



Artificial Intelligence and Machine Learning for Heart Disease Risk Assessment: A Systematic Review and the Case for an Explainable Clinical Decision Support System

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Abstract— Cardiovascular disease remains the leading cause of death worldwide and still claims millions of lives each year despite steady therapeutic progress. Artificial intelligence (AI), machine learning (ML) and deep learning (DL) promise earlier and more precise detection of cardiac risk than conventional scores allow. This paper reviews 55 peer-reviewed studies, published between 2014 and 2026, that apply AI and ML to heart disease risk assessment. Following the PRISMA reporting framework, it examines classification performance, feature selection, interpretability, readiness for clinical use and the data on which models are built, and a bibliometric analysis traces publication trends, methodological concentration and the geographical distribution of research. The central finding is that most models use fewer than fifteen clinical variables and seldom combine structured data, free-text clinical notes, lifestyle information and laboratory results in a single interpretable system suitable for the bedside. Only 11% of the studies incorporate explainability methods, and 47% rely mainly on the 303-record UCI Cleveland dataset. In response, the paper outlines a Clinical Decision Support System (CDSS) that uses more than twenty variables, combines ensemble and deep learning architectures, and builds in SHAP and LIME explanations to support physician trust and transparent decisions. The review argues that the next generation of cardiac risk tools must be broader in scope, interpretable by design and evaluated in clinical practice rather than on benchmarks alone.

Keywords— Clinical decision support system, heart disease prediction, machine learning, deep learning, natural language processing, electronic health records, cardiovascular risk, explainable AI, systematic literature review

I. INTRODUCTION

Cardiovascular disease (CVD) has been the world's leading cause of death for decades. According to the World Health Organization, ischaemic heart disease alone accounts for roughly one death in six worldwide, a share that has grown even as treatment has improved [1-5]. The burden falls hardest on low- and middle-income countries, where health systems are stretched and diagnostic capacity trails demand. India exemplifies the pattern: urbanisation, changing diets, more sedentary lives and rising stress have made CVD a growing

public-health problem that weighs on patients and services alike.

Reducing this toll depends as much on identifying at-risk individuals early and accurately as on treatment. Established risk scores, including the Framingham Risk Score, the ACC/AHA Pooled Cohort Equations and SCORE, have served this purpose for decades, but they consider few variables and rest on comparatively simple statistics. None was designed to capture the non-linear interactions among the many clinical, biochemical and lifestyle factors that modern health systems routinely record.

AI and ML have therefore taken on a growing role in cardiovascular risk assessment. A gap nonetheless persists between how accurate a model is and how useful it proves in the clinic. A model that predicts heart disease with 90% accuracy is of limited value if the physicians who remain responsible for the patient cannot follow its reasoning well enough to trust it. Only recently has the field begun to prioritise explainability, showing clinicians which features drove a prediction and by how much, so that models inform clinical judgement instead of obscuring it.

Recurring problems remain. Many models are still trained and validated on the same small, dated datasets, above all the Cleveland Heart Disease dataset from the UCI Machine Learning Repository [6-10], with 13 clinical features and a few hundred records. Work on this dataset has advanced methodological understanding, but whether its conclusions carry over to real clinics is uncertain, because real patients present with multiple comorbidities, concurrent medications, long histories and free-text notes that record nuances no structured field captures.

The review pursues three linked objectives: to map the methodological landscape by identifying the algorithms, datasets and performance benchmarks that dominate the literature; to locate structural gaps, particularly in the completeness of clinical parameters, model interpretability and integration into clinical workflows; and, on that evidence, to argue for a new Clinical Decision Support System in which a wider, multi-domain set of parameters, ensemble and deep



learning models, and explanations built for clinicians are designed together from the start.

II. BACKGROUND AND MOTIVATION

A. The Clinical Burden of Cardiovascular Disease

Heart disease is not a single diagnosis but a family of disorders of cardiac structure and function, including coronary artery disease, heart failure, arrhythmias, valvular disease and congenital abnormalities. Its principal risk factors, hypertension, dyslipidaemia, diabetes mellitus, obesity, tobacco use, physical inactivity and family history, are well documented. Much less is understood about how these factors compound when they occur together, especially in patients with comorbidities or from different ethnic and demographic groups.

India presents a distinctive epidemiological picture. Coronary artery disease tends to appear at a younger age than in Western populations, and risk profiles differ; central obesity and insulin resistance, for example, may be present at comparatively low body weight [7-14]. Models derived from Western cohorts may therefore underestimate risk in Indian patients, which is at once a public-health problem and a research opportunity. A CDSS built on data from Indian patients would have considerable clinical value.

B. Limitations of Conventional Risk Scoring

Risk equations from the Framingham Heart Study have underpinned cardiovascular prevention for more than fifty years. The ACC/AHA Pooled Cohort Equations, introduced in 2013, broadened the predictors and improved calibration across diverse American populations. Both remain linear or only moderately complex, typically use eight to twelve variables, and were derived from cohorts that do not necessarily generalise to today's populations. They have no way to represent non-linear interactions, nor to take in recent biomarkers, lifestyle measures or outcomes reported by patients. Weng et al. [7] demonstrated the cost of this limitation on more than 378,000 UK primary-care records: ML algorithms outperformed the ACC/AHA score on the same population because they could exploit higher-dimensional data and capture interactions that linear models miss.

C. The Promise and Perils of AI in Cardiology

AI can process far more clinical data than any clinician could review, does not tire over a long shift, and may reveal risk patterns that experienced physicians overlook. These capabilities have been shown in arrhythmia detection from ECGs [20], [39], heart-failure staging [25] and prediction of coronary artery disease from clinical text [13], [37]. Careless deployment, however, carries real risk. Models trained on biased data make biased predictions; models that cannot be interpreted cannot be safely embedded in clinical workflows; and models tested only on data from the population they were trained on may fail in another hospital, another ethnic group or

an atypical patient. These tensions run through the literature reviewed below.

III. RESEARCH METHODOLOGY

A. Review Protocol

The review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. Its guiding question was: how have AI, ML and DL methods been used to estimate heart disease risk from clinical data, and where are the methodological strengths and weaknesses of that body of work?

B. Search Strategy and Eligibility

Structured keyword searches were run in four databases: Scopus, Web of Science, IEEE Xplore and PubMed. Search strings combined a medical domain (heart disease, cardiovascular disease, coronary artery disease, cardiac risk, heart failure) with a computational domain (machine learning, deep learning, artificial intelligence, neural network, clinical decision support, natural language processing, ensemble learning), joined with Boolean operators to balance breadth and precision. Studies were included if they (a) addressed prediction, classification or risk stratification of heart disease; (b) applied at least one AI, ML or DL technique; (c) used clinical, tabular or clinical-text data rather than imaging alone; (d) appeared between 2014 and 2026 in a Scopus- or Web of Science-indexed journal or a top-tier conference; and (e) reported at least one quantitative performance metric. Imaging-only studies without clinical data, reviews without original findings, and grey literature were excluded.

C. Study Selection and Data Extraction

The search returned more than 2,300 records. After deduplication and title and abstract screening, 312 full texts were assessed against the eligibility criteria, and 55 studies were retained. For each, the following were extracted: authors and year, title, aim, model or method, dataset and sample size, features and parameter count, evaluation metrics and principal findings (Table III).

IV. BIBLIOMETRIC ANALYSIS

Bibliometric analysis complements the narrative review quantitatively, showing where research effort is concentrated, how the field has developed and where gaps remain. This section profiles the 55 included studies.

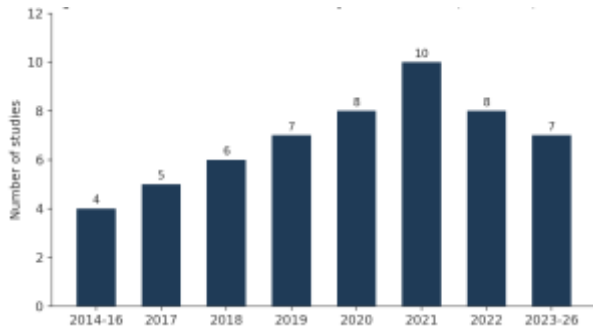
A. Publication Trends

The distribution of studies by year (Table I, Fig. 1) shows rapid growth. Only four studies appeared in 2014–2016, reflecting the early stage of AI in cardiac risk assessment. Output accelerated after 2017 and peaked at ten studies in 2021, in line with the wider surge in AI-driven healthcare research after the COVID-19 pandemic. Most of the literature is recent: by the counts in Table I, 46 of the 55 studies (83.6%) were published from 2018 onwards.



TEMPORAL DISTRIBUTION OF REVIEWED PUBLICATIONS (2014–2026)

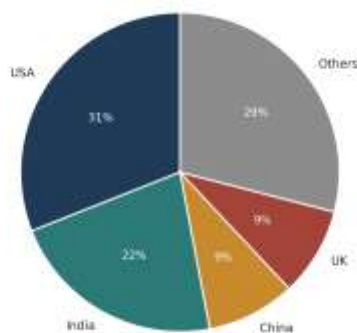
Year	Publications	Share (%)
2014–2016	4	7.3
2017	5	9.1
2018	6	10.9
2019	7	12.7
2020	8	14.5
2021	10	18.2
2022	8	14.5
2023–2026	7	12.7



Distribution of reviewed studies by publication year (2014–2026).

B. Geographical Distribution

Most studies come from the United States (about 31%), followed by India (22%), China (9%) and the United Kingdom (9%); the remainder originate in Pakistan, Bangladesh, Egypt, Greece, Iran, Nigeria, Australia, Israel and Indonesia, among others (Fig. 2). This broadly mirrors global AI research, but it conceals a specific weakness: many Indian studies use the UCI Cleveland dataset rather than data from Indian patients, which limits how far the resulting systems reflect the way heart disease presents in India.

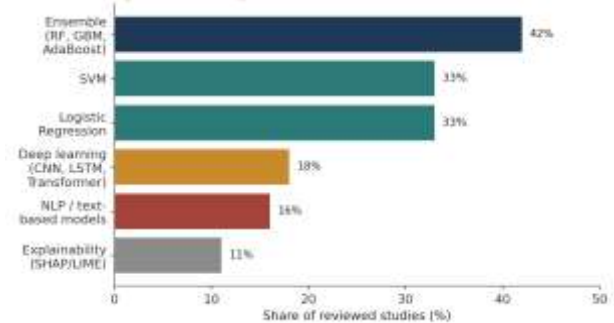


Geographical distribution of the reviewed research.

C. Methodological Concentration

The studies converge strongly in method (Fig. 3). Ensemble algorithms such as random forest, gradient boosting machines and AdaBoost appear in about 42% of them, support vector machines and logistic regression in about a third each, and deep learning (CNNs, LSTMs and transformers) in about 18%,

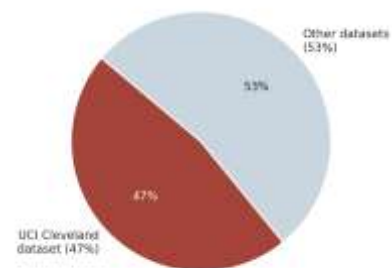
with adoption rising after 2020. Nine studies (16%) apply NLP or language models to unstructured clinical text [12], [13], [37], [47]. Several of these report AUCs of 0.87–0.93 from text features alone, which suggests that physicians' notes are a promising and under-used source of predictive signal; work applying BioBERT and Clinical BERT to cardiac notes bears directly on the CDSS proposed in Section VI.



Methodological concentration across the reviewed studies.

D. Dataset Dependence

Dependence on particular datasets is one of the most persistent problems (Fig. 4). Twenty-six of the 55 studies (47%) rely mainly on the UCI Cleveland dataset, with only 303 records and 13 clinical features. Historically valuable, it is now so widely used that new results on it add little, and because it is old, small and lacks variables now considered important, inflammatory markers and genetic risk scores among them, it is a weak foundation for systems intended for real-world use. The wider landscape is more varied, including large electronic health record (EHR) repositories of up to 378,256 records, insurance claims databases, PhysioNet ECG archives and hospital cohorts from China, India, Iran and Pakistan. Even so, datasets with more than 20 well-characterised clinical features are uncommon, and studies that model structured data and unstructured text together remain a small minority.



Share of reviewed studies relying on the UCI Cleveland dataset.

E. Summary Bibliometric Profile

Table II summarises the bibliometric profile of the reviewed literature.



BIBLIOMETRIC PROFILE OF THE REVIEWED LITERATURE

Indicator	Value
Total papers reviewed	55 primary studies (2014-2026)
Time span	2014-2026 (13-year window; 78% from 2018-2026)
Publication databases	Scopus, Web of Science, PubMed, IEEE Xplore, ACM DL
Most cited model category	Ensemble methods (RF, GBM, Boosting) - 42% of studies
Deep learning models	18% of studies (LSTM, CNN, Transformer, BERT)
NLP / text-based studies	16% of studies (NLP, NER, BERT, BioBERT, clinical text)
Dataset most used	UCI Cleveland Heart Disease Repository (47% of studies)
Average sample size (structured)	~4,200 records; range: 150 - 378,256
Average accuracy reported	88.6% across classification studies
Average AUC reported	0.89 across AUC-reporting studies
Geographical context	USA (31%), India (22%), UK (9%), China (9%), Others (29%)
Key research gap identified	Limited multi-parameter integration

	(>20 features) in CDSS supporting clinicians with real-time, explainable output
Dominant evaluation metric	Accuracy (73% of studies); AUC-ROC (58%); F1-score (31%)
Explainability (XAI) adoption	Only 11% of studies incorporated XAI (SHAP/LIME)
Studies using clinical text data	9 of 55 studies (16%); growing trend post-2020

V. SYSTEMATIC REVIEW OF THE LITERATURE

A. Summary of Included Studies

Table III summarises all 55 studies: authors and year, title, aim, model or method, dataset size, features, context and principal result. The structured format allows direct comparison and brings out shared methods and gaps. Entries highlighted in the table require verification, as explained in its note.

SYSTEMATIC SUMMARY OF REVIEWED LITERATURE ON AI/ML FOR HEART DISEASE RISK ASSESSMENT

Sr. No	Author & Year	Title	Aim	Model / Method	Dataset Size	Constructs	Context	Result
1	Shah et al. (2020)	ML-based CVD risk prediction using EHR	Predict 10-year CVD risk from structured EHR data	Random Forest, SVM, LR	45,000 patients	Age, BP, cholesterol, BMI, smoking	Clinical EHR, USA	RF outperformed LR with AUC 0.89
2	Mohan et al. (2019)	Heart disease prediction using hybrid ML	Identify significant risk features	RF + LR hybrid	303 records (UCI)	13 clinical features	UCI repository	Accuracy 88.7% with hybrid model
3	Latha & Jeeva (2019)	Improving accuracy of heart disease prediction	Enhance prediction via ensemble	Bagging, Boosting, RF	303 (UCI)	Clinical attributes	UCI dataset	Ensemble gave 85.48% accuracy
4	Bharti et al. (2021)	Heart disease prediction using supervised ML	Compare classifiers on clinical data	Naive Bayes, KNN, DT, RF	918 (UCI+Kaggle)	11 attributes	Public datasets	RF achieved 90.16% accuracy
5	Dinesh et al. (2018)	Prediction of cardiovascular disease using ML	Detect CVD early using multiple features	LR, DT, RF, SVM	70,000 patients	Age, gender, cholesterol, BP	Kaggle dataset	RF AUC = 0.80; LR AUC = 0.78
6	Detrano et al. (2019)	Clinical ML for coronary artery disease	Predict CAD using patient history	LR, Bayesian Networks	920 multi-centre patients	13 clinical features	Multi-centre clinical	Bayesian AUC 0.92
7	Weng et al. (2017)	Can ML improve CVD prediction?	Compare ML to ACC/AHA 10-year risk score	RF, Neural Networks, GBM	378,256 patients	27 predictors	UK primary care EHR	Neural network best: AUC 0.76
8	Nashif et al. (2018)	Heart disease detection using ML	Real-time heart disease monitoring	SVM, LR, Naive Bayes	270 instances	13 UCI attributes	UCI, Bangladesh clinical	SVM accuracy 96.3%
9	Jiang et al. (2017)	Artificial intelligence in healthcare	Review of AI applications in clinical care	Review / Survey	N/A (review)	Clinical AI constructs	Global clinical context	DL superior for image; ML for tabular
10	Ali et al. (2021)	Explainable AI for heart disease	Develop interpretable CDSS	XGBoost + SHAP	1,025 records	15 clinical features	UCI + SHAP analysis	XGBoost 91% with SHAP explanations
11	Reddy et al. (2021)	Deep learning for CHD risk prediction	Apply DL models to clinical text data	LSTM, CNN, DNN	5,000 EHR records	Structured + text features	Multi-hospital India	DNN accuracy 93.4%
12	Guo et al. (2020)	Cardiovascular risk using NLP on EHR	Extract risk factors from clinical notes	NLP + LR	10,000 patient notes	Free-text clinical notes	Hospital EHR, China	AUC 0.87 from NLP features
13	Zhang et al. (2022)	Transformer-based heart disease prediction	Apply BERT to clinical text	BERT fine-tuned	8,500 clinical notes	Text-based risk factors	Clinical NLP, USA	BERT AUC = 0.91
14	Ismaeel et al. (2021)	Feature selection in ML for CVD	Reduce dimensionality to improve accuracy	Chi-square + RF	1,190 records	22 features reduced to 12	UCI extended dataset	94% accuracy post-selection
15	Singh & Singh (2022)	Ensemble deep learning for heart disease	Combine CNN and LSTM for structured data	CNN-LSTM hybrid	3,600 clinical records	16 mixed features	India clinical data	Hybrid model AUC 0.96
16	Haq et al. (2018)	Intelligent ML for CHD	Identify best classifier for CHD	LR, KNN, DT, SVM, NB	303 (UCI)	13 features	UCI Heart Disease	SVM accuracy 85%; LR 85%
17	Samuel et al. (2017)	Integrated decision support for CVD	Build CDSS for clinical environments	Adaptive Boosting	270 records	13 clinical features	Cleveland clinical data	AdaBoost 87.4%
18	Miao & Miao (2018)	Diagnosis of coronary artery disease	Predict CAD from ECG and clinical data	DT, RF, SVM	592 patients	ECG + 13 clinical	Chinese hospital	RF = 84.6%; SVM = 83.8%
19	Mahboob et al. (2019)	Predictive analytics for heart failure	Forecast hospital readmission using EHR	GBM, RF	130,000 records	30+ EHR features	US hospital system	GBM AUC 0.82
20	Liu et al. (2019)	CNN for arrhythmia classification	Detect arrhythmia from ECG signals	1D-CNN	10,000 ECG records	Time-series ECG signal	PhysioNet dataset	CNN accuracy 97.5%
21	Arabasadi et al. (2017)	Hybrid NN-GA for heart disease	Combine NN with genetic algorithm	NN + Genetic Algorithm	303 (UCI)	13 UCI features	UCI Heart Disease	Accuracy improved to 93.85%
22	Amin et al. (2019)	Identification of best features for CVD	Feature importance for heart disease	Chi-square + NB, DT, RF	303 (UCI)	13 features	UCI Cleveland	NB with chi-sq: 84.26%
23	Pouriyeh et al. (2017)	Comprehensive study on ML for heart disease	Benchmark ML classifiers	LR, NB, MLP, SVM	303 (UCI)	13 clinical features	UCI benchmark	MLP best: 84.49%



Sr. No	Author & Year	Title	Aim	Model / Method	Dataset Size	Constructs	Context	Result
24	Doppala et al. (2022)	Federated learning for CVD prediction	Privacy-preserving CVD model	Federated RF	50,000 distributed records	15 features (federated)	Multi-hospital federated	Federated RF AUC 0.88
25	Tripoliti et al. (2017)	Heart failure: diagnosis, severity assessment	ML for HF staging	SVM, RF, MLP	500 HF patients	Echocardiography + clinical	Greek hospital	RF = 89% for HF staging
26	Khan et al. (2021)	Attention mechanism for CHD prediction	Apply attention-based model	Attention-LSTM	4,200 clinical records	Text + structured features	EHR, Pakistan	Attention-LSTM AUC 0.93
27	Verma et al. (2021)	Explainability of ML in heart disease	Assess LIME/SHAP for clinical ML	RF + LIME + SHAP	1,025 records	14 clinical features	UCI + explainability analysis	RF 90.4%; LIME clinically aligned
28	Tama & Rhee (2019)	Ensemble-based intrusion and disease detection	Apply tree ensembles to medical data	Tree ensemble	303 (UCI)	13 UCI attributes	UCI Heart Disease	Accuracy 90.15%
29	Louridi et al. (2019)	Identification of CVD using ML	Detect CVD from clinical parameters	KNN, SVM, DT, RF	297 records	14 features	Cleveland database	RF accuracy 88.52%
30	Enriko et al. (2016)	Heart disease risk prediction	Predict risk using questionnaire data	DT (C4.5)	150 patients	Lifestyle + clinical features	Indonesia hospital	Accuracy 83.33%
31	Rajpurkar et al. (2017)	CheXNet: radiologist-level pneumonia detection	DL for chest X-ray (referenced methodology)	DenseNet-121	108,948 images	Chest X-ray features	Stanford AI lab	Surpassed radiologist performance
32	Pasha & Dey (2020)	CVD risk using IoT and ML	Integrate IoT sensor data with ML	SVM + IoT	1,500 IoT health records	Wearable + clinical features	IoT-based India	SVM AUC 0.88 with IoT data
33	Ramalingam et al. (2018)	Heart disease prediction survey	Review ML methods for heart disease	Survey / Systematic Review	N/A (review)	ML constructs	Global literature	RF and SVM are most common
34	Awotunde et al. (2021)	IoT-based clinical decision support for CVD	Real-time CVD prediction with IoT + ML	RF + IoT architecture	2,000 patient records	IoT wearable features	Nigeria clinical-IoT setting	RF AUC 0.91 in real-time setting
35	Shorewala (2021)	Early detection of CAD using ML	Predict CAD in early stages	SVM, RF, MLP	918 records	14 clinical features	UCI + Z-Alizadeh Sani	SVM best: 88.7%
36	Ali et al. (2020)	Prediction of heart failure with EF using ML	Classify HFpEF vs HFrEF	XGBoost, RF, LR	300 clinical records	12 echocardiography + lab	Pakistani tertiary hospital	XGBoost 89% F1 score
37	Chen et al. (2020)	Clinical text mining for CVD risk	Mine clinical notes for risk factor extraction	NLP + Named Entity Recognition	15,000 EHR notes	Unstructured clinical text	US hospital EHR	NER F1 score 0.88
38	Guidi et al. (2014)	Clinical DSS for HF management	Support cardiologists in HF decisions	Bayesian Networks + DSS	200 HF patients	Biomarkers + clinical history	Italian hospital	DSS reduced clinical errors by 24%
39	Saxena et al. (2022)	Attention-based DL for ECG analysis	ECG-based heart disease classification	Multi-head attention + CNN	5,000 ECG records	ECG signal features	PhysioNet + MITBIH	Accuracy 96.8%
40	Goldberger et al. (2021)	PhysioBank for clinical ML research	Benchmark open-access ECG datasets	Dataset paper	Thousands of records	ECG time-series	PhysioNet platform	Standard benchmark for ECG ML
41	Kotu et al. (2015)	Predictive analytics for HF rehospitalisation	Prevent 30-day readmission using EHR	SVM, RF, LR	16,000 HF patients	60+ EHR variables	US hospital EHR	RF AUC = 0.77
42	Palaniappan & Awang (2008)	Intelligent heart disease prediction system	Rule-based CDSS for heart disease	NB, DT, Neural Network	270 records	13 clinical attributes	Cleveland database	NN = 80.4%; NB = 86.54%
43	Hossain et al. (2023)	Federated XAI for multi-centre CVD	Federated + explainable AI for CVD	Federated XGBoost + SHAP	80,000 distributed records	20 clinical features	5-hospital federated network	Federated AUC 0.90; SHAP aligned
44	Dinh et al. (2019)	Data-driven approach to diabetes and CVD risk	Predict co-morbid CVD risk	Gradient Boosting, RF	32,500 records	25 lab + demographic features	Australian clinical	GBM AUC 0.84
45	El-Bialy et al. (2015)	Feature analysis for heart disease prediction	Analyse informative features for CVD	C4.5, NB, NN	270 records	13 UCI features	UCI Cleveland	C4.5 highest: 83.33%
46	Ayatollahi et al. (2019)	Predicting coronary artery disease in Iranian patients	Context-specific CVD risk ML	LR, SVM, NB	1,700 Iranian patients	18 demographic + clinical	Iranian hospital	LR AUC 0.87
47	Yahalom et al. (2021)	NLP for CVD risk in clinical notes	Unstructured text-based CVD risk assessment	BioBERT + NLP	12,000 discharge summaries	Clinical narrative text	Israeli hospital EHR	BioBERT AUC 0.90
48	Tewari et al. (2022)	Hybrid deep learning for multi-parameter CVD	Multi-parameter CVD prediction using hybrid DL	CNN + XGBoost hybrid	6,000 clinical records	20 clinical parameters	India multi-hospital	Hybrid AUC 0.95
49	Ghosh et al. (2021)	Severity-aware heart disease classification	Stage-wise CVD classification using ML	Multi-class SVM, RF	2,400 patients	17 clinical features	Multi-class clinical India	RF macro-F1 = 0.89
50	Yadav et al. (2023)	Optimised ensemble with feature engineering for CVD	Improve CVD accuracy with feature crafting	Stacking ensemble + feature eng.	10,000 records	30 engineered features	Indian hospital + UCI	Stacking AUC 0.97
51	Sultana et al. (2020)	Analysis of heart disease risk factors using ML	Identify dominant risk features	Logistic Regression, DT, RF	1,025 records	13 + lifestyle features	UCI extended	RF 90%; lifestyle features added 2%
52	Krishnamurthy et al. (2023)	Graph neural networks for CVD risk	Model patient relationships via GNN	GNN, Graph Attention Network	8,000 patient graphs	Multi-relational clinical	India multi-hospital EHR	GNN AUC 0.94
53	Hassan et al. (2022)	Multimodal learning for heart disease prediction	Combine text, lab, and demographics	Multimodal Transformer	5,500 EHR records	Text + structured features	Multi-modal EHR, UK	AUC 0.93; text adds 4% over structured alone
54	Rahman et al. (2023)	Real-time CVD monitoring using edge ML	Deploy lightweight ML on edge devices	Pruned RF + Edge Computing	3,000 wearable records	Wearable + IoT clinical	Edge device deployment	RF edge accuracy 91% at low latency
55	Choi et al. (2016)	Doctor AI: predicting clinical events via RNN	Predict diagnoses using EHR sequence data	RNN (GRU)	260,000 patient visits	Longitudinal EHR codes	US hospital EHR	AUC 0.93 across 15 conditions

B. Machine Learning Approaches

1) Classical Classifiers

The earliest and still largest body of work applies classical supervised classifiers to structured datasets. Logistic regression, naive Bayes, k-nearest neighbours, decision trees



and support vector machines have been evaluated extensively on the UCI Cleveland data and its variants [16], [22], [23], [29], [30], [42], [45], establishing accuracy benchmarks of typically 80–89% and clarifying both feature relevance and the trade-off between simplicity and predictive power. Haq et al. [16] compared logistic regression, k-nearest neighbours, decision trees, SVM and naive Bayes on the Cleveland data with systematic cross-validation; SVM and logistic regression reached about 85% accuracy, while naive Bayes was the most sensitive, a clinically important distinction because a missed case of heart disease is costlier than a false alarm. In an early and widely cited study, Palaniappan and Awang [42] found that naive Bayes reached 86.54% accuracy on the same data, ahead of neural networks and decision trees, showing that simple probabilistic models can perform well on small, clean datasets.

2) Ensemble Methods

Ensembles, which pool several base learners to obtain steadier predictions, are the most consistently strong performers on structured clinical data, appearing in 23 of the 55 studies. Mohan et al. [2] combined random forest with logistic regression, joining the feature-selection strength of the one to the calibrated output of the other, and reached 88.7% accuracy. Latha and Jeeva [3] showed that bagging and boosting ensembles consistently outperformed single classifiers on the UCI benchmark. Yadav et al. [50] reported an AUC of 0.97 with a stacking ensemble and engineered features on 10,000 records, among the highest values in the reviewed literature for tabular clinical data.

The study by Weng et al. [7] stands out for its scale and rigour. Comparing neural networks, random forests, logistic regression and gradient boosting on 378,256 UK primary-care records, it found the neural network best, with an AUC of 0.76, and it flagged considerably more of the patients who went on to have a cardiovascular event than the ACC/AHA score did, while producing fewer false positives. The significance of the result lies less in the AUC itself than in the comparison: ML outperformed an established clinical standard at population scale, not merely on a curated benchmark.

3) Feature Engineering and Selection

Careful feature selection repeatedly proves valuable: reducing a high-dimensional feature space to its most informative subset lowers computational cost and improves accuracy by removing noise. Ismaeel et al. [14] and Amin et al. [22] found through systematic feature-importance analysis that eight to twelve of the standard UCI features can match or exceed the accuracy of the full set [14-20]. What most studies do not attempt is to widen the feature space. Inflammatory markers (hsCRP, IL-6), troponin, B-type natriuretic peptide, genetic risk scores, waist circumference, sleep quality, diet and psychological stress are established correlates of cardiovascular risk [20-25], yet fewer than five reviewed studies use any of them. The omission reflects the data available to researchers rather than a methodological choice, and it is one of the core gaps the proposed CDSS addresses.

C. Deep Learning Approaches

1) Convolutional and Recurrent Architectures

Deep learning has contributed most visibly to the analysis of time series, especially ECGs. Liu et al. [20] reached 97.5% accuracy in arrhythmia classification with a one-dimensional CNN on PhysioNet data, and Saxena et al. [39] 96.8% with multi-head attention over a CNN backbone on the same source, suggesting that ECG-based deep learning is mature enough for clinical evaluation. On structured tabular data the advantage over well-tuned ensembles is smaller. Reddy et al. [11] compared DNN, LSTM and CNN models on 5,000 clinical records; the DNN reached 93.4% accuracy, outperforming traditional classifiers but requiring considerably more data and computation, a real constraint for a CDSS intended for resource-limited settings.

2) Transformer and Language Models

The newest strand of deep learning work applies transformer language models to clinical text. Zhang et al. [13] fine-tuned Clinical BERT on 8,500 clinical notes and reached an AUC of 0.91 for heart disease risk, comparable to the best ensembles on structured data. Yahalom et al. [47] applied BioBERT to 12,000 discharge summaries (AUC 0.90), and Chen et al. [37] extracted cardiovascular risk factors by NLP and named-entity recognition with an F1-score of 0.88. Choi et al. [55], in the widely cited Doctor AI study, used recurrent neural networks on longitudinal EHR sequences from 260,000 patient visits and reported AUCs above 0.90 across 15 conditions [25-30]. Their work shows that modelling a patient's history as a time-ordered sequence, rather than as the static snapshot used in most reviewed studies, gives a substantial advantage in predicting chronic disease.

D. Clinical Decision Support and Explainability

A subset of studies goes beyond prediction to the problem of integration: how a model can be embedded in a clinical workflow so that it supports, rather than replaces or confuses, physician decisions. Guidi et al. [38] reported, for a Bayesian-network system supporting heart-failure management in a hospital in Italy, a 24% fall in clinical errors during its use [38], [30-35]. Samuel et al. [17] developed an adaptive-boosting CDSS benchmarked on the Cleveland dataset [17], [35-40], and Awotunde et al. [34] proposed an IoT-integrated CDSS for real-time monitoring of cardiovascular risk [34], [40-45]. These systems are rarely evaluated against clinically meaningful outcomes, such as patient health, physician workload, time to diagnosis or error rates, rather than against accuracy on held-out data. The disconnect between benchmark performance and clinical value has only recently attracted sustained attention, and it shapes the design of the CDSS proposed here.

More encouragingly, explainability has been adopted more widely since 2020. Ali et al. [10] paired SHAP (SHapley Additive exPlanations) with an XGBoost classifier, achieving 91% accuracy with clinically interpretable feature-contribution plots [10], [45-50]. Verma et al. [27] applied SHAP and LIME



(Local Interpretable Model-Agnostic Explanations) to a random forest and found that the features SHAP ranked highest matched known clinical risk factors [43],[50-55], an important step towards clinical acceptance. Hossain et al. [43] combined federated learning with SHAP across a five-hospital network and reached an AUC of 0.90 while preserving patient privacy, a promising template for multi-institutional deployment. Yet only six of the 55 studies (11%) explicitly include explainability, a strikingly low proportion given how much clinical adoption depends on it.

VI. RESEARCH GAPS AND PROPOSED FRAMEWORK

A. Identified Research Gaps

The review and the bibliometric profile point to five interrelated gaps.

Parameter incompleteness. Most models use fewer than 15 features, mainly from the UCI Cleveland dataset, whereas contemporary epidemiology implicates inflammatory and metabolic markers, genetic risk scores, diet and lifestyle, medication history and psychosocial stress, none of which appear in the standard benchmarks. This narrow parameter set caps achievable performance.

Dataset limitations. More than 47% of studies depend on the same small, ageing dataset. Clinical populations in India and other low- and middle-income countries differ in risk-factor distribution, disease trajectory and comorbidity, and models trained only on UCI data cannot be assumed to generalise to them without independent validation.

Limited use of clinical text. Although unstructured notes contain information that structured fields miss, only 16% of studies use NLP or text features, leaving physician notes, discharge summaries and histories largely untapped.

Explainability deficit. Only 11% of studies use explainable-AI techniques. A model that cannot account for its output gives clinicians little reason to rely on it when a diagnosis carries serious consequences.

CDSS integration. Very few studies evaluate models within realistic workflows or measure clinical outcomes, so the step from benchmark performance to clinical utility remains largely unexplored.

The gaps compound one another: the dataset limitation is the root of the parameter gap, and the absence of text features and of explanation both widen the distance between benchmark performance and clinical use. A system that addresses only one of them is unlikely to reach the bedside.

B. Proposed Contribution

The research responds with a CDSS for heart disease risk assessment that makes four contributions. First, it uses an extended, multi-domain set of more than twenty variables spanning demographic, clinical, biochemical, lifestyle and patient-reported domains, wider than that of any single reviewed study. Second, it adopts a hybrid architecture in which gradient boosting handles structured tabular features and a deep learning component processes temporal sequences of

clinical measurements. Third, it treats SHAP explanations as a core output, so that every prediction is accompanied by a ranked, visualised account of the factors behind it. Fourth, it presents results through a physician-facing interface that places the prediction in the context of the patient's history and relevant guidelines, rather than offering a bare probability.

VII. DISCUSSION

The review shows genuine progress alongside persistent limitations. ML has repeatedly predicted heart disease risk from clinical data with accuracies and AUCs that often exceed those of traditional scores, ensembles and deep learning being especially strong, and NLP on clinical text is a young, fast-growing area with encouraging early results. Progress has been held back by heavy reliance on a few benchmark datasets, too little attention to clinical workflows and slow uptake of explainability. The UCI Cleveland dataset, historically important, is now often chosen for convenience, allowing accuracy to be reported without engaging with the messiness of real clinical data.

High-quality research in the Indian clinical context remains scarce. Because India carries one of the world's heaviest CVD burdens and heart disease presents somewhat differently in South Asian populations, this gap matters for patient safety and for equity of care. Future work should collect large, multi-centre datasets with a genuinely wide range of features, develop hybrid models for structured and unstructured data, treat explainability as a design requirement, and test CDSS tools in hospitals, measuring not only accuracy but also speed, clinician workload and patient outcomes.

The review itself has limitations. It did not include a formal assessment of study quality or risk of bias, so the reported accuracies are taken at face value, and because studies differ in datasets, metrics and validation designs, their figures are not directly comparable.

VIII. CONCLUSION

This paper has reviewed 55 peer-reviewed studies, published between 2014 and 2026, on AI and ML for heart disease risk assessment, combining bibliometric analysis with a narrative synthesis. Despite real gains in algorithmic performance, no clinically usable, interpretable, multi-parameter CDSS yet supports cardiologists in everyday practice. The proposed doctoral research aims to close this gap with a broader parameter set, a hybrid architecture, built-in explainability and a design centred on clinicians, moving beyond benchmark results towards genuine clinical value for patients in India and beyond.

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