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# A Review Of Cardiovascular Disease Prediction Models Using Deep Learning And Transfer Learning In Cardiology

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**ABSTRACT**

Cardiovascular diseases (CVDs) represent the foremost cause of death on a global scale.According to a report by the World Health Organization, around 18.6 million individuals succumb to CVD annually. Key cardiac risks encompass arrhythmia and coronary artery disease, among others. Recent developments in Artificial Intelligence have become crucial for life-saving interventions in CVD treatment. This survey explores the latest advancements in Machine Learning, Deep Learning, and Pre-trained transfer learning models for classifying and predicting CVD, drawing on a review of 122 articles, which include 33 image datasets, 38 signal data, and 49 clinical data from diverse sources. The survey delves into risk factor of cardiovascular disease, cardiac impairment category, medical image processing techniques, performance metrics, and hybrid techniques. Studies on traditional neural networks like Convolutional Neural Networks, Artificial Neural Networks, and Recurrent Neural Networks often achieve accuracy rates ranging from 75% to 95%. By utilizing pre-trained architectures such as ResNet, DenseNet, Alex Net, Bi-GRU, Mobile Net, Efficient Net, and Google Net, BERT , transfer learning models consistently surpass other methods, frequently achieving accuracy levels exceeding 96%. Researchers employ various hybrid optimization algorithms to enhance the overall accuracy rate. The survey's findings support an accurate prognosis for patients with comorbidities The findings underscore challenges in combining multimodal data for real-time risk evaluation, while also offering valuable insights that could bridge existing gaps in cardiovascular disease prediction and support clinicians in early diagnosis and prognosis.

***Keywords:*** *Cardiovascular disease, machine learning, deep CNN,transfer learning, optimization hybrid. model*

## 1. INTRODUCTION

Cardiovasculardiseases (CVDs) are a major global health problem, causing millions of deaths each year and putting stress on healthcare systems. With the growth of digital health data, techniques like data mining and machine learning are helping doctors detect and treat heart disease more effectively. However, problems like imbalanced data and limited model variety can affect accuracyfatemehyazdi and shahrokhasadi et al [1].According to the World Health Organization, cardiovascular diseases (CVDs) are the leading cause of death globally, responsible for about 17.9 million deaths each year. Early diagnosis can save many lives. Tools like ECGs are commonly used to detect heart problems, but manual analysis can be slow and inaccurate. Advances in artificial intelligence, especially machine learning and deep learning, offer promising ways to automatically detect heart disease Abubaker et al [2].The heart is a powerful muscle that pumps blood throughout the body, but it can be affected by cardiovascular diseases, especially coronary artery disease (CAD). CAD occurs when the arteries supplying blood to the heart become narrowed due to a build up of fatty deposits, leading to reduced blood flow and chest pain (angina). Modern lifestyles play a major role in the rise of such conditions, making early awareness and prevention essential Maria Trigka and Elias Dritsas et al [3].The human heart's vital role is to pump blood, and Phono-cardiogram (PCG) signals help monitor its normality. Cardiovascular diseases (CVDs) are a leading cause of death, making accurate PCG signal classification crucial mehrezboulares and tarikalafif et al. [4].Modern technologies like machine learning and deep learning are being used to predict CVD more accurately by analyzing large medical datasets.This helps doctors make better, faster decisions and improve patient care M. Swathy and K. Saruladha et al.[5].ECG-based diagnosis being challenging due to complexity and variability. Machine learning techniques show promise, but lack interpretability, highlighting the need for more accurate and transparent models yehualashet megersa ayano et al. [6].

Developing countries encounter a major obstacle in the early detection of cardiovascular diseases (CVD) due to their limited healthcare infrastructure. The absence of adequate diagnostic tools, a shortage of medical personnel, and geographical barriers prevent patients from receiving necessary healthcare services. These nations also face increased cardiac risks stemming from malnutrition and polluted water sources. Machine learning (ML) and deep learning (DL) can analyze vast amounts of clinical data to offer personalized risk assessments, optimize treatment plans, and aid in the early detection and prevention of cardiac risks. Traditional diagnostic methods for heart disorders, such as electrocardiograms, echocardiograms, carotid ultrasounds, coronary computed tomography angiography, magnetic resonance imaging, and various clinical tests, encounter issues like invasiveness, radiation exposure, high costs, and inconsistent interpretations. These conventional approaches rely on risk scores and methodologies, including the Framingham Risk Score, American Heart Association Atherosclerotic Cardiovascular Disease (ASCVD) Risk Calculator, Registre Gironi del Cor, Systematic Coronary Risk Evaluation, and the United Kingdom Prospective Diabetes Study. However, they are limited by their static nature, restricted variables, assumptions of linear relationships, potential biases, lack of external validation, inconsistent reporting standards, and limited use of advanced data. To overcome these limitations, researchers are utilizing advanced machine learning, deep learning, and transfer learning techniques. These modern models analyze large datasets to identify patterns, improving the accuracy and precision of cardiovascular risk predictions. Machine learning models have been suggested for accurately classifying heart sounds, but their effectiveness is constrained by small datasets, which may affect their reliability in practical clinical settings. Performance can vary across different datasets, emphasizing the need to consider the limitations of machine learning algorithms, such as dataset dependency and interpretability, when applying them in real-world clinical environments. Deep neural networks are proposed to learn complex feature structures from raw data, enhancing classification accuracy and the diagnosis of coronary artery disease (CAD) compared to traditional machine learning methods. Training deep learning models can be time-consuming, especially with large datasets and complex architectures. Deep learning models often require high-performance GPUs and substantial memory, along with the spatial and portability challenges of deep-learning computers, which can be considered limitations of deep learning. Transfer learning is a powerful method that can successfully address these kinds of challenges. Transfer learning involves applying a pretrained model, usually trained on an extensive dataset, and adapting it for a new, associated task. Transfer learning model attains great accuracy while significantly reducing computational resource requirements. Transfer learning model offers a lightweight and efficient solution, enabling accurate arrhythmia detection on mobile devices. This promotes timely heart health monitoring and early diagnosis.

This section offers a detailed summary of current developments in predicting Cardiovascular Disease (CVD),while also addressing the key research inquiries that are being explored in the field.

**Q1. How effective is deep learning compared to traditional statistical models in predicting cardiovascular diseases?**

**Q2. What are the main challenges in applying transfer learning to cardiovascular disease prediction?**

**Q3. Which deep learning architectures (CNNs, RNNs, transformers) are best suited for cardiovascular disease prediction?**

**Q4. How can explainable AI (XAI) improve trust and adoption of deep learning models in cardiology?**

**Q5. How does multi-modal deep learning enhance cardiovascular risk stratification?**

**Q6. What role does federated learning play in ensuring data privacy in cardiovascular AI models?**

**Q7. What are the ethical concerns surrounding AI-driven cardiovascular disease prediction?**

**Objectives**

1. Conduct a review of deep transfer learning approaches used in diagnosing Coronary Artery Disease (CAD), Peripheral Artery Disease (PAD), and cardiovascular risk factors.
2. Explore the effectiveness of medical image processing tools and software for cardiovascular disease detection, with

an emphasis on techniques for image segmentation, registration, and visualization.

3. Examine the role of Machine Learning (ML), Deep Learning (DL), and Transfer Learning (TL) in predicting cardiac risks and improving the early detection of cardiovascular diseases.
4. Compare the performance of ML, DL, and TL methodologies in cardiac disease prediction, with a focus on critical performance metrics and their clinical relevance.
5. Investigate the effectiveness of hybrid deep learning models that integrate optimization techniques for predicting cardiovascular diseases.

## A. CARDIOVASCULAR DISEASES: RISK FACTORS, DISORDERS, AND DIAGNOSTIC METHODS

- Cardiovascular diseases refer to the malfunctions of the heart and blood vessels.
- Coronary Heart Disease results from the build-up of atheroma in the heart's arteries.
- Cardiovascular disorders encompass a wide array of conditions that impact the brain's blood vessels.
- Pulmonary Embolism occurs when blood clots travel to the lungs, obstructing the pulmonary artery.
- Peripheral arterial disease is characterized by the narrowing of arteries, which restricts blood flow to the extremities, specifically the arms and legs.
- Deep vein thrombosis (DVT) is a condition characterized by the formation of blood clots within a deep vein, typically located in the lower extremities.
- Rheumatic heart disease results from the inflammation and scarring caused by rheumatic fever, which adversely affects the heart valves and myocardium.
- Congenital Heart Disease is a condition that affects heart function from birth.

Fig.(1) illustrates a range of cardiovascular conditions, such as rheumatic heart diseases, hypertensive heart diseases, ischemic heart diseases,cerebrovascular diseases, inflammatory heart diseases and other heart diseases.

CVDs, or cardiovascular diseases: Cardiovascular disease (CVD) is a collection of illnesses affecting the heart and blood arteries. These diseases can disrupt normal circulation and function of the heart, brain, and peripheral organs.

1. Hypertensive heart disease is a condition resulting from persistently elevated blood pressure (hypertension), which exerts stress on the heart.
2. Cerebrovascular disorders are vascular diseases that impair the blood vessels of the brain.
3. Inflammatory Heart Diseases involve inflammation of heart tissues. It includes cardiomyopathy, pericardial disease, and valvular disease.
4. Other Heart Diseases Includes conditions like congenital heart disease and heart failure ashay jain et al.[7].

## B. CORONARY ARTERY DISEASE

Coronary artery disease (CAD), mainly caused by atherosclerosis ,Angina pectoris, a common CAD symptom, presents as chest pain due to myocardial ischemia, often triggered by exertion and relieved by rest or nitro-glycerine Shao et al. [8]. The D-F prediction model using contemporary patient data and evaluate its performance in predicting CAD prognosis in individuals presenting with suspected angina Reeh et al. [9].

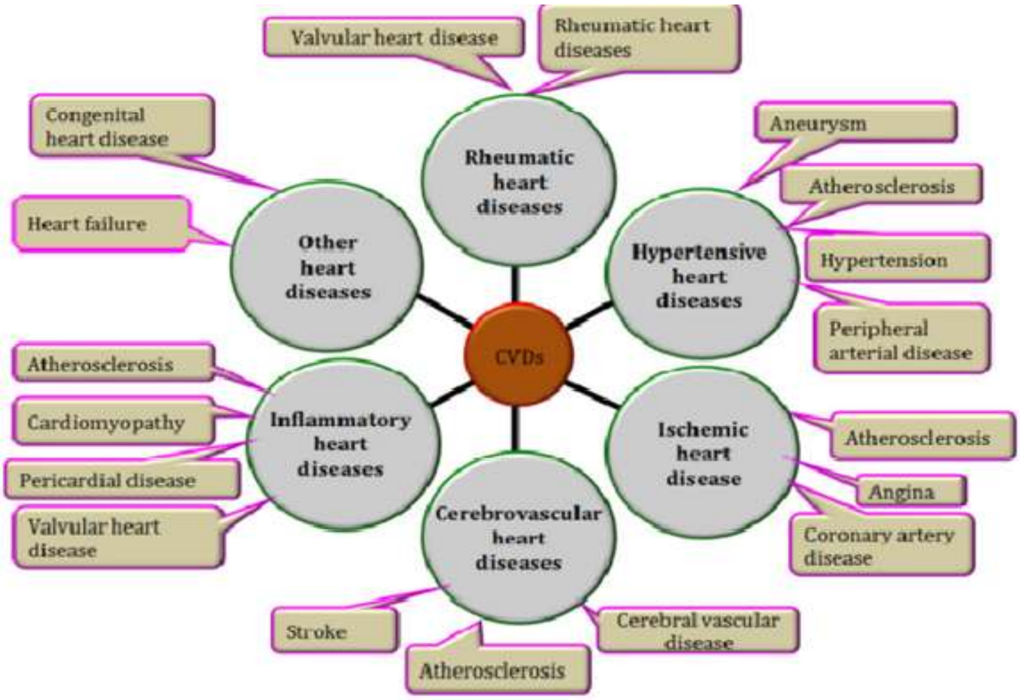


**Figure1.Cardiovascular disorders and their classifications.**

### C. PERIPHERAL ARTERIAL DISEASE

Peripheral artery disease (PAD) is a common yet underdiagnosed condition caused by atherosclerosis that restricts blood flow to the lower limbs, leading to impaired muscle function and altered gait.machine learning (ML) models that can accurately distinguish individuals with and without PAD using gait biomechanics data, offering a promising tool for early PAD detection Al-Ramini et al.[10]. Diabetic patients with PAD face a heightened risk of ischemic complications and long-term disability, making early diagnosis and intervention essential. the American Diabetes Association's recent consensus on PAD in diabetes, emphasizing the importance of early detection and outlining treatment strategies to reduce complications and improve patient outcomes Marso and Hiatt.[11].

### D. RISK FACTORS FOR CARDIOVASCULAR DISEASE

#### 1) HEART VALVE DISEASE

Pulmonary hypertension (PH) in patients with aortic and/or mitral valve disease typically signals a decompensated state, where left ventricular and atrial dysfunction occurs, diagnostic approach (both non-invasive and invasive), and recent research on PH in valve disease, highlighting gaps in evidence Maeder et al.[12]. Tricuspid disease, more common, occurs without direct valve abnormalities but is instead caused by dilation of the tricuspid annulus due to right ventricular dysfunction, often as a result of left heart disease (e.g., left ventricular or valvular issues). Diagnosis of tricuspid valve disease is aided by echocardiography, which can assess the severity of stenosis or regurgitation, and Doppler techniques are used to estimate pulmonary arterial pressure Turi [13].The pulmonary valve controls the flow of blood from the right side of the heart into the lungs for oxygenation Naeije [14].

#### 2) HYPERTENSION

Hypertension is a key risk factor for cardiovascular disease (CVD) that can harm the heart, blood vessels, and other organs. Primary hypertension is widespread, while secondary hypertension results from other health issues, like kidney problems or sleep apnea. White coat hypertension occurs when anxiety in a medical setting causes an increase in blood pressure Schrader and Middeke [15].Resistant hypertension is a condition where blood pressure remains high despite using multiple antihypertensive medications, Treatment typically involves addressing lifestyle factors, managing secondary causes of hypertension (such as sleep apnea or kidney disease), and using a combination of medications. However, genetic factors and broader mechanisms behind treatment resistance remain under-researched, and current pharmacological strategies are largely based on empirical evidence Calhoun et al. [16].Isolated systolic hypertension is common in older adults, where only the systolic (top) blood pressure reading is elevated, while the diastolic (bottom) pressure remains normal. This condition is particularly prevalent among the elderly and is often linked to age-related changes in blood vessel elasticity Amery et al.[ 17]. Masked hypertension is identified through ambulatory blood pressure monitoring, a method that measures blood pressure outside of a doctor's office, typically over a 24-hour period. This helps detect high blood pressure that may not be apparent during routine visits Pickering et al.[18]

### 3) HEART FAILURE

Heart failure happens when the heart is unable to pump enough blood to meet the body's needs, leading to symptoms like difficulty breathing, tiredness, and fluid retention, which can cause swelling in the legs, abdomen, or other areas Ponikowski et al. [19].Heart failure is categorised by cardiologists into diastolic and systolic forms. Indeed, thickening of the ventricular wall is associated with diastolic cardiac failure, which restricts. The diastolic and systolic cardiac failures of the heart are linked to ventricular dilatation and inadequate pumping function. Genet et al. [20].The symptoms of heart failure differ according to the side of the heart that is impacted. Blood flow to the brain and body is impacted by left-side failure, whereas right-side failure affects the lung blood flow Jessup and Brozena. [21]. The clinical illness known as right ventricular (RV) failure is characterised by the RV's improper filling or ejection of blood, which can result in arrhythmias, fluid retention, and inadequate cardiac output. RV ejection percent is the most widely used, albeit load-sensitive, metric for measuring RV dysfunction, which is defined as impaired filling or contraction without symptoms, Haddad et al .[22]

### 4) STROKE

A stroke is a serious neurological disease, and constitutes a major cause of death and disability throughout the world Mir et al. [23].There are two different kinds of strokes: hemorrhagic stroke and ischaemic stroke. Blocked blood vessels are the cause of cerebral ischaemia Fan et al. [24] blood artery bleeds from hemorrhagic strokes irritate the brain Perna and Temple [25].

The article is organized into ten sections. The literature on the risk of cardiovascular disease (CVD) is reviewed in Section II. Medical imaging-based CVD risk assessment is the main topic of Section III. several datasets and modeling approaches are examined in Section IV. Section V presents Performance metrics for assessing CVD risk variables. Performance comparisons are examined in Section VI. A improved hybrid model and its general architecture are shown in Section VII. Survey and discussion results are outlined in Section VIII. The clinical application and implications of the CVD prediction model are examined in Section IX and Section X concludes the further improvements in CVD prediction using ML and DL.

## 2. LITERATURE REVIEW

The literature review examined existing research on CAD and PAD prediction, the latest imaging modalities, and classification techniques.

### A. EXISTING RESEARCH ON CAD AND PAD

The most common treatment for CAD nowadays is coronary artery bypass graft (CABG), which works well but has extracorporeal circulation side effects. Off-pump coronary artery bypass (OPCAB) has shown promising outcomes in recent years, but there are still issues, including the high level of surgical skill and difficulties Guo Chunling et al. [ 26].A non-invasive technique that uses artificial intelligence (AI) to evaluate CT scans and identify patients with coronary artery disease who need invasive coronary angiography Robbert W. van Hamersveltet al[27].Accelerometer contact microphone (ACM) recordings of cardiac activity are used to develop a new, non-invasive technique for diagnosing peripheral artery disease (PAD)Shokouhmand et al [28].The symptom of peripheral artery disease (PAD) is atherosclerosis, which reduces blood flow to the legs and alters muscle structure and function as well as gait. Because PAD is underdiagnosed, therapy is delayed and clinical results are worse. This work aims to create machine learning (ML) models that differentiate between people with and without PAD in order to address this difficulty Ali Al-Ramini et al.[29].

### B. LATEST IMAGING MODALITIES AND CLASSIFICATION TECHNIQUE

Comprehend the most recent methods for diagnosing cardiovascular diseases, we have reviewed pertinent medical literature on machine learning (ML) and deep learning (DL) techniques.procedures like coronary artery bypass grafting (CABG) and angioplasty are essential in lowering the incidence of CVDs LeCun et al. [30].To identify cardiovascular disease (CVD), the most well-known technique is cardiac auscultation with a classical stethoscope (PCG: phonological cardiogram Boulares et al. [4]. Table 1 outlines some heart-related conditions.

## 3. CARDIAC RISK PREDICTION ON MEDICAL IMAGES

In this section we analysis the software tools for cardiac risk prediction and analysis techniques for image processing and feature extraction.

### A. ANALYSIS OF SOFTWARE TOOL FOR CARDIAC RISK PREDICTION

The use of extracted features and processed medical pictures, the DL-based application can evaluate and forecast CVD.Acharya et al.[39].Cardiovascular imaging solutions' CMRtools program is used to analyse myocardial perfusion and ventricular function. SuiteHEART is an additional MRI tool created by NeoSoft.Circle Cardiovascular Imaging generates CVI42, which is compatible with both CT and MRI. Terarecon created the iNtuition tool, which manages MRI, CT, and

SPECT.Medviso's segment program can be used to examine MRI, CT, and SPECT data. Siemens offers Syngo.via, which is helpful for MRI, CT, and SPECT modalities. Philips' IntelliSpace Portal processes data from echocardiography, CT, and MRI. Visualsonics' VevoLAB is helpful for echo analysis.Echocardiography instruments made by Philips include QLAB and TOMTEC Martin-Isla et al.[40]. Aligning object locations across several photos into a coherent and well-structured system is accomplished using the image registration approachRedlarski et al.[41].The CNN model offers details on the forms, volumes, and damaged areas of organs and is used for the categorisation and segmentation of ventricular arrhythmias Tarroni et al.[42].

**Table1. Cardiac Impairment Categories**

| Author | Framework | Disease classification | Data source |
|---|---|---|---|
| Ara,L et al.(2019) | ML and AI algorithmsfor predictingPAD based on the LEAD test. | investigating the impact of lead on the development of PAD | Health electronic medical record system |
| Hamad M et al.(2020) | Multi-level deep learning arrhythmia classifier | Arrhythmia | MIT-BIH |
| Saragih G S et al. (2020) | A two-stage classification process, employing a CNN for feature learning and a Random Forest for final classification, is used for IS data. | CT scan imaging in stroke patient evaluation | RSCM hospital<br>Indonesia. |
| Hasuan CAU et al. (2022) | Improved CVD prediction using tuned Gradient Boosting, MLP, and RF. | Consnary Artery Dura | UCI Repository |
| Zhang Der al. (2022) | Apply machine learning to discover and evaluate parameters for customizing PAD treatments to improve patient outcomes. | PAD | National Inpatiem Sample LIS |
| Fang M et al. (2023) | To determine a person's risk of hypertension, age and specific blood test values are incorporated into the assessment. | Hypertension data - EHR data | Hobhong University of Science and Technology, Union Shenzhen Hospital |
| Yun D et al. (2023) | A clear model helps physicians prepare for the complex management of both IDH and IDHTN | Electrical medical recond EMR data | Seoul National University Hospital |
| MohanadAlkhodari et al.(2024) | Deep learning approach based on the self-attention transformer network to automatically predict the occurrence of congenital murmurs in PCG recordings. | congenital heart disease (CHD) | CirCorDigiScope |

**B. TECHNIQUES FOR IMAGE PROCESSING AND FEATURE EXTRACTION**

Traditional auscultation, while cost-effective, is limited by human auditory perception, prompting interest in digital PCG analysis.The study introduces an enhanced machine learning approach by integrating the Least Mean Square (LMS) algorithm with Least Square Support Vector Machines (LSSVM). This hybrid method optimizes weight vectors during training to widen the separation margin between normal and abnormal heart sound clusters, improving classification accuracy regions Ari et al. [43]..Data mining techniques are increasingly being applied to healthcare to extract meaningful insights from complex medical data. Various machine learning algorithms for heart disease prediction, finding that Decision Trees and Naive Bayes classifiers demonstrate superior accuracy compared to K-NN and Neural Networks. The research further shows that applying genetic algorithms for feature selection enhances the performance of these predictive models, offering promising tools for clinical decision support in cardiovascular disease diagnosis Soni et al. [44], ML based system using 7 models (e.g., SVM, ANN, DT) and three feature selection methods to classify heart disease from healthy cases, validated on the Cleveland dataset Haq et al. [45].

## IV. DATASETS AND MODELING TECHNIQUES

In predicting cardiovascular risk, machine learning, deep learning, and transfer learning (TL) algorithms have demonstrated considerable promise. These models may identify intricate associations by examining large datasets, producing very precise and customised cardiovascular disease prediction models.

### A. OVERVIEW OF DATASETS USED FOR CARDIAC RISK PREDICTION

CVD detection is greatly impacted by the diversity and quality of the data. The effectiveness of various deep learning techniques on various datasets is examined in this section Cleveland Haq et al.[45].Employed 2-second ECG segments from the MITDB (360 Hz), CUDB, and VFDB (both 250 Hz) databases as well as public platforms to distinguish between shockable and non-shockable arrhythmias Kaggle Lakshmanarao et al.[46] Data from several sources is frequently employed in sound signal analysis for the prediction of cardiac disease. E-scope and PCG data sample waveforms Ari et al.[43] give recordings of physiological signals that are necessary for assessing heart function, such as PCG and ECG.[39]

### B. MODELING TECHNIQUES FOR CVD RISK PREDICTION INCLUDING ML AND DL APPROACHES

#### 1. THE LOGISTIC REGRESSION MODEL

Logistic regression (LR) shown in (1), which uses patient characteristics and clinical data to predict CVD risk Hossen [47]. For both binary and multi-class classification, it calculates the likelihood of assigning input X to a specific group.

$\mathrm{Exp}(\beta0+\beta1X)/\ 1+\exp(\beta0+\beta1X) = P(x)$ (1)

In this case,

$\beta0$ stands for bias, and

$\beta1$ for weight multiplied by inputX.

#### 2. DECISION TREE

Using age, gender, and blood pressure as criteria, the decision tree (DT) in Figure 2 divides individuals into low, medium, and high-risk CVD categories. Karandikar and Nikhar[48].

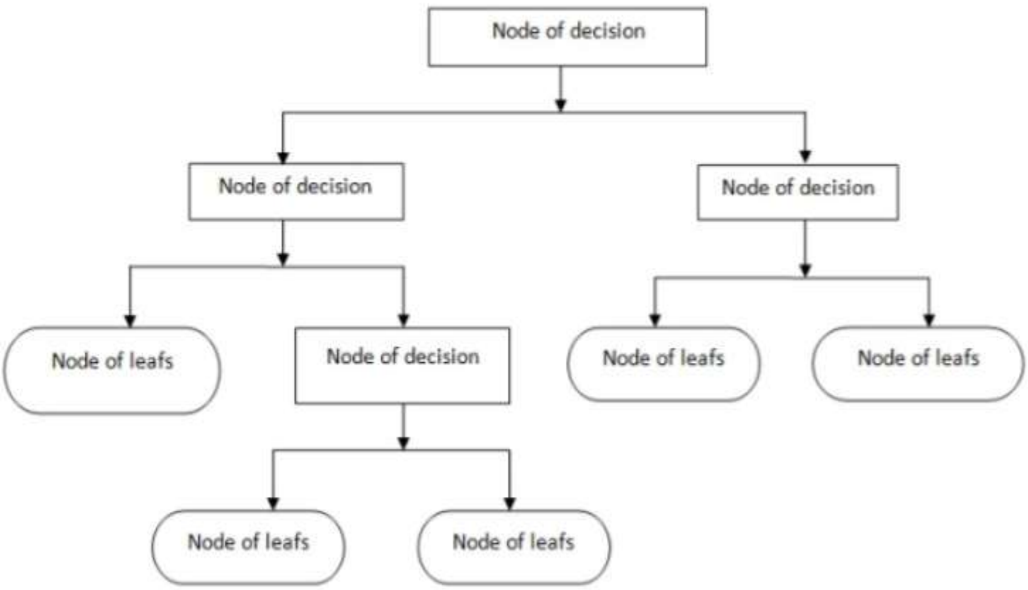


**Figure 2: Decision tree for cardiovascular disease risk prediction.**

#### 3. NAIVE BAYES

As demonstrated in (2), the Naïve Bayes (NB) bayesian classifier can identify diseases and carry out classification tasks, including those involving electronic health information. [46] Lakshmanarao et al.

$p(c)p(x|c)/_{p(x)}$ =p(x) (2)

P(x|c) – probability

P (c|x) - posterior probability

P(c) -class prior probability

P(x) - predicted prior probability.

**4. ARTIFICIAL NEURAL NETWORK**

In order to diagnose heart disorders, Mienye et al. [49] created a sparse autoencoder-enhanced ANN-based model, which is depicted in Fig. 3.

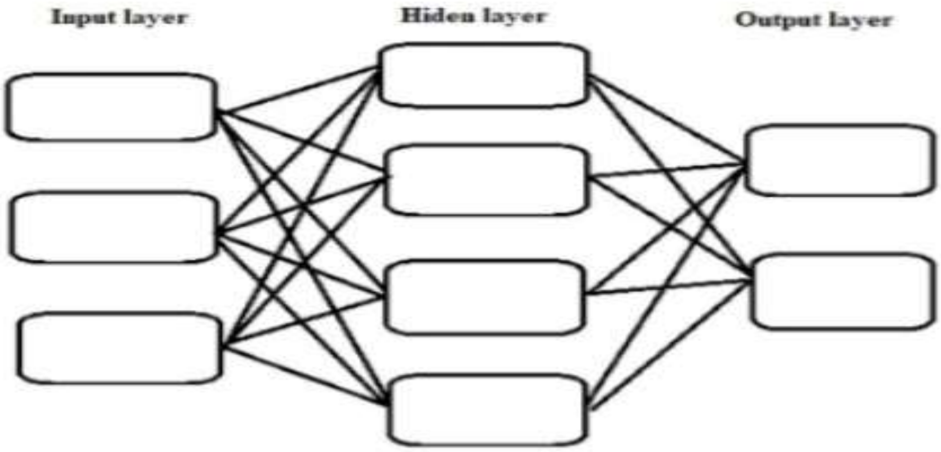


**Figure 3: An artificial neural network utilizes spectral characteristics to predict cardiovascular diseases.**

**5. RANDOM FOREST**

As shown in Fig. 4, CVD is predicted using random forest(RF) based on clinical data. The ultimate CVD forecast is computed by simply taking the average of each decision tree's probability within the ensemble model Pal and Yadav [50].

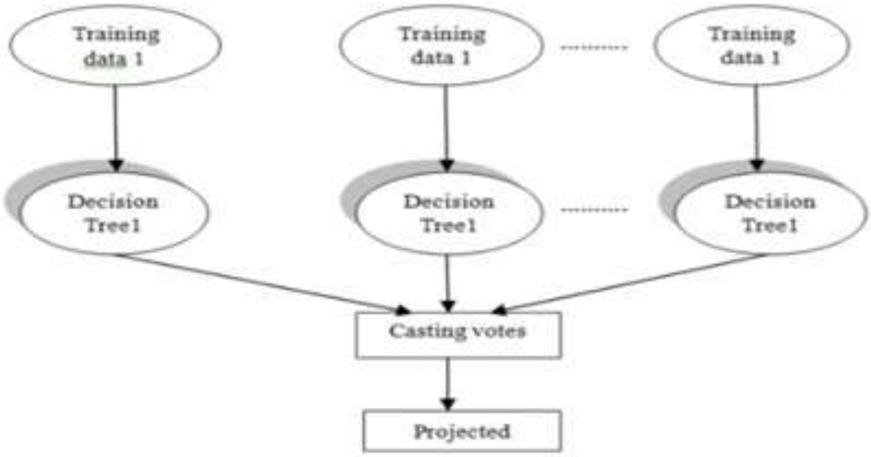


**Figure 4: A Random Forest model for estimating the risk of cardiovascular disease.**

**6. CONVOLUTIONAL NEURAL NETWORK (CNN)**

CNNs are increasingly being used to analyze medical imaging such as cardiac MRIs, echocardiograms, and ECGs in order to detect CVD early and accurately. Gu and associates [51]. In Figure 5, their functionality is depicted.

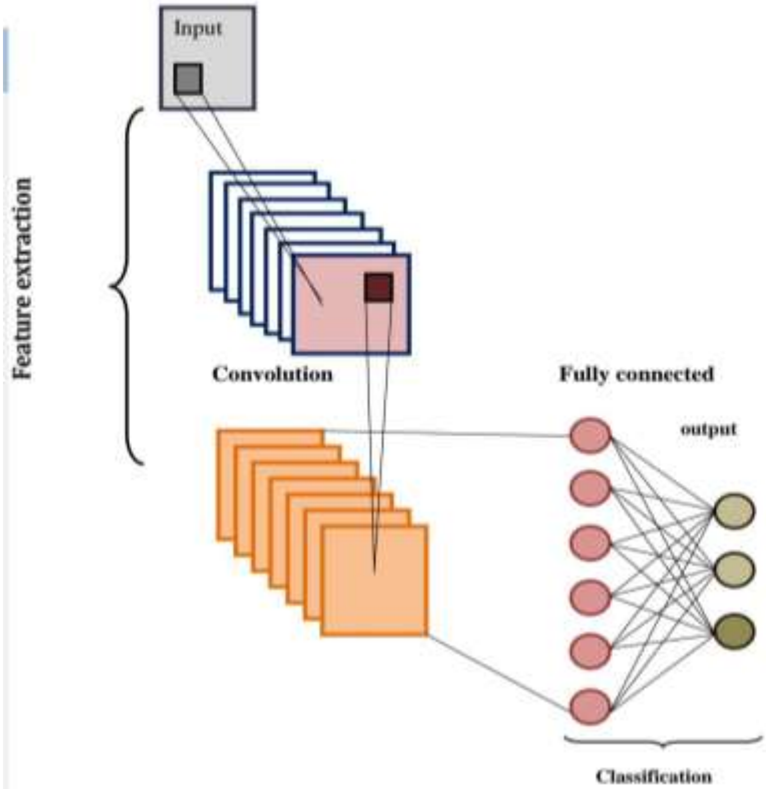


**Figure 5. A fully connected CNN for heart disease diagnosis**

## 7. GENETIC ALGORITHM

Genetic algorithms (GAs) provide cardiac risk prediction systems by using natural selection. Similar to how genes evolve over generations, GAs iteratively enhance models through processes of crossover, mutation, and selection. Than et al. demonstrated that an iterative method combining GAs and neural networks can identify coronary artery disease with an accuracy rate of 93.8%.[52].

## 8. MULTI-LAYER PERCEPTRONS

MLP is a kind of Artificial Neural Network (ANN) that uses feed-forward data processing. Hidden layers use non-linear activation functions to extract features from the data, and the layers are interconnected. The network categorizes ECG data as having a high or low risk of heart disease based on patterns it has learned from the training data Kumar and Kumari [53].

## 9. TRANSFER LEARNING MODELS

As shown in Table 2, transfer learning is a useful technique used in a number of cardiovascular disease prediction systems. By applying insights from previously trained models, researchers can increase the precision and effectiveness of models for forecasting and predicting cardiac illnesses. Neural network-based cardiac risk prediction has gained popularity among researchers. ANN and multi-layer perceptions are basic neural network architectures that analyze static data points like blood pressure and cholesterol levels and interpret data in a feedforward fashion. Investigating time-series data in ECG readings is a speciality of recurrent neural networks Yoo et al. [54], numerous cutting-edge deep learning techniques have surfaced that offer improved feature extraction capabilities for heart risk. AlexNet represented important advances in the classification of PCG signals and pictures, especially cardiac imaging, De Marco et al.[55]. ResNet uses skip connections to stop gradient deterioration Jahmunah and associates [56]. Every architectural style offers distinct advantages for heart illness prediction, enabling researchers to explore several approaches as well as computer requirements.

## 10. K-NEAREST NEIGHBOR'S (KNN)

The KNN method for clinical data-based cardiovascular disease prediction computes distance metrics between all training cases and fresh patient data, then uses Euclidean or Manhattan distances to find the K closest training samples. Heo, J et al.[57].

**Table 2.Utilising deep transfer learning to improve medical imaging-based CVD risk assessment**

| AUTHOR | DATASET | ARCHITECTURE |
|---|---|---|
| Acharya et al.(2018) [39] | PTB dataset | CNN |
| Wu D et al.(2019) [58] | 436 CCTA scans | MLP with Tree Lab-Net and Bi-Tree LSTM |
| Kim JH et al. (2019) [59] | MIT-BIH | Google Net-DNN |
| Mienye I D et al. (2020) [49] | CVD-Framingham, Massachusetts | SAE+ANN |
| Karimi-Bidhendi S et al. (2020) [60] | 64 CMR studies from paediatric patients Hospital Los Angeles | DCGAN |
| Yang P et al. (2021) [61] | MIT-BIH | MKELM with RF |
| Zhang, Y et al. (2021) [62] | MIT/BIH arrhythmia | 2-D ResNet 101 |
| Dhar P et al. (2021) [63] | PhysioNet | XWT+ AlexNet |
| Pal et al. (2021) [64] | MIT-BIH arrhythmia dataset | Cardio Net with Dense net |
| Abubaker M B et al. (2022) [2] | Public ECG images dataset | CNN with Squeeze Net, Alex Net |
| Dou S et al. (2022) [65] | PhysioNet, MIT-BIH, BIDMC | CWT+GoogLeNet |
| Cui-fang Z et al. (2022) [66] | MIT-BIH | ID to 2D AFF-Efficient Net |
| Wei, T. R et al. (2022) [67] | PhysioNet | Efficient Net B0 |
| Shin S et al. (2022) [68] | MIT-BIH | MobileNetV2-BiLSTM |
| De Marco F et al. (2022) [55] | MIT-BIH | Mobile Netv2 |
| Jahmunah V et al. (2023) [56] | Physikalisch-TechnischeBundesanstalt (PTB) database | DenseNet |
| Yashudas A et al.(2024) [69] | Framingham heart study(FHS),Kaggle | IoT-based deep learning |
| Cenitta D et al.(2025) [70] | UCI | Hybrid residual attention-enhanced LSTM(HRAE-LSTM) with attention residual learning. |

## 4. MEASUREMENTS OF PERFORMANCE

Performance criteria are used to evaluate deep learning models for cardiovascular prediction; the suggested CNN model then utilising the NB approach, the suggested CNN model has the highest score for feature extraction.

Accuracy, precision, recall, F1 score, and training and testing timeframes were employed for performance analysis. The data analysis in a confusion matrix serves as the foundation for these measurements.To learn the unique features of the new dataset, the transfer learning technique substitutes new layers for the pre trained network's last layers. After that, the model is improved by testing its performance measure on a fresh test dataset and training it on a fresh training dataset with particular training parameters. Performance metrics were acquired when the feature extractor was our suggested CNN model.Using features taken from SqueezeNet rather than AlexNet, we nearly obtained higher accuracy rates for SVM, RF, and NB algorithms when comparing the two networks.However, because the retrieved features were larger, SqueezeNet-based algorithms required more time for training and testing. Our suggested CNN model produced the best results on all performance metrics while having the smallest extracted feature size Abubaker and Babayigit [2].

### 1. CONFUSION MATRIX

The confusion matrix in Figure offers a thorough assessment of CVD prediction models. Accuracy, sensitivity, and specificity are calculated with its assistance, and it displays the real versus projected CVD status as positive or negative El Hamdaoui et al. [71].

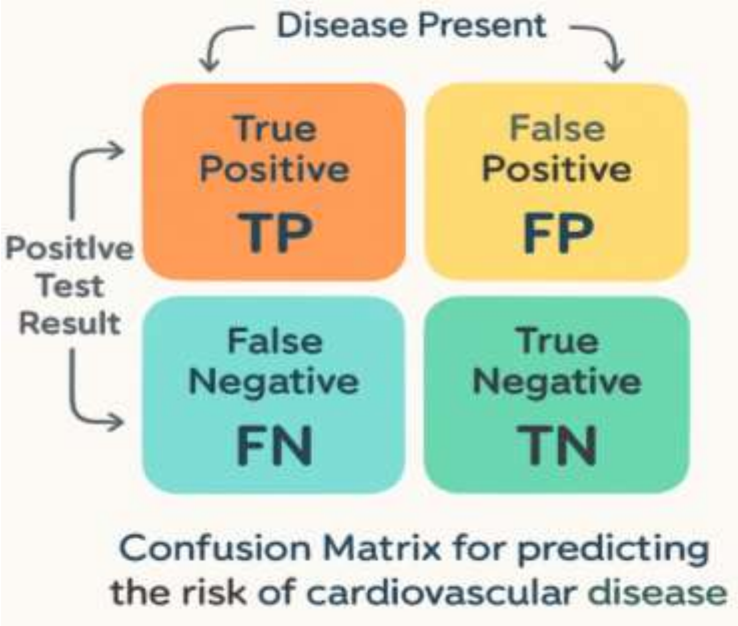


**Figure 6.Confusion matrix for predicting the risk of CVD.**

**2. ACCURACY**

The percentage of accurate cardiovascular diseases risk projections in the dataset is the accuracy displayed in (3). Abdar et al.[72]

$\frac{FP+FN}{N} = ACCURACY$ (3)

Here

FN stands for false negative,

TP for true positive,

FP for false positive,and

TN for true negative.

N=TP+TN+FP+FN

**3. PRECISION**

A fraction of affirmative predictions that suggest positive CVD risks is represented by the precision in (4). Abdulsalam and associates [73]

$\frac{TP}{FP+TP} = \text{PRECISION}$ (4)

**4. RECALL**

Recall is the ratio of favourably predicted observations to those in the true class.

Sensitivity, or the value of the person with positive CVD risk, is the recall that is shown in (5). The True Positive rate (TPR) is the word used to describe recall. Babayigit and Abubaker [2].

$\frac{\text{TP}}{FN + TP} = RECALL$ (5)

**5. F1-SCORE**

According to (6), the F1-score is a weighted average of our CVD risk diagnosis's recall and precision. Abdar and associates. [72]

$$^{2TP}/_{(2TP + FP + FN)} = F1 - score \qquad (6)$$

**6. AREA UNDER THE CURVE**

A quantitative indicator called the Area under the Curve is used to evaluate how well a binary classification algorithm predicts the risk of cardiovascular disease. In particular, it computes the area under the ROC curve to assess the model's capacity to distinguish between people at risk for CVD and those who are not. This number falls between 0 and 1. Zeleznik and associates [74].

**7. ROC**

The ROC (Receiver Operating Characteristic) curve is a graphical representation used to evaluate the performance of a binary classification model.The ROC curve, which is displayed in (7) and (8), shows how well the classification model predicts CVD across a range of threshold values. The TPR change when the FPR is changed from 0 to 1 can be computed using the ROC curve. The FPR is zero when the threshold is set to one, and one when the threshold is set to zero. The ROC curve is the TPR based on the change in the FPR value. The ROC curve was used to assess the model's performance Shin et al.[68].

$$\frac{False\ Negative + True\ Positive}{True\ positive} = TPR \qquad (7)$$

$$\frac{False\ Positive}{True\ Negative + False\ Positive} = FPR \qquad (8)$$

**8. MEAN AVERAGE**

The arithmetic mean is a statistical indicator of central tendency that is calculated by adding up all of the values in a dataset and dividing by the total number of values. Because it only captures the average and not the variability in risk factors, this measure is not used to forecast cardiac risk. Dhuli and Rajesh [75]

**9. WEIGHTED AVERAGE**

The weighted average assigns a particular weight to each data point according to its relative importance. The model ranks the most important variables first for a precise and individualised assessment of your risk for CVD. Ramesh et al.[76].

Federated learning aims to train a shared machine learning model without transferring all of the data to a central server, even while the data is dispersed among numerous devices (such as smartphones) Brendan McMahan.[77].

**10. CORRELATION MATRIX**

Use the correlation matrix to classify the best values or characteristics. The intensity and direction of a linear link between two quantitative variables are described by the statistical feature known as correlation. Hassan et al.[34]

## 5. COMPARING APPLICATIONS OF ML,DL, AND TL

### A. COMPARATIVE ANALYSIS OF DEEP LEARNING APPLICATIONS FOR CARDIOVASCULAR DISEASE PREDICTION

We have conducted research on ML, DL, and TL methods for estimating the risk of CVD.ML helps researchers create superior diagnostic instruments for analysing medical data. Researchers that use ML and DL approaches for cardiovascular disease prediction look at the following contributions.Kanagarathinam et al [78] built a cardiovascular disease risk prediction model utilising a CatBoost machine learning classifier for cardiovascular disease classification.Ordikhani et al. [79] utilise the Explainable Persian Atherosclerotic CVD Risk Stratification based on the Isfahan Cohort Study of Iranian individuals to use a genetic algorithm to predict CVD risk. Vinay et al. [80] developed an unsupervised Recurrent Neural Network-based Bidirectional Long Short-Term Memory machine learning algorithm and Generative Adversarial Networks to detect cardiovascular diseases early and automatically using phonocardiogram signals (recordings of heart sounds).Hasan and Bhattacharjee [81] presented a multi-dimensional deep CNN network approach that uses a modified ECG signal to predict CVD risk in order to identify various CVD. Paul and Karn [82] identified cardiac risk using the ANN approach's scaled conjugate gradient backpropagation. Samuel et al. [83] used a hybrid approach combining fuzzy analytical hierarchy process and artificial neural networks to create a clinical decision assistance platform. Yildirim et al. [84] developed DNN model to observe different rhythm classes from cardiac arrhythmias utilising 12-lead ECG signals. Kuila et al. [85] used an ELM-CNN classifier comprising a 1D 12-layer neural network to identify cardiac arrhythmia in order to reduce overfitting and increase learning rate. Kong et al. [86] suggested a temporal regression network architecture to identify End-Diastole and End-Systole frames in MRI sequences in order to track cardiovascular disease. Chen et al. [87] used neural networks to analyse the anatomy and performance of the heart based on cardiac magnetic resonance imaging.The K-means clustering algorithm, including Lloyd's approach, helps reduce dependencies and improve cluster quality. Zhang et al. [35].Hinchcliff et al. [88] employed unsupervised model-based clustering to study the role of the heart in systemic sclerosis, whereas Verma et al. [89] used clustering techniques for cardiac disorders.Quantum deep learning approaches, including quantum neural networks, particle swarm optimisation, and support vector machines, have been used to categorise and detect ECG images and CVDs. Prabhu et al. [90].Abdulsalam et al. [73] proposed an ensemble quantum ML technique for detecting cardiac risk.To make the model's outcomes more explainable. The SHapley Additive Explanation Framework evaluates and visualises the significance of each parameter in prediction.Bhatt et al. [91] developed a real-time CVD prediction system with Federated Learning (FL) and an ANN model trained on real stroke data. Degirmenci et al. [92] used ECG signal pictures to categorise arrhythmias such as normal, PVC, LBBB, RBBB, and PB using deep learning. Terrada et al. [93] analysed 835 clinical records of atherosclerosis patients from three data sources to create a medical diagnostic support system using ANN for better CVD identification.Dutta et al. [94] developed a CNN design that accurately classified 77% of CHD patients and 81.8% of non-CHD cases in testing data. The model accurately predicts coronary heart disease using the NHANES dataset at 85.7%.Ahmed et al. [95] employed techniques such K closest neighbour, support vector machine, multinomial naïve bayes, and gaussian naïve bayes to achieve 67.2% accuracy in CVD prediction. Ensemble models, including Gradient Boosting Classifier (GBC) with AdaBoost Classifier (ABC) and Random Forest with GBC, reached approximately 87% accuracy, while CatBoost achieved a maximum of 87.93% accuracy. Chen et al. [96] achieved maximum accuracy in cardiac MRI segmentation using CNN on an image dataset.The CNN model was used by Blanchard et al. [97] to identify the risks of cardiovascular events during sleep apnoea. The outcome displays a good AUC of 0.82 and sensitivity of 0.89.Ahmad et al. [98] accurately predicted CVD with their hybrid CNN+BiLSTM method. MohanadAlkhodari [38] predicted the model's performance using 10-fold cross-validation, which resulted in an average accuracy of 90.23% and a sensitivity of 72.41%, as well as 76.10% accuracy in distinguishing between the absence and presence of murmurs when tested on unseen data. Sarra et al. [99] designed an Enhanced-ANN model for cardiac detection that achieved 93.4% accuracy, 93.4% precision, 93.3% recall, and 93% F1-score on the Cleveland dataset. Yashudas et al.[69] DEEP CARDIO approach has an overall accuracy of 99.90%, while MABC-SVM, HCBDA, and MLbPM methods achieve 86.91%, 88.65%, and 93.63%, respectively.Clinical datasets, including Cleveland, Hungarian, and Z-AlizadehSaniTerrada et al. [93], provide useful information for diagnosing CVD.Physiological signal datasets such as MIT-BIH, PhysioNet PTB Safdarian et al. [71], Nagavelli et al. [100], and UCI repository Ramesh et al. [76], Subhadra and Vikas [101] provide recordings of ECG and PCG, which are important for analysing heart function.Lakshmanarao et al. [46] applied Kaggle and IEEE DataPort to clinical and ImageNet datasets. Redlarski et al. [41] employed sound signal analysis, namely S1 and S2 of diseased heart sounds, to predict cardiovascular disease.

**Table 3.Performance evaluation for predicting cardiovascular disease**

| **Author** | **Objective** | **Dataset used** | **ML and DL techniques** |
|---|---|---|---|
| Betancur J et al. (2018) [105] | The aim is to predict obstructive disease using myocardial perfusion imaging (MPI) data, specifically focusing on the total perfusion deficit (TPD) | National and International sites(Canada, Switzerland, Israel) | CNN |
| Abdar, M et al. (2019) [72] | The objective is to determine thepresence of Coronary Artery Disease (CAD) using information from Iranian patients | Z-AlizadehSani. | SVM |
| Yang H et al. (2021) [61] | The approach involved creating a biosensor and applying a deep learning technique to enable the identification of atherosclerotic disease. | Cleveland dataset | ANN |
| Rath A et al. (2021) [106] | To detect heart disease | MIT-BIH and PTB-ECG databases | GAN-LSTM |
| Kumar VD A et al (2022) [102] | To predict the occurrence of early cardiac disease | Heart Disease Training data | SVM |
| Anetta K et al. (2022) [107] | **The objective is to employ automated ICD coding to predict the diagnoses of patients based on their Polish electronic health record data.** | GCM-GH, Poland | ROBERTa and BERT(NLP) |
| Khan M U et al. (2022) [108] | Inexpensive self-developed Phonocardiography Analysis System | Real time PCG data | ANN |

| | | | |
|---|---|---|---|
| Feng Y et al. (2022) [109] | Creating personalized survival forecasts for hypertension patients. | Data from Alberta | RF,LR, GB, and ANN |
| Dami S et al. (2022) [110] | To detect cardiovascular events | KAGGLE, ShahidBehesthi, Hospital. Physionet site, UCI | LSTM-DEN |
| Srilakshmi Vet al. (2022) [111] | An efficient approach to predicting CVD risk involves analyzing retinal fundus images with a specifically designed model. | JSIEC | FC-HOA-DNFN |
| Almulihi A et al (2022) [112] | Creating a high-performing heart disease prediction model by integrating multiple deep learning models in a stacked ensemble. | Dataset 1, Cleveland Dataset | hybrid model: CNN-LSTM and CNN-GRU |
| Johri A M et al (2022) [113] | To develop coronary artery CAD or CVD using DL-based algorithms (AE 3DL | Multimodel data from Office, Laboratory and carotid ultrasound | RNN,LSTM |
| Oliveira BA et al (2023) [114] | Machine learning algorithms can automate CVD risk scoring for prevention | Private company | MLP,SVM,LR, RF XGB,and Cat Boost |
| Prabhu S et al. (2023) [90] | To classify ECG images to predict Cardiovascular Disease (CVD) | Omdena dataset | QNN andQPSO-SVM |
| Pujadas ER et al. (2023) [103] | Applying Cardiac Magnetic Resonance (CMR) to predict various heart disease | UK Biobank dataset cardiovascular magnetic resonance (CMR) images | SVM |
| Esmaeili P et al.(2023) [115] | To predict ASCVD risk | Tabriz University Medical Sciences employees | ANN |
| Mishra I et al. (2023) [116] | To detect accurate stroke prediction method. | Odisha hospital data | SVM, AdaBoost, KNN,DT , and NB |
| MohanadAlkhodari et al (2024) [38] | To develop a deep learning-based attention transformer model to automate the detection of heart murmurs caused by Congenital Heart Disease (CHD) in young patients. | The CirCorDigiScope dataset. | RNN,CNN and SVM |
| Yashudas A et al(2024) [69] | To introduce a novel Recommendation System for Cardiovascular Disease (CVD) Prediction using an IoT network, named DEEP-CARDIO. | Framingham heart study(FHS), Kaggle | Bidirectional-gated recurrent unit (BiGRU) |
| Maria Trigka et al (2025) [70] | To enhance the early prediction and management of Cardiovascular Disease (CVD) | Kaggle | CNN, RNN |
| Cenitta D et al (2025) [104] | To introduce a novel hybrid model that combines an LSTM network to improve the prognosis prediction of Ischemic Heart Disease (IHD). | UCI | LSTM |

Table 3 compares the performance indicators of ML and DL models for CVD prediction. It discusses the advantages, limits, and key findings of using machine learning and deep learning to predict CVD.

**B. DISCUSS THE STRENGTH AND LIMITATION OF EACH APPROACH**

The paper by Zeleznik et al. has the strength of developing a deep learning system that automates coronary calcium quantification from CT scans, accurately predicting cardiovascular events with high efficiency and reliability across diverse populations and clinical settings, but it has the limitation of requiring improvements in patient care and outcomes through healthcare process integration [74].Kumar et al.'s paper's strength is its use of SVM classification methods, which provide high accuracy and rapid training for cardiovascular disease prediction, albeit the system has to be validated over a broad population with various risk variables [102].Pujadas et al.[103]Radiomics characteristics' potential to improve the prediction of incident cardiovascular illnesses is tempered by the constraint that incorporating CMR scans for specific medical reasons could improve risk assessment methods.The study by Prabhu et al.[90] has the strength of introducing a novel QML approach for multi-class classification of CVDs; but its weakness is the difficulty of integrating quantum hardware and QML models into medical systems.Yashudas et al.[69] describes an IoT-based DEEP-CARDIO system that uses a BiGRU attention model for real-time cardiovascular disease prediction and personalised recommendations, with robust validation and low computation time. However, one limitation is the difficulty of securely collecting and transmitting sensitive physiological data over an IoT network.The study by Maria trigka et al. [104] has the advantage of creating a better SMOTE technique that maintains feature correlations, which greatly improves the predictive performance and generalisation of five deep learning models for the prediction of cardiovascular disease. The CNN model has the highest accuracy and AUC, but it also has the limitation that conventional data balancing methods frequently fail to maintain feature correlations.Compared to traditional machine learning and deep learning techniques, the cenitta[70] model has better specificity and sensitivity; however, it needs to be evaluated on distinct and separate datasets related to heart disease.

## 6. ENHANCED HYBRID MODEL

This section analyses and evaluates the performance of an upgraded mongrel model for cardiovascular complaint threat vaticination that combines deep literacy and a general armature.

### A.INVESTIGATION OF AN ENHANCED MONGREL MODEL USING DL WITH A GENERAL ARMATURE FOR CVD THREAT VATICINATION

Cardiac and cardiovascular conditions are among the most common and serious ails affecting mortal health. Using beforehand- stage symptoms to descry heart complaint in its early phases is a significant issue in the ultramodern world. Accordingly, there's a need for a less expensive as well asnon-invasive tool that can descry heart problems. Goswami [117]. The effectiveness of the mongrel point selection system while showcasing the pledge of slice- edge machine learning approaches for CVD vaticination Dr.Ramakrishnan Raman.[118]. Beforehand discovery of conditions like cancer, cardiovascular complaint, diabetes, HIV, AIDS, Lyme complaint, and tuberculosis leads to further effective treatment, lowers mortality rates, and lowers healthcare expenditures present a new Artificial Spider Monkey- grounded Random Forest( ASM- RF) mongrel frame that combines a Random Forest algorithm's prophetic analytics with Artificial Intelligence to estimate patient health data, identify patterns, diagnose minor suggestions, and automate intelligent opinions to ameliorate the healthcare system. The proposed ASM- RF mongrel frame uses a fitness function to assess the spider monkey's performance at the bracket subcaste and update delicacy and recall, performing in more accurate patient complaint judgments and automated treatment opinions that ameliorate the overall healthcare system. Irshad et al.[119].

### B. EVALUATION OF THE PROPOSED MODEL'S PERFORMANCE

This model involves contrasting a traditional Total Perfusion Deficit (TPD) approach with a deep learning (DL) model for obstructive coronary artery disease (CAD) prediction Betancur et al. [105]. Loss curves, ablation experiments, and comparisons with baseline techniques for motion reduction and frame interpolation are used in the study to assess network performance. It illustrates how well the network eliminates motion blurring and produces excellent outcomes. Results of frame interpolation and motion artefact removal are also shown Lyu et al.[120].

The outcomes show the model's potential for reliable clinical treatment plans and precise CVD detection. Navita [121]. According to the World Health Organisation, heart disease is a major cause of death globally, accounting for 17.9 million deaths per year. Its rising prevalence is caused by a number of conditions, such as excessive cholesterol, diabetes, and hypertension. In order to address this expanding health issue, early diagnosis and detection are essential. Ahmed Almulihi.[122]

## 7. SURVEY RESULTS AND DISCUSSION

### A. ANALYSIS OF THE SURVEY CONDUCTED ON CVD PREDICTION USING ML,DL AND TL

This section reviews a wide range of literature, including well-known works on ML, DL, and TL methods for heart illness diagnosis. The study's objective was to classify, assess and investigate different prognostic strategies used in the classification of CVD. Numerous forms of CVD, such as CAD and PAD, as well as risk variables such blood pressure, heart failure, stroke, and heart valve disease, were examined in the reviewed research. The classification of cardiac dysfunction and the prediction of CAD and PAD diseases were examined in the literature.

According to the report, the primary indicator of cardiac dysfunction is blood pressure. Furthermore, we used medical imaging and software programmes including CMRtools, suiteHEART, CVI42, and iNtuition tools that are helpful for MRI and CT imaging to look at heart diseases.For echocardiography, VevoLAB, QLAB, and TOMTEC are excellent choices. Additionally, SPECT analysis can benefit from the usage of iNtuition, Segment, and Syngo. CVI42 and iNtuition stand out among these choices as flexible approaches to handling various cardiovascular imaging data and analysis tasks. We surveyed a variety of datasets for our analysis, including clinical trials from the Cleveland, Framingham, and UCI repositories that included information on patient demographics and disease characteristics. While the imaging data included echocardiograms, CT, MRI, and coronary angiography from CADC and the UKBiobank, the signal data, which included ECG, PCG, and heart rate data, came from MIT-BIH, PTB.

On their cardiac medical imaging projects, the researchers carried out localisation, segmentation, detection, classification, and registration. To forecast cardiac disorders, a wide variety of modelling techniques were used, such as LR, DT, NB, ANN, RF, CNN, KNN, GB, XGBoost, GA, and MLP. CNN models had the highest accuracy rate of over 95% among these.

Tables 1, 2, and 3 are used to analyse the accuracy performance of several ML classifiers for the detection of cardiac disease. As shown in Fig. 8, we found that Random Forest, Adaboost, and K-Nearest Neighbour performed better than other ML classifiers, obtaining accuracies of almost 99.9%, 98.6%, and 98%, respectively.

A thorough analysis of Tables 1-3 shows how well several DL classifiers predict the diagnosis of CVD. As seen in Fig. 9, the two best-performing neural networks were the artificial neural network and the convolutional neural network, which achieved accuracies of almost 99.9% and 99.45%, respectively.
The top-performing TL classifiers in Table 2 were GoogleNet, DenseNet, and EfficientNet. achieved roughly 99.54%, 98.9%, and 98.3% accuracy rates, respectively.As seen in Fig. 10, these models proved to be quite successful in predicting heart disease.We examined every hybrid model that was assessed, including Fig. 11 illustrates machine learning, deep learning, and optimisation techniques. The accuracy rates of the ML, DL, and TL models range from 90 to 100. These methods effectively address the class imbalance problem, resulting in enhanced model performance.

**B. COMPARATIVE EVALUATION OF CVD CATEGORISATION BY HYBRID,ML,DL, AND TL APPROACHES**

Accuracy scores for ML models range from 92 to 99.9. The accuracy score of DL models ranges between 82 and 99.9. TL models have accuracy scores ranging from 80 to 99.54. while, Hybrid models exhibit accuracy scores ranging from 79 to 100.EfficientNet, ANN, and RF perform better than the other models. According to the study, hybrid optimisation, deep learning, and machine learning techniques have all demonstrated exceptional predictive power for heart disease.

While the hybrid Random Forest and Convolutional Neural Network model increased the accuracy to 100%, Random Forest and Artificial Neural Networks achieved accuracies of about 99.9%.

These results demonstrate the effectiveness of hybrid techniques for accurate and effective prediction of heart disease. When it comes to forecasting CVD, modern transfer learning models outperform older models.

**C. DISCUSSION OF KEY FINDINGS AND INSIGHTS**

**1. MAJOR FINDINGS**

In CVD prediction, Deep Learning (DL) and Transfer Learning (TL) models regularly outperform traditional Machine Learning (ML) techniques, with DL models achieving 70–95% accuracy and TL models frequently exceeding 96% accuracy. Hybrid methodologies that combine ML, DL, and optimisation algorithms further increase prediction accuracy, sometimes reaching 100%. Transfer learning, particularly with architectures like ResNet, DenseNet, AlexNet, MobileNet, EfficientNet, and GoogLeNet, proves to be highly effective for small and medium datasets in cardiology; multimodal data (clinical, signal, and imaging data) integration is still limited, indicating a significant future direction. Medical image processing techniques (segmentation, registration, localisation) are crucial for improving CVD detection, particularly with echocardiograms, MRIs, and CT images.

**2. KEY INSIGHTS**

Although machine learning can have limited generalizability across datasets, it is useful for smaller, organised clinical datasets.

They need big datasets and a lot of processing power, deep learning models perform better when dealing with unstructured data, such as raw signals and ECG images.By optimising pre-trained networks, transfer learning eliminates the r equirement for intensive training, which makes it perfect for CVD prediction in situations with sparse data.They whant intricate designs, hybrid models that combine neural networks and optimisation algorithms such as Random Forest + CNN and GA + RBF—produce better results.Blood pressure, cholesterol, diabetes, smoking, obesity, and age are significant risk factors for CVD.The application of AI methods such as explainable AI, federated learning, quantum deep learning, attention mechanisms, and wearable device data integration are examples of emerging developments.

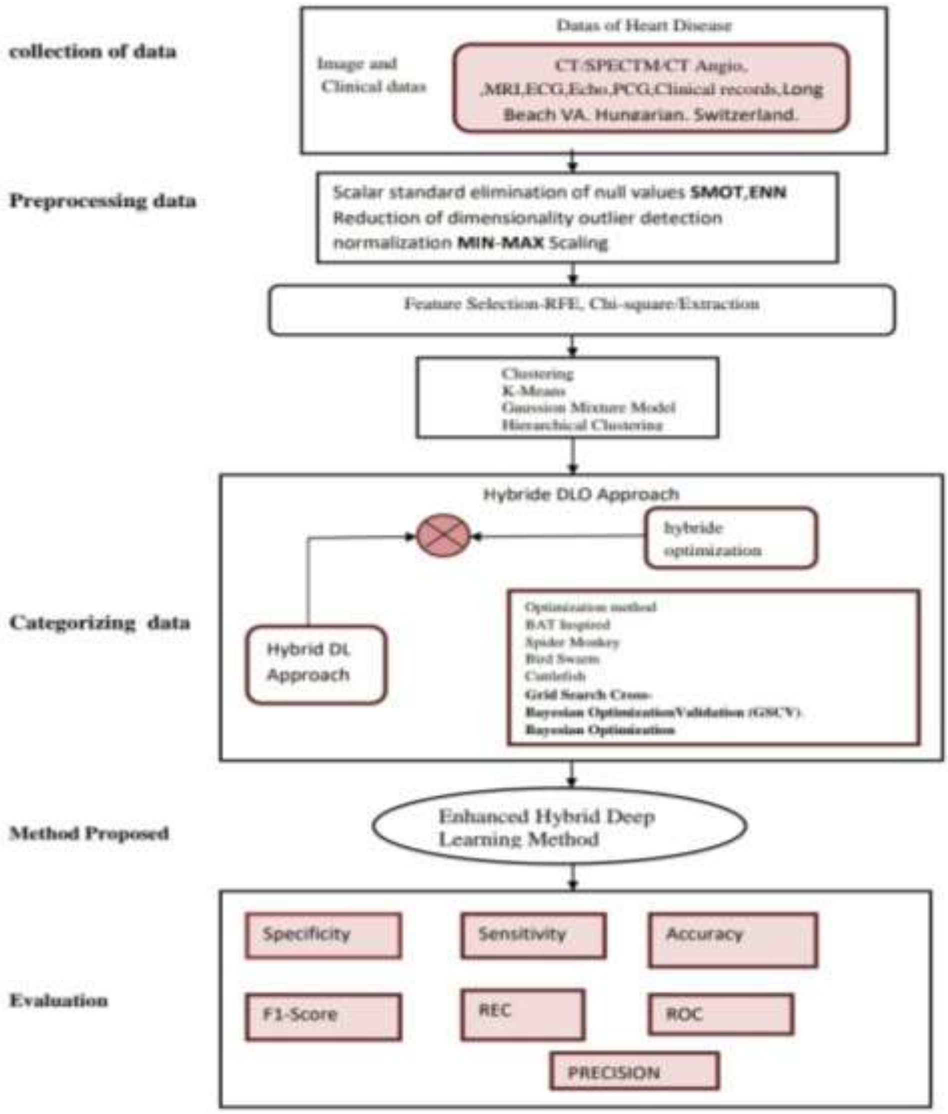


**Figure 7. A hybrid optimal deep learning method for CVD prediction.**

## 8. CLINICAL APPLICATIONS AND IMPLICATIONS

### A. DISCUSSION OF CLINICAL APPLICATIONS AND IMPLICATIONS OF CVD PREDICTION MODELS

### 1. CLINICAL APPLICATIONS

Remote and Mobile Monitoring: TL models facilitate real-time monitoring and early detection outside of clinical settings by enabling precise CVD risk prediction on mobile devices.

Clinical Decision Support Systems (CDSS): To help physicians with risk assessment and treatment planning, CDSS have been developed using hybrid AI models, such as ANN, in conjunction with fuzzy logic or optimisation algorithms.

Image-Based Diagnosis: Automated plaque recognition, disease staging, and classification of heart dysfunctions are achieved by applying deep learning models, such as CNNs, to cardiac MRI, echocardiograms, and CT angiograms.

Real-time Emergency Support: In emergency situations like as heart attacks and strokes, quick, privacy-preserving prediction is made possible via federated learning and lightweight neural networks.

Early Diagnosis: By enabling the early detection of diseases such as heart failure, stroke, peripheral arterial disease (PAD), and coronary artery disease (CAD), CVD prediction models assist physicians in taking action before serious consequences arise.

Personalised Risk Assessment: Physicians can create risk profiles and customised treatment regimens for patients by applying ML, DL, and TL models to clinical and imaging data (such as ECG, MRI, and CT scans).

## 2. CLINICAL IMPLICATIONS

**Greater Accuracy and Efficiency**: Compared to more conventional risk calculators like Framingham, modern models routinely attain accuracy levels between 70% and 100%.

**Clinical Workload Reduction**: AI-powered automation speeds up patient triage and eliminates the need for manual diagnostic labour.

**Resource Optimisation**: AI-based CVD risk prediction reduces the need for invasive and expensive procedures, making it practical in environments with limited resources.

**Interpretability Issues**: Although ML models are frequently interpretable, DL and TL models are opaque, which makes them difficult to adopt and build clinical trust.

**Problems with generalizability**: The performance of models might differ between datasets and populations, which emphasises the necessity of multimodal, diverse, high-quality training data.

**Future Trends:** To further improve CVD care, there is an increasing focus on Explainable AI, wearable technology, multimodal AI integration (combining imaging, genomics, and clinical notes), and real-time decision-making tools.

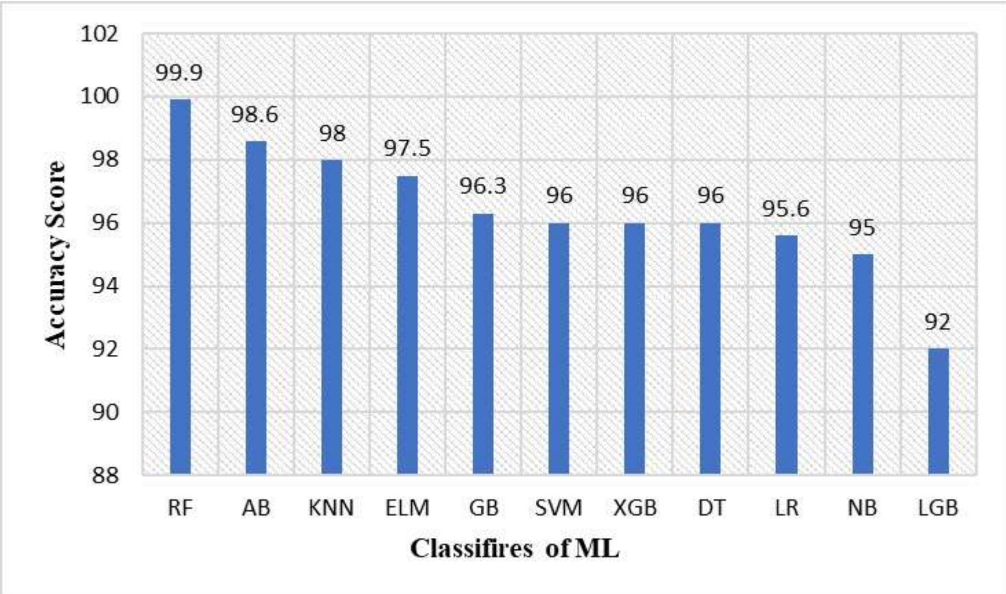


**Figure 8. Accuracy of ML classifiers.**

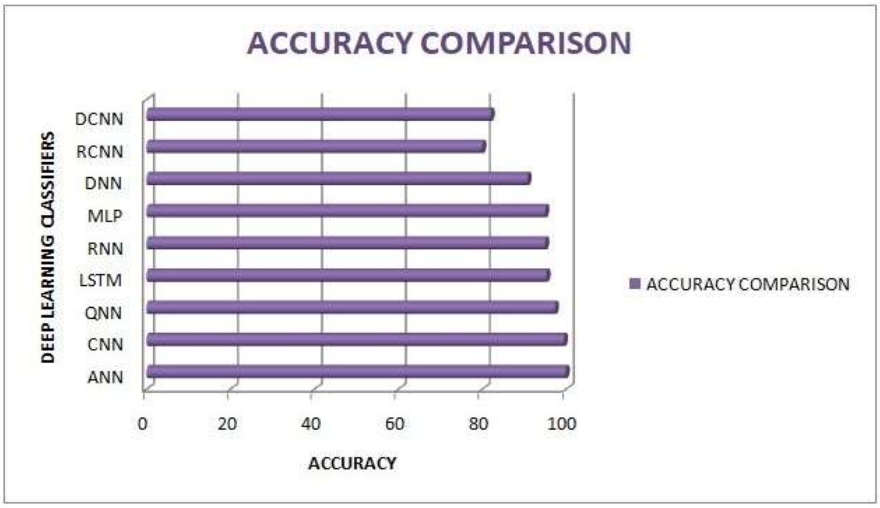


**Figure 9. Accuracy of DL classifiers.**


**Figure 10. Accuracy of TL classifiers.**

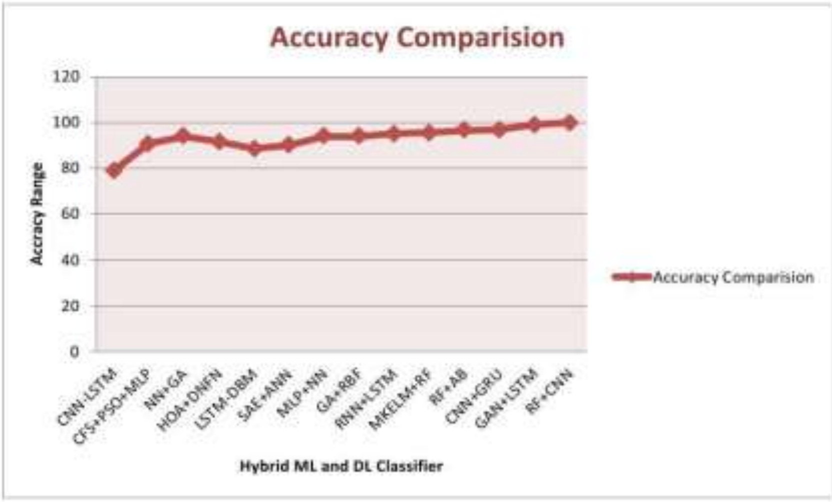


**Figure 11. Hybrid ML and DL classifiers using optimization methods.**

## 9. CONCLUSION AND FUTURE DIRECTIONS

Cardiovascular disease presents a major challenge for both individuals and governments aiming to eliminate it. The survey examined the gaps and hurdles in forecasting CVD. Accurate CVD prediction is essential for implementing proactive strategies. Various machine learning, deep learning, and transfer learning models have been assessed, alongside an investigation of optimization methods. The survey compared the performance metrics of current CVD prediction approaches. It shows that ML and DL models achieve accuracy rates ranging from 70% to 100%, while pre-trained transfer learning models demonstrate the highest validation accuracy (99.9%), sensitivity (96%), specificity (99%), F1-Score (90%), precision (95%), and AUC (0.98). The study found that ML, DL, TL, and hybrid models significantly improve the accuracy of cardiovascular disease prediction. Traditional models encounter numerous challenges, including high costs and invasiveness.

Modern approaches offer improved solutions for predicting cardiovascular disease (CVD) by utilizing clinical and imaging data. Deep transfer learning enhances the identification and classification of plaques, which in turn improves disease staging. The combination of AI and surgical robots is expected to further support conventional medical practices. Additionally, research can be expanded to explore deep hybrid models that incorporate bio-inspired optimization techniques to boost prediction accuracy. Future studies on cardiovascular disease prediction should aim to diversify datasets to increase model generalizability and enhance interpretability to help physicians understand model decisions. Incorporating real-time data from wearable devices could improve the accuracy and timeliness of cardiovascular disease predictions. Explainable AI, attention mechanisms, transformer models, knowledge distillation, and digital twins are potent AI techniques with considerable potential in healthcare. Multimodal AI, which integrates cardiac CT, cardiac magnetic resonance imaging (CMR), genome-wide association studies (GWAS), and genomic AI, will further advance AI capabilities in cardiac imaging, resulting in more precise diagnoses and personalized treatment plans.

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