

A Survey on Heart Disease Prediction Techniques Using Machine Learning and the Scope of Hybrid Quantum Machine Learning

Vinod A M, C J Harshitha, Deeksha Shetty B N, Deshik Prasad, Dheeraj R Kurli

Department of Computer Science and Engineering Malnad College of Engineering
Hassan, Karnataka, India

Abstract—Among the leading contributors to global mortality, cardiovascular conditions demand stronger attention toward automated and intelligent screening tools. When risk factors are flagged during initial stages, clinicians gain the opportunity to act decisively before irreversible damage occurs. The widespread digitization of patient health records has opened new avenues for data-driven models to support clinical workflows. Classification-oriented algorithms — spanning probabilistic methods, tree-structured learners, distance-based approaches, margin-maximizing classifiers, regression frameworks, ensemble strategies, connectionist models, and multi-layered deep architectures — have each been evaluated for their suitability in identifying cardiac risk. Public repositories such as the Cleveland database, Framingham cohort data, and electrocardiographic recordings have served as common evaluation grounds. In spite of measurable progress, the field continues to wrestle with recurring problems: models overfit to training distributions, rely excessively on curated feature subsets, suffer from imbalanced class representation, generalize poorly to external populations, and carry significant computational overhead. This work consolidates findings from prior studies spanning classical learning, representation-based deep models, and metaheuristic optimization frameworks applied to cardiac prediction. Unresolved research challenges are catalogued, and the potential of integrating quantum processing elements into classical learning pipelines is examined as one unexplored avenue. The central motivation is to evaluate the landscape of existing prediction frameworks and establish a basis for future work contrasting conventional supervised models against quantum-assisted learning paradigms.

Index Terms—Heart disease prediction, machine learning, deep learning, quantum machine learning, hybrid quantum-classical model, healthcare analytics.

I. INTRODUCTION

Globally, cardiovascular conditions account for a disproportionate share of preventable fatalities. Clinical outcomes improve substantially when abnormal cardiac indicators are detected before symptoms escalate into emergencies. Established diagnostic pathways rely on electrocardiograms, blood panels, imaging scans, and the interpretive judgment of experienced cardiologists. While these methods remain foundational, the exponential accumulation of digitized clinical records has created pressure to develop software-assisted tools capable of triaging patients more efficiently and at scale.

Within this context, supervised learning algorithms have attracted considerable interest for their capacity to mine

structured patient records and surface statistically significant associations between physiological measurements and disease outcomes. Attributes routinely considered in cardiac risk modeling include demographic variables such as age and biological sex, clinical indicators such as chest discomfort type, resting systolic pressure, serum cholesterol, fasting glucose status, resting electrocardiographic readings, peak exercise heart rate, exercise-provoked ischemia, ST depression (oldpeak), ST slope, vessel count from fluoroscopy, thalassemia status, and the binary outcome label. Trained on such feature sets, a classifier can assign incoming patients to risk categories with measurable reliability.

The body of published work in this domain is extensive and methodologically diverse, drawing on probabilistic classifiers, partitioning trees, proximity-based learners, hyperplane-based discriminators, linear probability estimators, committee-based aggregators, and multilayer perceptrons alike. Structured tabular data — particularly the well-cited Cleveland repository — has served as a repeated testbed, enabling rough comparisons across independent studies.

Despite the breadth of this work, several systemic weaknesses persist. Model behavior is highly sensitive to the upstream decisions of data cleaning, dimensionality reduction, and hyperparameter search. Classifiers that yield impressive in-sample metrics frequently fail to replicate those results on held-out or external cohorts. Architectures with many layers, while capable of encoding intricate dependencies, impose data and compute burdens that smaller clinical datasets cannot easily satisfy. These observations collectively motivate a structured reassessment of what current methods achieve and where their boundaries lie.

Quantum-enhanced machine learning represents a nascent intersection of quantum information science and statistical learning theory. Variational hybrid architectures — in which quantum circuit components handle portions of the computation while classical optimizers manage parameter updates — may introduce expressivity and optimization characteristics not available in purely classical systems. This survey investigates the current state of cardiac prediction research and frames a rationale for future comparative studies between conventional supervised learners and hybrid quantum-classical alternatives.

II. SURVEY METHODOLOGY

Literature for this review was gathered from published conference proceedings and peer-reviewed journals addressing cardiac risk prediction through supervised learning, associative pattern mining, committee-based classifiers, hierarchical neural architectures, and biologically or physically inspired optimization routines. Each selected study was examined with attention to the experimental data source, the algorithmic strategy adopted, the evaluation criteria reported, the numerical outcomes obtained, and the acknowledged boundaries of the approach.

The review serves two purposes: first, to map how prior researchers have framed and addressed cardiac prediction as a computational problem, and second, to surface recurring gaps that motivate a structured comparison between conventional machine learning pipelines and emerging hybrid quantum-classical prediction workflows.

III. BACKGROUND OF HEART DISEASE PREDICTION

Framing cardiac risk assessment as a binary supervised classification task is now standard practice in the computational health literature. A set of labeled patient observations constitutes the training corpus; the learned model then assigns a risk category to previously unseen individuals. The modeling pipeline typically proceeds through successive stages: cohort assembly, data cleaning and normalization, attribute selection, estimator fitting, inference, and metric-based evaluation.

A. Commonly Used Dataset

The Cleveland Heart Disease dataset occupies a central position in the benchmarking literature. Comprising 303 annotated patient entries across 14 clinical dimensions, its structured tabular organization and broad availability make it a natural reference point for assessing and contrasting supervised algorithms.

B. Performance Metrics

Quantifying prediction quality in medical contexts requires metrics that capture both the rate of correct classifications and the asymmetric costs of specific error types. Widely adopted measures include overall accuracy, positive predictive value (precision), sensitivity (recall), the harmonic F1-score, specificity, and the confusion matrix. Because both erroneous positive assignments and missed positive cases carry clinical consequences, recall and precision receive elevated emphasis relative to aggregate accuracy alone.

IV. REVIEW OF EXISTING TECHNIQUES

A. Naive Bayes

Rooted in conditional probability theory, Naive Bayes constructs a generative model over the feature space under the assumption that attributes contribute independently to the class posterior. Its low parameter count and minimal computational footprint make it practical for small to moderate clinical cohorts. Reported cardiac prediction results are frequently competitive with more complex baselines. The conditional

independence assumption, however, represents an idealization that clinical data routinely violates — many physiological indicators co-vary in ways the model cannot represent.

B. Decision Tree

Tree-structured classifiers partition the feature space through a recursive sequence of threshold-based splits, ultimately assigning each leaf to a predicted class. The resulting rule hierarchy is human-readable, which is valued in clinical contexts where transparency matters. The algorithm derives splitting criteria directly from labeled patient records. A persistent limitation is the tendency toward excessive depth: as the tree memorizes fine-grained training patterns, its error rate on new patients can degrade considerably.

C. K-Nearest Neighbour

This instance-based method defers class assignment until inference time, classifying each query point according to the plurality vote of its k nearest neighbors in the training set. No explicit model fitting is required, simplifying the preparation stage. However, reliable results depend on consistent attribute scaling and judicious selection of the neighborhood size k . As the dataset grows, retrieval cost scales with corpus size, creating latency concerns in larger deployments.

D. Support Vector Machine

Support Vector Machine identifies a maximum-margin separating boundary in the transformed feature space, with kernel functions enabling nonlinear decision surfaces. Its strong theoretical guarantees and empirical performance on moderately sized medical datasets have made it a recurring choice for cardiac classification. Kernel type and regularization coefficient selection, however, require systematic tuning, and training complexity increases with dataset dimensionality and volume.

E. Logistic Regression

By modeling the log-odds of class membership as a linear combination of input attributes, Logistic Regression produces calibrated probability estimates for binary outcomes. The framework is well suited to cardiac screening, where patients are partitioned into at-risk and low-risk groups, and where coefficient interpretability aids clinical reasoning. Its representational capacity is bounded by linearity in the feature space, limiting performance when attribute-outcome relationships are substantially nonlinear.

F. Random Forest and Ensemble Models

Random Forest constructs an ensemble of independently trained decision trees on bootstrapped subsets of the data and aggregates their votes at inference time. This procedure substantially attenuates the variance that afflicts individual trees and typically yields more reliable generalization. Boosting strategies such as AdaBoost and gradient-based methods follow a complementary philosophy, sequentially constructing weak learners to correct residual errors. Ensemble methods consistently raise the accuracy ceiling but at the cost of interpretability and inference-time computation.

G. Artificial Neural Network

Feedforward neural networks with one or more hidden layers can approximate arbitrary continuous functions, making them capable of encoding complex, non-monotonic attribute interactions. Applications in cardiac prediction have demonstrated consistently strong performance when architectures and training protocols are carefully calibrated. Sensitivity to the choice of learning rate, layer depth, unit count, and regularization strategy requires methodical experimentation, and convergence typically demands more iterations than shallow statistical models.

H. Deep Learning

Convolutional networks, recurrent sequence models, and composite deep architectures are primarily deployed when the input modality is inherently structured or sequential — raw ECG traces, phonocardiographic signals, or cardiac imaging data. In these settings, learned hierarchical feature detectors outperform hand-crafted representations. For tabular clinical datasets of modest size, however, the sample efficiency disadvantage of deep architectures often outweighs their representational advantages, and simpler models may generalize better.

I. Feature Selection and Optimization Techniques

Attribute selection methods — encompassing filter statistics, wrapper search procedures, and model-embedded importance estimates — prune irrelevant or redundant dimensions from the input space, benefiting both model accuracy and computational load. Population-based metaheuristics such as Genetic Algorithms and Particle Swarm Optimization have been adapted as global search strategies for feature subsets and hyperparameter spaces. Identifying attribute subsets that are simultaneously discriminative, computationally manageable, and clinically interpretable remains an open challenge.

V. COMPARATIVE ANALYSIS OF EXISTING WORKS

Surveying the collective body of cardiac prediction research reveals a consistent pattern: classical supervised methods handle structured tabular clinical data efficiently and with acceptable accuracy, while ensemble constructions further stabilize results by pooling diverse learner outputs. Deep architectures extend reach to unstructured signal and image data but impose heavier data and compute requirements. Across the full spectrum of reviewed work, a cluster of recurring problems — distributional overfitting, inadequate external validation, fragile feature dependencies, skewed class distributions, and computational cost — continues to limit practical deployment. A conspicuous gap in the literature is the near-absence of studies that systematically contrast classical supervised frameworks against quantum-augmented learning pipelines for cardiac risk prediction.

VI. RESEARCH GAPS IDENTIFIED

Examination of the surveyed literature surfaces the following unresolved challenges:

- A substantial proportion of studies rely on cohorts too small to support robust statistical conclusions about model behavior.
- Classifiers that achieve strong in-sample metrics frequently exhibit degraded performance when evaluated on held-out populations.
- Principled, stable, and clinically meaningful attribute selection continues to resist fully satisfactory solutions.
- Computationally intensive methods impose barriers to deployment in resource-constrained clinical settings.
- Aggregate accuracy dominates evaluation reporting, while clinical utility metrics such as calibration and reliability are rarely measured.
- Intercorrelations among clinical variables and latent structure within medical feature spaces remain insufficiently exploited.
- Representation-learning architectures carry data volume requirements that exceed what most single-institution cardiac datasets provide.
- No systematic comparative investigation of classical supervised learners versus hybrid quantum-classical pipelines for cardiac risk stratification has been published to date.

VII. PROBLEM STATEMENT

Contemporary cardiac prediction systems draw predominantly on supervised learning, pattern mining, and multi-layer neural architectures to classify patients from structured clinical inputs. Measurable predictive gains have been reported, yet the same cluster of limitations — overfitting to training distributions, insufficient generalization, sensitivity to feature engineering choices, computational cost, and deteriorating reliability on unseen cohorts — recurs across the literature. A rigorous side-by-side comparison between established classical supervised learners and hybrid quantum-classical architectures, conducted under identical experimental conditions, would help clarify whether quantum augmentation translates into practical predictive benefit.

VIII. NEED FOR HYBRID QUANTUM MACHINE LEARNING

At its intersection, quantum machine learning draws on superposition, entanglement, and quantum interference to construct computational processes that may not be efficiently replicable on classical hardware. For cardiac risk modeling specifically, hybrid variational architectures offer one pathway toward richer feature space representations, more efficient optimization landscapes, and sharper classification boundaries. These architectures preserve classical components for gradient-based parameter updates while delegating portions of the computation to parametric quantum circuits.

The gaps catalogued in Section VI provide direct justification for exploring this direction. Classical and deep learning approaches persistently struggle with overfitting, generalization beyond the training distribution, and compute cost. A hybrid quantum-classical system may navigate portions of the feature space more expressively and could, under controlled

TABLE I
COMPARISON OF EXISTING HEART DISEASE PREDICTION TECHNIQUES

Sl. No.	Author / Study	Technique Used	Dataset	Result / Observation	Limitation / Gap
1	T. John Peter and K. Somasundaram	Naive Bayes, KNN, Decision Tree, Neural Network	Heart disease dataset	Among the tested classifiers, the probabilistic model yielded the strongest classification outcome	Scope was narrow in terms of algorithm variety; results were tied to the distributional properties of the chosen data
2	Sellappan Palaniappan et al.	Decision Tree, Naive Bayes, Neural Network	Cleveland dataset	Probabilistic classifier reached approximately 86.12%; connectionist model attained around 85.68%; tree-based method scored near 80.4%	Breadth of methods tested was restricted; categorical encoding choices influenced outcomes
3	Syed Umar Amin et al.	Neural Network with Genetic Algorithm	Proprietary dataset	In-sample accuracy approached 96.2% while out-of-sample accuracy settled near 92%	Cohort was small and systematic weight initialization remained difficult
4	Carlos Ordonez	Association Rule Mining	Medical records	Frequent-pattern extraction surfaced co-occurrence relationships among cardiac indicators	Pruning and ranking candidate rules introduced complexity; direct classification capability was limited
5	Rahman et al.	Neural Network, Logistic Regression, Naive Bayes	Cleveland dataset	The integrated RIHDPS framework reported approximately 91.26% accuracy	Memory footprint and processing time were elevated relative to simpler baselines
6	Amit Malav et al.	K-Means and ANN hybrid model	Cleveland dataset	Coupling unsupervised clustering with a neural classifier yielded prediction gains	Bridging the clustering and classification stages introduced compatibility concerns; feature weighting lacked principled guidance
7	Harshit Jindal et al.	Logistic Regression and KNN	Heart disease dataset	The dual-model framework demonstrated utility as a clinical decision aid	Limited training data increased susceptibility to overfitting
8	Md Mamun Ali et al.	Supervised ML algorithms	Heart disease dataset	Strong accuracy figures were accompanied by informative feature ranking	A subset of evaluated models incurred disproportionately long training durations
9	E. I. Elsedimy et al.	SVM with quantum-behaved optimization	Cleveland database	Quantum-inspired metaheuristic improved the quality of selected features and bolstered prediction outcomes	Execution overhead was substantial and vulnerability to overfitting was not fully resolved
10	Nadiah Baghdadi et al.	Advanced ML techniques	Cardiovascular dataset	The approach advanced early identification capability for cardiovascular pathology	Record-level noise and incomplete attribute entries undermined model stability
11	Pronab Ghosh et al.	Bagging and Boosting	CVD dataset	Aggregated ensemble strategy improved both speed and predictive fidelity	Cross-population generalization remained questionable
12	Awais Mehmood et al.	CNN-based deep learning	Heart disease data	Convolutional architecture outperformed several prior reference systems	Elevated hardware demands and susceptibility to overfitting were noted limitations

evaluation, deliver measurable improvements in prediction quality for cardiac datasets.

IX. DISCUSSION

A cross-study reading of the surveyed literature makes one observation plain: no single algorithm dominates across all experimental configurations. The probabilistic classifier trades model richness for speed and simplicity. The tree-based learner offers interpretability but memorizes training noise. The margin-maximizing classifier provides strong discrimination but demands careful kernel and regularization choices. Connectionist networks capture nonlinear attribute interactions but impose tuning overhead. Committee methods raise the accuracy ceiling at the expense of transparency. Multi-layer architectures generalize well over rich modalities but are data-hungry.

Given these complementary trade-offs, the most productive direction for future work is a controlled experimental comparison in which classical supervised methods and hybrid quantum-classical models are trained and evaluated on the same preprocessed dataset under the same metric suite. Such a protocol would allow the community to determine whether quantum circuit components contribute a measurable, replicable advantage over well-tuned classical baselines for cardiac prediction.

X. CONCLUSION

This survey has reviewed the landscape of cardiac risk prediction methods spanning probabilistic classifiers, tree-based partitioners, proximity learners, margin-based discriminators, ensemble aggregators, connectionist networks, deep representation learners, and optimization-driven feature selectors. A consistent picture emerges: accuracy has improved incrementally across a succession of methodological advances, yet overfitting, dependence on careful feature engineering, limited external validity, and computational overhead persist as unresolved barriers. The review additionally identifies a conspicuous gap in comparative studies that directly evaluate classical supervised learning against hybrid quantum-classical pipelines. Filling this gap could establish whether quantum-augmented architectures offer practical improvements in accuracy, calibration, and cross-cohort generalization for cardiac prediction tasks.

REFERENCES

- [1] T. John Peter and K. Somasundaram, "An empirical study on prediction of heart disease using classification data mining techniques," IEEE International Conference on Advances in Engineering, Science and Management, 2012.
- [2] L. P. Koyi, T. Borra and G. L. V. Prasad, "A research survey on state of the art heart disease prediction systems," International Conference on Artificial Intelligence and Smart Systems, 2021.
- [3] M. Irshad and E. S. Mohamed, "Advancements and challenges in heart disease prediction model: A survey," International Conference on Self Sustainable Artificial Intelligence Systems, 2024.
- [4] S. Palaniappan and R. Awang, "Intelligent heart disease prediction system using data mining techniques," International Journal of Computer Science and Network Security, 2008.
- [5] C. Ordonez, "Improving heart disease prediction using constrained association rules," Seminar Presentation, University of Tokyo, 2004.
- [6] N. Guru, A. Dahiya and N. Rajpal, "Decision support system for heart disease diagnosis using neural network," Delhi Business Review, 2007.
- [7] H. G. Lee, K. Y. Noh and K. H. Ryu, "Mining biosignal data: Coronary artery disease diagnosis using linear and nonlinear features of HRV," Emerging Technologies in Knowledge Discovery and Data Mining, 2007.
- [8] L. Parthiban and R. Subramanian, "Intelligent heart disease prediction system using CANFIS and genetic algorithm," International Journal of Biological and Medical Sciences, 2008.
- [9] R. Agrawal and R. Srikant, "Fast algorithms for mining association rules," VLDB Conference, 1994.
- [10] J. Han, M. Kamber and J. Pei, Data Mining: Concepts and Techniques, Morgan Kaufmann, 2011.
- [11] M. Kavitha, G. Ganeswar, R. Dinesh, Y. Rohith Sai and R. Sai Suraj, "Heart disease prediction using hybrid machine learning model," International Conference on Inventive Computation Technologies, 2021.
- [12] V. Chang, V. R. Bhavani, A. Q. Xu and M. A. Hossain, "An artificial intelligence model for heart disease detection using machine learning algorithms," Healthcare Analytics, 2022.
- [13] H. Jindal, S. Agrawal, R. Khera, R. Jain and P. Nagrath, "Heart disease prediction using machine learning algorithms," IOP Conference Series: Materials Science and Engineering, 2021.
- [14] C. M. Bhatt, P. Patel, T. Ghetia and P. L. Mazzeo, "Effective heart disease prediction using machine learning techniques," Algorithms, 2023.
- [15] M. M. Ali, B. K. Paul, K. Ahmed, F. M. Bui, J. M. W. Quinn and M. A. Moni, "Heart disease prediction using supervised machine learning algorithms: Performance analysis and comparison," Computers in Biology and Medicine, 2021.
- [16] E. I. Elsedimy, S. M. M. AboHashish and F. Algarni, "New cardiovascular disease prediction approach using support vector machine and quantum-behaved particle swarm optimization," Multimedia Tools and Applications, 2024.
- [17] N. A. Baghdadi, S. M. F. Abdelaliem, A. Malki, I. Gad, A. Ewis and E. Atlam, "Advanced machine learning techniques for cardiovascular disease early detection and diagnosis," Journal of Big Data, 2023.
- [18] K. Divya, A. Sirohi, S. Pande and R. Malik, "An IoMT assisted heart disease diagnostic system using machine learning techniques," Cognitive Internet of Medical Things for Smart Healthcare, 2021.
- [19] P. Ghosh et al., "Efficient prediction of cardiovascular disease using machine learning algorithms with relief and LASSO feature selection techniques," IEEE Access, 2021.
- [20] D. P. Yadav, P. Saini and P. Mittal, "Feature optimization based heart disease prediction using machine learning," International Conference on Information Systems and Computer Networks, 2021.
- [21] M. N. Uddin et al., "Machine learning based diabetes and heart disease prediction system," Healthcare Technology Letters, 2019.
- [22] L. R. Guarneros-Nolasco et al., "Machine learning approaches for cardiovascular disease prediction and diagnosis," Applied Sciences, 2021.
- [23] C. Usha Kumari et al., "Arrhythmia classification using SVM and DWT," Biomedical Signal Processing, 2021.
- [24] P. R. L. Priya et al., "Gradient boosting based coronary heart disease prediction," Journal of Medical Systems, 2021.
- [25] A. Rahim et al., "MaLCaDD: Machine learning-based cardiovascular disease detection framework," IEEE Access, 2021.
- [26] L. J. Muhammad et al., "Machine learning predictive models for coronary artery disease," Informatics in Medicine Unlocked, 2021.
- [27] A. Newaz, N. Ahmed and F. S. Haq, "Survival prediction of heart failure patients using machine learning techniques," Informatics in Medicine Unlocked, 2021.
- [28] T. V. Truong et al., "Application of machine learning in screening for congenital heart diseases using fetal echocardiography," International Journal of Cardiovascular Imaging, 2022.
- [29] T. S. Roy, J. K. Roy and N. Mandal, "Classifier identification using deep learning and machine learning algorithms for detection of valvular heart diseases," Biomedical Engineering Advances, 2022.
- [30] A. Rath, D. Mishra, G. Panda and S. C. Satapathy, "Heart disease detection using deep learning methods from imbalanced ECG samples," Biomedical Signal Processing and Control, 2021.