A Systematic Literature Review on Automatic Recognition and Classification of Coronary Atherosclerosis

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Cardiovascular diseases have a high morbidity rate and per year it leads to 17 million deaths worldwide. Coronary Atherosclerosis is one of the chief causes of stroke and progressive heart disease marked by lipids and fibrous elements accumulation in the arteries. Artificial intelligence (AI) has established remarkable progress in recent times in clinical practice helping patients and healthcare professionals in the accurate and faster diagnosis of diseases. Prediction models in the identification of Atherosclerosis have set foot in the academic literature to assist in making medical decisions during urgent circumstances. This paper aimed to systematically review automatic atherosclerotic plaque detection algorithms. The advantages of these latest techniques in automatic recognition of atherosclerotic plaque, its composition, classification strategy and future predictions in terms of severity are elucidated in this review with limitations and research gaps. The findings suggest that deep learning models are the future of diagnosis and ensemble learning algorithms are best in non-invasive accurate detection of cardiovascular diseases.

Keywords: Atherosclerosis, Coronary Artery Diseases, Artificial Intelligence (AI), Non-Invasive Techniques, Deep Learning, Ensemble Learning.

2023. In Saroj Hiranwal & Garima Mathur (eds.), *Artificial Intelligence and Communication Technologies*, 409–427. Computing & Intelligent Systems, SCRS, India. https://doi.org/10.52458/978-81-955020-5-9-39

1 Introduction

Diagnostic assessments and clinical feasibility in detection of coronary heart disease have brought out incessant techniques and painful invasive procedures over the decades. Conventional retrospective invasive approaches in the diagnostic field has raised serious concerns which led to the advent of non-invasive approaches towards the detection of coronary artery disease (CAD), associated with pathologic process that affects coronary arteries called as Atherosclerosis, is asymptomatic even for several years[54]. A chronic inflammation disease of blood vessels is Atherosclerosis, triggered by various stimuli. Atherosclerosis is characterized by complex subintimal plaque formation restricting the flow of blood and has a tendency to erode or rupture leading to tissue damage and fibrosis[51]. Plaques are composed of lipids that constitute low-density lipoprotein accumulation that stimulates active inflammatory reactions in the arteries. Atherosclerosis results in stroke, heart attacks and peripheral arterial diseases.There are several risk factors that could cause atherosclerosis such as hypertension, hyperglycaemia, hypercholesterolemia, smoking and other genetic factors[12]. There are other risk factors like obesity, sedentary lifestyle, diet rich in saturated and trans-fatty acids.

CHD is likely cause of death and is rapidly increasing Worldwide. Events associated with CHD are apparently reported in healthy population with few or none of risk factors. Cardiovascular diseases have a high morbidity rate and per year it leads to 17 million deaths worldwide. CAD has mortality rate of 7 million annually [3]. About 33% to 65% of events of atherosclerosis incidence reported in men and in women it is observed to be 28% to 58% [37]. CHD is now observed even in middle age persons due to lifestyle factors and has a lower morbidity rate [21]. The prevalence of atherosclerosis is increased in the asymptomatic adults recently. The identification of the disease in the asymptomatic phase itself is the need of the hour to reduce the mortality in developing countries [7].

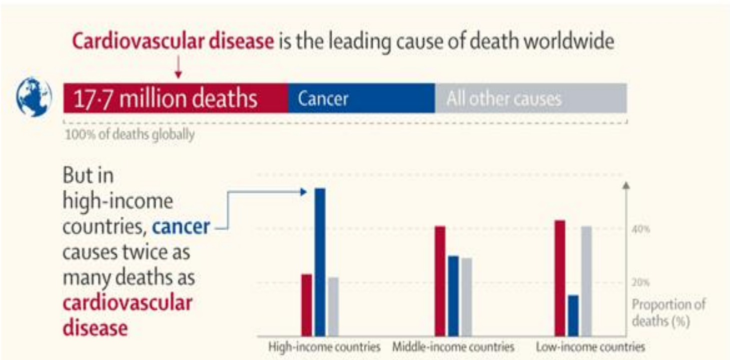

Fig. 1. Mortality rate of cardiovascular diseases in the World (**Source**: Lancet.com)

The detection indicators of coronary atherosclerosis used are calculated for its total cholesterol HDL and LDL, CRP levels and triglycerides in case of diabetes patients fasting plasma glucose [9] and ECG(Electrocardiogram). Silent episodes of CHD are detected by electrocardiographic changes. There are invasive methods in the detection process such as coronary angiography using cardiac catheterisation is known as conventional invasive method. Coronary angiography is referred to as the state of the art for its ability in coronary stenosis assessment and quality control of revascularization performed. However, it has a risk of serious complications. Non-invasive detection methods are employed to detect CHD. Coronary angiography without catheterisation is called Computer Tomography (CT) coronary angiography, it fulfils high technicality in rapid identification of coronary stenosis with true positive diagnosis at a lower cost [23].

Non-invasive techniques are modern imaging techniques to detect atherosclerosis and also facilitate in assessing the composition of the plaque and activity. For several decades, obstruction of luminal stenosis has been the clinical approach imaging of atherosclerosis. The intensity of luminal stenosis present in the carotid artery is diagnosed by using ultrasonography, magnetic resonance (MR) angiography and coronary computed tomography angiography (CTA) to decide on revascularization surgery[30]. CTA assess severity of luminal stenosis, functionality and flow reserve fraction, on the contrary myocardial results of plaque obstruction is only detected by myocardial stress perfusion imaging and stress echocardiography techniques. CTA renders high-resolution anatomic imaging of carotid arteries to identify plaque characteristics which need radiation and iodine contrast [18].

CTA is assessed to be less in sensitivity and specificity compared to MR angiography specially used in atherosclerotic characterization of plaques and for carotid plaque imaging with high resolution and detailed visualization. It also calculates thickness, volume and area of carotid plaque. Multispectral imaging is used to classify various types of tissue, quantification of lipid content and detection of fibrous rupture cap of carotid plaque. The ability of MR angiography is enhanced by administration of contrast of gadolinium to distinguish lipid core from fibrotic cap [19]. MR angiography operates with ultrasmall super-paramagnetic particles of iron oxide (USPIO) in targeting inflammation of atherosclerotic plaques. The increased uptake of USPIO indicates carotid artery plaques in cases after stroke attack and also in carotid stenosis asymptomatic patients[56]. Among different diagnostic methods employed, automatic detection of pattern recognition of abnormalities in heart and its classification has considerable advantages. With the advent of computer aided diagnostic systems with deep learning methods used in detection of pattern recognition will enable targeted focus on the treatment plan [29].

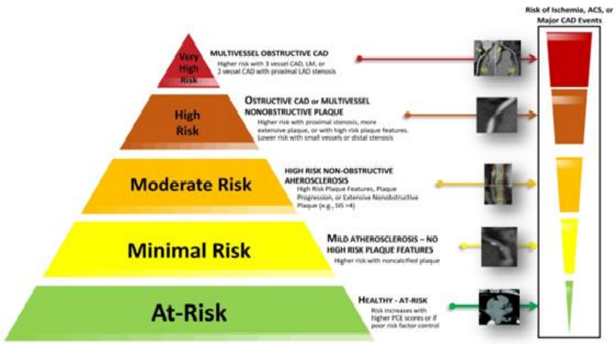

Fig. 2. a)Illustrations of Stages of Atherosclerosis by CCTA [55]

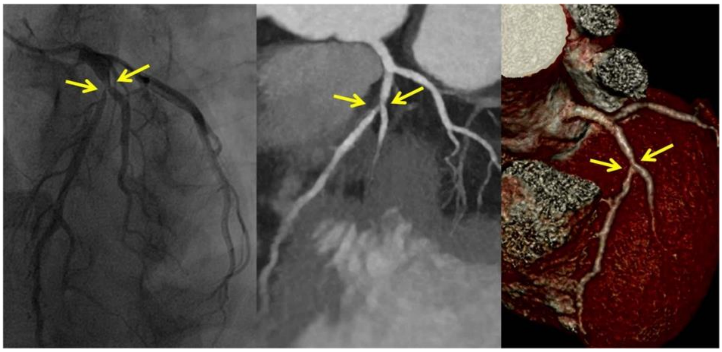

Fig. 3. a) Diagnosis by invasive method of coronary angiography b) by coronary computed tomographic angiography c) images of iterative model reconstruction algorithm [36].

2 Background

Artificial intelligence (AI) is the fifth industrial revolution triggering a great transformation of society. The scope of AI lies in image interpretation, diagnosis prediction with machine learning as well as deep neural network tools in three levels of AI – aided image interpretation, diagnostic findings, prediction and prognostication. AI has significant applications in medical imaging and in medicine due to its accurate prediction and analysis of complex medical data with minimum error and improved quality of life. AI tools facilitate the health providers to detect and treat patients with at most scrutiny and efficacy[46]. Deep learning infiltrates the medical field in image interpretation algorithms on detection techniques such as CT, chest radiography, Magnetic resonance imaging (MRI) and ultrasound (US). Deep learning algorithms function with pre-existing architecture like AlexNet, VGG, Inception and others which are complex deep learning network structures [11]. AI alludes to machine learning belonging to numerous types of networks then especially refers to deep neural systems that detects subtle pattern recognition in nonlinear manner to read mammograms and ECGs. Machine learning is a tool that incorporates risk factors of non-traditional and unknown origin implemented in cardiovascular risk stratification [43]. Radiomics, Machine and deep learning is applied to assess non-invasively coronary atherosclerosis by coronary CT angiography (CCTA). Radiomics, a phenotypic precision method, creates a phenogram of atherosclerotic plaque, a fingerprint that describes specific lesion where radiomics is fed as an input to ML in identification. DL raises the accuracy of diagnosis in myocardium characterization from images of CCTA [33].

Deep learning features surpass conventional methods with its accuracy, specificity and sensitivity and change modelling of computer aided diagnosis [42]. Data augmentation is another technique in deep learning in which the quantity of training samples is increased with the similar raw data that identifies complex hidden information by image segmentation in cardiac imaging on a continuous basis [34]. Risk analysis of cardiovascular diseases is performed with deep learning approaches such as Autoencoder and Softmax for classification and feature extraction, output of Softmax is risk interpretation between environmental status and cardiovascular diseases[28]. Deep learning algorithms classify video of electrocardiography without ECG data, signifying the use of computer aids in the advancement of the diagnostic field. Multi-layer perceptron (MLP) study is used in prediction of coronary artery disease from CTA.

Convolutional Neural Network (CNN) refers to neural framework advancement built upon multi-layer perceptron architecture in exploiting strong spatial local correlation observed in the medical image.

Deep learning solves issues exhibited by non-learning-based methods effectively and segmentation accuracy is improved[65]. Artificial neural networks (ANN) are networks which are fully connected that identify the relationship among different clinical variables not noticed by clinicians. CNN acts as a detection software in annotating lesions/defects in image unnoticed by physicians, it has detected obstructive CAD from SPECT myocardial imaging [20]. Recurrent neural network (RNN) classified under neural networks, known for its specialization in processing sequential data. It utilizes recurrent layers in learning the clinical text representation in contrast to CNN. There are three variants of RNN in extracting cardiac risk factors from electronic medical records such as long short-term memory (LSTM), second variant is gated recurrent unit (GRU) and third variant is bidirectional long short-term memory (BLSTM). Applicability of deep learning is compared with hybrid approaches in classification of clinical text [16]. Machine learning systems lack a smart system to utilize varied sources of data as it uses conventional methods in predicting heart disease.

An alternate automated approach with variables of myocardial deformation and machine learning models provides a system of rapid decision support from 2D ultrasound of cardiac images that derives left ventricular filling pressure (LVFP) information. An ensemble prototypical of Machine Learning algorithms is implemented in a speckle tracking echocardiography (STE) predicted elevated LVFP same as invasively measured by right cardiac catheterization [53]. Deep learning outperforms traditional learning methods in analysis of complex data as in images and text, extracts key features from unstructured raw data and returns as classification or regression as output. Direct diagnosis and auto-analysis is possible using deep learning from echocardiographic images, best studied signal for cardiovascular diseases[31]. VanRosendael, A. R*et al.*, [63] provides a cardiac CTs utility overview for risk stratifying patients on the basis of assessment of atherosclerotic plaque. Three CCTA features put forth as a powerful risk assessment for patients with suspected CAD. First CCTA feature was exclusion associated with very low risk assessment of myocardial infarction at follow-up of 5 years. Second feature was detection of non-obstructive CAD undetectable by stress testing. Third feature was detection of obstructive CAD led to prevention of coronary artery revascularization. CCTA is the tool of central imaging for patients triaging with possible CAD diagnosis. A bibliometric and content analysis was performed [61]. Uncovered AI models in medical diagnostics in robotics in cardiac surgery in 20.4% publications and in stroke rehabilitation in 22.8% publications with more convenient, better, faster and safer management. It is utilized to make a rapid screening process and prognostication of heart diseases.

3 Research Methodology

A systematic literature review was executed descriptively as per the directions of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [49]. The prime aim of this systematic review of literature is to target automatic recognition in coronary atherosclerosis and its implementation of neural networks, deep learning and ensemble learning algorithms in screening of CAD in asymptomatic individuals, diagnosis of CAD with accuracy and prediction in symptomatic population and preventing serious complications. The following research questions are considered during the conduction of systematic literature review process:

RQ1. What are the recent advancements in coronary atherosclerosis detection?

RQ2. How deep learning is applied in automatic recognition of atherosclerosis?

RQ3. How ensemble learning algorithms could improve the process of atherosclerosis detection and classification?

3.1 Search Terms

A structured search of articles published in reference to the keywords 'coronary atherosclerosis', 'automatic recognition in cardiovascular diseases', 'Angiographic plaque detection', 'Prediction of coronary heart disease', 'Artificial intelligence in recognition','Deep learning algorithms in Atherosclerosis', 'Ensemble learning algorithms', 'neural networks in detection', ' CT Angiography', were searched in PubMed, Scopus, Medline, Springer, Taylor & Francis, Scopus, Science direct and Google Scholar extensively from database published between 2012 to 2021. A total of 200 articles were obtained from the search strategy.

3.2 Inclusion and Exclusion Criteria

Studies consisting of atherosclerosis CAD in prediction, published in well-renowned peer-reviewed journals are categorized in the inclusion criteria. The data of the studies evaluated independently and 200 articles were initially categorized and was reduced to 160 after the removal of duplicates. 160 abstracts were analysed further for relevancy and lead to the exclusion of titles/abstracts lack Atherosclerosis/CAD resulted in 130 articles with 30 being excluded. Manuscripts which did not have prediction, detection methods in coronary atherosclerosis were excluded and resulted in 95 studies. Complete evaluation of the studies streamlined in context to the artificial intelligence, deep learning and ensemble learning algorithms in coronary atherosclerosis resulted in 39 studies with 56 studies being excluded for not in relevance with algorithms in detection and classification. Among various algorithms used in the detection of coronary atherosclerosis, deep learning and ensemble learning algorithms involved in precision diagnosis and classification of CAD was assessed in the manuscripts which resulted in 39 studies from the search strategy and eligible for qualitative review synthesis illustrated in PRISMA flowchart in Figure 4.

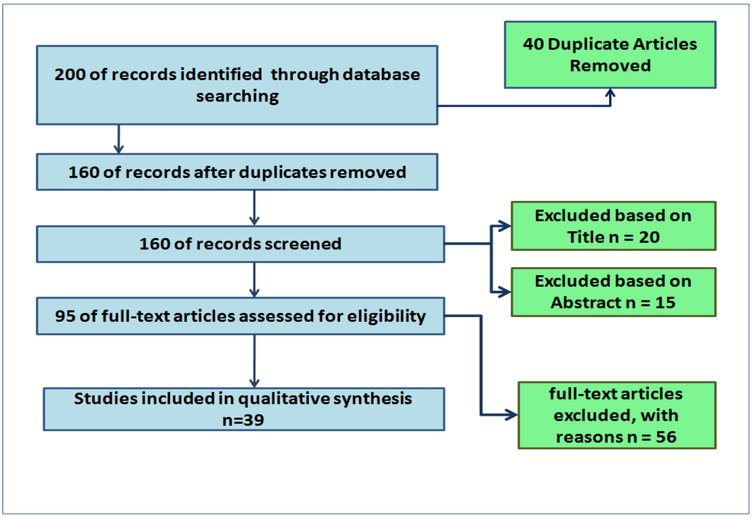

Fig. 4. Flowchart of article selection

3.3 Qualitative Review Synthesis

Seminal contributions have been made by number of studies earlier on imaging techniques established past years in radiology, CT, MRI to identify coronary atherosclerosis for its composition and classification [23][19],[30]. These imaging methods tend to change eventually with minor upgrades and give a better performance in diagnosis in a reduced time span, however implementations of artificial intelligence have taken the clinical diagnosis to the next level. Studies included in the review were determined for its quality standard in the techniques and summarized to elucidate the main concept of coronary atherosclerosis detection by means of deep learning as well as ensemble learning algorithms. The papers were compared systematically for similarities and differences in the approach in the diagnostic study. Comparative analysis of deep learning and ensemble learning methods were analysed in relevance to achieve precision in accuracy and classification derived at a comprehensive finding.

4 Literature Review

A detailed review of thirty-nine studies included in the qualitative synthesis illustrates the detection of coronary atherosclerosis using neural network algorithms, mainly used in this context are deep learning and ensemble learning listed out in the table with findings, advantages and research gaps involved.

4.1 Diagnostic Algorithms in Automatic Detection and Classification of Coronary Atherosclerosis

He et al. [27] predicted coronary atherosclerosis with kernel extreme learning machine (KELM) is enhanced with Salp Swarm Algorithm (SSA) towards arriving at a diagnostic model providing an auxiliary function for physicians. The mechanism of Space transformation was introduced into SSA to balance local search capability and global search in a better way. KELM-SSA comparison was widely used in machine learning methods and demonstrated superior prediction accuracy. It has exhibited consistent and higher performance of classification than machine learning algorithms and effectively implied in diagnosing coronary heart disease.

Removal of coronary plaque obtained as of CT images is the prime focus of [41]**.** The study concentrated on recent methods employed in plaque extraction on CT-based images, based on this it is distinguished into 2D and 3D imageries. From 3D geometry of plaques, more multidimensional geometric patterns are derived. The accuracy of extraction of coronary plaque improved by de-blooming algorithms, using more detailed classification and standardized datasets. There is a lacuna in the 3D geometric image of coronary plaque investigation.

Nakanishi et al. [50] summarizes the state of atherosclerosis in recent studies investigating imaging by coronary CTA and compared with invasive imaging modalities. Plaque dimensions using semi-automated software for plaque was assessed in comparison with qualitative coronary plaque measures; its semi-automated method is time-saving. There is various coronary CTA automated quantitative software (QCT) to identify inner and outer vessels lumen boundaries, with automated algorithms for plaque volume and its characteristic features are calculated with accuracy. Non-calcified plaque on coronary CTA which possess fibrous, fibro-fatty composition, low attenuation plaque was evaluated by software vendors. Coronary CTA approach is a potential method as a complete coronary vessel was examined for atherosclerosis with elaborate ischemia identification unlike any invasive modalities.

Zhao et al. [68] proposed a computer-aided framework that provides automatic multi-class atherosclerosis detection of plaque that identifies three categories of plaques as in calcified, non-calcified and mixed plaques. In the extraction of multiple features such as local curvature, second-order gradient, intensity statistically and texture by introducing randomness, this classification framework increases accuracy and robustness in detection. First original CTA image transformed into transverse cross sections series along coronary centerline, then random radial symmetry (RRS) feature vector was designed and extracted on each cross section provided various features of plaque and augmented training data, which is then fed onto a classifier as in SVM or else Random forests to perform detection of plaques of varied class.

Tripoliti et al. [62] presented a machine learning method in the heart failure assessment. Models estimated subtypes, assessed severity of heart failure and predicted adverse events like destabilization or re-hospitalization or mortality were focussed in the management of heart failure. These extensive literature findings from potentially relevant research papers have addressed the question RQ1 as to the advancements in detection and class recognition of coronary atherosclerosis conducted in a recent time frame with increased accuracy and reduced risk factor.

4.2 Deep Learning-Based Approaches for Heart Diseases Detection

An assessment of deep learning-based systems employed in tomography techniques as listed in the table 1 tailored in CHD diagnostic procedures. Application of deep learning algorithm in automatic detection is an important question RQ2 to be addressed, it was elucidated with an exhaustive list of deep learning techniques with advantages and accuracy rate with respect to training time in the execution process of the detection.

Avendi et al. [6] employed deep learning algorithm with deformable models combined to evaluate 45 short-axis cardiac MRI dataset with a tool of automatic segmentation for left ventricle (LV). Ali et al. [2] devised a system of smart healthcare in recognition of heart disease using ensemble deep learning method as well as feature fusion approach. This feature fusion approach fused extracted features of sensor device data and electronic medical archives to create valued data of health care. Taking up the relevant data by eliminating irrelevant features reduced computational load and enhanced system activity. The data of heart disease in comparison to traditional classifiers obtained 98.5% accuracy higher than existing systems and more effective in prediction of heart disease.

Existing studies in classification of cardiac diseases are disease specific based approaches. On the contrary, [22] determined single best architecture in classifying heart ailments like arrhythmia, atrial fibrillation and heart attack. Architectures such as CNN, RNN, LSTM and GRU compared and arrived at a transferable approach for hyperparameters in disease classification. GRU is considered as a sole architecture for all the three heart ailments as deep learning algorithms are transferable in different disease classification by the same source of signal. Litjens et al. [40] presented more than 80 papers for modalities that range from echocardiography, cardiac magnetic resonance and CT. Different machine learning algorithms were applied, CNN commonly used with potential implication in anatomy, function and intraoperative heart tomography across CT, cardiac MR, single-photon emission CT and ultrasonography, with specific emphasis on cardiovascular image analysis by deep learning method. Li, Y et al., [38] proposed CraftNet, an architecture of deep neural systems to identify handcraft features accurately with stronger ability of classification and less affected by imbalance of data. Novel P-S loss was devised to increase sample distance effectively and to improve generalization capacity. CraftNet was verified on the public Massachusetts Institute of Technology- BethIsrael Hospital (MIT-BIH) with an arrhythmia dataset achieved 86.82% to 89.25% average sensitive accuracy. An ensemble of designed classifiers was built to classify four classes such as Normal (N), Supraventricular ectopic (S), Ventricular ectopic (V) and Fusion (F) heartbeat of ECG signals.

Wang et al., [64] extracted an expert feature of RR intervals and constructed a LSTM convolutional neural network in automatic extraction of deep learning structures. An effective predictor of congestive heart failure (CHF) is Heart rate variability (HRV) was used in the detection process by ensemble method with five open-source databases along with RR segment length types. An ensemble classifier was used with these features to detect CHF by blindfold validation with 99% accuracy. Kwon, J. M et al., [35] aimed at validating an ECG based prediction model of mortality with deep learning to predict heart disease in a multicenter retrospective cohort study. Predictor variables were extracted by text mining and developed deep learning-based prediction model and subgroup analysis of coronary heart disease was conducted and compared with predictive model score for internal and external validation and results outperformed other models more accurately than machine learning models. Tatsugami et al. [60] devised a CT image restoration method, it is a deep learning-based image restoration (DLR) process with deep convolutional neural network (DCNN) fitted with a noise and artifact reduction filter. The quality of coronary CTA scans was compared with DLR also known as hybrid iterative reconstruction (IR). DLR reduced image sound and improved quality of image at coronary CTA.

Poplin et al. [52]demonstrated a deep learning method to explore additional signals which are non-invasive in an outpatient setting such as retinal fundus image on 284,335 patients in prediction of cardiovascular risk. Anatomical features were used in trained deep-learning models like optic disc or blood vessels in prediction generation.

Table 1. Deep learning algorithm in Diagnosis of Heart diseases

Author	Findings	Algorithms Used	Advantages
Avendi, M. Ret al., [6]	An automatic segmentation mechanism from short-axis cardiac MRI datasets for the Left Ventricle (LV).	Convolutional Network	Compliance with the ground truth. Achieved a high correlation with reference contours
Gopika, P et al., [22]	Focussed on heart diseases like arrhythmia, atrial fibrillation and myocardial infarction	RNN, LSTM, GRU, residualCNN headed with transferable approach	Better Performance
Litjens, Get al., [40]	Presented explicit usage of deep learning systems in medical practice.	Deep Learning	Created increased awareness
Li, Yet al., [38]	Early detection of heart diseases by handcraft features and deep features from ECG	CraftNet	Good classification ability not affected by imbalance data
Wang, L et al., [64]	Congestive heart failure (CHF) prediction by HRV effectively.	LSTM convolutional neural network & ensemble classifier	good classification performance
Kwon, J. M, [35]	A multicenter cohort study of adult age cases admitted for heart disease who took up echocardiography with in-hospital mortality has been presented.	Deep Learning, logistic regression (LR), Random Forest (RF)	high performance in prognosis prediction

Tatsugami, Fet al., [60]	Comparison of quality of CTA scans using deep learning–based image restoration (DLR) method	Deep convolutional neural network (DCNN)	DLR reduced image noise and improved image quality of CCTA.
Madani, A, [45]	Artificial intelligence-assisted echocardiographic interpretation performed	Convolutional neural network	Recognized similarities and classification performed with image features of clinically relevance
Masuda, T et al., [47]	Machine-learning based CT histogram investigation to examine the structure of plaques and justification with IB-IVUS has been presented	Extreme Gradient Boosting (XGBoost)	High predictive value towards future cardiac episodes
Poplin, R, [52]	Trained deep-learning method with structural features as in blood vessels in predicting multiple cardiovascular risk factors, including age, gender and SBP was presented	Inception-v3 neural-network architecture37	It supports understanding cardiovascular risk factors that affect optic discs.
Candemir, Set al., [13]	An automated algorithm onto a deep learning framework enables detection of CCTA in detection of atherosclerosis.	3-dimensional convolutional neural network (3D-CNN)	Very useful for physicians in interpreting
Zhan, J [67]	To recognize atherosclerotic plaque development using a deep learning-based intravascular ultrasound	PCANet based analysis using a clustering PCA network	Algorithm effectively extracts details of plaque developed images with high- recognition efficiency
Summers, R. M et al., [58]	Recognition, segmentation and grading of abdominal aortic plaques on CT have been proposed	3DUNet deep learning method	Excellent agreement
Sung, J. J et al., [59]	The Artificial intelligence tools will be used regularly in health care as a part of industrial revolution	Deep neural network	Data value and proprietorship, transparency in governance, trust-building
ÖzalYıldırım et al., [66]	A novel deep learning method for seventeen classes of cardiac arrhythmia detection on long-duration ECG signal investigation	1D-CNN model	High performance, classification of various heart disorders and low computational complexity

Candemir et al. [13] derived a deep -learning-based method that could classify CAD with visualization of atherosclerosis per coronary artery as normal or abnormal. It is a fully automated system with no manual intervention, performance of the system initiated from scratch by using random weights without any pretrained model. It is described as one of the pilot studies which used 3D Convolutional neural network (CNN) architecture and displays learned behaviour of the architecture in coronary arteries classification by visualization algorithms. Evaluation was performed with 247 atherosclerosis patients and 246 controls. An accuracy of 90.9% was achieved with five-fold cross validation potentially used in interpreting physicians in identifying patients. 3D CNN provides details of coronary artery extracted volume, characterisation of pathological lesions and locates the region of atherosclerosis automatically with visual clues leading to classification of vessels from coronary computed tomography angiography (CCTA) image datasets.

Zhan et al. [67] devised a deep learning-based plaque algorithm to identify the development of plaque formation and its degree of recognition for classification was examined. Different regions of interest in plaque image were extracted, the size of the block of plaque region is determined. PCANet based principal component analysis vector designed as a clustering PCA network to cluster slices of small image then calculated principal components. For classification recognition, input image is enabled to adaptively select feature extractor of multi-plaque development. Convolutional neural networks were used to recognize plaque development to achieve high-efficiency recognition. Abdominal aortic plaque burden of atherosclerosis validated for non-contrast and postcontrast CT scans. The training data contains 114 non-contrast CT scans and 23 postcontrast CT urography scans. 922 CT colonography scans and 1207 paired non-contrast and postcontrast CT scans of renal donors constituted since the testing data set. Manual plaque segmentation in 137 training scans measurements was included as reference standard in 922 CTC scans. Complete automated detection, segmentation, scoring of pre and post contrast CT of abdominal aortic atherosclerotic plaques was assessed through a linear correction of 3D-UNet deep learning system calculating Agatston scores onto large non-contrast CTC dataset accurately. It was used in population studies of plaque weight, but individual patient valuation was not performed. Envision graphical display on original CT scan in orientation of axial, coronal and sagittal showed detected plaques by means of coloured intersection [58].

Madani et al. [45] developed a CNN to categorize 15 standard views of 12 videos and 3 still on labelled still pictures and videos simultaneously from 267 transthoracic echocardiograms. Model classified per 97.8% accuracy of 12 videos without overfitting clinically relevant images and provided a foundation for interpretation of artificial intelligence-assisted echocardiography. Masuda, T et al., [47] determined machine learning histogram study of CCTA for characterization of coronary plaque with median CT number. Seven parameters such as minimum mean value, maximum value, skewness, standard deviation, kurtosis and randomness of plaque CT number were recorded and measured using Gini index that rated importance of individual features by 5-fold cross validation. Prediction [60] Machine learning significantly yielded higher than conventional methods. Overall size of the dataset or population was very small for deep learning-based technique in cardiac disease [32], Poplin [52]. Candemir et al. [13] on supervising localization on coronary CTA with deep 3D CNN included only small-sized dataset and more accurate assessment is required in CCTA in imaging atherosclerosis.

AI trained to read coronary CT angiography images and detect calcification, stenosis, and severity effects of the heart. AI assisted diagnosis of cardiac arrhythmias from a single lead ECG recording made by machine learning using deep neural network algorithms with greater accuracy. AI predicts occurrences and outcomes of patients based on clinical datasets, medical images and genomic information. However, much effort is required in translating algorithms in clinical settings to improve outcomes [59]. Öet et al. [66] presented a deep learning-based system to quickly then efficiently classify cardiac arrhythmia. New ID-Convolutional Neural Network model (ID-CNN) is efficiently fast in real time classification and simple in usage of combined feature extraction, selection and one stage classification. Recognition of total accuracy of 91.33% used for 17 disorders of arrhythmia with 0.015sec was obtained from each 10-s ECG classification time per sample was achieved.

4.3 Ensemble Learning Based Approaches for Diagnosis of Heart Diseases

The individual neural networks in ensemble learning are called base learners. Ensemble approaches are combinations of outputs of a trained set of neural networks to get an accurate and reliable output [1].

Ensemble learning based approaches were widely used in image classification and enhancement of visualization data and the list of the algorithms employed shown in the table 2 addressed RQ3 as to improvements of ensemble learning algorithms in class recognition. Notable number of Ensemble learning algorithms was highlighted in the literature findings incorporated with new enhanced algorithms or combinations of one or more algorithms in diagnosis.

Mienye et al. [48] proposed an improved machine learning method in heart disease risk prediction. The method partitions dataset at random into further small subsets by mean based splitting approach modelled by classification and regression tree (CART). From different CART models a homogenous ensemble was developed with an accurate based weighted aging classifier ensemble (WAE) optimum performance was attained. Corchs et al. [17] investigated a combination of textual and visual data in identifying emotions from an image classification. Role of ensemble learning with reference to classification in Bayesian model averaging (BMA) method to predict by heterogeneous models. Su et al. [57] proposed ensemble learning technique using tangent space collaborative intended for hyperspectral classification of image such as TCRC- Bagging and Boosting. Results showed that both achieved better performance than traditional classifiers. Boosting framework found much more effective than Bagging framework. Chen et al. [15] investigated CNNs for hyperspectral image (HSI) classification for its ability of feature extraction. Ensemble-based learning also has the same potential, hence dual deep learning ensemble-based classification systems such as CNN ensemble as well as deep residual network ensemble used as individual classifiers and to transfer weights from single discrete classifier to another (CNNs) provided competitive results in relation to accuracy in classification. The algorithm blend has provided a significant potential in classification of hyperspectral images. This study was specifically included for its demonstration of advantages in context of accuracy rate on implementation of the ensemble algorithms and has scope of improvement on using this existing strategy in CAD detection.

Naji et al. [4] introduced a novel framework that utilizes three CNNs ensembles devised on three varied datasets to attain better performance than popular multi-focus image datasets, even better achieved with vast post-processing algorithms obtained as a result of qualitative and quantitative assessment. Hafiz et al. [25] aimed at ensemble learning in fusion integration, modelling and data mining into a unified model. Ensemble learning approach is proposed with multiple deep networks ResNet50, drawn inspired from binary decision/classification trees. It was compared against the baseline and this proposed approach outperformed on all experiments. Macko et al. [44] presented AdaNAS (Neural Architecture Search) algorithm that used ensemble techniques of small networks to compose neural networks. A novel technique was introduced to train small networks with previous ensembles, demonstrating improved accuracy. Hammou et al. [26] proposed a metric ensemble of gradient boosting (EGB) on the basis of resemblance in selected feature and ensemble learning. Feature capability extracted by CNN was analysed to distinguish the quality distance amid distorted and reference images, used as regression network input in image quality score prediction. Boosting regression models of Three gradients combined to get final quality score with results of proposed metric outperformed significantly.

Guo et al. [24] investigated multimodal medical imaging technique in clinical practice with a proposal of algorithmic architecture in analysis of supervised multimodal image through cross-modality fusion on feature learning, classifier and decision-making levels. A segmentation system of image was implemented on the basis of deep convolutional neural networks in contouring lesions present in soft tissue sarcoma with multimodal images as of MRI, CT and positron emission tomography (PET). Multimodal images network trained performed superiorly than network trained single modal images. Image fusion performed within the network in tumour segmentation obtained better results compared to fusion image at network output. An automatic method developed for segmentation of retinal layers as of OCT images by deep learning algorithm and created an ensemble-based architecture with four base models surveyed by DilatedReLayNet architecture and predictor block improved accuracy of segmentation compared to single DilatedReLayNet architecture also other methods. The proposed method was demonstrated on pathology of retinal scans and showed not a lot of difference in the execution. Grad-CAM visualization system showed that the model of different learning is far better than the single DilatedReLayNet model [5]. Chang et al. [14] improved Otsu method aimed at extracting vessels in medical imageries by means of resampling procedure in addition to ensemble learning to solve imbalanced classification pixels on vessel problem on Magnetic resonance angiography (MRA) image. Each pixel is numerous times sampled through multiple local patches in the image. Ensemble voting mechanism determines vessel tissue by a p-tile algorithm and this method outperformed traditional Otsu method more accurately in extraction of vessels in MRA images. Najiet al. [8] proposed an ensemble-based learning system of various neural frameworks then at random aggregate in sampling method. A data pre-processing step with feature selection was implemented to enhance performance of classification algorithms. An ensemble classifier by CNN model showed best classification performance of 91% accuracy and 96% F1 score for diverse types of heart related diseases. Peláez et al. [10] proposed a novel technique for automatic identification and interstitial lung abnormalities classification in CT images by CNNs which detected 2D and 3D architecture and enabled accurate classification. This ensemble algorithm performed with more than 90% sensitivity and specificity in identification of radiographic patterns has made it evident to adopt this approach in detection of heart disease in the future. Deep learning approaches in detection of cardiac diseases have brought out extensive research studies. Testing process on a large set of data of clinical origin and lack of sophisticated method in removing irrelevant features was not clearly presented in the literature [6] because of its missing values and noise management interrupted efficient results [2]. Set al. [39] concentrated on classification of abnormal ECG signals only, but failed to focus on image-based modalities in deep learning methods aimed at classification of heart attack, CAD and Congestive heart failure.

Table 2. Ensemble learning algorithm in Diagnosis of Heart diseases

Author	Findings	Algorithms Used	Advantages
Mienye, I. D et al., [48]	Prediction of risk involved in heart diseases	A homogeneous ensemble developed with accurateness on weighted aging classifier ensemble	Optimal performance
Corchs, S et al., [17]	Bayesian model averaging method-based ensemble learning using integration of visual data then textual data in identifying emotions as of image.	Naive Bayes (NB), Bayesian Network (BN), Nearest Neighbour (NN), decision tree (DT), and linear support vector machine (SVM).	High classification performance

Hafiz, A. M, [25]	Image Classification using CNN Trees	ResNet50	An ensemble learning approach is simple, efficient and sequential.
Macko, V [44]	Enhanced Neural Architecture for Search Image Classifiers	AdaNAS algorithm Ensemble model	Maintains same number of parameters in enhancing accuracy of a single neural network
Hammou, D, [26]	Accurate prediction of perceptual image quality has been proposed	VGG16, ensemble gradient boosting approach	High performance
Guo, Z et al., [24]	Designed an segmentation system of heart disease to contour lesions present in sarcomas with multimodule images obtained from MRI, CT and PET.	Fusion Networks	Superior performance
Anoop, B. N. [5]	A new deep ensemble learning approach devised in selective segmentation of retinal layers as of retinal Optical Coherence Tomography (OCT) scans.	Fully Convolutional Network (FCN) called as DelNet b	Improved segmentation accuracy
Chang, Y[14]	Presented a novel technique by for extracting vessel of MRA images	Maximum Intensity Projection (MIP), resampling method with ensemble learning	The detection of accurate vessel through multiple views
Bermejo-Peláez, D[10]	Devised an automated identification and classification method of Interstitial Lung Abnormalities (ILA) patterns as seen in CT images	Ensemble of deep convolutional neural networks (CNNs)	Enabled accurate classification
Ali, F et al., [2]	Developed a smart healthcare framework for predicting heart related diseases.	Ensemble deep learning model, and ontology-based technique	98.5%accuracy of systems higher than existing systems. Faster detection

Baccouche, A et al., [8]	Heart Disease Classification: Mexico based case study	Ensemble classifier by BiLSTM/BiGRU system with a CNN	High accurate models suited for clinical diagnosis and real data
Lih, O. S et al., [39]	Classification of heart attack, CAD and CHF.	Blend of CNN and LSTM models	98.5% accuracy of classification was achieved.

5 Research Gaps

- There are key questions and notions that are still not discussed in the literature review of coronary atherosclerosis such as lack of inclusion of more data[41], failed to tackle feature selection problems in prediction of atherosclerosis heart diseases [27]. Candemir et al. [13] on supervising localization on coronary CTA with deep 3D CNN included only small-sized dataset and more accurate assessment is required in CCTA in imaging atherosclerosis [50]. Coronary atherosclerotic plaque load assessed from abdominal CT by deep learning method only derived results and useful for population analysis, assessment was not suitable to be performed on an individual patient[58]. In automatic multi-class coronary atherosclerosis of plaque detection performed at an increased training time and neighbouring cross sections was not taken into consideration [68].
- Artificial intelligence in healthcare has many potential applications however there are few drawbacks, for instance lack of AI literacy to keep up with clinical knowledge in using novel devices and much effort is required to translate the algorithms in problem solving tools in clinical outcomes [59][31]**.** Tran et al. [61] missed out on extensive discussion on AI model reliability and clinical utility validation. Yıldırım al. [66] study on detection of cardiac arrhythmia by deep learning approach was performed on only one class of ECG signal, other classes and physiological signals were not mentioned.
- Deep learning approaches in detection of cardiac diseases have brought out extensive research studies. Testing methods on a large set of data obtained clinically and lack of sophisticated method in removing irrelevant features was not clearly presented in the literature [6] because of its missing values and noise management interrupted efficient results [2]. Transferable approach proposed by [22] did not take into account pathological measures such as phonocardiogram in diagnosing cardiac diseases. Li et al. [38] proposed method had drawbacks as it was not a comprehensive framework in early diagnosis of cardiovascular diseases. Naji et al. [8] proposed method lacked implementation of neural networks as in GAN or Attention-based recurrent neural z
- network and human interpretation needed in precision medicine of echocardiography [45]. Overall size of the dataset or population was very small for deep learning-based techniques in cardiac disease prediction [60], [52].
- A closer look at the literature on ensemble learning techniques in heart disease detection, however, reveals a number of gaps and shortcomings. For overall performance of model prediction in an improved ensemble learning approach more training samples in the study was lacking [48] and more training time was required in ensemble learning of Bayesian model [57] [5]. Ensemble learning approaches have a major drawback for its computational complexity directly impacted on training and testing time and hardware cost [44][24].

6 Conclusion

Coronary atherosclerosis detection is an essential part in attaining a complete diagnosis of a patient. This systematic review has charted out an extensive and elaborate nuance in non-invasive precision detection of atherosclerotic plaque with artificial intelligence interventions. Deep learning-based algorithms and ensemble learning-based algorithms used in detection of CAD with advantages over traditional approaches, radiographic techniques and limitations of the techniques were illustrated. Numerous studies have implemented deep learning algorithms, however, ensemble learning algorithms in medical imaging showed promising performance in image segmentation, accuracy and prediction of severity of the disease. Compared to deep learning techniques, ensemble learning such as the fusion approach has a much higher precision in diagnosis and its complexity requires more interpretation in clinical practice. The findings of the systematic literature review concludes that ensemble learning proves better than other algorithms in automatic recognition and classification of atherosclerosis. Coronary computed tomography angiography (CCTA) is reimbursed with artificial intelligence based deep learning in particular ensemble learning algorithms to attain high diagnostic performance in comparison to invasive reference standards.

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