances, translation into clinical routine remains limited. The obstacles are multifaceted: data fragmentation, lack of external validation, regulatory ambiguity, algorithmic bias, and insufficient interpretability. Addressing these requires comprehensive strategies encompassing federated data infrastructures, explainable-AI frameworks, and standardized validation protocols aligned with global regulatory bodies. Prospective clinical trials and real-world implementation studies will be vital to evaluate the safety, efficacy, and cost-effectiveness of AI-driven decision support.

The ultimate goal is to shift cardiovascular medicine from reactive treatment to proactive prevention. Integrating AI systems into electronic health records can enable continuous risk monitoring, personalized therapy optimization, and population-level surveillance. In parallel, equity-focused approaches must ensure that AI tools benefit diverse populations and do not amplify existing healthcare disparities.

As computing power, data quality, and clinical collaboration advance, AI-powered predictive analytics are poised to become an indispensable component of preventive cardiology. With sustained commitment to transparency, regulation, and interdisciplinary research, these intelligent systems could redefine cardiovascular care—transforming early detection into a powerful instrument for saving millions of lives globally.

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