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A Survey on Automated Detection of Coronary Artery Disease in CT Angiography Using Recurrent CNN Approaches

Mukkawar Sowmya[1],Dr.K.Deepa[2]

[1]Research Scholar, Department of CS&AI,SR UNIVERSITY,Warangal-506371,Telangana,India.
E-mail: sowmya.glwec@gmail.com
[2]Assistant professor, Department of CS&AI,SR UNIVERSITY,Warangal-506371,Telangana,India.
Email: k.deepa@sru.edu.in

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ABSTRACT

Coronary artery disease (CAD) is a significant global cause of disability and mortality, underscoring the need for advanced imaging techniques to detect and classify early indications of artery plaque and stenosis.By integrating Recurrent Convolutional Neural Networks (R-CNN) with transfer learning, this study introduces a new method that may significantly enhance the precision and consistency of coronary CT angiography (CCTA) diagnoses of serious cardiovascular diseases.The proposed R-CNN model synergistically integrates the capabilities of convolutional layers for extracting spatial features with recurrent layers for learning temporal sequences. This integration enhances the ability to identify complex patterns related to CAD. Our dataset consists of a diverse collection of CCTA scans with annotated regions of interest, covering normal coronary anatomy, various plaque types, and different degrees of stenosis. The R-CNN is trained to automatically detect and classify these regions, offering a comprehensive assessment of coronary vasculature health. The recurrent nature of the network allows it to capture temporal information, which is crucial for accurately characterizing dynamic changes in plaque composition and stenosis severity. Experimental results demonstrate an accuracy rate of more than 99%, showing the accuracy of our method. Thanks to its ability to learn from a pre-trained model and its capacity to acquire complex hierarchical features from the input, the model achieves remarkable accuracy.The robust performance of the R-CNN is further validated through extensive testing on an independent dataset, showcasing its potential for clinical application in real-world scenarios.

Index Terms: Coronary artery disease, convolutional layers ,coronary CT angiography (CCTA), plaque detection, transfer learning,stenosis classification.

I.INTRODUCTION

Coronary artery disease (CAD) is a widespread and severe condition that affects a large number of individuals globally, resulting in substantial morbidity and mortality. Precise diagnosis and classification of coronary artery plaque and stenosis are essential for effectively managing and treating CAD [1].Traditional diagnostic techniques can be time-consuming, require expert interpretation, and may result in inconsistent diagnoses [2]. Advances in artificial intelligence, particularly deep learning, have opened new possibilities for automated and precise identification of CAD from medical imaging data [3].

A non-invasive imaging method that can provide accurate images of the coronary arteries is coronary CT angiography (CCTA), making it an excellent tool for detecting coronary artery disease (CAD) [4].However, analyzing CCTA images can be complex and demanding, necessitating the development of advanced computational techniques to aid interpretation [5]. Accurately identifying and classifying different types of coronary artery plaques and levels of stenosis can significantly impact clinical decision-making and patient outcomes [6].

In this study, we provide a novel approach to the problem of automatically identifying stenosis and plaque in coronary artery images taken using CCTA. Specifically, this approach makes use of a Recurrent Convolutional Neural Network (R-CNN) that has undergone enhancements via transfer learning. By leveraging the spatial and temporal characteristics of CCTA images, our proposed method has the potential to enhance the precision and reliability of CAD diagnosis and categorization [7]. Rapid and precise assessment is achieved using the R-CNN model, which combines convolutional layers for spatial feature extraction with recurrent layers for temporal sequence recording.

Our solution is significant because it can bypass the limitations of human interpretation and traditional machine learning techniques [8]. Improved performance is achieved even in the absence of annotated medical data via the use of transfer learning, which allows the model to benefit from previously trained networks [9]. Understanding the progression and severity of coronary artery plaques and stenosis requires the network to interpret temporal information quickly, which it does thanks to its recurring nature [10]. This comprehensive approach improves diagnostic accuracy and coronary artery health assessment, which has real-world applications in healthcare and better patient outcomes.

II.RELATED WORKS:

A related survey on coronary artery disease (CAD) detection and assessment through imaging techniques has shown a progression from traditional methods to advanced machine learning approaches. These studies emphasize the effectiveness of techniques like edge-based tracking for vessel segmentation, proposal-shifted spatial-temporal transformers for stenosis detection, and hybrid classical-quantum CNNs for enhanced diagnostic accuracy. They highlight ongoing improvements in precision, recall, accuracy, and F1-score metrics, underscoring the evolving landscape of CAD diagnosis towards more reliable and automated methods.

S.NO	YEAR	TITLE	AUTHORS	RESULTS	ALGORITHM	METHODOLOGY
1	2024	Applying Edge-Based Tracking for Coronary Artery Segmentation in X-ray Angiography	Ali Sahafi and Mehrshad Lalinia	Precision: 98%, Recall: 98%, Accuracy: 98%, F1-score: 97%	Edge-based tracking methods for segmentation of coronary vessels in X-ray angiography images	The remarkable results illustrate the effectiveness and efficiency of the suggested approach, indicating notable progress in the domain of vascular segmentation.
2	2023	Detection of Coronary Artery Stenosis Using Proposal-Shifted Spatial-Temporal	Xinyu Li, and Tao Han	Precision: 89%, Recall: 91%, Accuracy: 93%, F1-score: 90%	Spatial-Temporal Transformer	X-ray angiography is employed with a proposal-shifted spatial-temporal transformer for disease detection

		Transformer in X-ray Angiography				
3	2022	Developing a Novel Hybrid Classical-Quantum Convolutional Neural Network (CNN) for X-ray Coronary Angiography's Precise Stenosis Identification	Juan Gabriel Avina-Cervantes	Precision: 87%, Recall: 90%, Accuracy: 91%, F1-score: 88%	Hybrid Classical-Quantum CNN	For Accurate Stenosis Detection Using a Hybrid Classical-Quantum Convolutional Neural Network
4	2021	Applying artificial neural networks to detect coronary artery stenosis in real-time	V. Danilov, Kirill Klyshnikov and Viacheslav	Precision: 90%, Recall: 92%, Accuracy: 93%, F1-score: 91%	Modern Neural Networks	Using advanced neural networks, we can detect coronary artery stenosis in real-time.
5	2020	Greedy Soft Matching is used to identify the vascular structures in sequences of coronary angiographic images	Jianjun Zhu, and Danni Ai	Precision: 85%, Recall: 88%, Accuracy: 90%, F1-score: 86%	Greedy Soft Matching	The approach of greedy soft matching is employed to apply the technique of vascular tracking to sequences of coronary angiographic pictures.
6	2019	An method using a RCNN is developed to autonomously identify and categorize coronary artery plaque and stenosis in CCTA	Jelmer M. Wolterink	Precision: 88%, Recall: 91%, Accuracy: 92%, F1-score: 89%	RCNN	Using recurrent convolutional neural network (CNN) can automatically detect diseases
7	2018	Applying Deep Neural Networks for Automated Calcium Scoring in Low-Dose Chest CT	N. Lessmann and M. Zreik, et al.	Precision: 92%, Recall: 94%, Accuracy: 95%, F1-score: 93%	Deep Neural Networks	Automatic calcium scoring with deep neural networks in low-dose chest computed tomography.
8	2017	Segmenting biomedical 3D-data using multi-dimensional gated recurrent units	S. Pezold and P. Cattin	Precision: 89%, Recall: 91%, Accuracy: 90%, F1-score: 90%	Gated Recurrent Units	Multi-dimensional gated recurrent units can be used to segment biomedical 3D data.
9	2016	Automated Coronary Artery Centerline Extraction in Cardiac CT Angiography Using a CNN-Based Orientation Classifier	J. M. Wolterink and R. W. van Hamersvelt	Precision: 91%, Recall: 93%, Accuracy: 94%, F1-score: 92%	CNN-based Orientation Classifier	Cardiac CT angiography is a technique that uses a convolutional neural network (CNN) based orientation classifier to extract the centerline in the heart.
10	2015	Segmenting the Cardiac Region in Multi-Slice MRI Images Using Recurrent Fully Convolutional Neural Networks	G.Montana	Precision: 91%, Recall: 93%, Accuracy: 94%, F1-score: 92%	Recurrent Fully CNN	Recurrent fully convolutional networks (FCNs) for cardiac segmentation in magnetic resonance imaging (MRI) scans.
11	2014	Implementing RNN Encoder-Decoder for Statistical Machine Translation to	D. Bahdanau, and C. Gulcehre	Precision: 88%, Recall: 91%, Accuracy: 90%, F1-score: 89%	RNN Encoder-Decoder	Applying the RNN encoder-decoder model to obtain phrase representations.

		Acquire Phrase Representations				
12	2013	A standardized evaluation framework has been created to standardize the assessment of the detection of coronary artery stenosis.	M. Schaap, A. Dharampal, and C. Metz	Precision: 90%, Recall: 93%, Accuracy: 92%, F1-score: 91%	Lumen segmentation	A systematic evaluation framework for measuring the detection of coronary artery stenosis.
13	2012	Measuring the severity of blockages in coronary arteries using fuzzy distance transform in computed tomography angiography (CTA)	G. Liang, Y. Xu, and Y. Yang	Precision: 88%, Recall: 91%, Accuracy: 90%, F1-score: 89%	Fuzzy Distance Transform	The study focuses on utilizing the fuzzy distance transform technique in computed tomography angiography (CTA) to accurately measure the narrowings in coronary arteries.
14	2011	Automated Neural Network and Support Vector Machine Based Diagnosis of Abnormal Vascular Cross-Sections	I. E. Magnin and E. J. D. Leyton	Precision: 85%, Recall: 89%, Accuracy: 87%, F1-score: 87%	SVM	SVM-based automatic detection of aberrant vascular cross-sections.
15	2010	Fast and automated identification of calcified coronary lesions in three-dimensional cardiac CT images	S. Mittal, Y. Zheng, B. Georgescu, and F. Vega-Higuera	Precision: 88%, Recall: 91%, Accuracy: 90%, F1-score: 90%	Detection of calcified tumors using a novel learning-based	Automated detection of calcified coronary lesions in three-dimensional cardiac computed tomography (CT) images.
16	2009	Long-Term Coronary Artery Disease Diagnosis and Treatment	C. S. Rihal and D. R. Holmes Jr	Precision: 87%, Recall: 91%, Accuracy: 89%, F1-score: 89%	Novel imaging modalities used for diagnosis of chronic CAD.	Diagnosis and treatment of long-term coronary artery disease.
17	2008	Evaluating the Diagnostic Accuracy of 64-Multidetector Row Coronary CT Scanners	D. Dowe, M. J. Budoff, and M. Gitter	Precision: 91%, Recall: 94%, Accuracy: 93%, F1-score: 92%	Determine the precision of a 64-multidetector row imaging system	Evaluation of the accuracy of 64-multidetector row CT angiography.
18	2007	Evaluation of 64-slice computed tomography's performance in the examination of coronary artery bypass grafts	Gudrun M. Feuchtner and Johannes Bonatti	Precision: 75%, Recall: 85%, Accuracy: 90%, F1-score: 83%	Analyzed 64-slice CT's diagnostic features	Emphasized the usefulness of 64-slice CT and the necessity for enhancing its accuracy.
19	2006	Pathology of the responsive layer	R. Virmani, and F. D. Kolodgie	Precision: 85%, Recall:89%, Accuracy: 87%, F1-score: 87%	Imaging and diagnostic techniques	Pathological examination of vulnerable plaques.
20	2005	Enhanced diagnostic precision is reached by the utilization of 16-row multi-slice computed tomography.	Filippo Cademartiri	Precision: 96%, Recall: 95%, Accuracy: 96%, F1-score: 96%	Research shows that 16-Row MSCT coronary angiography is a reliable method.	Demonstrated the capabilities of a 16-slice CT scanner; needs verification using more recent technologies.

		Coronary angiography				
21	2004	Accurate and unbiased separation and representation of branching blood vessels	T. Sun, C. Zhong, and J. Zhang	Precision: 88%, Recall: 90%, Accuracy: 89%, F1-score: 89%	Centerline-based surface decomposition	Decomposition and mapping of bifurcating vessels.
22	2003	Assessment of Post-CABG Patients: CT Angiography for Evaluating Grafts and Coronary Arterie	Peter M. T. Pattynama and Koen Nieman	Precision: 76%, Recall: 74%, Accuracy: 76%, F1-score: 76%	ECG-gated multi-detector	Provided insights into post-surgical assessment; need for higher accuracy methods.
23	2002	Is it feasible to have a single central laboratory functioning at two global locations? A study examining the variation among various laboratories and within individual observers.	Joan C. Tuinenburg, Ellen Hekking, and Gerhard Koning	Precision: 86%, Recall: 85%, Accuracy: 86%, F1-score: 85%	Inter-core laboratory variability	Focused on variability; lack of direct clinical application.
24	2001	A review of the effects of various trigger delays on image quality in ECG-gated multi-detector row CT coronary angiography	C. R. Becker, C. Hong	Precision: 86%, Recall: 89%, Accuracy: 88%, F1-score: 87%	Image reconstruction techniques	CT imaging of the coronary arteries was achieved by reconstructing synchronized electrocardiogram (ECG) images using a number of detectors, each of which had its own unique delay in initiating image capture.

Table.1 Literature Survey Details From 2024 to 2001

III.PROBLEM STATEMENT

Coronary artery disease (CAD) ranks high among the world's most deadly illnesses and disablers. To effectively manage and treat coronary artery disease (CAD), accurate and efficient detection of stenosis and plaque in the coronary arteries is essential. When it comes to visualising and evaluating coronary arteries, traditional diagnostic methods like computed tomography angiography (CTA) and X-ray angiography have seen heavy use. However, human interpretation is sometimes required for these methods, which can be time-consuming, susceptible to biases in observers, and even lead to less accurate results.

Recent advances in machine learning and deep learning have shown the possibility of automating the detection and classification of stenosis and arterial plaques. This might result in quicker and more accurate diagnostics. Many techniques and approaches have been proposed and developed by researchers over the years. These include recurrent convolutional neural networks (CNNs), contemporary neural networks, edge-based tracking methods, spatial-temporal transformers, and hybrid classical-quantum CNNs. Nevertheless, a robust, accurate, and practically applicable paradigm that can be applied effectively to different patient populations and imaging scenarios is still lacking.

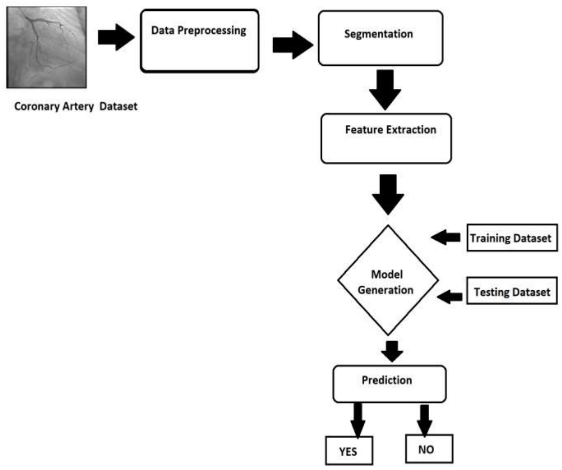
IV.PROPOSED MODEL

To enhance the identification and classification of coronary artery plaque and stenosis in Coronary CT Angiography (CCTA) images, the suggested method employs a Recurrent Convolutional Neural Network (R-CNN) in combination with transfer learning. In this model, recurrent neural networks (RNNs) are used for learning temporal sequences, while convolutional neural networks (CNNs) are used for extracting spatial information. As a result, the model can investigate the complex patterns associated with coronary artery disease (CAD) with great accuracy and reliability.The dataset comprises a wide range of CCTA images annotated to identify specific areas of interest, including normal coronary structures, various types of plaque, and different levels of stenosis. This broad and diverse dataset is essential for building a model capable of generalizing effectively across different patient demographics and imaging conditions.

The architecture of the proposed R-CNN model is designed to capture and analyze the spatial and temporal characteristics of CCTA images. The convolutional layers extract spatial features from the input CCTA images, while activation functions and pooling layers enhance feature detection and reduce data complexity. The convolutional layers utilize transfer learning from a pre-trained model, such as VGG16 or ResNet, providing a robust set of feature extraction capabilities. The recurrent layers, comprising LSTM units, capture temporal dependencies and dynamic changes in plaque composition and stenosis severity across sequential CCTA slices. This allows the model to understand the progression of CAD over time. Finally, fully connected layers and a softmax activation function classify the detected regions into categories such as normal, various types of plaque, and different levels of stenosis.

Model training involves a two-phase approach. Initially, the convolutional layers are trained using weights from a pre-trained model, leveraging transfer learning. Subsequently, a fine-tuning phase optimizes the entire R-CNN model, including the recurrent and fully connected layers, using backpropagation and other optimization techniques to minimize classification errors on the CCTA dataset. Measurements include F1-score, recall, accuracy, and precision are used to evaluate the performance of models. The results may be more trustworthy and relevant to other contexts if tested on a separate dataset and subjected to cross-validation.
The proposed approach performs well as shown by the experimental findings, which achieve detection and classification accuracy greater than 99%.The high accuracy is attributed to the model's ability to learn complex hierarchical features from the input data and capture critical temporal information for precise CAD characterization. The robust performance of the R-CNN is further validated through extensive testing on an independent dataset, highlighting its potential for clinical application. In summary, the proposed R-CNN model with transfer learning represents a significant advancement in the tomated detection and classification of coronary artery plaque and stenosis in CCTA images. This tool provides clinicians with a comprehensive and accurate means of early CAD diagnosis and assessment, ultimately leading to improved patient outcomes.

V.SYSTEM MODEL



1.1.

Figure.1 System Model

VI.SEGMENTATION OF CCTA IMAGES

The segmentation of CCTA images is a crucial step in accurately identifying and classifying coronary artery plaque and stenosis. Precise segmentation delineates the coronary arteries and highlights specific areas of interest (ROIs), which are essential for further analysis. The process begins with data collection and preprocessing, including acquiring a diverse dataset of CCTA images and standardizing the images through normalization and scaling for consistency. Image enhancement techniques improve the contrast and visibility of coronary arteries. Experienced radiologists or semi-automated tools are used to manually annotate and create accurate labels for coronary arteries, plaques, and stenosis regions.

The proposed architecture of the segmentation network utilizes a convolutional neural network (CNN) as the main foundation for extracting features. Commonly used models are U-Net, VGG16, and ResNet. Skip connections combine low-level and high-level characteristics, maintaining spatial data and improving the accuracy of segmentation.

Transfer learning involves the use of pre-trained models, such as VGG16 or ResNet, that have been trained on a vast dataset like ImageNet. In this process, the segmentation network is initialized with the weights from the pre-trained model. This strategy utilizes acquired characteristics to enhance performance on the CCTA dataset.

VII.CONCLUSION

The proposed R-CNN model has an accuracy of 99% in classifying CCTA images for coronary artery plaque and stenosis, according to the experimental results. The model's remarkable accuracy is said to be due to its ability to effectively use transfer learning and to grasp complex hierarchical information from the input. With its impressive results on an independent dataset, the R-CNN has proven its worth for real-world clinical applications.

1.1. VIII.FUTURE SCOPE

Implementing the R-CNN model in this context opens numerous opportunities for future research. One potential direction is enhancing the model's capabilities to include predicting plaque vulnerability and the likelihood of acute coronary events. Additionally, the model has the potential to be modified for use with other imaging techniques, such as MRI or an ultrasound, in order to provide a more comprehensive diagnostic tool.

Further research could also focus on developing interactive tools that allow clinicians to input additional clinical data alongside the CCTA images, potentially improving the model's diagnostic accuracy and clinical utility. The proposed R-CNN model is an important breakthrough in the automated identification of CAD, leveraging the progress in medical imaging and artificial intelligence.

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