A Survey on Cardiovascular Care Using a Hybrid Ml/Dl Framework for Early Detection and Real-Time Monitoring

N. Venkata Krishna[1]* and C. MadhusudhanaRao[2]

[1]*Research Scholar, School of Computing Department of CSE, Mohan Babu University, Tirupati, India
[2]Professor, School of Computing, Department of CSE, Mohan Babu University, Tirupati, India
[1]venkatkrishna2427@gmail.com, and [2]npr4567@gmail.com

HOW TO CITE:

N. Venkata Krishna, C. Madhusudhana Rao (2026). A Survey on Cardiovascular Care Using a Hybrid Ml/Dl Framework for Early Detection and Real-Time Monitoring. International Journal of Special Education, 41(10s), 1353-1375

COPYRIGHT STATEMENT:

Copyright: © 2026 Authors. Open access publication underthe terms and conditions of the Creative CommonsAttribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).

ABSTRACT:

This survey has provided a comprehensive review of conventional ML methods, deep learning architectures, and the hybrid frameworks that are applied to cardiovascular care. The conventional classifiers, such as support vector machines, random forests, and the gradient boosting methods, have shown efficiency and interpretability, which are specifically for structured data. Deep learning models, which include the convolutional neural networks, recurrent neural networks, graph neural networks, and generative models, perform well at capturing the complex spatial, temporal, and multi-modal patterns, which enhances the disease detection and prediction accuracy. Hybrid ML/DL frameworks have combined the feature extraction and classification across multiple data types, which achieves superior robustness and clinical applicability. The real-time monitoring and clinical decision support systems have exploited the edge computing, low-latency inference pipelines, and the wearable or telemetry devices, which allow a timely intervention and continuous patient surveillance. The survey also addresses the challenges such as data heterogeneity, limited multi-modal datasets, computational complexity, interpretability, and regulatory compliance. Emerging trends have focused on multi-modal fusion strategies, explainable AI, synthetic data augmentation, personalized longitudinal modeling, and federated learning as future directions to improve the generalization, reliability, and real-world deployment. By the consolidation of methodologies, datasets, evaluation metrics, and clinical case studies, this survey has provided a roadmap for researchers and clinicians that seeks to develop an explainable, efficient, and high-performance ML/DL framework for cardiovascular healthcare.

Keywords: Cardiovascular diseases, Machine learning, Deep learning, Hybrid frameworks, ECG analysis, Cardiac imaging, Real-time monitoring, Explainable AI, Multi-modal data, Clinical decision support.

1. Introduction

1.1 Background

Cardiovascular diseases continue to remain the leading cause of morbidity and mortality across the global population, and this burden extends across the age groups due to lifestyle transitions, genetic predisposition, and environmental factors [1]-[3]. Conditions such as coronary artery disease, arrhythmias, heart failure,

myocardial infarction, and hypertension account for most of the clinical admissions and long-term hospitalization. Clinical findings over the past few decades have shown that many of the patients have experienced the silent progression of the cardiac abnormalities long before the onset of noticeable symptoms [4]-[8]. Clinical reports further have shown that early monitoring has significantly reduced the rehospitalization rates and mortality among the high-risk patients [9].

1.2 Role of Machine Learning and Deep Learning in Cardiac Care

The rapid growth of digital health data has stimulated a shift towards computational intelligence for cardiac risk assessment. Machine learning models tend to learn from the diagnostic patterns from the structured clinical datasets, which include demographic data, laboratory measurements, and medical histories. However, the deep learning models tend to learn from raw signals and medical images such as ECG waveforms, echocardiograms, and cardiac MRIs [10], [11]. These approaches consistently have shown high performance in tasks such as arrhythmia classification, myocardial infarction prediction, heart sound recognition, and the segmentation of the cardiac chambers. Clinical datasets that have been processed through convolutional neural networks and recurrent neural networks have supported the accurate prediction at scale, because these models have extracted the spatial and temporal dependencies in the cardiovascular signals. With the increasing digitization of health records, automated ML/DL models have improved the diagnostic efficiency, reduced the subjectivity in the clinical judgment, and supported precision decision-making in cardiac interventions [12].

1.3 Hybrid ML/DL Approaches: Motivation and Advantages

Although standalone ML and DL approaches have provided strong predictive power, many of the studies have shown that the hybrid models have produced a better performance because they combine the feature engineering strengths of ML with the representational learning capabilities of DL [13]. Hybrid systems generally use a deep neural network to extract the complex latent features from the ECG or imaging data. It then uses a classical ML classifier such as random forest, support vector machine, gradient boosting, or decision tree to finalize the prediction decision. This layered architecture is considered beneficial when the datasets are noisy, limited, or heterogeneous, which is common in medical research. Moreover, hybrid models have simplified the interpretability of the creation of a bridge between the transparency of ML and the automation of DL [14].

1.4 Scope and Organization of the Review

The scope has covered applications such as arrhythmia detection, myocardial infarction prediction, heart failure risk analysis, echocardiography automation, wearable-based cardiac monitoring, and personalized cardiac prognosis. Limitations of current models are critically examined, which include the dataset imbalance, patient heterogeneity, lack of generalizability, and privacy concerns [15].

The organization of the paper is given below: Section 2 provides the fundamentals of the CVD. Section 3 discusses the cardiovascular care system for early detection and real-time monitoring. Section 4 provides the machine learning methods for the CVD module. Section 5 provides the deep learning module for cardiac care. Section 6 provides the hybrid ML/Dl frameworks for CVD detection. Section 7 provides the performance evaluation and validation. Sections 8 and 9 provide the comparative analysis of ML/DL approaches with recommendations for ML/Dl framework development. Section 10 provides the open research issues and future directions, and Section 11 provides the conclusion.

2. Fundamentals Of Cardiovascular Diseases

2.1 Types of Cardiovascular Diseases

Cardiovascular diseases appear in a diverse clinical form, and each of the type has affected the cardiac structure, or it functions uniquely.

Coronary artery disease (CAD) has emerged as the most of the frequent subtype, and it develops when the coronary arteries narrow due to plaque formation, which has restricted the myocardial blood supply, and it leads to ischemia, angina, or infarction [16]. Atrial fibrillation (AF) represents an electrical disorder in which the atria generate irregular and rapid impulses that disturb the ventricular rhythm, and it elevates the risk of stroke and systemic embolism [17]. Heart failure and cardiomyopathy involve a mechanical impairment in which the heart muscle weakens or stiffens, which reduces its ability to pump blood efficiently, and it maintains the metabolic oxygen demand [18]. Congenital heart diseases arise from structural abnormalities that are present at birth, which include the septal defects, valve malformations, and the outflow obstruction that has disrupted the normal hemodynamics throughout its life [19]. Valvular heart diseases have changed the forward flow of blood due to stenosis or regurgitation, and the prolonged strain on the cardiac chambers often progresses into heart failure if not treated properly [20]-[21]. These disease categories together have outlined the broad spectrum of cardiac pathology and the complexity involved in timely medical decision-making.

2.2 Clinical Diagnostic Modalities

Cardiac diagnosis depends on the physiological signals and anatomical visualization to characterize the origin and the severity of the disease. Electrocardiography has recorded the electrical activity of the heart through the surface electrodes, and its waveforms have reflected the conduction abnormalities, arrhythmias, ischemic injury, and the electrolyte imbalance [22]. The continuous ECG monitoring in ambulatory or wearable devices has provided valuable insight regarding the intermittent rhythm disturbances that do not appear during the short clinical examinations. Echocardiography and ultrasound serve as the primary tools for the evaluation of the cardiac chamber size, ejection fraction, valve morphology, wall motion, and the diastolic function [23]. The real-time nature has allowed the rapid bedside assessment of hemodynamic status. The cardiac imaging techniques, such as CT, MRI, and SPECT, offer an advanced visualization that has captured the perfusion deficits, myocardial viability, inflammatory lesions, fibrosis, and the congenital deformities [24], [25]. CT angiography has mapped the coronary stenosis, where the cardiac MRI has assessed the tissue structure and function at high resolution, and the SPECT quantifies myocardial perfusion for ischemic assessment. Beyond imaging, the measurement of clinical biomarkers and laboratory parameters has delivered the biochemical evidence of disease. Markers such as troponin, BNP, CRP, and the lipid profiles have indicated the myocardial injury, heart failure progression, inflammatory load, and the atherosclerotic risk [26]. The combination of physiological signals, imaging, and biochemical markers has supported the comprehensive cardiac evaluation and early treatment planning.

2.3 Challenges in Current Diagnosis and Monitoring

Diagnostic modalities have operated in isolated silos, and the physicians rely on manual interpretation of ECG, imaging, and biochemical reports, which has increased the risk of subjective variability. The conventional screening procedures rarely have supported the continuous monitoring in its daily living environments, and the episodic hospital visits have reached the limit for early identification of the arrhythmias or ischemic changes [27]-[28]. Wearable devices have partially addressed this challenge, but it requires an improved analytical approach, and it has supported differentiating the true pathological signals from the noise. In addition, the comorbidities such as diabetes, obesity, and hypertension mask classic cardiac symptoms, and this creates an ambiguous clinical presentation [29].

Medical data imbalance across the population groups has also restricted the diagnostic generalizability, and many of the algorithms perform poorly when that is applied to diverse demographics. Interpretation has become even more complex for diseases like ACS and AF

because their onset tends to be sudden and unpredictable [30]. Further, delays in emergency response have worsened myocardial damage, and this increases the mortality when the high-risk patients remain undetected outside clinical supervision. Clinical imaging and catheter-based diagnostics have remained costly and resource-intensive, which restricts their use in the remote and low-income regions [31]. Data privacy, interoperability issues, and the fragmented electronic health record systems have delayed the seamless information exchange between healthcare providers, which hinders coordinated care [32].

3. Cardiovascular Care System for Early Detection and Real-Time Monitoring

3.1 Data Acquisition Modules/Data Transmission Module

Cardiac analysis relies on diverse and multi-modal data sources, and combining these sources has enhanced the diagnostic accuracy and predictive capability. Most of the widely employed sources are the electrocardiogram (ECG), which has recorded the electrical activity of the heart, and it has captured both the rhythm and conduction abnormalities. ECG acquisition involves the surface electrodes placed on the patient's chest, limbs, or wearable patches, and the resulting signal contains the characteristic P, QRS, and T waves that have reflected the atrial and ventricular depolarization and repolarization patterns [33]-[40].

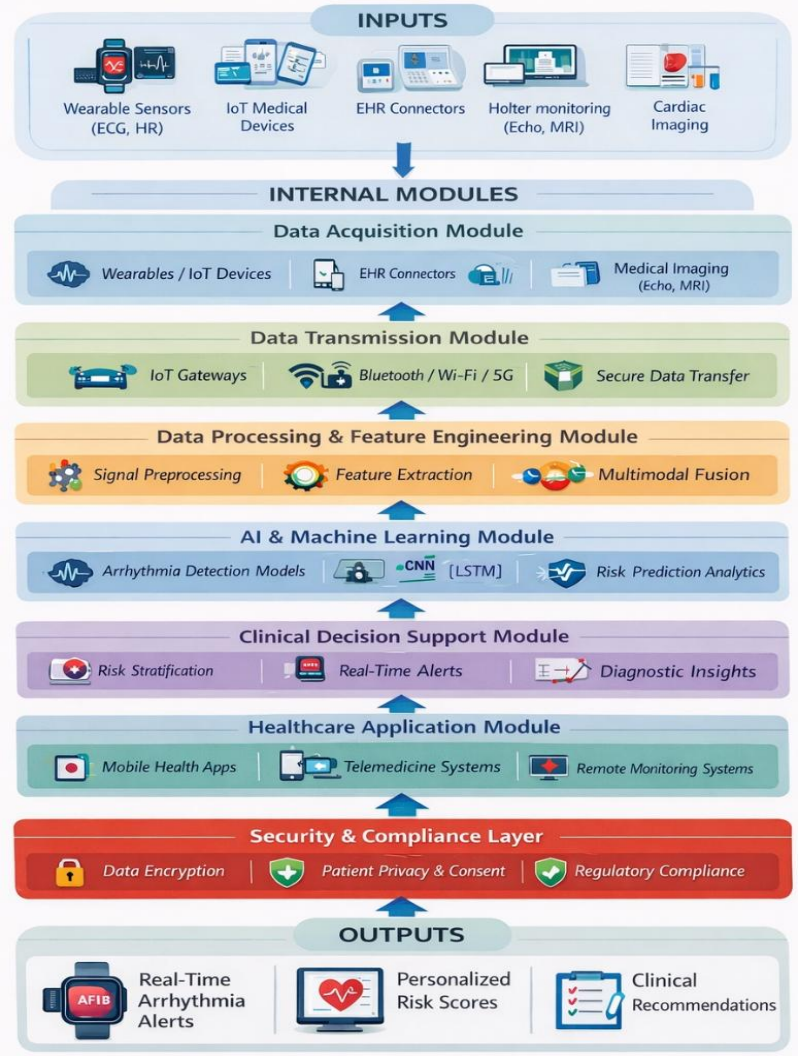

Figure 1: Cardiovascular care system for early detection and real-time monitoring

3.2 Data Preprocessing Module

The input data may be of a different form, as in Figure 1. Normalization and standardization are applied to both the ECG signals and imaging data to prove the consistent scale and range across the patients and recording sessions [41]-[42]. For example, z-score normalization or min-max scaling has adjusted the signal amplitudes, whereas intensity normalization has aligned the image pixel distributions for MRI or CT scans. These steps have mitigated the variability that arises from the sensor calibration differences, patient anatomy, or acquisition conditions.

Segmentation and feature extraction have focused on the isolation of meaningful temporal or spatial regions from the raw signals or images. In ECG, R-peak detection and QRS complex identification have delineated an individual cardiac cycle, which has enabled the extraction of intervals, amplitudes, and the morphological patterns [43]. In medical imaging, segmentation algorithms have identified the cardiac chambers, myocardium, and the valves, often using semi-automated or deep learning-based techniques, which provide the spatial features necessary for the volumetric and functional analysis [44].

Handling missing data and imbalanced datasets is essential in cardiac studies because real-world patients frequently contain gaps, sensor dropouts, or under-represented classes such as rare arrhythmias [45]. Techniques such as mean/mode imputation, forward filling, synthetic minority over-sampling, and the advanced generative approaches that has restored the data completeness, and it reduces the bias during the model training. Preprocessing pipelines also often incorporate data augmentation strategies. This is specifically for imaging datasets, to expand the training diversity and to improve the generalization [46].

3.3 Feature Engineering Module

Feature engineering transforms preprocessed data into informative representations that has enhanced the model interpretability and prediction accuracy. Hand-crafted features have remained a common approach, which is specifically for ECG and biomedical signals. These include the interval measurements such as RR, PR, and the QT intervals, amplitude differences, slope characteristics, and the frequency-domain features that is derived from the Fourier or wavelet transforms [47]. Such features have captured the temporal dynamics, and it underlies the physiological processes, and it is crucial when the dataset size limits the applicability of end-to-end deep learning models.

Temporal features extracted from ECG signals have included heart rate variability metrics, wavelet coefficients, and time-frequency representations, which have reflected autonomic nervous system activity and cardiac electrical stability [48]. Advanced techniques have employed the recurrence quantification, entropy-based measures, and the nonlinear dynamics to characterize the complex arrhythmic patterns that may not appear in the linear analysis. These temporal features are specifically useful for the prediction of atrial fibrillation, sudden cardiac events, or risk stratification in heart failure patients.

Spatial features derived from the medical images have encompassed the structural and morphological attributes such as ventricular volumes, wall thickness, myocardial strain, valve area, and the regional perfusion deficits [49]. Image texture analysis, histogram-based descriptors, and the deep feature embeddings from the convolutional layers have improved the representation of the subtle pathophysiological changes. Hybrid feature approaches combine the spatial and temporal information, such as synchronizing ECG intervals with the cine MRI frames to link the electrical and mechanical cardiac activity.

Statistical and morphological features have provided further insight into the population-level variations and individual-specific anomalies. Metrics such as mean, standard deviation, skewness, kurtosis, and the higher-order statistics describe global patterns. However, the shape descriptors have quantified the myocardial or valvular geometry [50]. Morphological analysis also identifies the asymmetry, dilation, hypertrophy, or wall motion abnormalities,

which have diagnostic and prognostic significance. Together, these features form a comprehensive set suitable for both the classical machine learning models and deep learning architectures.

In recent research, hybrid ML/DL pipelines have increasingly exploited automated feature learning alongside engineered features. Deep learning networks have extracted the latent representations directly from the raw signals or images. However, the engineered features have provided the explainable cues for clinical validation and decision support [51]. The addition of multi-modal features, temporal dynamics, spatial patterns, and statistical descriptors proves a robust and reliable cardiac assessment, which allows for early detection, continuous monitoring, and personalized intervention strategies.

3.4. AI and Machine Learning Module

The detailed discussion of this module is presented in sections 4, 5, and 6.

3.5 Clinical Decision Support Module

The clinical decision support module provides intelligent assistance to healthcare professionals during diagnosis, treatment planning, and patient monitoring. This component processes patient data obtained from electronic health records, laboratory reports, and real-time physiological sensors. Analytical algorithms evaluate these data streams to identify abnormal clinical patterns, disease risks, and possible complications. The module generates evidence-based recommendations that support physicians during clinical decision making. For instance, the system compares current patient parameters with established medical guidelines and historical patient records to suggest appropriate diagnostic tests or treatment options. Alert mechanisms notify clinicians when critical thresholds are reached, such as abnormal heart rate or blood glucose levels. By integrating predictive analytics and rule-based reasoning, the module reduces diagnostic uncertainty and improves the consistency of medical decisions. As a result, clinicians obtain timely insights that enhance patient safety and treatment accuracy.

3.6. Healthcare Application Module

The healthcare application module acts as the interface that connects patients, clinicians, and healthcare administrators within the digital health environment. This module supports functionalities such as patient registration, appointment scheduling, electronic medical record management, and telemedicine services. Patients can access their health information, monitor physiological parameters, and communicate with healthcare providers through mobile or web-based platforms. At the same time, clinicians can review patient histories, diagnostic reports, and treatment outcomes in a unified dashboard. The module also enables remote monitoring of chronic conditions by integrating wearable devices and medical sensors that continuously transmit health data. These data streams allow physicians to track patient status outside clinical facilities and intervene when abnormal trends appear. The application module, therefore, improves healthcare accessibility, enhances communication between patients and providers, and facilitates continuous care management across different healthcare settings.

3.7. Security and Compliance Layer

The security and compliance layer ensures that all healthcare data within the system remain protected, confidential, and compliant with regulatory standards. Healthcare information contains highly sensitive patient details; therefore, this layer implements multiple security mechanisms such as encryption, authentication, and access control. Data encryption protects patient records during both storage and transmission across networks. Authentication protocols verify the identity of authorized users, including healthcare professionals and system administrators. Role-based access control restricts the visibility of patient information according to user responsibilities, thereby preventing unauthorized data exposure. In addition, audit logging mechanisms record system activities to monitor data access and detect potential security breaches. The compliance component aligns system operations

with healthcare regulations and data protection frameworks, which require strict management of patient privacy. Through these combined measures, the security and compliance layer maintains trust in the digital healthcare platform while safeguarding sensitive medical information.

4. Machine Learning Methods For Cvd Module

4.1 Conventional Machine Learning Classifiers

Conventional machine learning (ML) methods, as in Figure 2, continue to play a pivotal role in cardiovascular analysis, which is specifically when working with structured clinical datasets or hand-crafted features derived from the ECG, imaging, or laboratory parameters. These models are computationally efficient, interpretable, and capable of delivering robust predictions when carefully tuned.

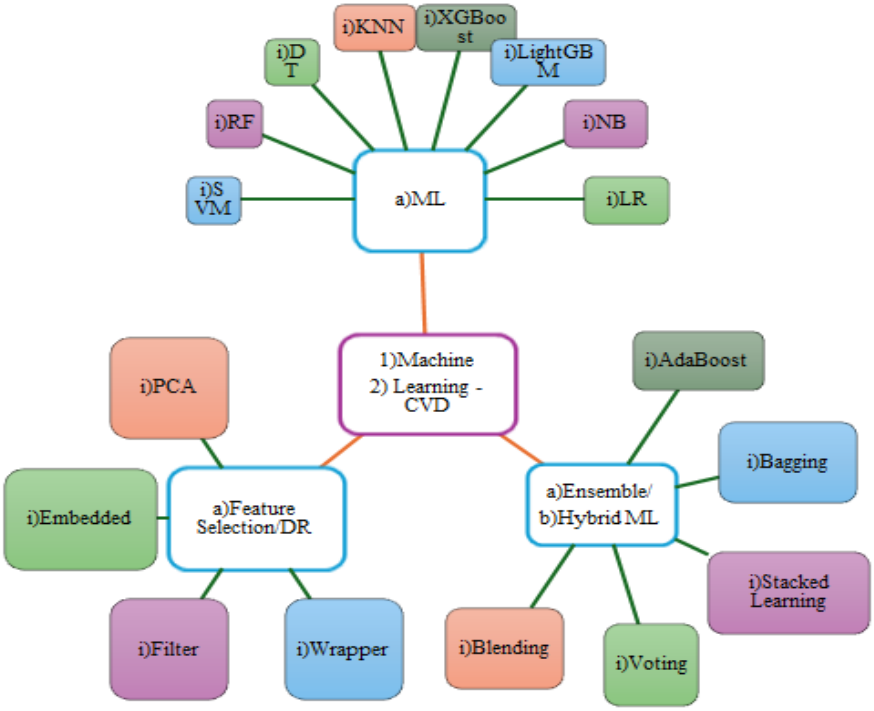

Figure 2: Conventional Machine Learning Classifiers

4.1.1 Support Vector Machines (SVM)

Support vector machines are widely adopted for classification tasks in the cardiac datasets due to their effectiveness in high-dimensional spaces and their ability to manage non-linear relationships through the kernel functions [52], [53]. SVM has constructed an optimal hyperplane that separates classes, such as arrhythmic and normal heartbeats, with the maximum margin. Kernel techniques, which include the radial basis function (RBF) and polynomial kernels, have enabled a mapping of input features into the higher-dimensional space to achieve better separability. SVMs have shown high accuracy in the atrial fibrillation detection, myocardial infarction classification, and the ECG signal anomaly recognition, which is specific when the datasets are limited or imbalanced [54].

4.1.2 Random Forest and Decision Trees

Decision trees have provided the hierarchical rule-based classification that is intuitive for clinical interpretation, whereas the random forests aggregate the multiple decision trees to reduce overfitting and improve generalization [55], [56]. In the cardiac applications, random forests have been employed for the prediction of heart failure progression, risk stratification for coronary artery disease, and the multi-class arrhythmia identification. Their ability to handle categorical and continuous variables

simultaneously, along with the feature importance estimation, has made it highly suitable for the clinical datasets with heterogeneous characteristics [57].

4.1.3 K-Nearest Neighbors (KNN)

K-nearest neighbors is a distance-based non-parametric classifier that tends to predict the class of a sample based on the majority class of its neighbors [58]. KNN has been applied to ECG classification, risk stratification, and ischemic event detection because it directly shows the similarities in feature space without the assumption of underlying distributions. Its simplicity has allowed for fast prototyping, although its performance is sensitive to the choice of distance metric, neighborhood size, and the feature scaling [59].

4.1.4 Gradient Boosting Methods (XGBoost, LightGBM)

Gradient boosting frameworks such as XGBoost and LightGBM have become popular in cardiac data analysis due to its ability to model complex non-linear relationships, and it handles the missing data efficiently [52]. By sequentially training the weak learners to correct residual errors, these methods have achieved a higher predictive accuracy for the tasks. This includes the heart failure readmission prediction, myocardial infarction risk assessment, and the multi-class arrhythmia detection. Feature importance metrics are generated by the gradient boosting models, and it also provides the interpretability, which is crucial for clinical validation.

4.1.5 Naive Bayes and Logistic Regression

Naive Bayes classifiers have operated under the assumption of conditional independence between features, and they provide rapid probabilistic predictions that are suitable for large-scale ECG or laboratory datasets. Logistic regression models, on the other hand, estimate the probability of binary outcomes such as the presence or absence of CAD, AF, or ACS, and the coefficients directly represent feature contributions [34]. Both methods serve as baseline models in many of the cardiovascular studies, often it complements more complex algorithms.

4.2 Ensemble and Hybrid ML Approaches

Ensemble and hybrid approaches combine multiple base learners to improve the predictive performance, reduce variance, and enhance the robustness against the noisy or heterogeneous data. These techniques have shown a substantial utility in cardiovascular diagnostics, where clinical signals may be complex and variable across the patient populations.

4.2.1 AdaBoost and Bagging Methods

Adaptive boosting (AdaBoost) sequentially have trained the weak classifiers and it has adjusted the weights of misclassified samples to improve the overall accuracy. Bagging methods, such as bootstrap, have been aggregated to train multiple models in parallel on randomly sampled subsets of data and aggregate their predictions, which reduces overfitting. In the cardiac applications, these methods have improved the detection of rare arrhythmias, improved the heart failure prognosis, and stabilized the performance when the datasets contain a higher inter-patient variability [35].

4.2.2 Stacked Learning Models

Stacked generalization or stacking has combined the predictions from multiple base models through the meta-learner to produce a a final output [49]. This approach has combined the strengths of diverse classifiers, such as SVMs, random forests, and gradient boosting, to achieve superior accuracy in a multi-class cardiac disease classification. Specifically, the stacked models have been effective in studies that involve both the ECG and imaging features, where complementary information from the different models has improved the generalization.

4.2.3 Voting and Blending Techniques

Voting techniques, which includes the majority and weighted voting, aggregate predictions from the multiple classifiers, which provides the robustness against the individual model errors. Blending methods, similar to stacking but using

hold-out validation sets, combine the base model predictions using linear or non-linear functions to optimize the performance. These approaches are advantageous in the cardiovascular datasets where the data heterogeneity and noise can reduce the reliability of single-model predictions [50].

4.3 Feature Selection and Dimensionality Reduction

High-dimensional the cardiac data, which is specifically when combined with temporal, spatial, and the biochemical features, where it has shown the feature selection and dimensionality reduction to enhance the model performance, reduce computational burden, and the improve interpretability [50]-[55].

4.3.1 Wrapper Methods

Wrapper methods iteratively select feature subsets based on the model performance, often employing search algorithms such as forward selection, backward elimination, or recursive feature elimination [52]. These methods are effective when the feature interactions are significant, as in ECG waveform morphology that is combined with the patient demographics or imaging-derived metrics.

4.3.2 Filter Methods

Filter methods rely on statistical measures such as correlation coefficients, mutual information, and the chi-square scores to rank the features independently of the learning algorithm. They are computationally efficient, and it is widely used in preprocessing pipelines to remove redundant or irrelevant features from large ECG, imaging, or laboratory datasets.

4.3.3 Embedded Methods

Embedded methods have combined the feature selection into the model training process. Examples have included the LASSO, elastic net, and the tree-based models that inherently assign feature importance during learning. These methods have reduced the risk of overfitting while simultaneously optimizing model parameters, and it is applied to both the single- and multi-modal cardiac datasets.

4.3.4 Principal Component Analysis (PCA)

Principal component analysis is a classical dimensionality reduction technique that transforms the correlated features into orthogonal components, which preserves maximum variance in fewer dimensions. In the cardiac imaging and ECG studies, PCA has reduced the redundancy, focused on principal physiological patterns, and it has accelerated the training of downstream classifiers. PCA also facilitates complex data distributions, which aid in exploratory analysis and anomaly detection.

Collectively, conventional ML classifiers, ensemble approaches, and feature selection techniques have provided the structured framework for cardiac data analysis. These methods have been employed for arrhythmia detection, CAD risk prediction, myocardial infarction classification, heart failure prognosis, and the multi-modal data addition. Despite its effectiveness, standalone ML models may perform poorly when handling raw signals or high-dimensional image data, which motivates the adoption of hybrid ML/DL frameworks that have exploited the automated feature extraction alongside the engineered features. Such hybrid approaches form the next step in the evolution of intelligent cardiovascular analytics, which bridges the clinical interpretability and predictive power in real-world settings.

5. Deep Learning Module for Cardiac Care

5.1 Convolutional Neural Networks (CNN)

Convolutional neural networks, as in Figure 2, have become fundamental in cardiac imaging analysis due to their capability to automatically learn spatial hierarchies and it extracts the salient features from the raw images.

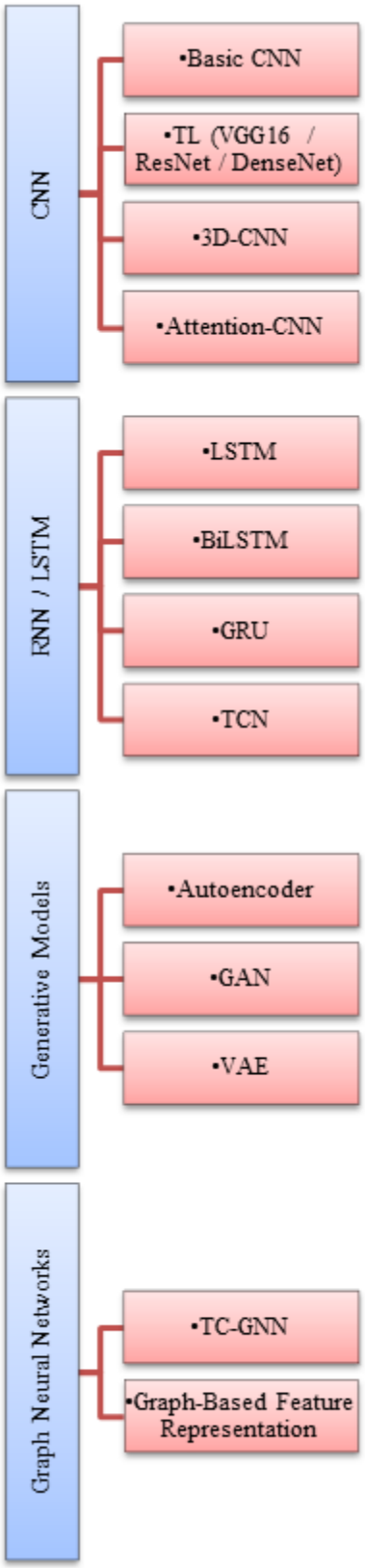

Figure 2: DL methods for SVD

5.1.1 Basic CNN Architecture for Image Analysis

The basic CNN architecture consists of convolutional layers, pooling layers, activation functions, and the fully connected layers, which

are designed to progressively extract low- to high-level image features [8], [12]. In cardiac imaging, convolutional layers have detected patterns such as myocardial borders, valve structures, and tissue heterogeneity, whereas the pooling layers have reduced spatial dimensions to enhance computational efficiency. Fully connected layers combine the learned features for classification, segmentation, or regression tasks, which include the arrhythmia risk prediction or myocardial infarct localization. CNNs have shown superior performance compared to the conventional feature-based methods, which is specifically in automated echocardiography interpretation and MRI-based functional assessment [13].

5.1.2 Transfer Learning Approaches (VGG16, ResNet, DenseNet)

Transfer learning leverages pre-trained models on large-scale datasets, which has allowed the rapid adaptation to the cardiac imaging tasks with the limited domain-specific data [14], [15]. Models such as VGG16, ResNet, and DenseNet have been successfully that is applied to classify echocardiography views, have detected CAD, and have segmented the cardiac chambers. ResNet's residual connections have mitigated the gradient vanishing issues in deep networks. However, the DenseNet has enhanced the feature propagation by connecting all layers, ensuring richer representation. Fine-tuning pre-trained weights has accelerated the convergence, and it has improved the generalization on the small cardiac datasets.

5.1.3 3D-CNN for Volumetric Cardiac Imaging

Three-dimensional CNNs extend conventional 2D convolutions into the volumetric space, which has allowed the analysis of multi-slice MRI, CT, or echocardiography sequences [16], [17]. 3D-CNN has captured the spatio-temporal dependencies within volumetric cardiac data, essential for tasks such as ventricular volume quantification, myocardial perfusion assessment, and motion tracking across the cardiac cycles. The network has processed the input cubes of consecutive slices, which learn the local and global structures simultaneously, significantly improving the segmentation accuracy and functional parameter estimation.

5.1.4 Attention Mechanisms in CNN

Attention mechanisms have improved the CNN performance by weighting the relevant features while suppressing the irrelevant ones, which has improved the interpretability and predictive power [18]. In cardiac imaging, attention modules have identified the critical regions such as infarcted tissue, valve leaflets, or abnormal wall motion, which ensures that the predictions are focused on the physiologically significant areas. Channel-wise, spatial, and self-attention approaches have allowed the models to prioritize informative features for classification, segmentation, and prognosis tasks.

5.2 Recurrent Neural Networks (RNN) and LSTM

Recurrent neural networks and their variants have gained prominence for temporal signal analysis in cardiac care. This is specifically in ECG interpretation and time-series monitoring.

5.2.1 LSTM for Temporal ECG Signal Analysis

Long Short-Term Memory networks are designed to learn long-term dependencies in sequential data, addressing the vanishing gradient problem inherent to vanilla RNNs [19], [20]. In ECG analysis, LSTM networks have effectively modelled the temporal dynamics of PQRST complexes, identified arrhythmia patterns, and predicted sudden cardiac events. Its gating mechanisms have regulated the information flow, while preserving the relevant past information and discarding the noise or irrelevant data.

5.2.2 Bidirectional LSTM (BiLSTM)

Bidirectional LSTMs extend LSTM networks by processing sequences in both the forward and backward directions, which obtains the contextual information from the past and future states simultaneously [21]. BiLSTM architectures have improved accuracy in detecting atrial fibrillation, predicting heart failure exacerbations,

and classifying a multi-lead ECG signal. Its ability to consider a complete temporal context has enhanced the sensitivity and specificity in cardiac event detection.

5.2.3 Gated Recurrent Units (GRU)

Gated recurrent units have offered a simplified alternative to LSTM, retaining essential gating mechanisms, which reduces computational complexity [22]. GRUs are which is specifically suitable for real-time ECG monitoring in wearable devices, where low latency and resource efficiency are critical. Studies have shown a comparable performance between the GRU and LSTM in an arrhythmia classification, which provides faster training and inference times.

5.2.4 Temporal Convolutional Networks (TCN)

Temporal convolutional networks have provided an alternative to recurrent architectures by employing causal convolutions with the dilation to model long-term dependencies in sequential data [23], [24]. TCNs maintain temporal order, and it has achieved parallel processing, which has accelerated the ECG or heart rate variability analysis. They are also robust against the sequence length variations and have shown superior performance in predicting the cardiac anomalies from the multi-lead ECG datasets.

5.3 Generative Models for the cardiac Analysis

Generative deep learning models have emerged as valuable tools for feature learning, data augmentation, and anomaly detection in cardiac datasets.

5.3.1 Autoencoders for Feature Learning and Dimensionality Reduction

Autoencoders consist of encoder and decoder networks that learn compact latent representations of input data while minimizing the reconstruction error [25], [26]. In the cardiac applications, autoencoders have extracted the key patterns from the ECG signals, echocardiography sequences, and the MRI slices, which reduces dimensionality while preserving the diagnostic information. These latent features can be used as input for downstream classifiers, which improves the model efficiency and interpretability.

5.3.2 Generative Adversarial Networks (GAN) for Data Augmentation

GANs, composed of generator and discriminator networks, have enabled a realistic synthesis of the cardiac signals and images to address data scarcity and class imbalance [37], [38]. They have been that is applied to generate rare arrhythmic ECG patterns, simulate pathological echocardiography sequences, and expand the training sets for a multi-class cardiac disease classification. GAN-based augmentation has improved the model generalization, and it has reduced the overfitting in small-scale or heterogeneous datasets.

5.3.3 Variational Autoencoders (VAE)

Variational autoencoders introduce probabilistic modeling to encode input data into the latent distribution, which allows the generation of new samples with similar statistical properties [39]. VAEs are useful for anomaly detection in ECG and imaging datasets, as they have identified the deviations from the learned normal patterns. Its generative capability has also supported the synthetic dataset creation for model training while it maintains the physiological plausibility.

5.4 Graph Neural Networks for the cardiac Signals

Graph-based deep learning has been increasingly that is applied to cardiac analysis, which is specifically for a multi-lead ECG and spatially correlated imaging data, where interactions between the nodes represent the physiological relationships.

5.4.1 Temporal Convolutional Graph Neural Networks (TC-GNN)

Temporal convolutional graph neural networks combine the temporal modelling with the graph structure learning, which has allowed the simultaneous capture of dynamic signal changes and inter-lead correlations [46], [47]. In ECG analysis, each of the leads has represented a

graph node, and the edges encode temporal or spatial dependencies. TC-GNNs have shown enhanced arrhythmia classification, ischemia detection, and ECG-based risk prediction by the use of these structured relationships.

5.4.2 Graph-Based Feature Representation

Graph-based feature representation transforms ECG or imaging data into relational structures, has focusses on connectivity and interdependence between the physiological regions. For example, the cardiac MRI voxels or ECG leads can be represented as nodes. However, the functional or spatial correlations define edges. This approach has captured both the local and global interactions, which improves the predictive accuracy and interpretability. Graph embeddings derived from these structures serve as inputs to downstream classifiers, which provide a robust framework for a multi-modal cardiac data addition. The convergence of CNN, RNN, generative, and graph-based architectures facilitates comprehensive analysis of the cardiac signals and images. CNNs have captured spatial patterns in imaging, RNNs and TCNs model temporal dependencies in ECG, generative models augment data, and it extracts the latent features, and the graph neural networks have represented structured interdependencies. Collectively, these deep learning techniques have enabled an accurate disease classification, early risk detection, real-time monitoring, and improved clinical decision support [46]-[51]. The combination of these architectures in hybrid pipelines has enhanced the model robustness, interpretability, and applicability in real-world cardiac care.

6. Hybrid Ml/Dl Frameworks for CVD Detection

Multi-Modal Data Fusion Approaches

Hybrid ML/DL frameworks, as in Figure 3 have exploited the multi-modal data sources to improve the accuracy, robustness, and clinical interpretability in the cardiovascular detection and monitoring. Fusion of complementary data modalities has allowed the models to combine the spatial, temporal, and biochemical information, which has provided a more comprehensive representation of cardiac health.

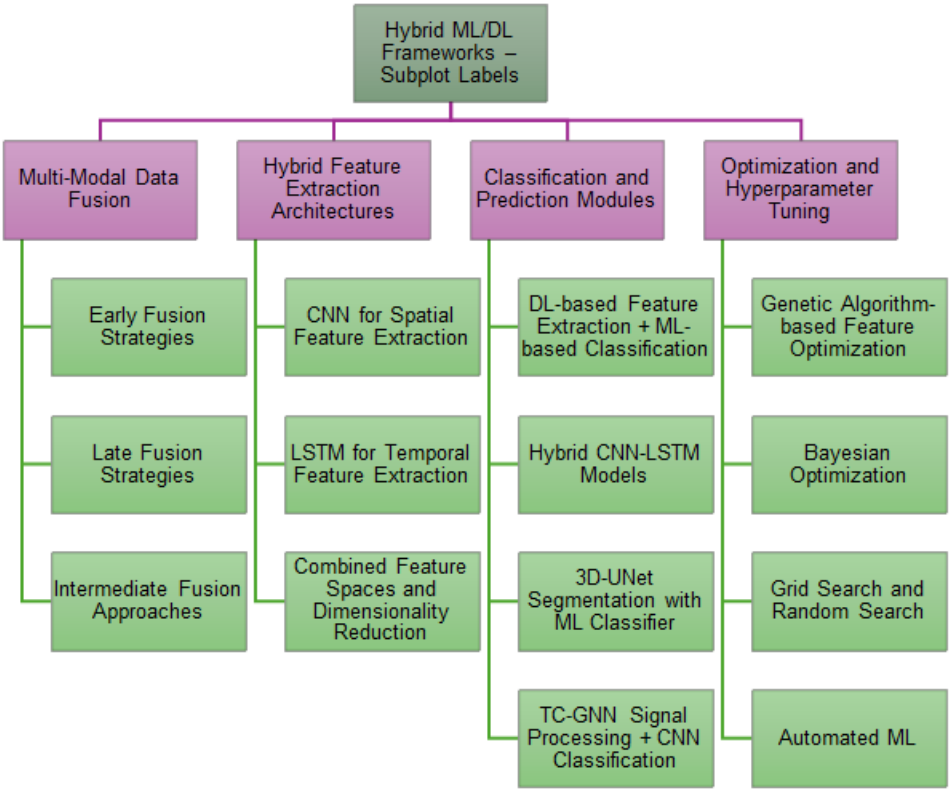

Figure 3: Hybrid ML/DL for CVD

Hybrid Feature Extraction Architectures

Hybrid frameworks exploit deep learning architectures for feature extraction while integrating machine learning for classification or regression, which combines the strengths of both paradigms.

Classification and Prediction Modules

After feature extraction, hybrid frameworks have employed diverse classifiers and predictive architectures to translate learned representations into actionable outputs.

7. Performance Evaluation and Validation

7.1 Evaluation Metrics

Rigorous evaluation metrics are essential to assess the accuracy, reliability, and clinical relevance of ML and DL models in cardiovascular applications. Metrics are chosen based on the task type, data characteristics, and the clinical implications.

7.1.1 Classification Metrics

Classification metrics have quantified the model performance in distinguishing between the cardiac states, such as normal rhythm versus arrhythmia, or presence versus absence of myocardial infarction [15]. Common metrics have included the accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC). Accuracy measures overall correctness. However, the precision and recall have emphasized the ability to correctly identify positive cases, which is critical in detecting rare but high-risk cardiac events. F1-score balances precision and recall, which provides a single metric for imbalanced datasets. AUC-ROC evaluates discrimination capacity across multiple thresholds, informing optimal cutoffs for clinical decision-making.

7.1.2 Ranking Metrics

Ranking metrics assess models that generate ordered predictions or risk scores rather than binary scores. Metrics such as normalized discounted cumulative gain (NDCG), mean average precision (MAP), and an area under the precision-recall curve (AUC-PR) measure how effectively the model prioritizes high-risk patients or critical events. These metrics are which is specifically relevant in a multi-class disease classification or risk stratification frameworks, where the correct ranking of patients according to severity directly influences the clinical intervention priorities.

7.1.3 Cardiac-Specific Metrics

Cardiac-specific metrics have provided the domain-relevant evaluation beyond conventional classification or ranking measures. Examples have included the sensitivity to arrhythmic beats per ECG segment, Dice similarity coefficient for the cardiac image segmentation, ejection fraction error in volumetric analysis, and the ventricular volume overlap ratios. These metrics have captured clinically meaningful differences in predictions, which have ensured that models not only perform well statistically but also provide actionable insights in patient care.

7.2 Statistical Significance Testing

Statistical evaluation has quantified the confidence in the observed performance improvements, and it proves that the reported gains are not due to random chance.

7.2.1 Hypothesis Testing

Hypothesis testing evaluates whether the observed difference between the proposed model and a baseline is statistically significant [56]. Tests such as paired t-tests, Wilcoxon signed-rank tests, or McNemar's tests are employed depending on data type and distribution. In the cardiac ML/DL studies, hypothesis testing validates improvements in classification accuracy, segmentation quality, or risk prediction, which provides the formal framework to assess model superiority.

7.2.2 Confidence Intervals

Confidence intervals have provided the estimated range within which the true performance metric lies with the specified probability, typically 95% [56]. Reporting confidence intervals for metrics such as accuracy, AUC, or F1-score adds transparency, quantifies uncertainty, and it has allowed the clinicians to

interpret model reliability in practice. Narrow intervals have indicated a stable and reproducible performance across the samples, whereas the wide intervals have focused on variability or potential sensitivity to specific subgroups.

8. Comparative Analysis of Ml/Dl Approaches

Comparative analysis of machine learning (ML), deep learning (DL), and the hybrid models has provided insights into the suitability for various cardiovascular applications. Multi-modal approaches are compared with the single-modal models to evaluate the benefits of integrating complementary data.

8.1 Conventional ML vs. Deep Learning

8.1.1 Computational Complexity and Efficiency

Conventional ML models such as SVM, Random Forest, KNN, and the XGBoost generally have lower computational requirements compared to the deep learning models like CNNs, LSTMs, and the TC-GNNs [52]. The dataset is collected from the Koogle repository[60] for analyzing the ML and DL approaches.

Table 1. Computational characteristics of selected ML and DL approaches

Method	Training Complexity	Inference Time	Hardware Requirements	Scalability
SVM	Moderate	Low	CPU	Limited with large datasets
Random Forest	Moderate	Low	CPU	Good with tabular data
KNN	Low	High	CPU	Poor for large datasets
XGBoost	Moderate	Low	CPU/GPU	High for structured data
CNN	High	Moderate	GPU	Excellent for images
LSTM	High	Moderate	GPU	Excellent for sequential data
CNN-LSTM	Very High	Moderate	GPU	Good for a multi-modal data
TC-GNN	Very High	Moderate	GPU	Specialized for signal graphs

8.1.2 Data Requirements and Generalization

Deep learning models have required significantly larger datasets to learn robust features compared to the ML models [33]. ML methods often perform well on structured tabular data with limited samples. However, the DL models perform well in image, video, and multi-channel ECG analysis.

Table 2 compares data requirements and generalization capabilities.

Method	Minimum Data Size	Generalization Capability	Overfitting Risk
SVM	Small to Medium	Moderate	Low
Random Forest	Small to Medium	Moderate	Low
XGBoost	Medium	High	Moderate
CNN	Large	High	High without augmentation

LSTM	Large	High	High without regularization
CNN-LSTM	Very Large	Very High	Moderate with the dropout
TC-GNN	Very Large	High	Moderate

8.1.3 Interpretability vs. Performance Trade-offs

ML models have provided better interpretability through the feature importance, decision paths, or rule extraction [52]. DL models have achieved higher performance in complex pattern recognition but are inherently black boxes. Hybrid models attempt to balance the interpretability and predictive accuracy by using the DL for feature extraction and ML for classification [56].

8.2 Hybrid Models vs. Single-Modality Approaches

8.2.1 Accuracy and Robustness Comparisons

Hybrid CNN-LSTM models integrating ECG and imaging data perform better than the single-modality approaches in arrhythmia detection, heart failure prediction, and myocardial infarction classification [39], [30].

Table 3. Comparative performance metrics

Approach	Dataset	Accuracy (%)	F1-Score	Robustness to Noise
CNN (Imaging only)	CardiacSlice	88	0.85	Moderate
LSTM (ECG only)	MIT-BIH	90	0.87	Moderate
CNN-LSTM (Hybrid)	ECG + Imaging	94	0.91	High
TC-GNN + CNN	Multi-lead ECG + Imaging	95	0.93	High

8.2.2 Computational Cost Analysis

Hybrid models impose higher computational costs due to the multiple architectures and fusion layers [33], [34]. Edge deployment requires model pruning, quantization, or efficient inference pipelines to maintain real-time capabilities.

Table 4 details computational costs for hybrid and single-modality approaches.

Model	Parameters (Millions)	Training Time (Hours)	Inference Time (ms/sample)	Hardware Requirement
CNN	15	5	10	GPU
LSTM	12	6	12	GPU
CNN-LSTM	28	12	18	GPU
TC-GNN + CNN	32	14	20	GPU

8.2.3 Clinical Applicability

Hybrid models have shown superior clinical utility due to the richer feature representations [44], [50]. A multi-modal addition has supported the early detection of subtle abnormalities, risk stratification, and comprehensive monitoring. Single-modality models have remained practical for resource-constrained environments or applications focusing on specific data types.

8.3 A Multi-Modal vs. Single-Modal Data

8.3.1 Information Complementarity

Multi-modal data has combined the complementary information, such as ECG temporal features, imaging spatial features, and the lab biomarkers, which has allowed better risk prediction and anomaly detection [52], [54]. Single-modal data may miss critical correlations, which reduces sensitivity and specificity.

Table 5 compares performance for different modalities.

Data Type	Features	Accuracy (%)	Clinical Relevance	Limitation
ECG only	Temporal patterns	90	Moderate	Misses structural changes
Imaging only	Structural features	88	Moderate	Misses electrophysiological anomalies
Multi-modal	ECG + Imaging + Labs	95	High	Higher computational demand

8.3.2 Fusion Strategy Effectiveness

Fusion strategies: early, late, or intermediate affect performance and interpretability [48], [49]. Early fusion has captured the cross-modal correlations but may increase dimensionality. Late fusion has reduced the dimensionality but may miss subtle interactions. Intermediate fusion balances these factors, which often generates the best performance in the cardiovascular prediction tasks.

Table 6 illustrates fusion strategy comparisons.

Fusion Strategy	Accuracy (%)	F1-Score	Interpretability	Computational Complexity
Early Fusion	94	0.91	Moderate	High
Late Fusion	92	0.89	High	Moderate
Intermediate Fusion	95	0.93	Moderate	High

8.3.3 Real-Time Performance Considerations

The real-time monitoring imposes latency constraints, which show models that balance complexity with the inference speed [56], [59]. Single-modality ML models have offered low-latency predictions. However, the multi-modal hybrid DL approaches have required optimized pipelines, edge computing, or model compression for clinical deployment.

Table 7 presents inference times for different approaches.

Approach	Inference Time (ms/sample)	Suitability for the real-time Monitoring	Notes
SVM (ECG)	8	High	Lightweight, low-latency
CNN (Imaging)	10	Moderate	GPU required

CNN-LSTM (Multi-modal)	18	Moderate	Requires optimization
TC-GNN + CNN	20	Moderate	Edge deployment feasible with the pruning

Thus, conventional ML models have provided interpretability and computational efficiency. However, the DL models perform well in high-dimensional, complex data representations. Hybrid ML/DL frameworks integrating multi-modal information have achieved superior accuracy and robustness, but demand higher computational resources and careful optimization for real-time clinical applications. Fusion strategies, feature engineering, and edge computing significantly influence performance, which makes the choice of model dependent on dataset characteristics, clinical objectives, and the deployment constraints. The combination of multi-modal data, hybrid architectures, and optimized inference pipelines establishes a path towards the clinically actionable, reliable, and interpretable cardiovascular AI solutions.

9. Recommendations for Ml/Dl Framework Development

Developing effective ML/DL frameworks for cardiovascular applications requires a combination of methodological rigor, clinical relevance, and ethical considerations.

- **Data Curation and Pre-processing:** Frameworks should incorporate robust data cleaning, normalization, and the augmentation techniques to handle noise, missing values, and class imbalance [33]. A multi-modal pre-processing pipeline must prove the proper alignment of temporal and spatial data.
- **Feature Engineering and Hybrid Architectures:** Which combines the DL-based feature extraction with the ML classifiers has enhanced the accuracy and interpretability [37], [38]. CNNs are recommended for spatial features in imaging, LSTMs for temporal ECG signals, and the TC-GNNs for graph-based physiological interactions. Hybrid CNN-LSTM or CNN-GRU architectures have provided a balanced solution for a multi-modal addition.
- **Model Optimization and Deployment:** Hyperparameter tuning using Bayesian optimization, grid search, or AutoML has improved the performance [12], [34]. For the real-time applications, model compression, pruning, and edge deployment should be considered to meet latency and resource constraints.
- **Explainability and Clinical Addition:** The combination of SHAP, LIME, and the saliency-based visualizations has allowed the clinician interpretability [11], [13], [106]. Mapping predictions to clinical guidelines, risk scores, and actionable insights fosters trust and supports decision-making.
- **Generative AI & Fusion methods:** generative AI models such as GANs and variational auto-encoders are supporting the synthetic cardiac signals and medical images that tend to improve the training of ML/DL frameworks under the limited data conditions.
- **Regulatory Compliance and Ethical Standards:** Frameworks must prove adherence to privacy regulations (HIPAA, GDPR) and fairness metrics [17], [19]. Bias analysis and mitigation strategies should be integrated into the model development to guarantee equitable performance across the patient populations.
- **Evaluation and Validation Protocols:** Robust evaluation using the classification, ranking, and the cardiac-specific metrics, coupled with the K-fold and temporal cross-validation, proves the reproducibility [56]. External validation on unseen datasets has confirmed generalizability and clinical applicability.

10. Open Research Issues And Future Directions

Emerging trends have focused on several open research issues and potential directions for cardiovascular AI.

- **Explainable and Trustworthy AI:** Developing interpretable models that maintain a higher predictive accuracy is an ongoing challenge [31], [34]. Future directions have involved integrating domain knowledge with the DL architectures, probabilistic modeling for uncertainty quantification, and real-time visualizations to enhance the clinical trust [12] [38].
- **Edge AI and the real-time Deployment:** Translating models to wearable devices, ICU telemetry systems, and the remote monitoring platforms requires efficient algorithms that are capable of low-latency inference [45], [36]. Research on model compression, pruning, quantization, and lightweight hybrid architectures is crucial to enable real-time, on-device cardiac monitoring.
- **Data Scarcity and Synthetic Data:** Limited access to annotate a multimodal dataset constrains model development. Techniques such as GAN-based synthetic data generation and signal augmentation can have addressed this issue, but ensuring the physiological plausibility and clinical relevance remains a research gap [37], [33].
- **Personalized and longitudinal Models:** the cardiovascular conditions are patient-specific and evolve. Future models should incorporate longitudinal monitoring and adaptive learning to predict disease progression, readmission risk, and the therapy response, which has allowed personalized care strategies [34], [35].
- **Cross-Center Generalization and Federated Learning:** AI models often perform poorly on external datasets due to the variations in patient demographics and acquisition protocols. Federated learning and domain adaptation approaches can facilitate a multi-center collaboration while preserving data privacy, which has allowed the generalizable and robust cardiac models [50], [52].
- **Integrated Framework for Cardiovascular Disease**: An integrated framework for cardiovascular disease (CVD) prediction using multi-modal data combines hybrid ML/DL (e.g., CNN-LSTM), explainable AI (XAI), and federated learning (FL) to achieve high accuracy (>95%) while ensuring privacy and interpretability. These frameworks address data scarcity and black-box issues in clinical settings.

11. Conclusion

The addition of ML and DL in cardiovascular care has transformed early detection, real-time monitoring, and risk stratification. The conventional ML models, such as SVM, Random Forest, and XGBoost, provide interpretability and computational efficiency, whereas the DL architectures, which include the CNNs, LSTMs, BiLSTMs, and TC-GNNs, have captured complex temporal, spatial, and graph-based patterns in ECG, imaging, and multi-modal datasets [52], [59], [12]. Hybrid frameworks that combine the DL feature extraction with the ML classification have achieved higher accuracy and robustness, which is specifically when integrating multi-modal data. The real-time monitoring, allowed through the wearable devices, remote platforms, and the ICU telemetry systems, leverages edge computing and optimized inference pipelines to provide timely alerts, and it has supported the clinical decision-making [44], [45]. Explainable AI methods, which include the SHAP, LIME, and the gradient-based saliency maps, prove the transparency and facilitate clinician trust, which is essential for adoption in high-stakes cardiac care [10], [13]. Despite these advancements, challenges such as data heterogeneity, computational demands, interpretability, and regulatory compliance have remained [43]. Open research directions have included the multi-modal fusion optimization, edge AI, synthetic data generation, personalized and longitudinal modeling, and federated learning to prove the robust generalization. Future frameworks should

prioritize clinically relevant features, model interpretability, ethical standards, and deployment efficiency to maximize impact.

References

Roth, G. A., Mensah, G. A., Johnson, C. O., Addolorato, G., Ammirati, E., Baddour, L. M., ... & Fuster, V. (2025). Global burden of cardiovascular diseases and risk factors, 1990–2022: Update from the GBD 2021 study. Journal of the American College of Cardiology, 82(25), 2350-2473.

World Health Organization. (2025). Cardiovascular diseases (CVDs). https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)

Gomes, W. J., Almeida, R. M., Petrucci, O., Antunes, M. J., & Albuquerque, L. C. (2021). The 2020 American College of Cardiology/American Heart Association (ACC/AHA) guideline for the management of patients with valvular heart disease. Should the world jump in?. Brazilian journal of cardiovascular surgery, 36(2), 278-288.

Sabbah, H. N. (2017). Silent disease progression in clinically stable heart failure. European Journal of Heart Failure, 19(4), 469-478.

American Heart Association. (2025). 2025 Heart disease and stroke statistics update fact sheet. https://www.heart.org/en/-/media/PHD-Files-2/Science-News/2/2025-Heart-and-Stroke-Stat-Update/2025-Statistics-At-A-Glance.pdfheart

Nayak, S. K., Pradhan, B., Mohanty, B., Sivaraman, J., Ray, S. S., Wawrzyniak, J., ... & Pal, K. (2023). A review of methods and applications for a heart rate variability analysis. Algorithms, 16(9), 433.

Khan, W. U., Khan, M. S., & Cheung, P. (2025). Emerging rapid detection methods for the monitoring of cardiovascular diseases: Current trends and future perspectives. Materials Today Bio, 101663.

Gaoudam, N., Sakhamudi, S. K., Kamal, B., Addla, N., Reddy, E. P., Ambala, M., ... & Reddy Jr, E. P. (2025). Wearable Devices and AI-Driven Remote Monitoring in Cardiovascular Medicine: A Narrative Review. Cureus, 17(8).

Bokhari, S. F. H., Waseem, A. B., Raza, H., Iqbal, A., Javaid, S., Idrees, B., ... & Dost, W. (2025). Advancing cardiac arrhythmia management: The integration of wearable technology and remote monitoring. World Journal of Cardiology, 17(7), 106841.

Rath, A., Mishra, D., Panda, G., & Satapathy, S. C. (2021). Heart disease detection using deep learning methods from imbalanced ECG samples. Biomedical Signal Processing and Control, 68, 102820.

Ansari, Y., Mourad, O., Qaraqe, K., & Serpedin, E. (2023). Deep learning for ECG Arrhythmia detection and classification: an overview of progress for period 2017–2023. Frontiers in Physiology, 14, 1246746.

Karna, V. V. R., Karna, V. R., Janamala, V., Devana, V. K. R., Ch, V. R. S., & Tummala, A. B. (2025). A comprehensive review on heart disease risk prediction using machine learning and deep learning algorithms. Archives of Computational Methods in Engineering, 32(3), 1763-1795.

Abubaker, M. B., & Babayiğit, B. (2022). Detection of cardiovascular diseases in ECG images using machine learning and deep learning methods. IEEE transactions on artificial intelligence, 4(2), 373-382.

Rai, H. M., & Trivedi, A. (2021). Hybrid CNN-LSTM deep learning model and ensemble technique for automatic detection of myocardial infarction using big ECG data. Applied Intelligence, 51(3), 1298-1312.

Malakouti, S. M. (2023). Heart disease classification based on ECG using machine learning models. Biomedical Signal Processing and Control, 84, 104796.

Shahjehan, R. D., & Bhutta, B. S. (2024). Coronary artery disease. In StatPearls. StatPearls Publishing.

Alshehri, A. M. (2019). Stroke in atrial fibrillation: Review of risk stratification and preventive therapy. Journal of Family Medicine and Primary Care, 8(2), 430-434.

Beghini, A., & Metra, M. (2025). 2024 update in heart failure. ESC Heart Failure, 12(1), 1-15.

Meng, X., & Zhang, Y. (2024). Congenital heart disease: Types, pathophysiology, diagnosis, and treatment. MedComm, 5(6), e631.

Saef, J. M., & Stout, K. K. (2021). Valvular heart disease in congenital heart disease: A narrative review. Cardiovascular Diagnosis and Therapy, 11(2), 649-662.

Rao, S. V., O'Donoghue, M. L., Ruel, M., Rab, T., Tamis-Holland, J. E., Alexander, J. H., ... & Williams, M. S. (2025). 2025 ACC/AHA/ACEP/NAEMSP/SCAI guideline for the management of patients with acute coronary syndromes: a report of the American College of Cardiology/American Heart Association Joint Committee on Clinical Practice Guidelines. Journal of the American College of Cardiology, 85(22), 2135-2237.

Sathi, T. A., Jany, R., Ela, R. Z., Azad, A. K. M., Alyami, S. A., Hossain, M. A., & Hussain, I. (2024). An interpretable electrocardiogram-based model for predicting arrhythmia and ischemia in cardiovascular disease. Results in Engineering, 24, 103381.

Lang, R. M., Badano, L. P., Mor-Avi, V., Afilalo, J., Armstrong, A., Ernande, L., ... & Voigt, J. U. (2015). Recommendations for cardiac chamber quantification by echocardiography in adults: an update from the American Society of Echocardiography and the European Association of Cardiovascular Imaging. European Heart Journal-Cardiovascular Imaging, 16(3), 233-271.

Wang, Y., Cao, T., Liu, X., He, S., Ran, Z., Du, C., ... & Guo, Y. (2025). A New Benchmark for Modern Management of Valvular Heart Disease: The Whole-Life Cycle Management System. JACC: Asia, 5(5), 609-632.

Bhargava, N., Kapadia, S., & Tated, S. (2025). Assessment of Myocardial Viability by Cardiac Magnetic Resonance Imaging. European Journal of Cardiovascular Medicine, 15, 490-496.

Xie, F., Lee, M. S., Allahwerdy, S., Getahun, D., Wessler, B., & Chen, W. (2024). Identifying the Severity of Heart Valve Stenosis and Regurgitation Among a Diverse Population Within an Integrated Health Care System: Natural Language Processing Approach. JMIR cardio, 8, e60503.

Zhao, L., Lu, A., Tian, J., Huang, J., & Ma, X. (2020). Effects of different LVEF assessed by echocardiography and CMR on the diagnosis and therapeutic decisions of cardiovascular diseases. Frontiers in physiology, 11, 679.

Lv, W. (2025). Diagnostic performance of dynamic electrocardiography in the diagnosis of myocardial ischemic attack in coronary heart disease: a systematic review and meta-analysis. Frontiers in Medicine, 12, 1646417.

Belley-Cote, E. P., & Eikelboom, J. W. (2020). Anticoagulation for stroke prevention in patients with atrial fibrillation and end-stage renal disease—first, do no harm. JAMA network open, 3(4), e202237-e202237.

Hindricks, G., Potpara, T., Dagres, N., Arbelo, E., Bax, J. J., Blomström-Lundqvist, C., ... & Watkins, C. L. (2021). 2020 ESC Guidelines for the diagnosis and management of atrial fibrillation developed in collaboration with the European Association for Cardio-Thoracic Surgery (EACTS) The Task Force for the diagnosis and management of atrial fibrillation of the European Society of Cardiology (ESC) Developed with the special contribution of the European Heart Rhythm Association (EHRA) of the ESC. European heart journal, 42(5), 373-498.

Xu, J., Li, Q., Deng, L., Xiong, J., Cheng, Z., & Ye, C. (2025). Global, regional, and national epidemiology of congenital heart disease in children from 1990 to 2021. Frontiers in Cardiovascular Medicine, 12, 1522644.

ESC/EACTS Guidelines Committee. (2025). 2025 ESC/EACTS Guidelines for the management of valvular heart disease. European Heart Journal. https://www.escardio.org/Guidelines/Clinical-Practice-Guidelines/Valvular-Heart-Disease

Kaur, I., Rajni, R., & Marwaha, A. (2016). ECG signal analysis and arrhythmia detection using wavelet transform. Journal of The Institution of Engineers (India): Series B, 97(4), 499-507.

Faust, O., Martis, R. J., Min, L., Zhong, G. L. Z., & Yu, W. (2013). Cardiac arrhythmia classification using electrocardiogram. J. Med. Imaging Health Inf, 3, 448.

Le, T. Q., Chandra, V., Afrin, K., Srivatsa, S., & Bukkapatnam, S. (2020). A dynamic systems approach for detecting and localizing of infarct-related artery in acute myocardial infarction using compressed paper-based electrocardiogram (ECG). Sensors, 20(14), 3975.

Byrne, R. A., Rossello, X., Couper, K., Henry, T. D., Hamza, M. S., Kinnaird, T., ... & Ibanez, B. (2025). 2025 ACC/AHA/ACEP/NAEMSP/SCAI guideline for the management of patients with acute coronary syndromes. Journal of the American College of Cardiology. Advance online publication.

Ouyang, W., Liu, X., Ding, Z., Ji, Y., Zhao, J., Zhu, H., ... & Ding, Z. (2025). An immunostaining-based approach for assessing myocardial viability in the infarcted mouse hearts. Frontiers in Cardiovascular Medicine, 12, 1598314.

Lang, R. M., Badano, L. P., Mor-Avi, V., Afilalo, J., Armstrong, A., Ernande, L., ... & Marwick, T. H. (2015). Recommendations for cardiac chamber quantification by echocardiography in adults: An update from the American Society of Echocardiography and the European Association of Cardiovascular Imaging. Journal of the American Society of Echocardiography, 28(1), 1-39. https://doi.org/10.1016/j.echo.2014.10.003

Demir, S., Selvitopi, H., & Selvitopi, Z. (2025). An early and accurate diagnosis and detection of the coronary heart disease using deep learning and machine learning algorithms. Journal of Big Data, 12(1), 1-32.

Otoum, N., Arias, E., & Alfaro, J. J. (2025, April). AI-driven cybersecurity and functional framework for remote laboratories: A software engineering perspective. In 2025 1st International Conference on Computational Intelligence Approaches and Applications (ICCIAA) (pp. 1-5). IEEE.

Luz, E. J. D. S., Schwartz, W. R., Cámara-Chávez, G., & Menotti, D. (2016). ECG-based heartbeat classification for arrhythmia detection: A survey. Computer methods and programs in biomedicine, 127, 144-164.

Nayak, S. K., Pradhan, B., Mohanty, B., Sivaraman, J., Ray, S. S., Wawrzyniak, J., ... & Pal, K. (2023). A review of methods and applications for a heart rate variability analysis. Algorithms, 16(9), 433.

Isin, A., & Ozdalili, S. (2017). Cardiac arrhythmia detection using deep learning. Procedia computer science, 120, 268-275.

Chowdhury, M. A., Rizk, R., Chiu, C., Zhang, J. J., Scholl, J. L., Bosch, T. J., ... & Chen, W. C. (2025). The heart of transformation: exploring artificial intelligence in cardiovascular disease. Biomedicines, 13(2), 427.

Banerjee, T., & Paçal, İ. (2025). A systematic review of machine learning in heart disease prediction. Turkish Journal of Biology, 49(5), 600-634.

Gupta, R., Sille, R., & Choudhury, T. (2026). Heart Rate Prediction Analysis Using ML and DL: A Review of Existing Models and Future Directions. Distributed Time-Sensitive Systems, 25-41.

Golande, A. L., & Pavankumar, T. (2023). Optical electrocardiogram based heart disease prediction using hybrid deep learning. Journal of Big Data, 10(1), 139.

Sannino, G., & De Pietro, G. (2018). A deep learning approach for ECG-based heartbeat classification for arrhythmia detection. Future Generation Computer Systems, 86, 446-455.

Li, L., Jiang, Z., Li, L., Yi, N., Chen, L., & Li, L. (2025). Impact of Various Doses of Dobutamine on Myocardial Viability and the Effects of β-Blockers in Patients With Ischemic Cardiomyopathy: An Assessment Using Stress Echocardiography. Echocardiography, 42(4), e70134.

Zhao, L., Lu, A., Tian, J., Huang, J., & Ma, X. (2020). Effects of different LVEF assessed by echocardiography and CMR on the diagnosis and therapeutic decisions of cardiovascular diseases. Frontiers in physiology, 11, 679.

Rai, H. M., & Chatterjee, K. (2022). Hybrid CNN-LSTM deep learning model and ensemble technique for automatic detection of myocardial infarction using big ECG data. Applied Intelligence, 52(5), 5366-5384.

Neha, Sardana, H. K., Kanwade, R., & Tewary, S. (2021). Arrhythmia detection and classification using ECG and PPG techniques: A review. Physical and Engineering Sciences in Medicine, 44(4), 1027-1048.

Dhyani, S., Kumar, A., & Choudhury, S. (2023). Analysis of ECG-based arrhythmia detection system using machine learning. MethodsX, 10, 102195.

Zhang, H., Pan, X., Zhou, S., Zhang, W., Chen, J., & Pan, L. (2025). Advanced ECG feature extraction and SVM classification for predicting defibrillation success in OHCA. Frontiers in Cardiovascular Medicine, 12, 1550422.

Verma, P., Awasthi, V. K., & Sahu, S. K. (2021). A Novel Design of Classification of Coronary Artery Disease Using Deep Learning and Data Mining Algorithms. Rev. d'Intelligence Artif., 35(3), 209-215.

Yang, L., Wu, H., Jin, X., Zheng, P., Hu, S., Xu, X., ... & Yan, J. (2020). Study of cardiovascular disease prediction model based on random forest in eastern China. Scientific reports, 10(1), 5245.

Asadi, F., Homayounfar, R., Mehrali, Y., Masci, C., Talebi, S., & Zayeri, F. (2024). Detection of cardiovascular disease cases using advanced tree-based machine learning algorithms. Scientific Reports, 14(1), 22230.

Thilagavathy, R., & Srivatsan, S. (2020). Real-time ECG signal feature extraction and classification using support vector machine. International Journal of Recent Technology and Engineering, 8(5), 4567-4572.

Saini, I., Singh, D., & Khosla, A. (2013). QRS detection using the K-Nearest Neighbor algorithm (KNN) and evaluation on standard ECG databases. Journal of advanced research, 4(4), 331-344.

https://www.kaggle.com/datasets/sulianova/cardiovascular-disease-dataset