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A Review on Earlier Diagnosis of CVD Using Chest CT Image Segmentation and Classification

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Abstract

In recent years, cardiovascular diseases (CVDs) have become a major global cause of death. These illnesses start with mild symptoms that worsen over time. During the early stages of CVD, fatigue, dyspnea, oedema, fluid retention, and other indications are frequently seen. Among the most common CVDs are angina, mitral regurgitation, congenital heart defect (CHD), arrhythmia, cardiomyopathy, and coronary artery disease (CAD). The best tools for identifying CVDs include clinical techniques such as blood tests, electrocardiography (ECG), and medical imaging. Among them, cardiac computed tomography (CT) is increasingly used for CVD diagnosis, tracking, planning, and prediction. Healthcare practitioners find it difficult to diagnose CVD despite the benefits of CT imaging data because of a number of factors, including inadequate contrast and a large amount of data. The diagnosis of CVDs using CT imaging has incorporated machine learning (ML) and deep learning (DL) approaches, and research in this area is now underway. To better understand the potential applications of machine learning (ML) and deep learning (DL) techniques for chest CT image segmentation and classification—with an emphasis on CVD detection—this review presents a thorough overview of studies that have explored these areas. To that end, we have carefully reviewed 77 papers gathered from various databases, such as Google Scholar, PubMed, and Springer, among others. The research under consideration has undergone rigorous evaluation to highlight the key characteristics, advantages, and disadvantages of the numerous methods established to date for using CT scans to identify CVD.

Keywords: Cardiovascular disease, CT Image, segmentation, classification, diagnosis, Machine learning, deep learning

1. Introduction

According to reports in recent years, CVD is the primary cause of death for humans [1]. If patients take their medications and treatments diligently and on time, early identification of cardiac disease may save many lives [2]. In the population screened for lung cancer, cardiovascular disease ranks higher than lung cancer as the primary cause of death. Furthermore, it has been demonstrated that individuals at risk of developing CVD can be identified using chest CT scans, which are also frequently utilized for lung cancer screening. [3][4][5, 6]. It's interesting to note that the CT examination, which is used to diagnose lung cancer, may also be used to quantify arterial calcifications, which are a powerful indicator of cardiovascular events in a variety of different contexts [7]. The advantages and affordability of chest CT-based diagnostic for cardiovascular disease in heavy smokers may be increased by including cardiovascular illness in the screening procedure since both initial and subsequent preventive actions can lower cardiovascular morbidity and death [8]. Nevertheless, the predictive power of chest CT for lung cancer screening in predicting cardiovascular events remains unclear. A non-invasive imaging method used to identify a range of CVDs, brain disorders, etc., is CT (computed tomography) [9, 10]. Specifically, cardiac CT provides an anatomical assessment of the heart, particularly for CAD [11]. The early identification and diagnosis of CVD, as well as the forecasting of outcomes and the evaluation of prognosis, can be greatly aided by artificial intelligence (AI) techniques, including ML, DL, and cognitive computing. Enormous databases (numerical, subjective, and procedural data) have been created by the widespread data collection of electronic health records (EHRs), necessitating the interpretation of AI approaches [12]. Recent advancements in ML and AI now enable automation to quickly and accurately evaluate each CT scan and produce queryable, consistent interpretations. When used properly, these algorithms could help doctors diagnose patients more quickly and provide better care.

2. Cardiovascular disease – Diagnosis

A thorough medical history and examination of the body are necessary for the proper diagnosis of CVD, with special attention to the cardiovascular system. A number of factors need to be carefully taken into account, including obesity, angina, decreased exercise tolerance, orthopnea, paroxysmal nocturnal dyspnea, syncope or presyncope, and claudication. The doctor should perform a more thorough history and physical examination if any of the aforementioned symptoms are evident. Depending on the clinical situation, ancillary diagnostic tests, including cardiac enzyme testing and electrocardiograms, could also be required, particularly for patients who are suffering from chest pain. It is crucial to concentrate the majority of our attempts on preventing CVD in the first place in addition to detecting it based on clinical suspicion. This can be accomplished by identifying those with risk factors and applying all available treatments to the risk factors that can be changed. It is advised that patients have lipid measurements and learn about CVD-associated variables beginning at age 20 [13].Your risk of having CVD can be calculated using a number of calculators that take into account various risk variables in addition to your HDL and LDL cholesterol levels. You can use these calculators to get a 10-year as well as 30-year CVD rating, which may assist you in determining if you need to take aspirin and statins for primary prevention or further treatments. In general, these therapies are advised if your chance of getting CVD is above ten percent[14]. Particularly for patients with diabetes and hereditary hypercholesterolemia, these calculators have limitations. A personalized approach is advised because the cohorts from which these calculators were created did not include individuals older than 79. Every four to six years, experts advise re-evaluating CVD risk [13].

Utilizing deep learning techniques, the study offered a brand-new, incredibly powerful tool for CVD identification. In this paper, we suggest a multiclass algorithm with two stages. ECG segmentation is carried out in the first stage using convolutional bi-directional short-term and long-term neural networks that integrate attention mechanisms. ECG beats taken from the first stage are sent into a second stage's time-adaptive convolutional neural networks for multiple time intervals (from 10s to 5min). The Short-Time Fourier Transform is utilized to transform ECG beats into 2D pictures, which is then used to forecast sudden cardiac death and automatically distinguish between normal ECG and cardiac unfavourable events, including arrhythmia and congestive heart failure. The accuracy of the model was examined over various time intervals. The models were trained and tested using data taken from the MIT/BIH-PhysioNet databases[15].

3. Machine learning methods for earlier diagnosis of CVD

Using various machine learning techniques, researchers have been attempting to anticipate the onset of cardiovascular disease. [16] carried out the RF algorithm, the Logistic Model Tree, and the J48 Tree Technique, concentrating on various strategies. Out of all of them, the J48 tree method was suggested with an accuracy rate of 56.76%. However, [17] used four different algorithms and got the best accuracy from KNN, which was 87%. However, in order to predict heart disease, [18] employed Gradient Boosting, SVM, RF, Naïve Bayes Classifier (NBC), and Logistic Regression (LR). Ultimately, RF with a stratified K-fold model was suggested, and it had an accuracy of 86.12%.

Additionally, in order to forecast and detect cardiac illness, [19] used four machine algorithms: LR, RF, SVM, and Stochastic Gradient Boosting (SGD). Even with the use of tenfold cross-validating in SVM and GB, LR demonstrated the highest accuracy (87%), yielding the best results. Utilizing the data set from UCI with 14 attributes, [20] implemented a number of machine learning approaches and achieved the best accuracy of 90% utilizing the hard voting ensemble method. [21]Experimented with a dataset of cardiac illness using the backward elimination approach, a machine learning feature. Out of the five algorithms implemented, LR had the highest accuracy (87.1%) in predicting heart disease.On the other hand, [22] has developed an application that uses Spark MLlib in conjunction with Spark streaming to analyze and monitor data. They have compared the execution times of the Spark and traditional frameworks and discovered a notable improvement in the Spark framework. They accomplished an accuracy of 87.5%, sensitivity of 86.66%, and specificity of 88.37%. However, in order to forecast cardiac disease,[23] presented a hybrid machine learning model called the hybrid random forest alongside linear model (HRFLM), which combines the features of a linear model with RF.

Using the Genetic Algorithm (GA) for event decision-making, cross-over, and mutation, the fitness function was inferred. The model's total accuracy comes in at 88.4%. It forges a fresh route for the application of neural networks in this realm. In light of the previously mentioned studies, their research aimed to improve accuracy and yield more satisfying results in regard to other performance metrics in order to address and detect cardiovascular illnesses more effectively. Different MLprocedures have been used in their work to better correctly predict CVD in order to help physicians diagnose patients at an early stage.

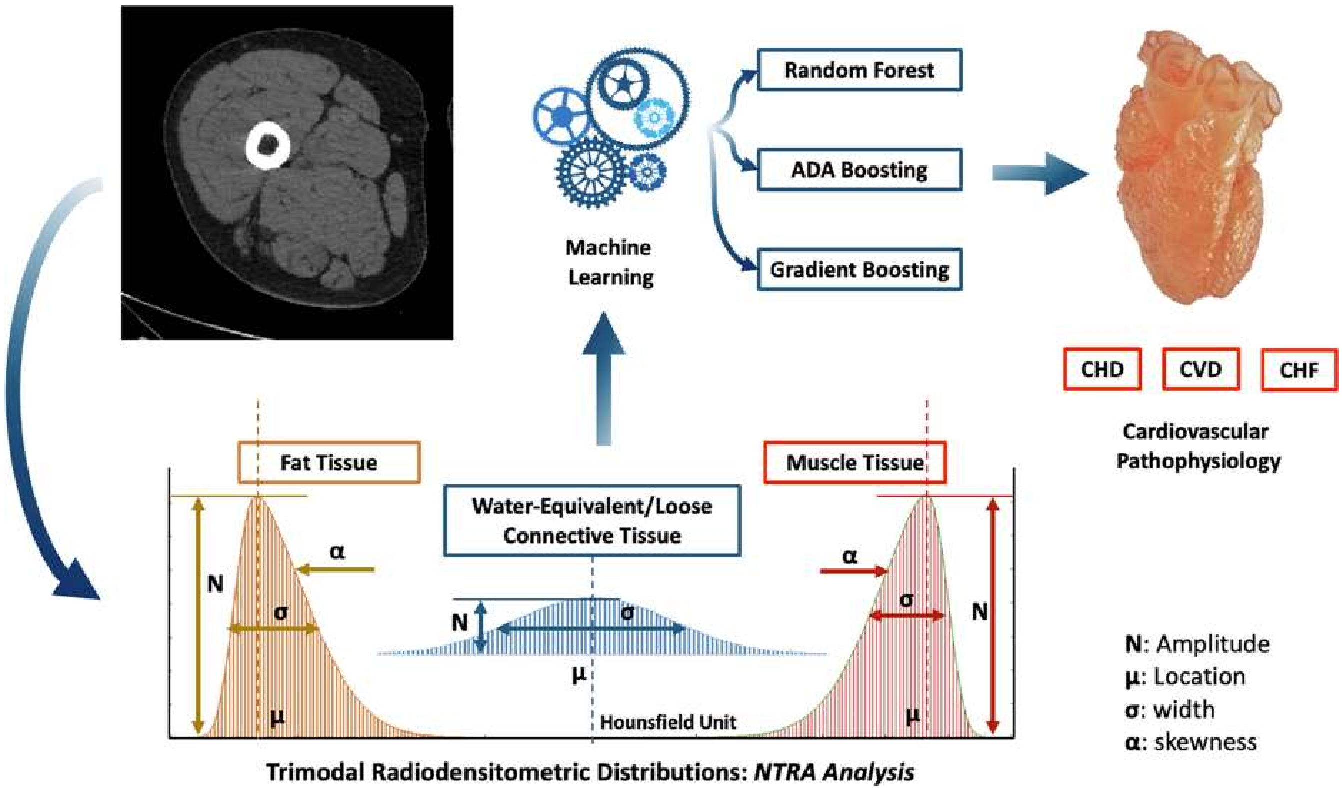

Figure 1: Evaluating CVD risks from a mid-thigh CT image using ML techniques[24]

i. Segmentation

The author of [25, 26] stated that cardiac CT segmentation is essential for the diagnosis of heart illness. Accurate data about the variations in the boundary thicknesses of the two chambers of the *human heart* have been obtained using automated segmentation techniques. Several segmentation techniques have been discussed, including contour-based segmentation, FCNN, pixel classification, and others. The author of [26] offers a system that, using earlier anatomical criteria, aids cardiac image segmentation.

To classify CVD into seven diverse classes, such as normal sinus rhythm (NSR), atrial fibrillation (AFIB), premature ventricular contraction (PVC), ventricular bigeminy (VB), left bundle branch block beat(LBBBB), and right bundle branch block beat (RBBBB), a fusion Paradigm established on ML models, comprisingdecision tree (DT), k-nearest neighbour (KNN), random forest(RF), native bayes(NB), linear discriminant analysis (LDA), Support vector machines(SVM) and quadratic discriminantanalysis(QDA)It has evolved. The developed method comprises four steps: pre-processing, segmentation, post-processing, and analysis. The results show that the QRS complex can be detected with sensitivities, specificities, accuracies, and Matthews's correlation coefficients (MCCs) of 94.75%, 95.57%, 95.57%, and 0.90, respectively. Sensitivity, specificity, accuracy, and MCC of CVD class classification are 92.33%, 92.50%, 92.41%, and 0.85, respectively [27].

Table 1: Non-linear regression analysis is utilized to assess CVD risks using ML algorithms[24]

	Algorithm	Accuracy Mean [%]	Accuracy Max [%]	Sensitivity [%]	Specificity [%]	Recall [%]	Precision [%]	AUCROC
CHD	GB	75.9	77.7	70.0	81.7	70.0	79.3	0.864
	RF	85.0	87.4	81.7	88.4	81.7	87.6	0.936
	ADA-B	79.5	82.2	74.9	84.1	74.9	82.4	0.873
CVD	GB	73.1	75.7	67.1	79.1	67.1	76.2	0.834
	RF	82.1	83.9	78.8	85.5	78.8	84.5	0.914
	ADA-B	70.2	77.0	63.3	77.2	63.3	73.5	0.766
CHF	GB	88.6	90.3	85.0	92.1	85.0	91.5	0.962
	RF	95.9	96.5	95.0	96.9	95.0	96.8	0.994
	ADA-B	94.0	95.4	92.1	95.8	92.1	95.7	0.987

ii. Classification

Investigated numerous ML methods that could be applied to the classification of CVD. They examined the precision of the DT, KNN, and K − Means algorithms. According to the study[28], DT provides the maximum accuracy and can be made more effective by blending different approaches and adjusting parameters. [29], Created an ML model that contrasts five different approaches. We used a hasty prospector, which offered a considerably higher degree of exactness than Weka and MATLAB.

This study assessed the pertinence of the classification breakthroughs DT, LR, NB, and SVM. The most accurate algorithm was the decision tree one. The classifier's accuracy was evaluated using a range of feature counts with classification techniques NVB, KNN, DT, and neural networks. [30]Predicted CVD using SVM and NVB classification. The RMS error, the sum of squared error, and the mean absolute error Are the functioning metrics utilised in the research? Accuracy tests have demonstrated that SVM outperforms NVB.This research discusses a unique machine-learning-based method for predicting cardiovascular disease at an early stage. Based on their clinical signs and medical observations, CVD patients are divided into groups using Support Vector Machines (SVM). Cardiovascular disease is detected by analyzing the health data using the SVM classification method. [8]This study proposes an ensemble-based method for estimating an individual's risk of cardiovascular disease using ML and DL models. This study[30] uses the Cardiovascular Disease dataset. Models of classification: For their experiment[31]We used two deep learning models, DNN and KDNN, together with four machine learning methodologies: RF, KNN, DT, and XGB. With an accuracy gain of 1.47% and an accuracy score of 88.70%, the ML Ensemble model demonstrates how well it performed in detecting cardiovascular illness. The findings showed that the ML Ensemble model had the highest predictive accuracy for cardiovascular illness [32].

Table 2: Overview of ML-based diagnosis of CVD

References	ML Techniques used	Disease Identified	Accuracy
[33]	dual-tree discrete wavelet transform	Coronary artery disease	96.05%
[34]	SVM	myocardial infarction	98.33%
[35]	Random forest, Gradient boosting	Cardiovascular disease (CVD)	99%

[36]	Decision Tree, KNN classifier	CVD	90%
[37]	support vector machine, random forest, and light gradient boosting	cardio-cerebrovascular disease (CVD)	85.3%
[38]	random forest (RF), logistic regression (LR), Naïve Bayes (NB), and support vector machine (SVM)	CVD	92.11%
[39]	gradient boosting, and random forest algorithms	CVD	82%

4. Deep learning methods for earlier diagnosis of CVD

Heart disease, rheumatic heart disease, high blood pressure, and cerebrovascular illness are all frequent conditions known to pose a threat to human health. The detection of CVD primarily uses cardiac ultrasonography, CV angiography, CV magnetic resonance imaging, and CT. Additionally, CV medical imaging is becoming a crucial component of the evaluation and treatment of CVD and is increasingly significant. Currently, classification, detection, and segmentation are the most often used task types in the context of CV radiological image scrutiny[40]. The field of CV diagnostic image interpretation has inscribed the big data aeon due to the quick advancement of medical imaging technologies. The challenge now is to identify meaningful information from an enormous volume of CV anatomical image and give a more reliable foundation for anatomic analysis.

Conventional paradigm acknowledgment or ML techniques used for CV image exploration, however, necessitate a priori removal from the ingenious details in order to instruct the discriminative model, which may lead to over-fitting issues and make generalization difficult to ensure. DL techniques in computer vision have advanced over the past 20 years, and DL algorithms have proven to be fully capable of resolving the problem that traditional CV images present, as well as helping medical professionals achieve high-precision intelligent identification of CVD[41].

i Segmentation

The authors of [42] proposed a vanilla CNN as an accurate method for bulk segmentation of mammographic images. For MG, the method aids in forecasting an accurate pixel-by-pixel segmentation. Use CT scans for myeloma in [43] and put on DL segmentation. The principles of image segmentation and DL, as well as DL frameworks for image segmentation and several effective applications of DL techniques, are covered in [44]. Provide an overview of various picture segmentation methods for the diagnosis of cardiovascular conditions in [45]. They talk about future directions for research and compare how well the strategies perform. Create FCNN in [46] after examining various resolution layers. To identify CVDs, experiments on the topological structure of picture data have been conducted [47]. A faster approach has been developed for predicted initialisation and to obtain a compatible cylindrical topology. Prior to initiating the segmentation process, the authors of [48] have established a foundation for the automatic detection of the region of interest surrounding the let ventricle (LV). In 86% of the cases, the programmed credentials of the ROI were determined to be accurate after applying the entire approach to MICCAI 2009. In a manually managed process, a fully automated step can serve as the initial step to reduce the overall number of interactions. The LV-segmentation paradigm from the image dataset was implemented and examined in [49] by combining DLA and deformable models. Utilizing convolutional networks, the LV chamber has been identified. LV-form layered autoencoders were employed, in sum. Several deep learning models for segmenting pictures of the right and left ventricles are compared in [50]. The hybrid models outperform other stand-alone DL models, as shown in a comparison of convolutional and recurrent models. A dataset of 4,000 photos is used to test the outcomes of several DL techniques.

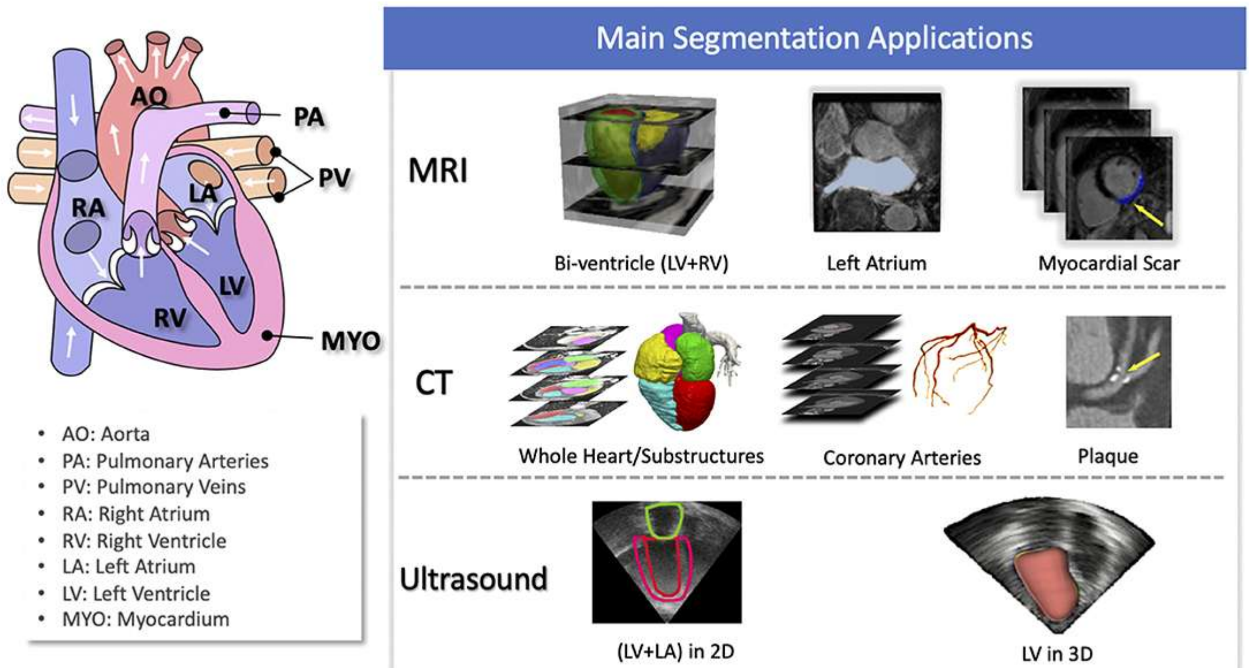

Figure 2: Segmentation of Cardiac images by using CT, MRI and ultrasound[51]

ii. Classification

A branch of AI and ML called deep learning uses unsupervised data to learn. Classical machine learning models can be laborious to scale up. By developing more effective depictions of unorganized information with numerous levels of abstraction, deep learning approaches can get around this problem. Many medical specialities, including cardiology, electroencephalography, pulmonology, inheritance, medical chemistry, pathology, ophthalmology, obstetrics, and gynaecology, use artificial neural networks (ANNs) [52]. Significant research is also being done on the diagnosis of cardiac disease. The multifaceted problem of predicting CVD based on a range of characteristics and symptoms can lead to erroneous assumptions and unpredictable negative outcomes [53]. Because DLT is so skilled at image processing, many AI researchers are creating medical images with Neural Networks to interpret, analyze, and forecast diseases from them. One sort of neural network that is especially well-suited for analysing MRI scans and X-rays is a convolutional neural network, or CNN. These are also more accurate than diagnosticians in imaging investigations, since they can work better with larger images. Accurately detecting the ED and ES frames by an automated image-driven technique is necessary for CVD prediction. In medical applications, including CVD Prediction Systems, Cancer Detection, Tumour Detection, Gene Classification, Neural Cell Classification, etc., CNNs and RNNs (Recurrent Neural Networks) have experienced tremendous growth. The primary benefit of this is that, unlike previous methods, it can automatically identify the crucial characteristics of prediction networks without human involvement [54]. While RNNs may be used to discover temporal correlations, CNNs can help extract image features. In addition, these are computationally more efficient than previous prediction methods. These models can also be used to predict time-series data [55, 56], such as a patient's medical history, electronic health records, electronic prescriptions, and so on, as the data is retained across the network. Regression Modules can receive the final results from these networks in order to make predictions.

Table 3: Overview of DL applied in CVD imaging studies

	Purpose	Imaging Techniques	Techniques	References
Classification	Classification of ECG video Images	Echocardiography	CNN	[57]
	Plaque classification	Intravascular optical coherence tomography	feed-forward neural networks connected to random field	[58]
	Echocardiography video images	ECG	Fusion neural networks	[59]
Segmentation	LV segmentation	MRI	Simplified pulse-coupled neural network	[60]
	RV segmentation	MRI	Deep belief network	[61]
	Myocardium, LV, RV segmentation	ECG	Fully CNN	[62]
	Segmentation of LV	Echocardiography	DBN	[63]

5. Comparative analysis- CVD using Chest CT Image Segmentation and Classification

The tabulated data (Table 4) below provides a comprehensive comparative analysis of the segmentation and classification methodologies employed in earlier research studies for the diagnosis of CVD using CT images. This analytical study aims to evaluate the efficacy of different techniques used in prior research to diagnose CVD. This critique strives to pinpoint the potencies and liabilities of a piece approach and deliver discernment into how these methods can be enhanced in future studies. The outcomes of this study will be instrumental in developing more precise and efficient diagnostic techniques for CVD using CT images.

Table 4: Comparative analysis of previous research

S.no	Author	Segmentation or Classification technique	Outcomes of study	Futuristic recommendation
1.	[64]	Convolutional neural networks	They experimented with classifying healthy and sick hearts using a convolutional neural network based on 2D or 3D patches. Examining CT scans may be useful in rapidly identifying individuals who are at risk of cardiovascular disease.	In order to identify individuals at risk, future research will classify patients based on a single volume of the complete heart and compare them to healthy patients who have experienced a CVD event.
2.	[65]	K-means clustering	Because the spine mask's convex hull could not be generated, the study concluded that segmenting the heart into its four chambers was preferable to segmenting the complete heart.	Their research will go forward using an unsupervised deep-learning strategy to get around constraints.
3.	[66]	-----	Low-dose CT imaging biomarkers can detect early stages of lung cancer, COPD, and CVD. Quitting smoking is the most effective way to reduce the burden of these diseases.	Adding screening for COPD and CVD along with lung cancer can improve the cost-effectiveness of low-dose lung cancer screening in the future. Further studies are needed to confirm this hypothesis.
4.	[67]	CNN	Their research demonstrates that in	In the future, their carcinoma detection tool

			high-risk patients, deep learning can transform LDCT for lung cancer detection into a dual-screening quantitative tool for estimating CVD risk.	needs to be enhanced by using advanced deep learning methods to estimate CVD risk.
5.	[68]	CNN	Multimodal data fusion and machine learning hold promise for cardiovascular medicine research. However, only some use cases have been found to date. Combining data from multiple modalities can address weaknesses. However, complex algorithms and data quality are essential to prevent errors.	Future research should validate the utility of multimodal fusion modelling through prospective studies comparing it to conventional modelling or current standards of care.

6. Discussion

The word "cardiovascular disease" (CVD) describes a collection of disorders affecting the heart and blood vessels, including damage to arteries in the kidneys, heart, brain, eyes, and other organs. Even in young people, CVD is a major cause of death in both industrialized and developing nations globally. To better understand how ML and DL techniques might be used for segmentation and classification, this survey aims to compile recent research on the use of CT scans for CVD prediction. Numerous modalities are covered in [69], including physiological signals, cardiac CT imaging, electronic health data, and heart sounds. The [70] investigated the application of DL approaches for classification in addition to the usage of standard and hybrid ML systems. They also looked at how DL can use CT scans to quickly assess patients at risk of CVD. The study discovered that the drawbacks of DL models can be lessened by using large-sized patches, particularly in 3D patches. The accuracy of the left atrium 3D patch classification was compared with that of a subsample used to evaluate the CNN model [71]. The results showed that using large patches significantly improved the performance of DL models. The authors also compared the accuracy of segmentation results obtained with various models. They found that vanilla CNNs and Fully Convolutional Neural Networks (FCNNs) yielded the most accurate results. Conversely, ResNet needed help to generate precise forecasts. The segmentation outcomes of the real image, the segmentation image, and the anticipated image values were also shown in the [72]. If the models correctly predict the data using the corresponding model, this can be diagrammatically confirmed by the segmentation results. Additionally, [73] investigated how CNN architectures for transfer learning in Intravascular Optical Coherence Tomography (IVOCT) image classification achieved an AUC of 99.72%, surpassing previous studies on cardiac images. According to [74], transfer learning may be a helpful strategy for raising CVD classification accuracy. The [75] combined the Random Forest and Linear models to create a novel prediction model that produced a promising accuracy of 88.7% utilizing hybrid machine learning approaches. According to [76], this method outperformed conventional classifiers and may be useful for CVD prediction. CVD was predicted using SVM in a recent study [77] using patient scans obtained at rest. SVMs present a promising substitute for intrusive therapeutic methods.SVM may be a more useful tool for identifying those at risk of CVD than traditional techniques. This method has broad ramifications for patient care and represents a major breakthrough in medical diagnostics. All things considered, this overview of current studies on the use of ML and DL methods for CT image analysis in CVD prediction provides other researchers with a valuable resource. The study emphasizes how these methods may be used to decrease the requirement for invasive therapy and increase the accuracy of CVD categorization.

i. Distributive analysis

The objective of this study was to analyze the literature on the diagnosis of CVD through the use of CT scans. A total of 77 papers from the period 2000 to 2023 were included in our review. We thoroughly evaluated the literature, reviewing one paper in each of the years 2000, 2002, 2010, 2011, 2012, and 2016. Two papers were reviewed in 2014, while in 2013 and 2015, three papers were reviewed each. In 2017, we examined five papers, and in 2018, we sourced 11 papers. In 2019, 13 papers were reviewed, and in 2020, 12 papers underwent evaluation. Ten papers were evaluated in 2021, while six papers each were reviewed in 2022 and 2023. Our literature review provides a comprehensive overview of the current state of knowledge on the use of CT scans for the diagnosis of CVD. This study's results have consequential essences for clinical trials and emphasize the necessity for further investigation in this area.

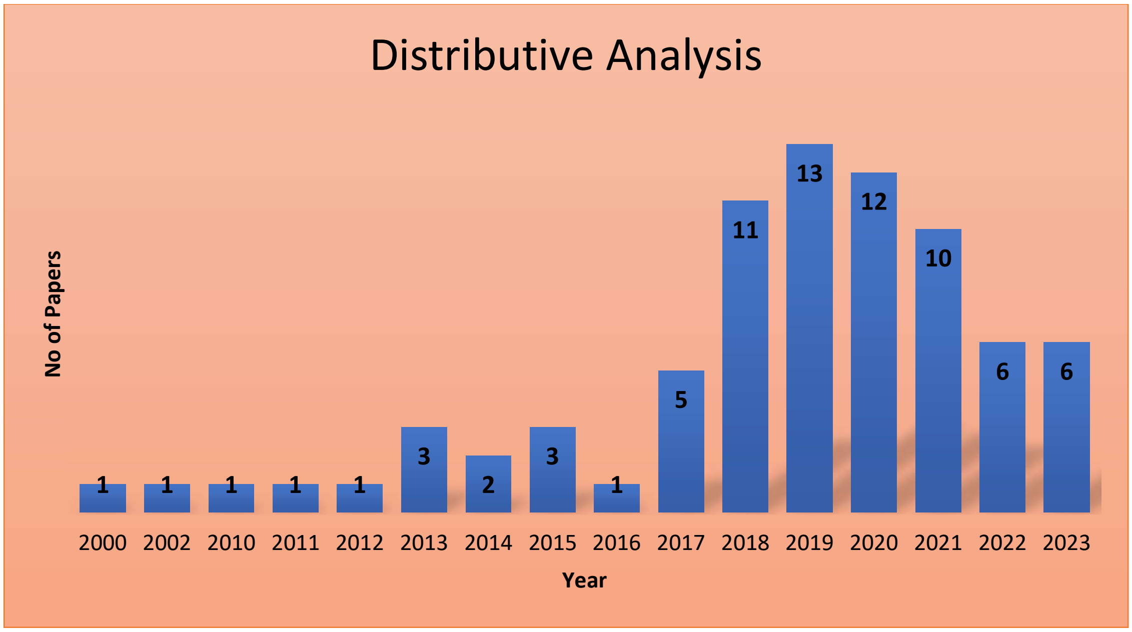

Figure 3: Bar chart of Distributive analysis

7. Conclusion

Worldwide, CVDs damage blood vessels and the heart. The most serious kinds are myocarditis, HCD, CAD, arrhythmia, and heart failure. CVDs are often brought on by fatty deposits in the arteries and blood clots. Unchecked high blood pressure narrows blood vessels by thickening and hardening the arteries. In this paper, we suggest a meticulous analysis of how chest CT scans and ML and DL methods are used to diagnose CVD. We investigate key elements of machine learning and deep learning models, including image segmentation and classification, used for the diagnosis of cardiovascular disease. Seventy-seven academic papers were examined and collected for this research from reliable databases such as Google Scholar, PubMed, and Springer. To conduct our research, we compared the diagnostic methods used in these trials with those in earlier studies and thoroughly assessed their effectiveness at identifying CVD. After performing comprehensive research, we have concluded that algorithms utilising ML and DL have significant promise in transforming the diagnosis of CVD. These computational methods may effectively identify and separate CVD-related anomalies from chest computed tomography (CT) scans, enabling prompt, efficient intervention and, ultimately, better patient outcomes. Furthermore, our review indicates that the creation of useful tools for CVD detection that utilize ML and DL algorithms is becoming closer. Diagnosis techniques need to be precise and effective because CVD is becoming more and more common. Although DL and ML approaches have shown promise in improving CVD diagnosis, more research is needed to realize their full potential. This study highlights the crucial role that ML and DL methods can play in diagnosing CVD and underscores the importance of continued research in this field. We can improve patient outcomes and lessen the burden of this crippling condition by utilizing these potent tools to improve our capacity to identify and treat CVD.

REFERENCES

[1] B. Patel and P. Sengupta, "Machine learning for predicting cardiac events: what does the future hold?," Expert review of cardiovascular therapy, vol. 18, no. 2, pp. 77-84, 2020.

[2] M. Kavitha, G. Gnaneswar, R. Dinesh, Y. R. Sai, and R. S. Suraj, "Heart disease prediction using hybrid machine learning model," in 2021 6th international conference on inventive computation technologies (ICICT), 2021: IEEE, pp. 1329-1333.

[3] P. C. Jacobs et al., "Coronary artery calcium can predict all-cause mortality and cardiovascular events on low-dose CT screening for lung cancer," American Journal of Roentgenology, vol. 198, no. 3, pp. 505-511, 2012.

[4] C. Chiles et al., "Association of coronary artery calcification and mortality in the national lung screening trial: a comparison of three scoring methods," Radiology, vol. 276, no. 1, pp. 82-90, 2015.

[5] Gupta, Rajesh, Nutan Gusain, Bajirao Subhash Shirole, Mahendra T. Jagtap, Sanjose A. Thomas, and S. A. N. T. O. S. H. Kumar. "Optimizing healthcare management systems with AI and machine learning." *South Eastern European Journal of Public Health* (2025): 2973-2985.

[6] B. D. De Vos et al., "Automatic machine learning based prediction of cardiovascular events in lung cancer screening data," in Medical Imaging 2015: Computer-Aided Diagnosis, 2015, vol. 9414: SPIE, pp. 85-90.

[7] C. Iribarren, S. Sidney, B. Sternfeld, and W. S. Browner, "Calcification of the aortic arch: risk factors and association with coronary heart disease, stroke, and peripheral vascular disease," Jama, vol. 283, no. 21, pp. 2810-2815, 2000.

[8] T. A. Pearson et al., "AHA guidelines for primary prevention of cardiovascular disease and stroke: 2002 update: consensus panel guide to comprehensive risk reduction for adult patients without coronary or other atherosclerotic vascular diseases," Circulation, vol. 106, no. 3, pp. 388-391, 2002.

[9] S. G. van Velzen et al., "Deep learning for automatic calcium scoring in CT: validation using multiple cardiac CT and chest CT protocols," Radiology, vol. 295, no. 1, pp. 66-79, 2020.

[10] G. Singh et al., "Machine learning in cardiac CT: basic concepts and contemporary data," Journal of Cardiovascular Computed Tomography, vol. 12, no. 3, pp. 192-201, 2018.

[11] H. Kirişli et al., "Standardized evaluation framework for evaluating coronary artery stenosis detection, stenosis quantification and lumen segmentation algorithms in computed tomography angiography," Medical image analysis, vol. 17, no. 8, pp. 859-876, 2013.

[12] M.K. Gaddam, "Architecting Observability for AI-Driven Microservices at Scale." In 2025 3rd International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI), pp. 1830-1838. IEEE, 2025.

[13] W. C. Members et al., "2010 ACCF/AHA guideline for assessment of cardiovascular risk in asymptomatic adults: executive summary: a report of the American College of Cardiology Foundation/American Heart Association Task Force on Practice Guidelines," Circulation, vol. 122, no. 25, pp. 2748-2764, 2010.

[14] V. Sharma, "Interoperability and Vendor Neutrality in O-RAN Deployments." International Journal of Emerging Trends in Computer Science and Information Technology (2025): 88-94.

[15] M. S. Haleem et al., "Time adaptive ECG driven cardiovascular disease detector," Biomedical Signal Processing and Control, vol. 70, p. 102968, 2021.

[16] J. Patel, D. TejalUpadhyay, and S. Patel, "Heart disease prediction using machine learning and data mining technique," Heart Disease, vol. 7, no. 1, pp. 129-137, 2015.

[17] A. Singh and R. Kumar, "Heart disease prediction using machine learning algorithms," in 2020 international conference on electrical and electronics engineering (ICE3), 2020: IEEE, pp. 452-457.

[18] M. A. Alim, S. Habib, Y. Farooq, and A. Rafay, "Robust heart disease prediction: a novel approach based on significant feature and ensemble learning model," in 2020 3rd international conference on computing, mathematics and engineering technologies (iCoMET), 2020: IEEE, pp. 1-5.

[19] N. B. Muppalaneni, M. Ma, S. Gurumoorthy, R. Kannan, and V. Vasanthi, "Machine learning algorithms with ROC curve for predicting and diagnosing the heart disease," Soft computing and medical bioinformatics, pp. 63-72, 2019.

[20] R. Atallah and A. Al-Mousa, "Heart disease detection using machine learning majority voting ensemble method," in 2019 2nd international conference on new trends in computing sciences (ictcs), 2019: IEEE, pp. 1-6.

[21] S.L. Bandla, "Modeling and Optimization of Blood Circulation for Improved Cardiovascular Health." Authorea Preprints (2025).

[22] A. Ed-Daoudy and K. Maalmi, "Real-time machine learning for early detection of heart disease using big data approach," in 2019 international conference on wireless technologies, embedded and intelligent systems (WITS), 2019: IEEE, pp. 1-5.

[23] S. Mohan, C. Thirumalai, and G. Srivastava, "Effective heart disease prediction using hybrid machine learning techniques," IEEE access, vol. 7, pp. 81542-81554, 2019.

[24] S.L. Bandla, "Neural Stem Cells and Their Role in Regenerative Therapies for Spinal Cord Injury and Neurodegenerative Diseases." Authorea Preprints (2025).

[25] M. R. Avendi, A. Kheradvar, and H. Jafarkhani, "Automatic segmentation of the right ventricle from cardiac MRI using a learning-based approach," Magnetic resonance in medicine, vol. 78, no. 6, pp. 2439-2448, 2017.

[26] Z. Xu and R. Jiang, "Cardiac CT image segmentation," in 2016 4th International Conference on Machinery, Materials and Information Technology Applications, 2017: Atlantis Press, pp. 1291-1294.

[27] E. Sehirli and M. K. Turan, "A novel method for segmentation of QRS complex on ECG signals and classify cardiovascular diseases via a hybrid model based on machine learning," International Journal of Intelligent Systems and Applications in Engineering, vol. 9, no. 1, pp. 12-21, 2021.

[28] A. Golande and T. Pavan Kumar, "Heart disease prediction using effective machine learning techniques," International Journal of Recent Technology and Engineering, vol. 8, no. 1, pp. 944-950, 2019.

[29] F. S. Alotaibi, "Implementation of machine learning model to predict heart failure disease," International Journal of Advanced Computer Science and Applications, vol. 10, no. 6, 2019.

[30] N. M. Lutimath, C. Chethan, and B. S. Pol, "Prediction of heart disease using machine learning," International journal Of Recent Technology and Engineering, vol. 8, no. 2, pp. 474-477, 2019.

[31] V. Bharadwaj Meruga, P.V. N. Raju, "Neuro Vision: Deep Learning Framework for Automated Brain Tumor Detection and Classification," Proceedings of the 5th International Conference on Communication, Computing and Electronics Systems (ICCCES-2026), 341-345, 2026.

[32] A. Alqahtani, S. Alsubai, M. Sha, L. Vilcekova, and T. Javed, "Cardiovascular disease detection using ensemble learning," Computational Intelligence and Neuroscience, vol. 2022, 2022.

[33] U. Raghavendra et al., "Automated technique for coronary artery disease characterization and classification using DD-DTDWT in ultrasound images," Biomedical Signal Processing and Control, vol. 40, pp. 324-334, 2018.

[34] A. K. Dohare, V. Kumar, and R. Kumar, "Detection of myocardial infarction in 12 lead ECG using support vector machine," Applied Soft Computing, vol. 64, pp. 138-147, 2018.

[35] S. Shu, J. Ren, and J. Song, "Clinical application of machine learning-based artificial intelligence in the diagnosis, prediction, and classification of cardiovascular diseases," Circulation Journal, vol. 85, no. 9, pp. 1416-1425, 2021.

[36] Jansi, S., Vishal Bharadwaj Meruga, Leeladhar Gudala, Bharath Kumar Eilane, P. Venkateswarlu Reddy, and D. Ganesh. "Edge-AI Perimeter Surveillance for Autonomous Wildlife-Conflict Mitigation." In 2025 5th International Conference on Evolutionary Computing and Mobile Sustainable Networks (ICECMSN), pp. 1654-1658. IEEE, 2025.

[37] T. Oh et al., "Machine learning-based diagnosis and risk factor analysis of cardiocerebrovascular disease based on KNHANES," Scientific reports, vol. 12, no. 1, p. 2250, 2022.

[38] Dhivya, R., Sreenivas Reddy Sagili, Purushothapatnapu Naga Venkata VamsiLala, and A. Sangeetha. "Predictive Modelling of Osteoporosis using Machine Learning Algorithms." In 2024 4th International Conference on Ubiquitous Computing and Intelligent Information Systems (ICUIS), pp. 997-1002. IEEE, 2024.

[39] J. O. Kim, Y.-S. Jeong, J. H. Kim, J.-W. Lee, D. Park, and H.-S. Kim, "Machine learning-based cardiovascular disease prediction model: a cohort study on the Korean national health insurance service health screening database," Diagnostics, vol. 11, no. 6, p. 943, 2021.

[40] K. Subhadra and B. Vikas, "Neural network based intelligent system for predicting heart disease," International Journal of Innovative Technology and Exploring Engineering, vol. 8, no. 5, pp. 484-487, 2019.

[41] S. Mukherjee and A. Sharma, "Intelligent heart disease prediction using neural network," International Journal of Recent Technology and Engineering, vol. 30, no. 5, 2019.

[42] D. Abdelhafiz, J. Bi, R. Ammar, C. Yang, and S. Nabavi, "Convolutional neural network for automated mass segmentation in mammography," BMC bioinformatics, vol. 21, pp. 1-19, 2020.

[43] A. Bhan, P. Mangipudi, and A. Goyal, "An assessment of machine learning algorithms in diagnosing cardiovascular disease from right ventricle segmentation of cardiac magnetic resonance images," Healthcare Analytics, vol. 3, p. 100162, 2023.

[44] R. Ghali and M. A. Akhloufi, "Deep Learning Approaches for Wildland Fires Remote Sensing: Classification, Detection, and Segmentation," Remote Sensing, vol. 15, no. 7, p. 1821, 2023.

[45] S. Minaee, Y. Boykov, F. Porikli, A. Plaza, N. Kehtarnavaz, and D. Terzopoulos, "Image segmentation using deep learning: A survey," IEEE transactions on pattern analysis and machine intelligence, vol. 44, no. 7, pp. 3523-3542, 2021.

[46] D. Mishra, S. Chaudhury, M. Sarkar, and A. S. Soin, "Ultrasound image segmentation: a deeply supervised network with attention to boundaries," IEEE Transactions on Biomedical Engineering, vol. 66, no. 6, pp. 1637-1648, 2018.

[47] S. Queirós et al., "Fast automatic myocardial segmentation in 4D cine CMR datasets," Medical image analysis, vol. 18, no. 7, pp. 1115-1131, 2014.

[48] Sagili, Sreenivas Reddy, Chandrashekhar Goswami, V. C. Bharathi, S. Ananthi, K. Rani, and R. Sathya. "Identification of Diabetic Retinopathy by Transfer Learning Based Retinal Images." In 2024 9th International Conference on Communication and Electronics Systems (ICCES), pp. 1149-1154. IEEE, 2024.

[49] N. Painchaud, Y. Skandarani, T. Judge, O. Bernard, A. Lalande, and P.-M. Jodoin, "Cardiac segmentation with strong anatomical guarantees," IEEE transactions on medical imaging, vol. 39, no. 11, pp. 3703-3713, 2020.

[50] Sagili, Sreenivas Reddy, Senthilnathan Chidambaranathan, Nagarjuna Nallametti, Harana M. Bodele, Laxmi Raja, and P. G. Gayathri. "NeuroPCA: Enhancing Alzheimer's disorder Disease Detection through Optimized Feature Reduction and Machine Learning." In 2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), pp. 1-9. IEEE, 2024.

[51] Reddy, Kunam Subba, Monelli Ayyavaraiah, B. Lalithadevi, A. Mohanadevi, Sreenivas Reddy Sagili, and V. C. Bharathi. "Implementation of InceptionV3 Model for Skin Disease Detection and Classification." In 2025 6th International Conference on Mobile Computing and Sustainable Informatics (ICMCSI), pp. 1479-1485. IEEE, 2025.

[52] M. I. Hassan, A. H. Osman, and E. M. Hussein, "Heart Disease Diagnosis Using Diverse Neural Network Categories," in Emerging Trends in Intelligent Computing and Informatics: Data Science, Intelligent Information Systems and Smart Computing 4, 2020: Springer, pp. 373-385.

[53] R. Bharti, A. Khamparia, M. Shabaz, G. Dhiman, S. Pande, and P. Singh, "Prediction of heart disease using a combination of machine learning and deep learning," Computational intelligence and neuroscience, vol. 2021, 2021.

[54] Sagili, Sreenivas Reddy. "Leveraging Linear Discriminant Analysis for the Onset of Parkinson's Disorder." In 2024 Asian Conference on Intelligent Technologies (ACOIT), pp. 1-5. IEEE, 2024.

[55] S. Ambekar and R. Phalnikar, "Disease risk prediction by using convolutional neural network," in 2018 Fourth international conference on computing communication control and automation (ICCUBEA), 2018: IEEE, pp. 1-5.

[56] Y. An, N. Huang, X. Chen, F. Wu, and J. Wang, "High-risk prediction of cardiovascular diseases via attention-based deep neural networks," IEEE/ACM transactions on computational biology and bioinformatics, vol. 18, no. 3, pp. 1093-1105, 2019.

[57] Viswanathan, R., N. M. Anirudh, and N. V. Keerthana. "Detecting Fetal Brain Abnormalities from Ultrasound Images by Deep Learning Methods." In 2025 7th International Conference on Innovative Data Communication Technologies and Application (ICIDCA), pp. 1238-1243. IEEE, 2025.

[58] C. Kolluru, D. Prabhu, Y. Gharaibeh, H. Bezerra, G. Guagliumi, and D. Wilson, "Deep neural networks for A-line-based plaque classification in coronary intravascular optical coherence tomography images," Journal of Medical Imaging, vol. 5, no. 4, pp. 044504-044504, 2018.

[59] X. Gao, W. Li, M. Loomes, and L. Wang, "A fused deep learning architecture for viewpoint classification of echocardiography," Information Fusion, vol. 36, pp. 103-113, 2017.

[60] Y. Ma, L. Wang, Y. Ma, M. Dong, S. Du, and X. Sun, "An SPCNN-GVF-based approach for the automatic segmentation of left ventricle in cardiac cine MR images," International Journal of Computer Assisted Radiology and Surgery, vol. 11, pp. 1951-1964, 2016.

[61] Tripathi, Bhaskar, Senthilnathan Chidambaranathan, Thangavel Murugan, Shermin Shamsudheen, Bhraguram Thayyil Madhusudana Panicker, Anne Anoop, Nithya Rekha Sivakumar et al. "Deep learning-based facial recognition system with privacy-preserving features." U.S. Patent Application 19/214,023, filed September 11, 2025.

[62] Sagili, Sreenivas Reddy, K. Veeranjaneyulu, Balaram Puli, Pandian Sundaramoorthy, R. Murugadoss, and N. V. Keerthana. "Advancing Cervical Cancer Identification using Generative-based Adversarial Networks: An Integrative Learning Methodology." In 2025 6th International Conference for Emerging Technology (INCET), pp. 1-5. IEEE, 2025.

[63] G. Carneiro, J. C. Nascimento, and A. Freitas, "The segmentation of the left ventricle of the heart from ultrasound data using deep learning architectures and derivative-based search methods," IEEE Transactions on Image Processing, vol. 21, no. 3, pp. 968-982, 2011.

[64] J. D. Dormer, M. Halicek, L. Ma, C. M. Reilly, E. Schreibmann, and B. Fei, "Convolutional neural networks for the detection of diseased hearts using CT images and left atrium patches," in Medical Imaging 2018: Computer-Aided Diagnosis, 2018, vol. 10575: SPIE, pp. 671-677.

[65] B. Rim, S. Lee, A. Lee, H.-W. Gil, and M. Hong, "Semantic cardiac segmentation in chest CT images using K-means clustering and the mathematical morphology method," Sensors, vol. 21, no. 8, p. 2675, 2021.

[66] M. A. Heuvelmans et al., "Screening for early lung cancer, chronic obstructive pulmonary disease, and cardiovascular disease (the Big-3) using low-dose chest computed tomography: current evidence and technical considerations," Journal of thoracic imaging, vol. 34, no. 3, pp. 160-169, 2019.

[67] Sharma, Adarsh, Himanshu Sharma, Sudeep Varshney, and Nutan Gusain. "Heart Disease Prediction: A Comparative Analysis of Machine Learning Algorithms." *Journal Press India* 3, no. 2 (2023).

[68] S. Amal, L. Safarnejad, J. A. Omiye, I. Ghanzouri, J. H. Cabot, and E. G. Ross, "Use of multi-modal data and machine learning to improve cardiovascular disease care," Frontiers in cardiovascular medicine, vol. 9, p. 840262, 2022.

[69] Gusain, Nutan. "Cardiovascular Disease Prediction through Machine Learning: A Comparative Study of Ensemble Techniques." *Revolutionary Advances in Computing and Electronics: An International Journal* (2025): 27-40. [70] A. Fantazzini et al., "3D automatic segmentation of aortic computed tomography angiography combining multi-view 2D convolutional neural networks," Cardiovascular engineering and technology, vol. 11, pp. 576-586, 2020.

[71] J. V. Sundgaard, K. A. Juhl, K. F. Kofoed, and R. R. Paulsen, "Multi-planar whole heart segmentation of 3D CT images using 2D spatial propagation CNN," in Medical Imaging 2020: Image Processing, 2020, vol. 11313: SPIE, pp. 477-484.

[72] J. D. Dormer, L. Ma, M. Halicek, C. M. Reilly, E. Schreibmann, and B. Fei, "Heart chamber segmentation from CT using convolutional neural networks," in Medical Imaging 2018: Biomedical Applications in Molecular, Structural, and Functional Imaging, 2018, vol. 10578: SPIE, pp. 659-664.

[73] M. Miyagawa, M. G. F. Costa, M. A. Gutierrez, J. P. G. F. Costa, and C. F. F. Costa Filho, "Detecting vascular bifurcation in IVOCT images using convolutional neural networks with transfer learning," Ieee Access, vol. 7, pp. 66167-66175, 2019.

[74] C. M. Bhatt, P. Patel, T. Ghetia, and P. L. Mazzeo, "Effective heart disease prediction using machine learning techniques," Algorithms, vol. 16, no. 2, p. 88, 2023.

[75] E. Dritsas and M. Trigka, "Efficient data-driven machine learning models for cardiovascular diseases risk prediction," Sensors, vol. 23, no. 3, p. 1161, 2023.

[76] C. B. C. Latha and S. C. Jeeva, "Improving the accuracy of prediction of heart disease risk based on ensemble classification techniques," Informatics in Medicine Unlocked, vol. 16, p. 100203, 2019.

[77] O. Taylan, A. S. Alkabaa, H. S. Alqabbaa, E. Pamukçu, and V. Leiva, "Early prediction in classification of cardiovascular diseases with machine learning, neuro-fuzzy and statistical methods," Biology, vol. 12, no. 1, p. 117, 2023.