

A Review on Different Approaches to Computer-Aided Diagnosis of Heart Disease

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Abstract

This is the age of rising technology and the domain that is one of the biggest beneficiaries of this rapid change is healthcare. Nowadays, early detection of any heart irregularity has become a crucial public health concern. This paper reviews various different approaches that have been taken on for computer aided diagnosis (CAD) of heart disease, and provides a comprehensive study and analysis on the same. For ease of understanding and clarity, the paper has been divided into five distinct heart diseases namely, Coronary Artery Disease, Cardiac Arrhythmia, Congenital Heart Disease (CHD), Myocardial Infarction (Heart Attack) and lastly, Cardiac Arrest. The different approaches to computer aided diagnosis possibilities in each category has been reviewed from recent studies and has been further sub-categorized and discussed.

Keywords: CAD, Deep Learning, Heart Disease, Machine Learning, Prediction.

Introduction

The human heart is the predominant organ of our circulatory system. It is a four chambered muscular organ nearly as big as a closed human fist, located behind and to the left to the sternum, i.e. breastbone. It consists of two chambers on top and two on the bottom which equates to a total of four chambers. The heart pumps blood through different kinds of blood vessels like arteries (those which carry blood which is rich in oxygen from the heart to the rest of the body), veins (carry blood which is poor in oxygen poor blood back to the heart) and capillaries that form the connection between arteries and veins and act as a medium for exchange of materials between the blood and the cells.

Heart Diseases are a term used to refer to conditions that affect optimal cardiac performance. They are one of the most common types of diseases and proven to be the primary reason for death in many countries. The number of individuals dying from cardiovascular diseases (CVDs), the predominant factor of death worldwide, is gradually rising. There are a number of irregularities that affect how the heart beats, such as cardiac murmur or artifact. The various types of heart diseases include blood vessel diseases (like Coronary Artery Disease), diseases

that cause irregular heartbeat, congenital heart diseases (diseases that one is born with), heart muscle irregularities and heart valve diseases. Most of these diseases can be prevented simply with a healthy choice of lifestyle. One heart disease that is the most common heart condition that affects people is said to be Coronary Artery Disease. In this condition, the primary arteries delivering oxygen-rich blood to the heart are impacted by the accumulation of cholesterol (most common reason). These deposits in the arteries are known as atherosclerosis and this condition diminishes blood circulation not only to the heart but also to various regions of the body. This usually leads to chest pain (angina), stroke or heart attack. According to the World Health Organization (WHO), CVDs are the leading cause of death globally, accounting for nearly 18 million deaths each year. CVDs are also a leading cause of mortality in India, responsible for approximately 28% of all deaths annually. India has witnessed a rapid increase in the prevalence of heart disease over the past few decades due to factors such as urbanization, lifestyle changes, and an aging population. The prevalence of coronary artery disease in urban areas is around 10%-12% while in rural areas; it is around 4-5% (1). This difference

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highlights the varying impact of heart disease across different regions and accompanying lifestyles. These insights underscore the importance of improving diagnostic techniques to combat the high prevalence and significant impact of cardiovascular diseases in India.

The development of CAD systems for heart disease has evolved significantly over the past few decades. Starting in the 1980s with basic rule-based systems, CAD technology advanced in the 1990s to incorporate statistical models and automated ECG analysis. The early 2000s saw the introduction of machine learning algorithms, improving diagnostic accuracy and enabling sophisticated image-based diagnostics. The 2010s brought a powerful technology with deep learning, enhancing the analysis of medical images for more personalized diagnostics for patients. Now, in the 2020s, CAD systems are leveraging artificial intelligence (AI) and big data for real-time monitoring and diagnostics, utilizing wearable technology and cloud-based platforms to provide more accessible healthcare solutions. In recent years, the field of CAD has been driven by these cutting-edge technologies and is shaping the future of cardiac care. One interesting trend that has been occurring is the development of hybrid models, particularly through ensemble learning which has improved the robustness and reliability of CAD systems. Al Bataineh *et al.*, combined multiple machine learning and deep learning algorithms to create a hybrid model, which leveraged the strengths of each to provide superior diagnostic accuracy (2). Another area of interest to researchers has been the advent of transfer

learning, where pre-trained models are fine-tuned for specific diagnostic tasks and has further accelerated the development of highly accurate CAD systems, addressing the challenge of limited annotated medical datasets. Additionally, the fusion of traditional image processing techniques with AI models has enhanced feature extraction and analysis, further improving the performance of these systems and are revolutionizing modern healthcare. Yi *et al.*, demonstrated this by performing image reconstruction and evaluate the stenosis of images on a per-lesion basis (3).

Early and timely diagnosis of heart related problems is critical to prevent further injury to the patient and save lives. The integration of telemedicine and CAD systems with the fields of Machine Learning (ML) and Deep Learning (DL) has enabled the effective prediction heart diseases. For instance, Apollo Hospitals in India have incorporated CAD systems to assist in the interpretation of cardiac MRI scans and CT scans, such as the 640 - slice CT scan. This integration has improved diagnostic efficiency and accuracy, especially in detecting coronary artery disease and cardio-myopathies. The computer-aided diagnosis systems have enhanced the hospital's ability to provide accurate diagnoses in a timely manner. Most studies have recently been showing significant performance enhancement brought by employing deep learning in the ultrasonic CAD system as a result of the efficacy of deep learning in image segmentation and classification. A typical example on how a CAD system works is depicted in Figure 1.

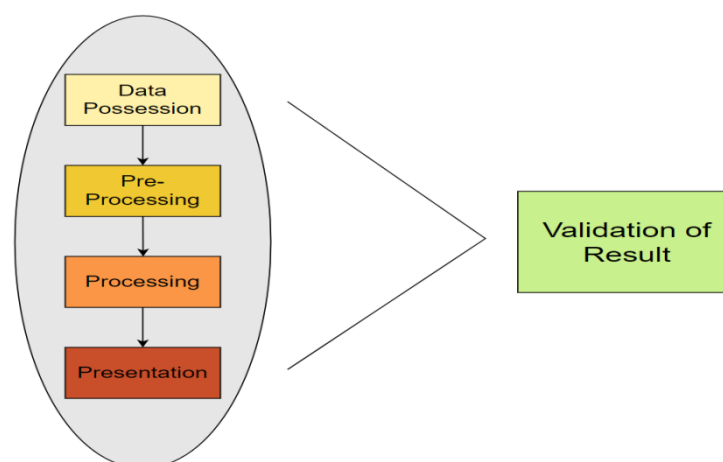


Figure 1: Process Flow of Typical CAD System (The 4 P's)

But among the traditional techniques, angiography is considered the best-known technique yet for

diagnosing heart problems, but it comes with its drawbacks. Patients who undergo angiography do

not always have complications, but there is always a possibility of minor complications, such as infections, or mild reactions to dye or major complications. Kidney damage, heart attack, damage to blood vessels leading to internal bleeding, serious allergic reactions are among these. Due to these reasons, focus has gradually shifted to computational techniques based on intelligent learning models that make the prediction and diagnosis process much faster and more efficient. Yanase *et al.*, however, proved that there is a lack of a universal algorithm applicable

to all aspects of computer aided diagnosis (4). This study systematically examines and synthesizes insights from a comprehensive selection of 60 papers. The primary focus is on aggregating information from prior studies dedicated exclusively to the utilization of DL and ML models for prediction, classification, and diagnosis of heart disease. The paper will embark on an extensive exploration of computer-assisted diagnosis methods for heart diseases, with a specific focus on categorizing these conditions into five distinct groups as shown in Figure 2.

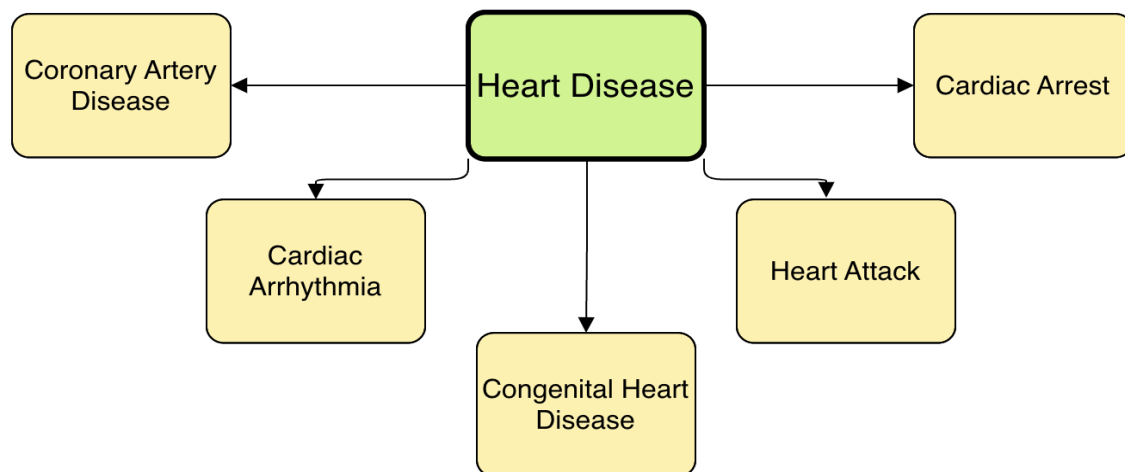


Figure 2: Types of Heart Diseases

The five groups are:

1. Coronary Artery Disease
2. Cardiac Arrhythmia
3. Congenital Heart Disease
4. Heart Attack
5. Cardiac Arrest

This study aims to delve into the existing body of research surrounding these categories, providing a comprehensive understanding of their computer-based diagnostic approaches. Further sections discuss in depth, the work done and technologies employed in each of these disease predictions and the subsections are further classified based on prediction methodologies they utilize.

Coronary Artery Disease

Coronary artery disease is a disorder where plaque formation causes the arteries that carry blood to the heart to narrow and harden, potentially resulting in decreased blood flow and an increased risk of issues related to the heart. It frequently causes chest discomfort and heart attacks.

Image Processing Models

Betancur *et al.*, compared the results of a deep learning (DL) system trained on stress 99mTc-sestamibi myocardial perfusion imaging (MPI) scans using a new-generation Single-photon emission computed tomography (SPECT) scanner with an on-site clinical read. Further, the DL system showed a greater sensitivity compared to the clinical read, with no statistically significant difference (5). Han *et al.*, evaluated the use of DL in processing Coronary Computed Tomographic Angiography (CCTA) imaging for coronary artery stenosis. The outcomes showed CCTA-AI had better diagnostic accuracy than traditional CCTA (6). Rim *et al.*, created a deep learning model named RetiCAC score, utilizing retinal images for predicting the probability of Coronary artery calcium (CAC). Incorporation of RetiCAC into the Pooled Cohort Equation (PCE) led to enhanced cardiovascular risk stratification within the intermediate range and borderline-risk groups, resulting in a continuous reclassification index of 0.261 (7). Yi *et al.*, compared the quality and diagnostic precision of Deep Learning-driven

Image Reconstruction (DLR) in conjunction with subtraction CCTA images (CTADLR) to that of traditional subtraction CCTA images (CTAHIR). The results showed that CTADLR had a higher diagnostic accuracy in identifying calcification-related obstructive diameter stenosis (83.73%) compared to CTAHIR (65.66%), while the diagnostic accuracy of traditional subtraction CCTA images (CTAsHIR) was 75.30% (3). Zreik *et al.* introduced an approach for the automated and non-invasive identification of individuals necessitating Intracoronary Atherectomy (ICA) leveraging deep unsupervised analysis of entire coronary arteries in cardiac (CT) Computed Tomography angiography. Assessment through repeated cross-validation trials showed an area under the ROC Curve of 0.81 ± 0.02 present in artery-level with 0.87 ± 0.02 at the patient-level (8). Meng *et al.*, presented a novel deep learning architecture termed U-Net 3+, integrating comprehensive skip connections and deep supervisions. The framework employs transfer learning and a hybrid loss function for enhanced coronary artery extraction which resulted in a higher performance than previous models (U-Net and U-Net++). The model achieved a substantially good Dice score (9).

Convolutional Neural Networks (CNN)

Zreik *et al.*, underwent a study on a combination of CNN and a Convolutional Autoencoder (CAE) to evaluate the segmentation of the left ventricular (LV) myocardium in 20 images. The results showed the mean absolute distance between the segmented and reference left ventricular boundaries of 0.7mm, indicating a high accuracy in identifying individuals exhibiting substantial coronary artery stenosis (10). Wang *et al.*, performed a study using a 12-layer CNN to detect Breast Arterial Calcifications (BACs). Performance evaluation was conducted utilizing two methodologies: free-response receiver operating characteristic (FROC) analysis and calcium mass quantification analysis. The findings indicated a high accuracy in detecting BACs (11). Li *et al.*, proposed a new framework that fuses features from multiple domains and deep learning-based features of heart sounds to improve accuracy in medical diagnosis. The proposed approach demonstrated superior accuracy compared to conventional methodologies (12).

Cho *et al.*, had 598 intravascular ultrasound sets of coronary arteries from 598 patients partitioned into a training and test set ratio of 5:1. These sets were categorized into one of three classes: attenuated plaque, calcified plaque, or plaque without attenuation or calcification. The model achieved an overall accuracy of 93% (13). Lee *et al.*, applied 3 traditional CNN models (Resnet 50, VGG and Inception Resnet v2) to train CT images of coronary artery calcium scores. The results showed very high accuracy and sensitivity, indicating high accuracy in using these CNN models for this purpose (14). Kamel *et al.*, created a Deep Convolutional Neural Network (DCNN) trained on calcium score CT scans to forecast the presence of coronary artery calcium (CAC) in chest radiographs. The binary classification distinguishing between zero and non-zero total calcium scores yielded an AUC (Area Under the Curve) of 0.73 on frontal radiographs, with a comparable performance observed on lateral radiographs (15).

Cardiac Arrhythmia

Cardiac arrhythmias are abnormal heartbeats that could make the heart beat excessively quickly, slowly, or randomly. Blood flow can be disrupted by these disturbances, which can cause symptoms ranging from mild discomfort to serious consequences.

CNN-Based ECG Classification

Isin *et al.*, solved the electrocardiogram (ECG) pattern recognition and classification problem using 4 steps: Artificial Neural Network (ANN) for ECG signal classification, signal pre-processing, QRS detection, and ECG feature extraction using transferred deep learning. The combination of transferred DL and a conventional backpropagation ANN resulted in high performance rates with a very high obtained correct recognition rate (16). Chen *et al.*, created a CNN model to classify and detect Cardiac Arrhythmias (CAs) utilizing a vast 12-lead ECG dataset consisting of 6,877 recordings. The model built on single-lead information performed similarly to those based on all 12 leads, demonstrating the ability of the CNN model to accurately predict CA types (17). Swapna *et al.*, used various deep learning models, including RNN, GRU (Gated Recurrent Unit), hybrid CNN-RNN structures and LSTM, to detect abnormalities in

ECG signals for CA diagnosis. They accomplished a 5-fold cross-validation accuracy of 0.834 in discriminating between normal and abnormal ECG signals by leveraging a CNN-LSTM (Convolutional Neural Network Long Short-Term Memory) model (18). He *et al.*, proposed a framework for detection of arrhythmia from ECG signals collected through IoT (Internet of Things) devices. The framework comprises two modules: a heartbeat classification module and a data cleaning module. The framework was evaluated using two methods: DHCAF (Distributed Hybrid Convolutional and Attention Forest) and MHCNN (Multi-Scale Convolutional Neural Network). The findings demonstrated that the proposed framework attained a superior accuracy using MHCNN and comparatively lower accuracy using DHCAF (19). Yildirim *et al.*, presented a novel DL approach for detecting 17 different classes of CA based on analysis of long-duration ECG signals. The main contribution is the design of a 1D-CNN model, which resulted in an accuracy of 91.33% in classifying the arrhythmias and had a classification time of 0.015 seconds per sample. However, it was not capable of classifying ECG signals containing more than one class (20).

Probabilistic-Enabled Mathematical Models

Aseeri *et al.*, incorporated a probabilistic approach into an AI model to account for the uncertainty inherent in the model's predictions. The method uses a Bayesian-based approximation method and does not require additional parameters or substantial alterations to the network's architecture. The probabilistic-enabled AI method achieved high F1 scores on the MIT-BIH dataset (21). Mousavi *et al.*, proposed a methodology for analyzing ECG signals from the MIT-BIH arrhythmia database, employing both intra-patient and inter-patient paradigms, and assessed the outcomes based on the AAMI EC57 standard. In the inter-patient scheme, a positive predictive value of 96.46% and sensitivity of 100% were observed, whereas in the intra-patient scheme, a positive predictive value of 92.57% and sensitivity of 88.94% were achieved (22).

Deep Learning Models

Jyothi *et al.*, aimed to review and analyze research on PCG (Phonocardiogram) detection techniques. For heart sound classification, the authors used the Multi-Level Basis Selection (MLBS) of the WPD (Wavelet Packet Decomposition) method and achieved high sensitivity and specificity rates (23). The methodology adapted in the study is depicted in Figure 3.

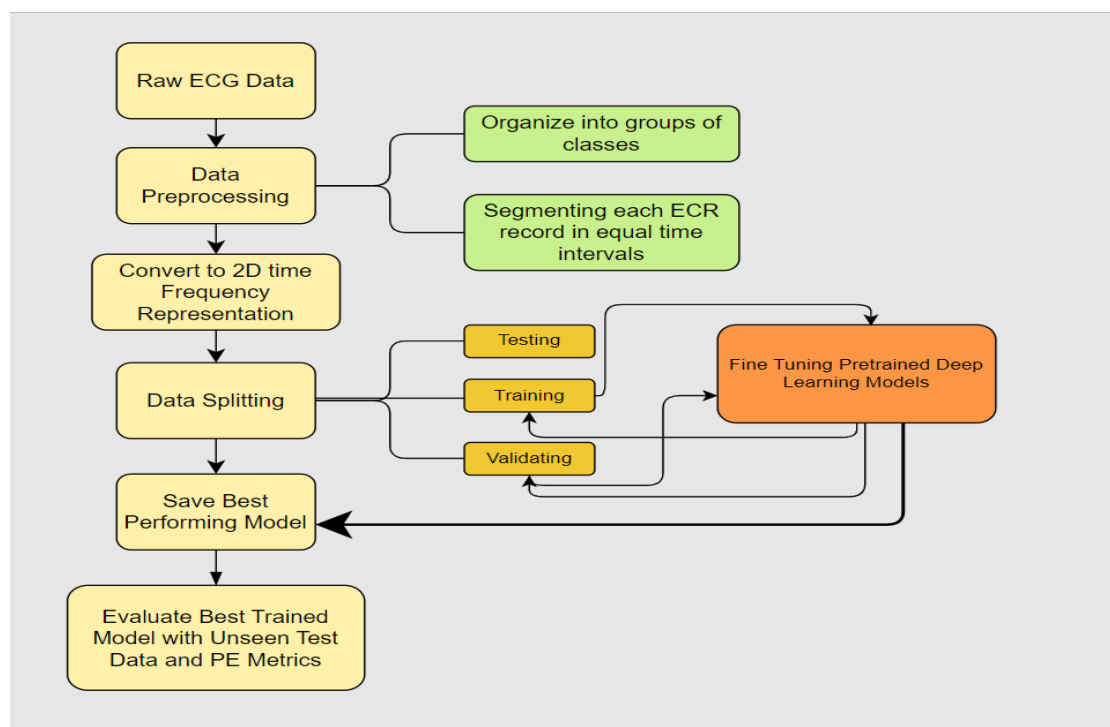


Figure 3: Overall Methodology Used in Paper (23)

Ullah *et al.*, introduced a 2-D CNN model designed for classifying ECG signals across 8 distinct classes. The 1-D ECG signals undergo transformation into 2-D spectrograms via a short-time Fourier transform. The algorithm showed high performance, sensitivity and high accuracy (24). Kiyasseh *et al.*, introduced a continual learning strategy named CLOPS, utilizing a replay buffer. The deep-learning system, utilizing the per-instance loss, achieved a slightly higher AUC. However, one drawback of this approach is the assumption that a portion of the data used for training can be temporarily stored in a buffer for future utilization (25). Khan *et al.*, explored the practically implementable arrhythmia classification techniques. The RNN, LSTM, Autoencoder, CNN, DNN (Deep neural Network), and DBN (Deep Belief Network) were identified as the most common DNN methods used for arrhythmia classification (26).

Congenital Heart Disease

When the heart's capacity to pump blood is impaired, fluid accumulates in the lungs and other bodily tissues, resulting in congenital heart failure symptoms including swelling and shortness of breath. It's a significant ailment that requires immediate medical management in order to enhance heart function and reduce symptoms.

Machine Learning Models

Shi *et al.*, created a machine learning model aimed at predicting malnutrition in children diagnosed with CHD. The XGBoost algorithm achieved the highest accuracy among the five algorithms used. The top three features used in the model were 1-month postoperative weight for age Z-score (WAZ), discharge WAZ score, and preoperative WAZ score. Utilizing these scores, the child's nutritional status was determined by comparing their weight with that of children of the same height, length, and gender (27). Al Bataineh *et al.*, made a comparison between several leading edge ML algorithms and the Multilayer Perceptron Particle Swarm Optimization Algorithm (MLP-PSO) derived from 13 medical features extracted from the Cleveland Heart Disease dataset. The MLP-PSO was found to diagnose the disease more effectively and accurately, with an accuracy of 84.61%, outperforming all other algorithms.

However, a drawback of all neural network models is the lack of guarantee for an optimal solution (2). Meda *et al.*, developed three predictive algorithms using KNN, Logistic Regression and SVM in Python, with SVM achieving the highest accuracy of 73%. Further comparison with additional models is suggested as future work (28). Marelli *et al.*, compiled a database comprising more than 60,000 patients diagnosed with at least one CHD associated condition. The database was partitioned into 80% training and 20% testing datasets, and a gradient boosting algorithm with 5-fold cross validation was employed to achieve an AUC-ROC (Area under the Receiver Operating Characteristic Curve) of 0.97 for the training and test sets, indicating the absence of underfitting or overfitting issues (29). Hoodbhoy *et al.*, conducted a systematic review of four ML studies on Congenital Heart Disease diagnosis using heart sounds acquired through a digital stethoscope and primarily using neural networks. The study achieved a sensitivity of over 90% but faced limitations due to the heterogeneity of the data (30). Chu *et al.*, analyzed two prediction models for pregnant mothers with Congenital Heart Disease (CHD) due to its adverse effects after delivery. The models, using machine learning techniques, showed that around 13% of the studied mothers and 30% of the studied neonates experienced adverse events. However, the small sample size may have caused potential bias, and the researchers plan to improve this by increasing the patient sample size for better research conclusions as future work (31). Guo *et al.*, conducted an ML study aimed to forecast the postoperative blood coagulation function of children diagnosed with Congenital Heart Disease (CHD). Three models, namely Naive Bayes, Decision Tree, and Support Vector Machine), achieved an accuracy rate of over 75%. Improved models such as AdaBoost and Random Forest also achieved true positive rates above 80% (32). Bertsimas *et al.*, developed machine learning models to anticipate the postoperative mechanical ventilatory support time (MVST), hospital length of stay (LOS) for patients, and mortality of patients diagnosed with Congenital Heart Disease (CHD). Classification trees performed better than other ML methods. The most prominent predictors of mortality were

age, weight, days since the previous admission, and the procedure (33).

Deep Learning Models

Diller *et al.*, built DL models to achieve high accuracy in classifying disease complexity, New York Heart Association (NYHA) class, and diagnostic groups. As future work, their plan is to convert this into an online-based decision-making tool (34). Zolfaghar *et al.*, reviewed big data guided studies to predict the 30-day risk of rehospitalization for Congestive Heart Failure (CHF) incidents. The relevant features were extracted from the Nationwide Inpatient Sample (NIS) dataset, and mining models were developed using scalable data to predict the risk (35). Li *et al.*, carried out a study where an ANN and a BPNN (Back Propagation Neural Network) were devised to forecast the risk of CHD in pregnant women. The optimal prediction model selected was a 3-layer BPNN with 15 neurons in the input layer, 12 neurons in the hidden layer, and 1 neuron in the output layer. It achieved an accuracy of 91% on the training dataset and 86% on the testing dataset. Yet, given the limited sample size, sensitivity and specificity were disregarded, and only accuracy was reported (36).

Heart Attack

A heart attack, medically termed as a myocardial infarction, ensues when a blocked coronary artery obstructs blood flow to a segment of the heart muscle and results in tissue damage and potentially fatal effects. It's essential to get medical care as soon as possible to reduce damage and improve recovery prospects.

Machine Learning Models

Takci *et al.*, aimed to ascertain the optimal machine learning method and feature selection algorithm for predicting heart attacks using the Statlog Heart dataset. The findings revealed that the SVM linear kernel machine learning algorithm, coupled with the reliefF feature selection algorithm produced a combined accuracy of 84.81%. The reliefF feature selection algorithm works by eliminating non-discriminative features. The study highlights the need for further studies on feature selection methods for better predictions of heart attacks, which will be taken up as future work (37). Salman *et al.*, study consisted of two sections. The first compared different predictive models for acute myocardial infarction, while the second focused on

improving data processing for unbalanced data through the use of Chow-Liu and tree-augmented naive Bayesian methods. The C4.5 classifier was used as a decision tree and attained a peak accuracy of 94.2% among the classifiers used. However, it was concluded that there is no single best classifier for all criteria considered (38). Obasi *et al.*, proposed a decision support system for predicting the risk of heart disease employing Random Forest, Logistic Regression, and Naive Bayesian Classification. Upon splitting the data into training and testing sets (in an 8:2 ratio), Random Forest exhibited the highest accuracy compared to the other two methods. The only drawback was that the RF algorithm had lower accuracy with fewer features (39). Awoyelu *et al.*, developed a new model to forecast the likelihood of a heart attack in patients using traditional ML algorithms like Decision-tree, Naïve-Bayes, and Bagging classifiers with risk factors associated with a heart attack as inputs. The Naive Bayes algorithm with features selected using information gain and Naive Bayes Feature selection was identified as the optimal model due to its high accuracy and recall. The plan is to integrate the work into the Health Information System for further analysis in the future (40). David *et al.*, focused on using cardiac biomarkers to predict heart attacks or AMI (Acute Myocardial Infarction). A Super Learner model was developed using a combination of ML classifiers (SVM, LR, XGBoost, Decision Tree Classifier, Random Forest, and Gaussian Naïve Bayes) and found that Myoglobin, Troponin-I, and CK-MB (Creatine Kinase-Myocardial Band) were the main biomarkers for prediction. The Super Learner with a combination of Decision Tree and Cat Boost classifier with Logistic Regression achieved the highest accuracy (97%). However, the correlation of these biomarkers with other parameters like cholesterol, fasting blood sugar, and family history was not analyzed (41).

Deep Learning Models

Yilmaz *et al.*, aimed to develop and compare two predictive classification models, MLP Neural Network and Radial Basis Function, to identify risk factors for a heart attack. The three critical factors were found to be resting blood pressure, exercise induced ST segment depression, and cholesterol. The MLP model showed better results with better accuracy and a higher F score, compared to

accuracy and F score from the RBF (Radial Basis Function) model (42). Pokkuluri *et al.*, aimed to develop a robust classifier for heart attack prediction using a 80k dataset and thirteen features. A RNN network was used and achieved an accuracy of 94.73% with a low error rate and swift execution speed of less than 3 ms. Moreover, its F-measure, precision, sensitivity, and specificity scores outperformed those of most existing ML models. More datasets can be used for future work to achieve higher accuracy (43). Saygili *et al.*, planned to devise a new diagnostic model for optimized performance using the ReliefF feature selection algorithm. The results showed an improvement in accuracy, reaching 98.89%, but the study has a drawback of using a small dataset, similar to the previous study (44).

IoT-Based Prediction Models

Wang *et al.*, designed a new algorithm, UCO (Undersampling Clustering Oversampling), combining random undersampling, clustering, and oversampling techniques to forecast the potential of Heart Attack in stroke patients. SMOTE (Synthetic Minority Over-sampling TEchnique) is used to oversample the data and Random Forest algorithm is utilized to make predictions. The accuracy of the model is 70.28% with a precision of 70.05%. Future work involves integrating this with deep neural networks (45). Yahyaie *et al.*, developed and evaluated an IoT-based model for heart attack prediction utilizing a dataset comprising 19 regular features and 1 label feature, which is trained using a neural network. Cloud computing is also utilized for online data analysis, which contributes to improved accuracy. The NN model attained 89.5% accuracy in predicting heart disease (46). Sasidharan *et al.*, focused on developing a wearable cardiorespiratory monitoring device that presents real-time data of four parameters on a phone or computer screen. The device aims to provide accessibility to IoT at a low cost and plans to miniaturize it for daily wearability in future work (47). Solanki *et al.*, explored multiple ML models for predicting heart disease and found that Artificial Neural Network (ANN) and Support Vector Machine (SVM), leveraging the UCI Repository dataset, outperformed other algorithms in heart disease prediction (48). Sahoo *et al.*, developed and designed an IoT-based heart attack prediction and health monitoring model integrating features such

as vital sign sensors, location trackers, and web portal technology that allow remote real time sensing of the patient's health. Most importantly, it possesses the capability to forecast the onset of a heart attack. The novelty of this research lies in its fusion of IoT and ML-based technologies, enabling the monitoring and prediction of heart disease. The ML RBF SVM classifier was concluded to produce the highest accuracy. However, a time delay was noted between the transmission of messages from the client and their reception by the server. Integrating continuous monitoring of ECG signals as an additional feature was taken up as future work (49). Gupta *et al.*, presented a mathematical model for heart attack detection utilizing a fuzzy c-means clustering algorithm and studied the parameters involved in the prediction. They further create an alert system with IoT devices like the Arduino UNO, GSM (Global System for Mobile communication), etc. The model resulted in a competent accuracy which proved that the different approach taken with fuzzy c-means algorithms can produce accurate predictions too. Higher accuracy is the parameter driving them into future work in the same area (50).

Cardiac Arrest

Cardiac arrest occurs when the heart abruptly ceases to function, leading to the stop of heartbeat, resulting in an instant loss of consciousness and necessitating defibrillation and CPR (Cardiopulmonary Resuscitation) to resume regular rhythm and circulation. Without swift intervention, it can cause death in a matter of minutes.

Machine Learning Models

Kwon *et al.*, conducted a study of 50,000 patients admitted to two hospitals using neural network models to forecast the risk of cardiac arrest during hospitalization. The study found that a DL-based warning detection system outperformed traditional machine learning models. However, the study did not consider repeated cardiac arrests or deaths without attempted resuscitation (51). Nakashima *et al.*, developed a model using the XGBoost algorithm to forecast the incidence of out-of-hospital cardiac arrest. The model had a mean absolute error (MAE) of 1.314 in the training dataset and an MAE of 1.547 in the testing dataset. The study did not account for potential variability

among patients with already existing medical conditions (52).

Rajapaksha *et al.*, developed a DL-based Cardiac Arrest Prediction Model to forecast the likelihood of experiencing a cardiac arrest. The model utilized a RNN and a Decision Tree classification model. The RNN model outperformed existing detection systems with an accuracy of 96%, while the decision tree model had 80%. Additionally, the model also had high sensitivity with good confidence interval and specificity. A limitation of the study was limited resources (53). Kwon *et al.*, worked to develop and validate a DL-based out-of-hospital cardiac arrest prognostic system (DCAPS) to predict neurologic recovery and survival to discharge. The DCAPS had an AUROC of 0.953 in the prediction of neurologic recovery in the validation data, with a 95% confidence interval. These results significantly outperformed SVM, random forest, and logistic regression models. (54). Baral *et al.*, proposed combining Multilayer Perceptron (MLP) with an enhanced Bidirectional Long Short-Term Memory (LSTM) hybrid model for prediction. The model demonstrated superior performance for a combined dataset with a 1-hour prediction time window, with a high accuracy and sensitivity (55).

Deep Learning Models

Kwon *et al.*, created and validated a deep learning algorithm (DLA) for cardiac arrest prediction utilizing electrocardiography (ECG). The DLA exhibited areas under the ROC of 0.913 and 0.948 for predicting cardiac arrest within 24 hours, based on almost 50,000 ECGs from 25,000 adult patients admitted to two hospitals from 2016-2019 (56). Chae *et al.*, implemented shallow and DL algorithms to forecast cardiac arrest and compared their performance using LSTM-GRU, Decision Tree, GRU, Random Forest, LSTM, and Logistic Regression hybrid models. The study found that deep learning models showed enhanced

performance as per the unit size, with the best results for LSTM (96 units), GRU (128 units), and LSTM-GRU hybrid (96 units) (57).

Comparative Analysis

There are many ways to compare the performance between different models, namely sensitivity, specificity, accuracy and AUC-ROC. Sensitivity measures the ability to correctly identify patients with heart disease, while specificity assesses the correct identification of those without the disease. Accuracy reflects the overall correctness of the system, and AUC-ROC indicates its ability to discriminate between positive and negative cases across various thresholds. ML models like SVMs and random forests demonstrate fairly high sensitivity, specificity, and accuracy, but DL models exhibit superior performance due to their ability to capture complex patterns in medical images, resulting in very high sensitivity, specificity, and AUC-ROC. Recurrent neural networks (RNNs) also perform well in sequential data analysis, such as ECG signals. Traditional image processing techniques like edge detection and segmentation offer moderate improvements in diagnostic performance but are generally outperformed when combined with ML and DL models. Overall, DL models lead in all key metrics, providing enhanced diagnostic capabilities for computer aided diagnostic systems. Given below is a construction of a tabular column compiling few of the most relevant papers in this study, providing a comparison of the work they have done. Each of these papers have meticulously detailed the outcomes of their methodologies, employing diverse measurements such as AUC, F-score, accuracy and more, however, accuracy was the most commonly utilized metric. Table 1 below has included the accuracies achieved in each of these papers by employing their respective technologies.

Table 1: Comparative Analysis

Authors	Type of Heart Disease	Method/ Technology Used	Accuracy
Al Bataineh <i>et al.</i> , (2) 2022	All	MLP-PSO Hybrid Algorithm	84.61%

Han <i>et al.</i> , (6) 2020	Coronary Artery Disease	Deep Learning techniques	86%
Li <i>et al.</i> , (12) 2020	Coronary Artery Disease	Multi-Domain Feature Fusion Classification Model	90.43%
Isin <i>et al.</i> , (16) 2017	Cardiac Arrhythmia	DL Feature Extraction followed by with a conventional BPNN	92%
Ullah <i>et al.</i> , (24) 2020	Cardiac Arrhythmia	2-D CNN model	99.11%
Diller <i>et al.</i> , (34) 2021	Congenital Heart Disease	Deep Learning Algorithms working on disease complexity, and NYHA class	97.0%, 90.6%
Li <i>et al.</i> , (36) 2017	Congenital Heart Disease	Artificial Neural Network (ANN) Model	91% (Training) 89% (Testing)
Takci <i>et al.</i> , (37) 2018	Heart Attack	Support Vector ML Algorithm with the Linear Kernel	84.81%
David VK (41) 2021	Heart Attack	Super Learner with a fusion of Decision Tree and Cat Boost classifier with Logistic Regression.	97.9%
Sahoo <i>et al.</i> , (49) 2021	Heart Attack	IoT and ML Based Health Monitoring and Prediction System	80%
Rajapaksha <i>et al.</i> , (53) 2022	Cardiac Arrest	RNN Decision Tree Classification Model	96% 80%
Baral <i>et al.</i> , (55) 2021	Cardiac Arrest	MLP and enhanced Bidirectional LSTM	92.6%
Fitriyani <i>et al.</i> , (58) 2020	All	DBSCAN (Density-Based Spatial Clustering of Applications with Noise), SMOTE-ENN (Edited Nearest Neighbors) and XGBoost model	95.90% (Statlog Dataset) 98.40% (Cleveland Dataset)
Madani <i>et al.</i> , (59) 2018	Cardiac Diseases	CNN and Generative adversarial network (GAN) model	91.2%

Nissa <i>et al.</i> , (60) 2020	Cardiovascular Disease	Random Forest Decision Tree	97.29% 94.25%
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When trying to understand how technology can further evolve to provide better and more accurate results for patients, the development of customized computer aided diagnostic systems that adapt diagnosis and therapy suggestions to the specific characteristics of each patient is an emerging and promising field in this area of research. Customized computer aided diagnostic systems integrate comprehensive patient data from electronic health records, including medical history, genetic information, lifestyle factors, and previous diagnostic results. With cloud technology and AI becoming more prevalent in today's world, data from wearable health devices, such as heart rate monitors, smart watches, and fitness trackers, can provide continuous, real-time monitoring of a patient's cardiac health. Additionally, therapy monitoring can be used to track the patient's response to therapy in real time and medication dosages can be fine-tuned based on ongoing monitoring of blood pressure and heart rate.

Conclusion

This study has scrutinized the various ML and deep learning approaches used to provide a comprehensive overview on the diagnosis of different types of heart diseases namely Coronary Artery Disease, Cardiac Arrhythmia, CHD (Congenital Heart Disease), Myocardial Infarction (Heart Attack) and Cardiac Arrest. The approaches have been efficiently organized with their methodology, results along with their limitations. A tabular representation of the 15 most thorough papers has been listed towards the end. Results show that deep learning has a very high potential for increased accuracy in the detection of heart diseases and perhaps the medical sector in general. This paper hopes to be of great use to those seeking knowledge in the diagnosis of heart diseases.

Abbreviations

Nil.

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Author Contributions

Akash Venkat Ashok and Akshara Adhikesavalu have contributed in identifying and compiling all the computer aided techniques used in the diagnosis of heart disease. They have also created the table and all the figures used in this manuscript. Dr. Priya G has contributed in providing feedback and reviewing the manuscript throughout its history.

Conflict of Interest

Nil.

Ethics Approval

Not applicable.

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