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A Review on Artificial Intelligence – Assisted CCTA Imaging for CAD Diagnosis

Jenifer Sofia.A[1*], A.Ruhan Bevi[2]

[1] Research Scholar, Department of ECE, SRM Institute of Science and Technology, Chennai, Tamil Nadu, India.
[2] Assoicate Professor, Department of ECE, SRM Institute of Science and Technology, Chennai, Tamil Nadu, India.
*Corresponding Author Email: [1] ja4984@srmist.edu.in

Abstract

According to the statistics committee of the American Heart Association, Coronary Artery Disease (CAD) or myocardial ischemia is one of the most common Cardiovascular Diseases (CVD) that has high morbidity and mortality worldwide. Though Invasive Coronary Angiography (ICA) is recognized as the gold standard for the diagnosis of stenosis-related CAD owing to its ability to identify and classify stenoses precisely, it has severe complications and side effects. As a result, Image segmentation evaluation parameters and Automatic diagnosis have all benefited by using AI in non invasive technology known as CCTA (Coronary Computed Tomography Angiography). The purpose of this mini-review study is to understand the development of AI-assisted approaches for image processing, feature extraction, plaque recognition, and characterization in CCTA. Furthermore, the benefits, drawbacks, and potential applications of AI in diagnostic testing of atherosclerotic lesions are reviewed.

Keywords

Artificial Intelligence, Atherosclerotic plaques, Coronary artery disease, Coronary Computed Tomography Angiography.

INTRODUCTION

The characteristics of coronary atherosclerotic heart disease include abnormal fat metabolism, the accretion of fats in the coronary vessels, and build-up of atheromatous plaques (CAD)(Figure.2). It can cause symptoms including chest pain, tightness, or myocardial infarction, as well as luminal constriction or blockage that causes myocardial ischemia, oxygen deprivation, or necrosis.[1]. It occurs when there is a restriction in the flow of blood due to plaque formation in one of the two major arteries that supply oxygenated blood to the heart which are LCA (Left Coronary Artery) and RCA(Right Coronary Artery). The LCA branches into the Left descending artery which supplies blood to the left and front side of the heart and the circumflex artery which supplies blood to the dorsal side of the heart. The arteries that branch off from the RCA include the right descending artery and the marginal artery that supply blood to the septum of the heart[2]. Figure 1 shows the arteries present in the heart.

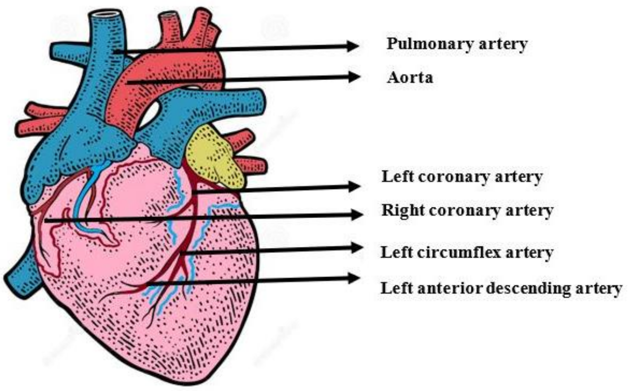
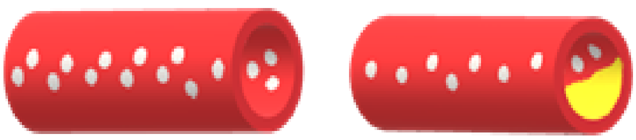


Fig 1: External view of Arteries of Heart

The most prevalent form of atherosclerosis that results in organ lesions and endangers people's lives is a heart attack. Ten million new cases of ischemic heart disease was recorded in 2017, and 8.9 million individuals died as a result. This illness affected 126.5 million people worldwide [1]. Key elements in the treatment of patients with hypertension include early prediction and identification of atherosclerotic plaques, categorization of their constituent parts, and risk assessment. Invasive assessments OCT(Optical Coherence Tomography) and IVUS (Intravascular Ultrasound) as well as non-invasive measurements like CT(Computed Tomography), MRI (Magnetic Resonance Imaging), and US (Ultrasonography)[3]. Due to new improvements in the sector of cardiac imaging, cardiac computed tomography angiography (CCTA) is used as the main investigation tool in patients with suspected heart stroke. CCTA provides important details on characterization of coronary artery plaque, total blood circulation, and luminal stenosis, as well as the potential to assess shape, plaque formation, and susceptibility[4], [5] . These procedures are currently conducted either manually [6] or self- operating by first using lumen segmentation and then characterizing the existence of stenosis [7].



a) Normal Artery **b) Atherosclerotic artery**

Fig2: Sectional View

Angiography is a conventional approach for diagnosing CAD that produces accurate results. This procedure is costly, invasive, and can result in consequences such arterial dissection, arrhythmia, and even death. To address these issues, the development of big data, machine learning techniques, and the availability of high computational power has resulted in various advancements in Artificial Intelligence (AI) techniques for detecting the amount of calcium present in the coronary arteries using medical image processing in recent years. For the early identification of CAD, these AI approaches are cost-effective, quick, non-invasive, and trustworthy[2]. Because it can analyse huge amounts of data in many ways, machine learning (ML), a subdivision of AI, is very helpful in CVD imaging. ML may integrate data from a multitude of sources and provide it to the practitioner in a relevant way. It can also automate a number of measures in a variety of imaging modalities. The advancement of precision medicine will be aided by the growth of AI [8].

ARTIFICIAL INTELLIGENCE APPLICATIONS

The study of theory, techniques, systems, and applications for replicating and enhancing human brain intelligence is the focus of the field of artificial intelligence (AI) . The incorporation, retrieval, and processing of enormous datasets can benefit greatly from the use of artificial intelligence, which was extensively utilized in medical research[1,9]. Additionally, it is employed in cardiovascular medicine to identify novel disease genetic traits, enhance cost-effectiveness, and, most importantly, risk stratification[10]. The AI's therapeutic uses have actually ramped up due to the increase in the volume and accessibility of medical imaging data. Early diagnosis of the formation of coronary plaques is essential for avoiding problems, and several Computer Vision methods have been created for the automatic detection and categorization of coronary plaques. CAD technology can boost clinical workflow efficiency by boosting the precision and dependability of image interpretation [9].

Machine learning in CCTA

The three forms of machine learning are, reinforcement learning (RL), supervised learning (SL), and unsupervised learning (USL). The reinforcement learning is a cross between SL and USL where SL trains labelled samples and USL trains unlabelled samples. The model is then used to map all inputs to the right outputs, and classification is achieved by making a straightforward assessment of the outputs. It is usually important to group the data and choose features using clustering since unsupervised learning data collected is not labelled.Examples of machine learning algorithms include the Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), Genetic Algorithm (GA), and Bayesian Network (BN) [1]. Pre-processing and segmentation, extraction of features, dimension reduction or feature grading, and classification are some of the crucial processes that these techniques are employed for. Because it increases image resolution or sharpness by using suitable filters like Gaussian and median, image pre-processing is a crucial first step. Before further categorization, the appropriate Region Of Interest (ROI) for coronary plaque identification must be extracted. The right characteristics are created utilising feature extraction strategies, processed for dimensionality reduction and then used to describe the plaques. [9].

Deep learning inn CCTA

AI algorithms have evolved efficiently in deep learning sector. Automated image identification has significantly advanced with the widespread adoption of deep learning (DL) techniques, particularly those built on a convolutional neural network (CNN) architecture [1]. DL often builds simple patterns into more complex ones. With bigger and more complex datasets, deep learning performs better than traditional machine learning frameworks. The structure of deep learning is analogous to the human neural structure. To get results from enormous data matrices that are ordered in a series of layers, data information from earlier to later levels is elaborately analysed. Other algorithms require intensive training to achieve superior outcomes. On the other hand, by boosting the training dataset or the network capacity, deep learning accuracy may be readily improved. Less domain knowledge is needed to carry out a function in DL. The famous deep learning frameworks is convolutional neural network (CNN). The initialization process involves feeding the input data into deep CNNs and propagating the data through convolution layer, pooling layer, activation unit, and dense layer. Both the feature extraction convolutional component and the classification convolutional component are fully coupled. In a fully connected network (FCNN), every unit is connected to every other unit in the level above it and the level below it. Recurrent neural networks (RNN) enrols feedback loops to evaluate a variety of inputs. CNN algorithms may effectively streamline the image processing process, resulting in time savings and increased productivity [8].

Characterisation, Quantification and Stenosis Detection of Atherosclerotic Plaque In CCTA

In atherosclerosis (AS), the interaction of epithelial cells, lymphocytes, and smooth muscle cells is a complicated process. Intimal smooth muscle cell aggregation is a hallmark of adaptive intima thickening in atherosclerotic lesions, that can develop into pathological intima congealing, which is further identified by the proximity of capillary lipid pools. Correct plaque component identification is essential for follow-up treatment because individual aspects of atherosclerotic plaques in the coronary arteries correspond to various processes and produce various consequences. Coronary plaques can be classified as calcified, noncalcified, or mixed plaques that have both traits. [3]

Calcified plaque – It is frequently measured using specialised enhanced non-contrast, electrocardiograph triggered calcium scanning images. An advanced software is used by the specialist to identify voxels in the coronary arteries with a volume larger than 130 Hounsfield units (HU).

The calcium scoring is then measured in terms of its volume or density. Although trained doctors do not consider calcium scoring to be a difficult technique, it does require time when performed on several pictures. Therefore, to overcome this automated.ML techniques are suggested. Deep learning-based techniques have not historically been used to classify candidate lesions; instead, single voxels have [11].

Non-calcified plaque – This is frequently prone to rupture and can cause thrombosis. In CCTA, analytic techniques have been developed for non-calcified plaque localization, characterization, and identification. The finding of coronary arteries using centreline extraction is a common pre-processing step for ML-based plaque analysis. The plaque detection and identification can be improved by rebuilding the centreline CCTA images [11]

Decades of study have led to the ability to monitor atherosclerotic plaques using a range of medical imaging methods. These methods might pinpoint the morpho - physiological abnormalities brought on by atherosclerosis, thorough details on plaque formation, and perhaps even assess the likelihood of atherosclerotic plaque generation. CT and MRI are indeed the two most widely used non-invasive methods for evaluating coronary atherosclerotic plaques. Overall component density of plaques, vasculature remodelling, and luminal stenosis can all be evaluated as well as identified and analysed using the CT scan. It has the ability to identify people who are asymptomatic but have high-risk plaques and classify the likelihood of cardiovascular disease as a non-invasive diagnosis. People with severe plaque are diagnosed by Major Adverse Cardiac Events (MACE) as either a standalone predictor of Acute Coronary Syndrome (ACS). The soft tissues can be well contrasted by MRI. This might also display the plaque deposition in addition to the arterial cavity and interior artery wall anatomy. The most frequent cause of ACS, the most lethal form of CAD, is susceptibility plaque rupture. Numerous inflammatory cells, a huge necrotic core, and very few smooth muscle cells are the pathogenic characteristics of the majority of vulnerable plaques. [3]

LIMITATIONS IN CAD DIAGNOSIS:

Though there are many advanced data processing and DL techniques there are also few avenues that need special and deep attention from researchers and professionals. The disadvantages in using ML techniques for CAD detection is as follows:

1. For each unique situation, a different ML approach is appropriate. While one method might work well on one dataset, it might not work well on others. As a result, picking the right algorithm for a certain dataset is crucial. Thus, selecting effective feature selection or classification is essential and posts a great and significant challenge.
2. To train ML algorithms, large datasets are typically required. These data sets must be exhaustive, balanced, and of high quality. Datasets must also be collected over time.
3. In order to provide findings with a high degree of confidence, machine learning algorithms need enough period to be programmed and analysed. These algorithms require a considerable number of materials and technology.
4. . Machine learning algorithms have difficulties with the validation problem. It's challenging to show that all of their predictions are accurate. Accurately interpreting the findings provided by machine learning techniques is still another issue we face.
5. Another downside of machine learning algorithms is their high mistake proneness. They produce imprecise outputs if they are trained with biased or wrong input. This could set off a cascade of errors, leading to treatment techniques being misled. When these problems are discovered, diagnosing the source of the faults takes time, and correcting them takes even more effort.
6. The datasets used for CAD diagnosis also has multiple issues like small sample sizes, limited features. The method of data analysis in earlier research is another issue.[2]

The mentioned shortcomings in CAD detection can be overcome by taking into consideration the following solutions

1. To find the most informative features, complex feature section approaches are used. This will result in formation of sparse model structures that are resistant to data uncertainty.
2. Model development and feature engineering computation is done using evolutionary algorithms. As a result, it boosts the accuracy of stenosis detection.
3. Algorithms for learning (ML). ML has demonstrated superhuman abilities in a variety of situations. Advances have sparked a surge in the use of deep learning to solve hard issues in a variety of industries.
4. The majority of ML-based CAD diagnosis research has focused on the development of individual models. Individually poor models can be significantly improved using ensemble-based learning (boosting and bagging) strategies [2].

CONCLUSION

The capacity of machine learning to relieve doctors of time-consuming chores and alter diagnostic methods may lead to a decrease in healthcare expenditures. In this succinct summary, atherosclerotic plaque and stenosis employing AI in cardiac CT are identified, described, and quantified. Machine learning was always at the heart of cardiac image processing, but the rise of deep learning has sped up development in the field. Artificial intelligence also has the ability to advance and enhance healthcare technologies for improved patient care by speeding up analysis times and offering professionals automated assistance on diagnosis and following treatment options. A fully convoluted network architecture algorithm for automatic identification and prevention of coronary artery plaque, as well as detection and classification of the anatomical relevance of coronary artery stenosis, will be included in a suitable workflow for the integration of machine learning and deep learning analysis of imaging modalities in clinical practise. The application of AI in cardiovascular imaging is positive due to advancements in computing, bioengineering, and medical image processing technologies, and the cooperation between researchers and doctors will be very advantageous.

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