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Coronary Computed Tomography Angiogram Analysis to Detect Coronary Atherosclerosis Using Deep Learning Techniques

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Abstract - **Coronary artery disease (CAD) remains a leading cause of morbidity and mortality worldwide. Coronary Computed Tomography Angiography (CCTA) is a widely utilized non-invasive imaging technique for assessing coronary artery morphology and identifying atherosclerotic lesions. In this project, we propose a novel approach that leverages the power of deep learning to enhance the accuracy and efficiency of CAD detection through CCTA images. Our method involves the development of a deep convolutional neural network (CNN) architecture tailored for the automatic detection of coronary atherosclerosis. To achieve this, we used a comprehensive dataset comprising many high- quality CCTA scans. This dataset was split into training, validation, and testing sets to trainand evaluate the performance of the proposed CNN model. The performance of different deep learning models was compared to determine the optimal approach for classifying CAD. In conclusion, this project aims to assist medical professionals in diagnosing coronary atherosclerosis with the help of CCTA images. The utilization of advanced CNN architectures and attention mechanisms paves the way for improved CAD diagnosis, potentially revolutionizing the field of cardiovascular imaging and patient care.**

Keywords: Convolutional Neural Network, Coronary atherosclerosis detection, Deep Learning, Healthcare, Image Classification, Machine Learning.

I. INTRODUCTION

Coronary artery disease (CAD) is sometimes called coronary heart disease or ischemic heart disease. CAD is caused by plaque buildup in the walls of the arteries that supply blood to theheart (called coronary arteries) and other parts of the body.

Plaque is made up of deposits of cholesterol and other substances in the artery. Plaque buildup causes the inside of the arteries to narrow over time, which can partially or totally block the blood flow. This process is called atherosclerosis. A computerized tomography (CT)coronary angiogram is an imaging test that looks at the arteries that supply blood to the heart. A CT coronary angiogram uses a powerful X-ray machine to produce images of the heart and its blood vessels.

Conventional CAD detection methods often rely on manual interpretation by experienced radiologists, which can be time-consuming and subjective. In contrast, our proposed methodology harnesses the potential of deep convolutional neural networks (CNNs) to autonomously identify and classify coronary artery plaques from CCTA images, reducing both interpretation time and variability.

This paper presents a comprehensive investigation into the development and evaluation of a tailored CNN architecture that empowers automated CAD detection from CCTA images. The model is engineered to scrutinize intricate features within the images, discriminating between different plaque types and offering a quantitative assessment of their severity. By doing so, our approach aims to provide clinicians with a reliable and efficient tool

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that aids in timely CAD diagnosis, subsequently improving patient outcomes and informing personalized treatment strategies.

II. METHODOLOGY

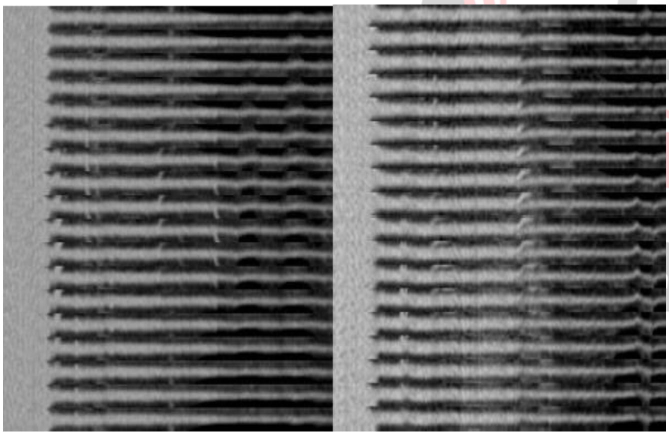
This section outlines the methodology employed for the detection of coronary atherosclerosis using Coronary Computed Tomography Angiography (CCTA) images, with a focus on the application of TensorFlow. The objective is to develop an accurate and efficient model for automated detection and classification of coronary artery lesions, contributing to the early diagnosis and management of coronary artery disease (CAD). The dataset used for training and evaluation was obtained from the Mendeley Data repository at https://data.mendeley.com/datasets/fk6rys63h9/1.

III. DATA PREPROCESSING

The dataset, sourced from the Mendeley Data repository, comprises a collection of CCTA images captured from diverse patient cohorts. Prior to model training, rigorous data preprocessing was conducted to ensure optimal model performance.

1.1. Data collection:

The dataset consists of annotated CCTA images in PNG format. These images depict varying degrees of coronary atherosclerosis, with corresponding lesion labels provided for supervision. A sample of our data is given below:



The initial image depicts a case with positive coronary atherosclerosis, followed by a subsequent image illustrating a negative instance.

1.2. Turning our data into batches:

We organized our data into batches of size 32 (as recommended by Yann LeCun) to ensure the efficient execution of the model.

1.3. Image Standardization:

Images were converted to standard image size (224,224) to facilitate compatibility with TensorFlow. Pixel values were normalized to the [0, 1] range, enabling consistent processing across images and enhancing model convergence.

1.4. Data splitting:

The dataset that was given to us contained:

1. Total number of images used -> 5008
2. Images with atherosclerotic lesions -> 2504
3. Images without atherosclerotic lesions ->2504

4668 images were used for training the model, 100 for validating the model and 120 for the test set

IV. MODEL ARCHITECTURE

TensorFlow was harnessed to develop a model for coronary atherosclerosis detection, with a focus on Convolutional Neural Networks (CNNs). In this study, an existing CNN architecture was chosen to capitalize on pre-trained weights and established feature extraction capabilities.

2.1 Custom Classifier:

A dedicated classifier head was appended to the convolutional backbone to tailor the model to coronary atherosclerosis detection. The classifier encompassed fully connected layers, dropout regularization, and an output layer with appropriate activation functions.

V. MODEL TRAINING

The model was trained utilizing the preprocessed dataset, optimizing parameters via appropriate loss functions and optimizers.

3.1 Loss Function - Binary Cross-Entropy:

Given the nature of the classification task at hand, we employed the binary cross-entropy loss function to effectively measure the disparity between the predicted outcomes and the actual ground truth labels. This loss function is particularly suited for binary classification scenarios, such as the detection of coronary atherosclerosis in our study. It quantifies the dissimilarity between the predicted probabilities and the corresponding true binary labels, thereby guiding the model's optimization process toward accurate classification outcomes. By utilizing the binary cross-entropy loss, we aim to enhance the model's ability to discern between normal and affected coronary regions, facilitating improved detection accuracy and contributing to more informed clinical decisions.

3.2 Optimization Algorithm - Adam:

For the optimization of our model's parameters, we employed the Adam optimizer, a well- established optimization algorithm that combines the benefits of both the Adagrad and RMSProp algorithms. Adam stands for "Adaptive Moment Estimation," and it is known for its efficiency in optimizing large-scale deep learning models.

Adam utilizes adaptive learning rates for each parameter, which are calculated based on both first-order moments (the average of the gradients) and second-order moments (the average of the squared gradients). This adaptiveness

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allows Adam to dynamically adjust learning rates for each parameter, facilitating rapid convergence and handling different gradients more effectively.

By incorporating momentum, which exponentially weighs the past gradients, and an element-wise scaling of gradients, Adam offers stability in the optimization process. This enables the model to navigate through complex loss surfaces and escape local minima more efficiently.

3.3 Activation Function - Sigmoid:

In the architecture of our model, the sigmoid activation function was employed within the classifier's output layer. Sigmoid is a fundamental activation function commonly used for binary classification tasks.

The sigmoid function maps the input to a range between 0 and 1, effectively transforming raw model outputs into probabilities. This aligns perfectly with our binary classification objective of identifying the presence or absence of coronary atherosclerosis in CCTA images. The sigmoid activation produces an interpretable probability score, indicating the likelihood of a positive (affected) class prediction.

By employing the sigmoid activation function, we not only facilitate a clear understanding of the model's predictions but also enable the interpretation of the prediction confidence level. This activation function is well-suited for cases where the model's output is intended to represent a probability of a certain class membership, making it an apt choice for our coronary atherosclerosis detection task.

Incorporating the Adam optimizer and the sigmoid activation function into our model architecture contributes to the optimization and interpretability of the model's outcomes. These choices are instrumental in enhancing the model's ability to accurately classify coronary artery lesions and provide valuable insights to medical practitioners.

3.4 Training Strategies - Early Stopping and TensorBoard Callbacks:

In our pursuit of training an efficient and effective model for coronary atherosclerosis detection, we employed two essential training strategies: the Early Stopping callback and the TensorBoard callback. These strategies contribute to streamlined training, enhanced model selection, and insightful monitoring of the training process.

3.4.1 Early Stopping Callback:

The Early Stopping callback is a regularization technique that prevents overfitting and optimizes the model's generalization capabilities. Overfitting occurs when a model learns to perform exceptionally well on the training data, but its performance deteriorates on unseen data. The Early Stopping callback tackles this issue by continuously monitoring the model's performance on a validation set and terminating training when performance ceases to improve.

By specifying a "patience" parameter, the callback monitors the validation loss over a set number of epochs. If the validation loss fails to decrease for the specified number of epochs, training is halted. This safeguard prevents the model from fine-tuning itself excessively to the training data, leading to better generalization and the avoidance of overfitting.

3.4.2 TensorBoard Callback:

The TensorBoard callback enhances the transparency of the training process and facilitates comprehensive model analysis. TensorBoard is a powerful visualization tool offered by TensorFlow that enables dynamic tracking and visualization of various training metrics.

By integrating the TensorBoard callback, we generated visualizations of key metrics such as training and validation loss, accuracy, and other customizable metrics. These visualizations offer real-time insights into the model's performance trajectory and the impact of different hyperparameters and training configurations.

TensorBoard also provides tools for visualizing the model's architecture, histograms of parameter distributions, and embeddings of high-dimensional data. This multifaceted visualization capability aids in diagnosing training issues, fine-tuning model parameters, and understanding how the model is learning from the data.

3.5 Synergy and Impact:

The combination of the Early Stopping and TensorBoard callbacks creates a synergistic effect in the training process. Early Stopping prevents overfitting by intelligently terminating training, while TensorBoard offers visualization tools to comprehend the learning dynamics and make informed decisions about the model's architecture and training settings.

By incorporating these strategies, we ensure efficient training, safeguard against overfitting, and gain valuable insights into the model's behavior. This meticulous training approach contributes to the development of a robust coronary atherosclerosis detection model, one that maximizes both accuracy and generalization capabilities.

VI. Model Evaluation

In this section, we present a comprehensive evaluation of the proposed deep learning model for detecting coronary atherosclerosis from Computed Tomography Coronary Angiography (CCTA) images. The evaluation encompasses both quantitative metrics and qualitative assessments to validate the effectiveness and robustness of our approach.

Performance Metrics:

We utilized a set of standard performance metrics to quantitatively measure the effectiveness of our model in detecting coronary atherosclerosis. These metrics include:

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- **Accuracy (ACC)**: The ratio of correctly predicted cases to the total number of cases.
- **Precision**: The proportion of true positive predictions among all positive predictions.
- **Recall (Sensitivity)**: The proportion of true positive predictions among all actual positive cases.
- **Specificity**: The proportion of true negative predictions among all actual negative cases.
- **F1-Score**: The harmonic mean of precision and recall, providing a balanced measure between them.
- **Area Under the Receiver Operating Characteristic Curve (AUC-ROC)**: A metric that evaluates the model's ability to distinguish between classes across different thresholds.

Hyperparameter tuning:

In this section, we outline the key hyperparameters that play a pivotal role in shaping the behavior and performance of the deep learning model developed for coronary atherosclerosis detection from CCTA images. These hyperparameters are carefully chosen and tuned to ensure optimal convergence, generalization, and effectiveness of the model. The following hyperparameters are identified as critical components of our model:

4.1 Learning Rate:

The learning rate is a fundamental hyperparameter that governs the rate at which the model adjusts its weights during the training process. It defines the step size taken towards minimizing the loss function. A higher learning rate can accelerate convergence but risks overshooting the optimal solution, while a lower rate might result in sluggish convergence. Our investigation explores various learning rates to determine the balance between speed and precision in convergence.

4.2 Batch Size:

The batch size represents the number of training samples processed together in each iteration of the training process. It significantly influences the computational efficiency and generalization capabilities of the model. Larger batch sizes can lead to efficient GPU utilization and quicker convergence. However, they might hinder the model's generalization, particularly when training with limited data. On the other hand, smaller batch sizes can offer more stable convergence but might require more iterations for training to converge.

4.3 Number of Epochs:

The number of epochs defines how many times the entire training dataset is presented to the model during training. This hyperparameter plays a critical role in achieving the right balance between underfitting and overfitting. Too few epochs may prevent the model from capturing intricate patterns, while excessive epochs might result in overfitting. Our experimentation focuses on identifying the optimal number of epochs to ensure convergence and generalization.

4.4 Network Architecture:

The selection of network architecture encompasses decisions regarding the arrangement of layers, activation functions, and connectivity patterns within the neural network. The architecture defines the model's capacity to capture complex features and relationships within the data. Our exploration includes variations in the depth, width, and complexity of the network architecture to determine the configuration that best suits our problem domain.

Each of these hyperparameters is pivotal in shaping the behavior and performance of our deep learning model for coronary atherosclerosis detection. The subsequent section elucidates our methodology for effectively tuning these hyperparameters and the outcomes of this tuning process on the model's overall performance.

VII. PREDICTION

In this section, we detail the process through which the trained deep learning model predicts the presence or absence of coronary atherosclerosis in patients using input Computed Tomography Coronary Angiography (CCTA) images. Our model, having undergone rigorous training and optimization, is now primed to make accurate and clinically relevant predictions based on unseen images.

5.1 Input Preprocessing:

Before making predictions, the input CCTA image undergoes preprocessing to ensure compatibility with the trained model. This preprocessing includes normalization of pixel values to a common range and resizing the image to match the dimensions the model was trained on. Additionally, any necessary image augmentation techniques are applied to enhance the model's robustness and generalization.

5.2 Predictive Inference:

The predictive inference process begins with feeding the preprocessed CCTA image into the trained deep learning model. The model's forward pass involves intricate calculations within its neural architecture, where learned weights and activations are utilized to extract relevant features from the image. These features are then processed to generate a prediction score.

5.3 Thresholding and Interpretation:

The prediction score generated by the model represents the model's confidence in the presence of coronary atherosclerosis. To determine the final prediction, a threshold is applied to the score. Depending on the context, this threshold might be chosen to maximize sensitivity, specificity, or an optimal balance between the two.

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Once the prediction is obtained, it undergoes interpretation to make it clinically meaningful. A prediction score exceeding the threshold indicates a positive prediction for coronary atherosclerosis, suggesting the presence of atherosclerotic lesions in the patient.

Conversely, a score below the threshold signifies a negative prediction, implying the absence of significant atherosclerotic lesions.

Clinical Decision Support:

The predictions made by our deep learning model provide valuable insights for clinical decision-making. Positive predictions alert medical practitioners to the potential presence of coronary atherosclerosis, prompting further diagnostic assessments and interventions.

Negative predictions offer reassurance regarding the absence of substantial atherosclerotic lesions, aiding in risk stratification and treatment planning.

Real-world Application:

The real-world application of our model's predictive capabilities holds promise for expediting and enhancing the diagnostic process. By swiftly analyzing CCTA images and delivering accurate predictions, our model can assist clinicians in efficiently identifying patients at risk of coronary atherosclerosis. This aids in early intervention and tailored treatment plans, ultimately contributing to improved patient outcomes and quality of care.

REFERENCES

[1] Neuhaus E, Weiss K, Bastkowski R, et al.. Accelerated aortic 4d flow cardiovascular magnetic resonance using compressed sensing: Applicability, validation and clinical integration. J Cardiovasc Magn Reson. 2019; 21:65. [PMC free article] [PubMed] [Google Scholar]

[2] Virani SS, Alonso A, Aparicio HJ, et al... Heart disease and stroke statistics-2021 update: A report from the American heart association. Circulation. 2021;143: e254–e743. [PubMed] [Google Scholar]

[3] Piepoli MF, Hoes AW, Agewall S, et al... 2016 European guidelines on cardiovascular disease prevention in clinical practice: The sixth joint task force of the European society of cardiology and other societies on cardiovascular disease prevention in clinical practice (constituted by representatives of 10 societies and by invited experts) developed with the special contribution of the European Association for Cardiovascular Prevention & Rehabilitation (EACPR). Eur Heart J. 2016; 37:2315–2381. [PMC free article] [PubMed] [Google Scholar]

[4] Conroy RM, Pyorala K, Fitzgerald AP, et al... Estimation of ten-year risk of fatal cardiovascular disease in Europe: The score project. Eur Heart J. 2003; 24:987–1003. [PubMed] [Google Scholar]

[5] D'Agostino RB, Sr, Vasan RS, Pencina MJ, et al... General cardiovascular risk profile for use in primary care: The Framingham heart study. Circulation. 2008; 117:743–753. [PubMed] [Google Scholar]

[6] Arnett DK, Blumenthal RS, Albert MA, et al... 2019 acc/aha guideline on the primary prevention of cardiovascular disease: A report of the American college of cardiology/American heart association task force on clinical practice guidelines. J Am Coll Cardiol. 2019;74:e177–e232. [PMC free article] [PubMed] [Google Scholar]

[7] Barkat M, Roy I, Antoniou SA, et al.. Systematic review and network meta-analysis of treatment strategies for asymptomatic carotid disease. Sci Rep. 2018; 8:4458. [PMC free article] [PubMed] [Google Scholar]

[8] Czarnecki A, Qiu F, Elbaz-Greener G, et al... Variation in revascularization practice and outcomes in asymptomatic stable ischemic heart disease. JACC Cardiovasc Interv. 2019; 12:232–41. [PubMed] [Google Scholar]

[9] van Assen M, Varga-Szemes A, Schoepf UJ, et al... Automated plaque analysis for the prognostication of major adverse cardiac events. Eur J Radiol. 2019; 116:76–83. [PubMed] [Google Scholar]

[10] Yamamoto H, Kihara Y, Kitagawa T, et al... Coronary plaque characteristics in computed tomography and 2-year outcomes: The predict study. J Cardiovasc Computed Tomogr. 2018; 12:436–443. [PubMed] [Google Scholar]

[11] Stone PH, Saito S, Takahashi S, et al... Prediction of progression of coronary artery disease and clinical outcomes using vascular profiling of endothelial shear stress and arterial plaque characteristics: The prediction study. Circulation. 2012; 126:172–181. [PubMed] [Google Scholar]

[12] Kolessar M, Szilveszter B, Merkely B, et al... Plaque imaging with CT-a comprehensive review on coronary CT angiography-based risk assessment. Cardiovasc Diagn Ther. 2017; 7:489–506. [PMC free article] [PubMed] [Google Scholar]

[13] Cau R, Flanders A, Mannelli L, et al... Artificial intelligence in computed tomography plaque characterization: A review. Eur J Radiol. 2021; 140:109767. [PubMed] [Google Scholar]

[14] Al-Mallah MH, Sakr S. Artificial intelligence for plaque characterization: A scientific exercise looking for a clinical application. Atherosclerosis. 2019; 288:158–159. [PubMed] [Google Scholar]

[15] Feuchtner G, Kerber J, Burghard P, et al... The high-risk criteria low-attenuation plaque <60 hu and the napkin-ring sign are the most powerful predictors of mace: A long-term follow-up study. Eur Heart J Cardiovasc Imaging. 2017; 18:772–779. [PubMed] [Google Scholar]

[16] Matsumoto H, Watanabe S, Kyo E, et al... Standardized volumetric plaque quantification and characterization from coronary ct angiography: A head-to-head comparison with invasive intravascular ultrasound. Eur Radiol. 2019; 29:6129–6139. [PMC free article] [PubMed] [Google Scholar]

[17] Saba L, Francone M, Bassareo PP, et al... Ct attenuation analysis of carotid intraplaque hemorrhage. AJNR Am J Neuroradiol. 2018; 39:131–137. [PMC free article] [PubMed] [Google Scholar]

[18] van Rosendael AR, Narula J, Lin FY, et al... Association of high-density calcified 1k plaque with risk of acute coronary syndrome. JAMA Cardiol. 2020; 5:282–290. [PMC free article] [PubMed] [Google Scholar]

[19] Sheahan M, Ma X, Paik D, et al... Atherosclerotic plaque tissue: Noninvasive quantitative assessment of characteristics with software-aided measurements from conventional ct angiography. Radiology. 2018; 286:622–631. [PMC free article] [PubMed] [Google Scholar]

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