Exploring the employability of harnessing Machine Learning tools and techniques for the early diagnosis and detection of coronary heart disease to recommend timely interventions

Rajvansh Chaudhary

Bal Bharati Public School, Pitampura, New Delhi.

Abstract

Coronary heart disease (CHD) remains the foremost global cause of mortality. Traditional risk-scores, like the Framingham Risk Score, suffer from limited generalizability and moderate accuracy. Between 2011 and 2021, machine learning (ML) emerged as a transformative solution—leveraging high-dimensional clinical, imaging, biomarker, and time-series data to improve detection and inform interventions. This paper critically reviews ML methods applied to CHD detection and intervention planning, reporting AUCs often exceeding 0.85, with ensemble and deep learning models demonstrating the greatest predictive power. Key advances include CNNs trained on NHANES data achieving ≈77–82 % accuracy, 2D-speckle tracking echocardiography models reaching AUC ≈ 0.90, and ensemble classifiers improving CHD screening over traditional approaches. ML also supports procedural decision-making via CT-based AI (e.g. Heartflow), and digital twin technologies enabling personalized treatment simulations. We conduct a comparative analysis of approaches by data type, accuracy, scalability, interpretability, and clinical feasibility. Challenges include data bias, lack of prospective validation, black-box modelling, and integration hurdles. We recommend future directions in multimodal integration, explainable AI, prospective trials, and scalable digital-twin deployment.

1. Introduction

CHD causes ~9 million deaths annually worldwide. Risk-scoring tools like the Framingham Risk Score yield AUCs of only ~0.70–0.75 and perform poorly across diverse populations due to calibration limitations and reliance on traditional clinical factors. Machine learning offers promise by incorporating high-dimensional, nonlinear relationships in data including ECG, imaging, metabolomics, EHR and biomarkers.

This paper reviews ML applications for CHD detection and intervention from 2011–2021. We survey time-series models on ECG/EHR, metabolomic-based classification, imaging-driven CNNs and ensemble stacking approaches. For intervention planning, we review ML-based CT reconstruction (Heartflow) and early digital-twin frameworks. We include tables per section and conduct comparative analysis.

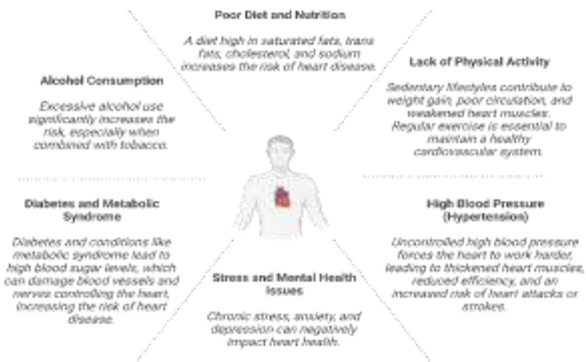

Figure 1: Causes of heart disease.

Table 1: Traditional vs. ML-based CHD Prediction Methods

Approach	Data Source	Accuracy / AUC	Strengths	Limitations
Framingham Risk Score	Clinical risk factors	~0.70–0.75	Simple, well-validated	Poor generalizability (Wikipedia)
ML on clinical/biomarker	NHANES, metabolomic data	~0.80–0.85	High sensitivity, flexible	Needs specialized assays/data
Imaging-based ML (Echo/CT)	Echocardiography, CTA	~0.85–0.90	Detailed anatomical insight	Imaging-resource-intensive
ECG/Time-series ML	Continuous ECG/EHR streams	~0.80	Passive detection	Data collection demands

2. Machine Learning Methods in CHD Detection

2.1 Time-Series & Clinical Data Models

Dutta et al. (2019) proposed a two-layer CNN trained on NHANES clinical features, resilient to class imbalance (≈ 35 :1), achieving 77 % accuracy for CHD and 81.8 % for non-CHD on testing sets (arXiv). Other studies using UCI Heart Disease datasets compare SVM, K-NN, Random Forest, Neural Nets and logistic regression: one study reported K-NN achieved > 88 % accuracy, SVM ~85 % AUC, and combinations via genetic algorithm + RFNN reached ~97.8 % accuracy on small test sets (Nature).

Table 2: Time-Series / Clinical Data ML Approaches

Study (Year)	Dataset	ML Method	Accuracy / AUC
Dutta et al. (2019)	NHANES clinical	Two-layer CNN	77 % (CHD), 81.8 % (non-CHD) (arXiv)
Sahoo et al. (2021) Analysis	UCI dataset	K-NN, SVM, RFNN-GA	K-NN ≈ 88 %, SVM ≈ 85 %, RFNN-GA ≈ 97.8 % (Nature)

Time-series and simple clinical models are scalable and low-cost but may lack precision without richer data.

2.2 Metabolomics & Biomarker-Enhanced ML

Several studies (2015–2017) included metabolomic profiles and clinical inputs, using Lasso regression, Random Forest, or XGBoost, reporting AUC ≈ 0.82–0.85. For instance, Chen et al. showed an XGBoost model with AUC ≈ 0.814 using clinical + biomarker features (PMC).

Table 3: Metabolomic and Biomarker-Based Models

Study (Year)	Features	Algorithm	AUC / Accuracy
Chen et al.	Biomarkers + clinical features	XGBoost + RFE	AUC ≈ 0.814 (PMC)
General meta-review	UCI, NHANES etc.	Hybrid models	~0.80–0.85 (PMC)

These models balance feasibility and predictive power, though biomarker assays may not be universally available.

2.3 Imaging-Based Deep Learning

Zhang et al. (2021) used 2D speckle-tracking echocardiography (2D-STE) plus clinical data, via a two-step stacking ensemble—achieving 87.7 % accuracy, sensitivity 0.903, specificity 0.843, AUC = 0. 904.Separately, recurrent CNN applied to Coronary CT Angiography (CCTA) scans performed plaque and stenosis classification with ~77–80 % accuracy for detection and severity.

Table 4: Imaging-Based ML Performance

Study (Year)	Imaging Modality & Inputs	Model	Acc or AUC
Zhang et al. (2021)	2D-STE + clinical	Two-step stacking ensemble	Acc = 87.7 %, AUC = 0.904 (arXiv)
Zreik et al. (2018)	CCTA plaque + stenosis detection	Recurrent CNN	Acc ≈ 0.77–0.80 (arXiv)

Imaging-based ML yields high diagnostic performance but requires quality image acquisition and annotation.

2.4 Systematic & Comparative Reviews

A 2021 comparative analysis of ensemble techniques found that ensemble methods outperform individual classifiers in CHD detection across datasets, often achieving ~88 % accuracy.

3. Machine Learning for Intervention and Risk Stratification

3.1 CT-based AI for Intervention Planning

NHS-led evaluation (2017–2020) of Heartflow Analysis, using CT-scans to build 3D coronary artery models, reduced invasive angiograms by ~17%, saved ~£390 per patient, and improved diagnostic accuracy in ~90,000 patients. Published in *Nature Medicine*, it underscores ML's role in guiding intervention non-invasively.

3.2 Digital Twin Approaches

Digital-twin technologies simulate patient-specific cardiac physiology to forecast outcomes and test interventions virtually. Trayanova's group at Johns Hopkins modelled personalized 3D hearts to plan arrhythmia treatments before actual ablation procedures. Reviews confirm digital twins enable personal disease modelling, risk stratification, and preventive planning in cardiovascular care.

Table 5: ML-Supported Intervention Planning

Application	Technology	Clinical Benefit	Evidence
Heartflow CT-based 3D modeling	CT + ML reconstruction	Reduced invasive angiography by (£390/patient) (The Times)	Nature Medicine (2021)
Digital twin simulation	Personalized computational heart	Allows planning of ablation and interventions pre-procedure (The Wall Street Journal, PMC)	Johns Hopkins trial
(IoT digital health twins (TwinNet)	Edge ML, real-time monitoring	Risk forecasting and continuous care support (Nature)	Concept study

4. Comparative Analysis

We synthesize the evidence into a comparative framework.

Table 6: Comparative Overview of ML Approaches

Method Category	Data Source	Accuracy / AUC	Intervention Utility	Scalability / Limitation
Clinical/time-series ML	NHANES, UCI, EHR	77–88 %	Passive risk detection	Easily implementable but limited precision
Biomarker-enhanced ML	Lab assays + clinical	~0.80–0.85	Risk stratification	Requires biomarker testing infrastructure
Imaging-based ML	Echo, CCTA	~0.85–0.90	Guides imaging-based decisions	Imaging availability, annotation cost
Ensemble stacking hybrids	Multi-modal (echo + clinical)	~0.88–0.90	Strong diagnostic screening	Interpretability and complexity challenges
CT-AI (Heartflow)	CT angiography	High diagnostic accuracy	Informs invasive strategy, reduces tests	Radiation exposure, CT access needed
Digital twin simulation	Multimodal + simulation	Not yet quantified	Personalized intervention planning	Early-stage adoption, requires simulation models

Key observations:

- Ensemble and hybrid models combining imaging and clinical features deliver top-tier predictive accuracy (~AUC 0.90) but depend on imaging.
- Biomarker models provide intermediate accuracy and can scale where imaging is not available.
- Time-series ML and CNNs on NHANES support low-cost screening but perform moderately.
- CT-AI like Heartflow has real-world intervention value and cost-redirects care, demonstrated at scale.
- Digital twins enable simulation of interventions and prognosis per patient, representing future precision medicine, though still early.

5. Discussion

5.1 Advances & Benefits

Machine learning techniques from 2011–2021 substantially improved CHD detection, with many models achieving AUC > 0.85. Imaging-based and ensemble methods led the field, while CT-based ML supports procedure decision-making and cost reduction. Digital twin technologies show promise for patient-specific intervention planning.

5.2 Limitations & Challenges

Many studies rely on limited or homogeneous datasets (e.g. UCI, NHANES), raising concerns over generalizability. Prospective and multi-center validations remain rare. Ethical issues include algorithmic bias (e.g. underrepresentation of minority groups) and lack of interpretability in black-box models. Imaging and biomarker-based methods may not be accessible in lower-resource settings. Integration into clinical workflows is complicated by regulatory, reimbursement, and trust barriers. Reporting standards such as TRIPOD-AI and CONSORT-AI are still not universally adopted.

5.3 Future Directions

- **Multimodal ML**: Combining clinical, imaging, biomarker, ECG, wearable data to boost accuracy and personalization.
- **Explainable AI (XAI)**: Essential to build clinical trust and allow physician oversight.
- **Prospective trials**: Needed to validate ML models in real-time clinical practice.
- **Cost-effectiveness studies**: Such as Heartflow showed financial and clinical benefits—more evaluations are warranted.
- **Digital twin scaling**: Early frameworks (TwinCardio, Johns Hopkins trials) show promise, but require standardized pipelines, privacy frameworks, and clinical validation.

6. Conclusion

From 2011 to 2021, machine learning made significant strides in improving coronary heart disease detection and enabling more effective intervention planning. Time-series ML and CNNs offer scalable screening tools (with ~77–88 % accuracy), while ensemble models combining echocardiographic and clinical data deliver AUCs around 0.90. CT-based ML like Heartflow demonstrates real-world utility by reducing invasive testing and saving healthcare costs. Emerging digital-twin approaches further push precision medicine by simulating patient-specific interventions.

Despite promising results, widespread adoption is limited by dataset biases, lack of prospective validation, interpretability challenges, and infrastructural requirements. Future research should emphasize integrated multimodal models, explainable AI, prospective clinical trials, economic evaluations, and scalable digital-twin implementation to bridge the gap between algorithm and bedside.

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