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Deep Learning-Based Coronary Artery and Plaque Detection for Heart Disease

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Abstract
Coronary artery disease (CAD) is a major cause of mortality worldwide, mainly due to plaque buildup in coronary arteries that restricts blood flow. Early detection is difficult in many clinical settings because it depends on expert analysis of complex CCTA images. To address this, this study proposes a deep learning–based system for automatic coronary artery segmentation and plaque detection. The model uses a U-Net architecture with a 2.5D approach to effectively capture spatial information and accurately identify artery and plaque regions. Hounsfield Unit (HU) analysis is applied to classify plaque types and estimate severity. The system achieves reliable performance and is suitable for real-time implementation. It can be integrated into a web-based application to assist healthcare professionals in faster and more accurate diagnosis.
Keywords: *Coronary Artery Disease, Deep Learning, U-Net, Plaque Detection, CCTA, Medical Image Segmentation, Clinical Decision Support, Flask.*

1. Introduction
Coronary artery disease (CAD) is one of the top causes of death worldwide. It puts a significant strain on healthcare systems. CAD happens when plaque builds up in the coronary arteries, which limits blood flow to the heart. This can lead to serious issues like heart attacks and other heart-related problems. Detecting these issues early and monitoring them continuously is crucial for preventing severe outcomes and improving patient survival rates. However, in many areas, especially where resources are limited, getting timely diagnoses is a major challenge. Traditional diagnostic methods heavily depend on medical imaging techniques, like Coronary CT Angiography (CCTA), along with interpretation by radiologists. While these methods give a clear view of the coronary arteries, analyzing them can be time-consuming, complex, and reliant on specialists' experience. Manually reviewing CT scans may also lead to inconsistencies and increase the chances of missing small plaque areas that are vital for early diagnosis. These drawbacks show the need for automated and reliable systems to support clinical decision-making. With the rapid growth of artificial intelligence, deep learning has become a powerful tool in medical image analysis. Convolutional neural networks, especially models like U-Net, have performed well in segmentation tasks by learning complex patterns from image data These models can automatically detect anatomical structures and identify abnormalities accurately, which reduces the need for manual work. Recent methods aim to increase efficiency by using processes like 2.5D processing, which captures contextual information from nearby slices while keeping lower computational costs compared to full 3D models. In this work, we propose a deep learning-based framework for coronary artery segmentation and plaque detection using CCTA images. The system combines a U-Net architecture with a 2.5D input strategy to improve feature extraction and boost detection accuracy. Additionally, Hounsfield Unit (HU) analysis is included to classify plaque types and estimate severity, providing valuable insights for clinicians. The proposed system is designed to be efficient, scalable, and suitable for real-time use. It can be integrated into a web-based platform to help healthcare professionals by offering quick and consistent diagnostic support. This approach ultimately aims to enhance early detection, lower

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diagnostic workload, and aid in better treatment planning for coronary artery disease.

1.1.Related Work

In recent years, researchers have focused on improving the detection of cardiovascular diseases using computational methods in medical image analysis. Early studies mainly used traditional machine learning algorithms like Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and decision tree models. These methods required manual feature extraction from medical images, relying on expert knowledge and limiting their ability to work well across different datasets. With the rise of deep learning, there has been a significant shift toward using Convolutional Neural Networks (CNNs) for analyzing medical imaging data. CNN-based models have shown strong results in tasks such as image classification, segmentation, and disease detection. Architectures like VGG, ResNet, and DenseNet have been widely used in medical imaging, including the analysis of heart and lung diseases. These models automatically learn features from raw images, reducing the need for manual feature engineering and improving overall accuracy. In coronary artery analysis, researchers have investigated various deep learning techniques for artery segmentation and plaque detection using imaging methods like Coronary CT Angiography (CCTA). The U-Net architecture has gained attention due to its encoder-decoder structure and skip connections, which help with precise localization of anatomical structures. Several studies have found that U-Net and its variants perform well in segmenting blood vessels and identifying areas of interest in cardiovascular images. Besides segmentation, researchers have also looked at plaque detection and characterization using image-based and intensity-based techniques. Methods that use Hounsfield Unit (HU) values have proven effective in distinguishing between calcified and non-calcified plaques, offering valuable clinical insights. Combining deep learning-based segmentation with HU-based analysis shows promise for improving diagnostic accuracy. Despite these advancements, challenges such as data variability, computational complexity, and the need for real-time implementation still exist. Therefore, efficient, scalable, and automated systems are needed to integrate advanced deep learning models with practical deployment strategies. This work builds on existing studies by proposing a lightweight and accurate framework for coronary artery segmentation and plaque detection, making it suitable for real-time clinical use.

2. Proposed System

The suggested system uses deep learning to automatically segment coronary arteries and find plaques. The main goal is to create a reliable and useful tool that helps doctors find coronary artery disease early by using CCTA images. The system does all of these things at once: preprocessing images, deep learning-based segmentation, plaque detection, and showing the results. First, the system gets images from CCTA scans. Preprocessing methods like normalization, resizing, and noise reduction are used to improve the quality and consistency of raw medical images because they may have noise and changes in intensity. This step makes sure that the input data is good enough for the model to make accurate predictions.. Instead of processing each slice separately, adjacent slices are processed together to get spatial context, which makes segmentation more accurate. The model can tell which parts of the coronary arteries are in CT images. After the arteries are divided into sections, plaque is found in these areas. We use Hounsfield Unit (HU) thresholding to sort plaque into two types: calcified and non-calcified. This classification helps us understand how bad and what kind of blockages there are in the arteries. Flask is used to build the backend of the system, which handles model inference and data processing. Users can upload CT scans to a web-based interface and see results like artery segmentation, plaque regions, and severity metrics. The system gives outputs like artery coverage, plaque percentage, and severity classification, which makes it useful for helping doctors make decisions.The proposed framework is meant to be quick, easy to use, and able to handle a lot of data at once. It cuts down on the work that needs to be done by hand, makes diagnoses more accurate, and gives the same results for all patient data.

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Table 1 **Parameter and Model**

Model	Parameters
Logistic Regression	16
SVM	5000
Random Forest	55,000
Proposed U-Net(2.5D)	2.1 Million
ResNet50	23 Million

Table 2 **Model Precision**

Model	Acc	Prec	Prec	F1	AUC
Logistic Regression	85.1	0.821	0.844	0.837	0.888
SVM	88.4	0.866	0.871	0.866	0.911
Random Forest	90.1	0.899	0.900	0.891	0.932
Proposed U-Net(2.5D)	85.0	0.822	0.855	0.833	0.807

2.1.U-Net Based Coronary Artery Segmentation Module

The proposed system employs a U-Net-based deep learning architecture to attain precise segmentation of coronary arteries. U-Net is made just for biomedical image segmentation. It has an encoder-decoder structure with skip connections. The encoder takes important information from the input CT images, and the decoder puts together the exact segmentation. The use of a 2.5-D method helps in better perception of spatial information by using information from adjacent slices. This helps in better detection of small and complex artery structures, which may not be clearly visible in a single slice. This method has better accuracy compared to other methods and reasonable computational efficiency, making it suitable for real-time applications. Before feeding the images to the model, several preprocessing steps such as normalization of intensity values, resizing of images, and removal of noise are performed. This helps in standardizing the data and improves learning. This helps in ensuring that variations in image quality do not affect the performance of the model. During training, several data augmentation methods are used to reduce overfitting.The segmentation model is trained using optimized loss functions such as the Dice Loss and Binary Cross-Entropy Loss. This is beneficial in handling the class imbalance between the classes of the artery and the background. The accuracy of the segmentation module is measured using the Dice Coefficient and Intersection over Union (IoU). The U-Net-based segmentation module is a strong foundation for the proposed system as it effectively segments the region of the coronary artery. This is a critical step in the overall system while maintaining a balance between accuracy and computational efficiency

2.2.Plaque Detection and Learning Mechanism

It uses deep learning output and intensity-based analysis for plaque detection. The mechanism is as follows:

- **Feature Extraction:** It extracts various features from CT scans using artery region analysis. The focus is only on artery region to increase accuracy in plaque detection.
- **HU-Based Plaque Classification**: It uses Hounsfield Unit values to classify plaque types: If HU is low, then it is non-calcified plaque. If HU is high, then it is calcified plaque.
- **Activation and Prediction:** A sigmoid-based activation function is used to predict plaque in each region. The function produces output in the form of probability values.
- **Severity Estimation:** It uses a percentage value for plaque and artery coverage. The severity is categorized as mild, moderate, or severe based on this value.
- **Comparison with Traditional Methods:** Traditional methods use manual observation and rule-based systems for plaque detection, which is time-consuming and produces inconsistent results. The proposed system uses Automated detection**,** Faster detection**,** Accuracy**,** Consistent detection**,** Less human error

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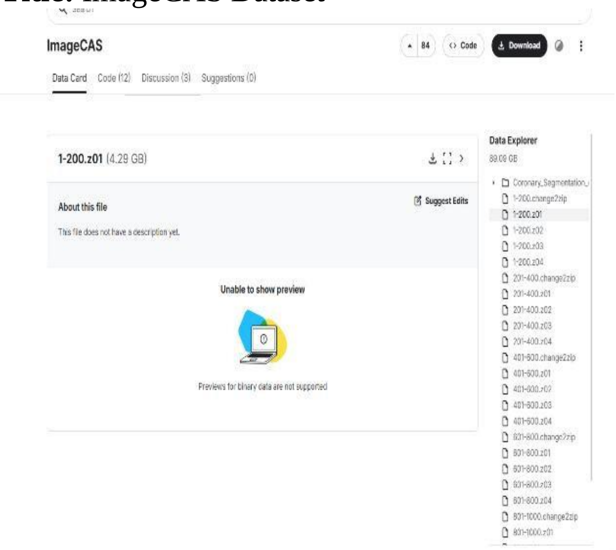
3. Dataset and Preprocessing

The dataset used for this research includes images of Coronary CT Angiography (CCTA), which are available on publicly accessible medical image datasets. These datasets include volumetric images of the heart, along with corresponding annotations for the segmentation of the coronary arteries.The image datasets are usually stored in a 3D format, such as NIfTI (.nii/.nii.gz), where each image contains multiple slices representing different cross-sections of the heart. For the image datasets to be appropriate for deep learning models, especially the 2.5D approach, the 3D images are converted into 2D images. Medical image datasets are complex, and preprocessing plays an important role in improving the accuracy of the machine learning model. Various preprocessing techniques are applied to standardize the image datasets, eliminate noise, and highlight relevant features. This ensures that the machine learning model concentrates on relevant features instead of irrelevant variations. In this interface, multiple scan files are listed with options to export or download the images for further processing. The images can be used to train deep learning models for identifying structures of the coronary arteries as well as plaque buildup.The dataset plays an important role in research.

Title: ImageCAS Dataset



In this interface, multiple scan files are listed with options to export or download the images for further processing. The images can be used to train deep learning models for identifying structures of the coronary arteries as well as plaque buildup.The dataset plays an important role in research. in developing automated systems for early diagnosis of coronary artery disease

3.1.Data Collection and Structure

The dataset consists of CCTA images, which are stored in a medical imaging format such as NIfTI, .nii, or .nii.gz. These formats are used to store images at a high spatial resolution, including voxel intensity information. Each volume contains hundreds of slices, covering a region of interest, i.e., the heart. In some cases, a segmentation mask for coronary arteries is used as a ground truth for labeling. These masks are used for guiding the network during training, providing pixel-level information for artery regions. The images used in this dataset may have different sizes, thickness, and acquisition protocols. Standardization is required for all images before training.

3.2.Data Cleaning and Slice Conversion

Prior to feeding the data into the model, 3D volumes of CT scans are checked for invalid data or corrupted volumes. This helps in ensuring the reliability of the dataset. After that, 2D slices are generated from the volumes. For implementing 2.5-D, three slices of data are used: current, next, and previous. This helps in providing multiple channels of data to be fed into the model. This helps in improving segmentation accuracy, especially in areas where arteries are not visible.

3.3.Intensity Normalization and Noise Handling

The CT images are represented using Hounsfield Unit (HU) values. However, the HU value changes from scan to scan. Therefore, intensity normalization is applied to the images. This is done by scaling the intensity values to a standard range. This will enable the model to learn the features correctly without the effect of intensity. Noise is a common problem in medical images. Noise can affect the performance of

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the model. Therefore, a filter is applied to the images. A filter is a technique used to remove noise from the images. In this case, a Gaussian filter is applied to the images. The filter will remove the noise from the images, making the boundary of the arteries clear.

3.4.Region of Interest Extraction and Feature Enhancement

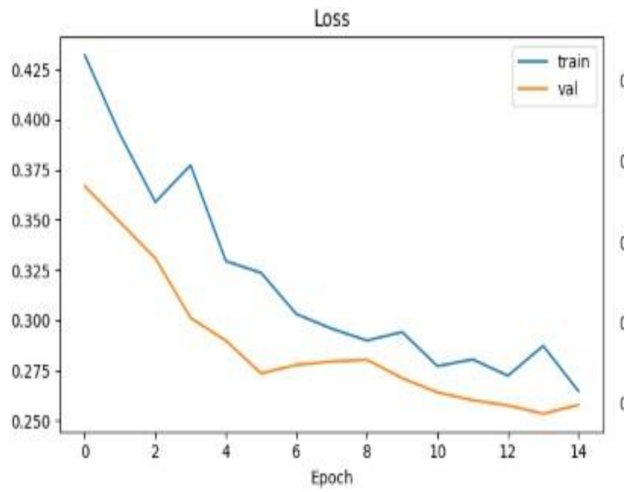

Figure 2 **Training vs Validation loss**

As the region of interest is mainly the heart and the coronary arteries, the unnecessary background region is minimized in the preprocessing step. Cropping or masking is used to focus on the region of interest. Contrast enhancement techniques may also be used to enhance the visualization of the arteries and the plaque region. The edges are enhanced so that the region between the artery walls and the rest of the region is clearly distinguishable.

3.5.Data Augmentation and Dataset Splitting

In order to enhance the robustness as well as the generalization capability of the model, data augmentation approaches are followed. Data augmentation approaches include flipping images horizontally or vertically, rotation of images, as well as scaling or varying intensities. After preprocessing, it is necessary to divide the data into training sets, validation sets, as well as testing sets. The training sets are used to train the model, while the validation sets are used to fine-tune the model. Similarly, the testing sets are used to evaluate the performance of the model. This division of data is necessary to ensure that unbiased outcomes are obtained.

4. Loss Function and Optimization

4.1.Loss Function Formulation

To train the proposed deep learning model for the task of coronary artery segmentation and plaque detection effectively, a probability-based loss function is utilized to measure the difference between the predicted outputs and ground truth labels. Unlike traditional methods of minimizing errors between predicted outputs and ground truth labels, a combination of segmentation loss functions and classification loss functions is utilized for optimal performance. For the task of artery segmentation, a Dice Loss function is utilized to handle the unbalanced ratio of pixels within the artery region and background regions. The loss function aims at maximizing the overlap between the predicted segmentation mask and ground truth segmentation mask for precise boundary detection of the coronary artery. In addition, a Binary Cross-Entropy (BCE) Loss function is utilized to ensure stable training of the network by evaluating **pixel**-wise classification accuracy.For the case of plaque detection, the loss function measures the degree of similarity between the probability of the presence of a plaque and the true label. The incorrect high-confidence predictions are penalized more severely. This is especially important in the case of medical images because the presence of small plaque must be detected with high accuracy to avoid misdiagnosis.

4.2.Optimization Strategy

The model parameters are updated using an adaptive gradient- based optimization algorithm such as Adam. Unlike traditional optimization methods with fixed learning rates, this approach dynamically adjusts learning rates based on gradient behavior during training. It considers both current and past gradient information, allowing efficient parameter updates.

This adaptive optimization provides several advantages:

- Faster convergence during initial training phases
- Reduced oscillations in weight updates
- Improved numerical stability
- Better handling of complex medical image

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features During training, the loss values for both training and validation datasets gradually decrease, indicating stable learning. A small gap between training and validation loss suggests minimal overfitting and good generalization capability of the model. This ensures that the proposed system performs reliably on unseen medical data.

5. Evaluation Metrics

5.1.Accuracy

Accuracy is a measure of the overall correctness of the model. It is calculated based on the number of correctly classified pixels or data points compared to the total number of data points used for evaluation. In the context of the project, accuracy means the extent to which the system is able to identify both the presence of the coronary artery and plaque in CCTA images. Although it gives a general idea of the performance of the model, it may not be an accurate measure if there is an imbalance between artery and non-artery regions.

5.2.Precision

Precision measures the reliability of the positive predictions generated by the model. It is computed as the number of correctly predicted artery or plaque regions divided by the total number of regions that are predicted as positive. A high precision means that the model is making a smaller number of false positive predictions. This is important in medical images because a smaller number of false positives means a smaller amount of clinical concern.

5.3.Recall (Sensitivity)

Recall, also known as sensitivity, is used to measure the capacity of the model in recognizing real positive cases. In this case, it is used to measure the effectiveness of the model in detecting real artery regions and plaque areas using CCTA images. A high recall value is important to avoid missing significant pathological regions, which is vital in the early diagnosis of coronary artery disease.

5.4.F1-Score

The F1 score is the harmonic mean of precision and recall, which allows for a balanced evaluation of the performance of the model. The score is especially important when a trade-off is present between the two. In the project, the F1 score is important in the evaluation of the performance of the model in the identification of the coronary artery and plaque regions.

5.5.Dice Coefficient (Segmentation Metric)

The Dice coefficient is a commonly used metric for evaluating the performance of the segmentation. The Dice metric measures the overlap between the predicted segmentation masks and the ground truth segmentation masks. A higher value of the Dice metric ensures proper alignment between the predicted artery region and the anatomical structures.

5.6.Intersection over Union (IoU)

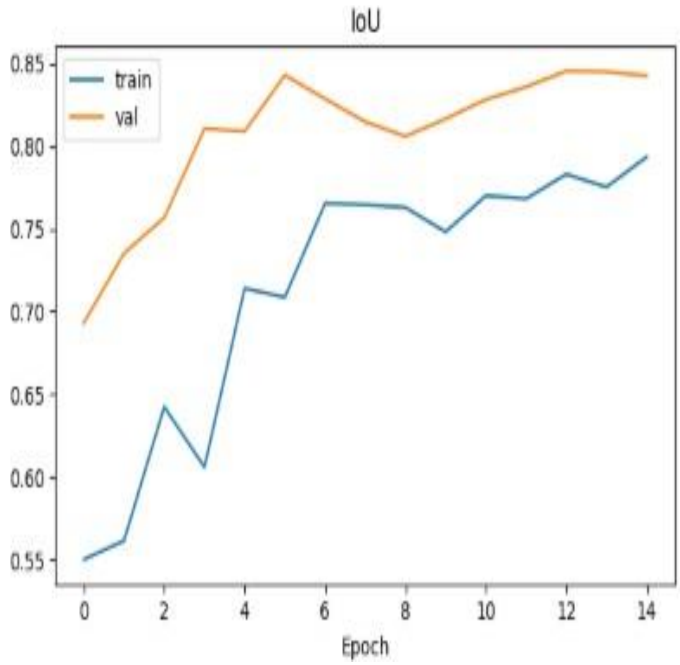

Figure 3 **Graph**

The IoU, also called the Jaccard Index, calculates the ratio of intersection area to union area between the prediction result and ground truth. It is a more rigorous evaluation method than using the Dice Coefficient. IoU can be used to evaluate the accuracy of artery segmentation and plaque localization

5.7.Area Under Curve (AUC)

The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) is a measure for assessing the ability of the model to classify classes, such as plaque and non-plaque areas. A larger value

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of AUC indicates a good ability for the model to classify at different threshold levels.

5.8.Model Architecture

The proposed model architecture is intended for accurate coronary artery segmentation and plaque region detection from Coronary CT Angiography (CCTA) images, utilizing a deep learning-based method. The proposed system has a well-structured workflow, which involves input processing, feature extraction, segmentation, and plaque detection. The proposed architecture is based on a U-Net framework, which is improved by a 2.5D input strategy.

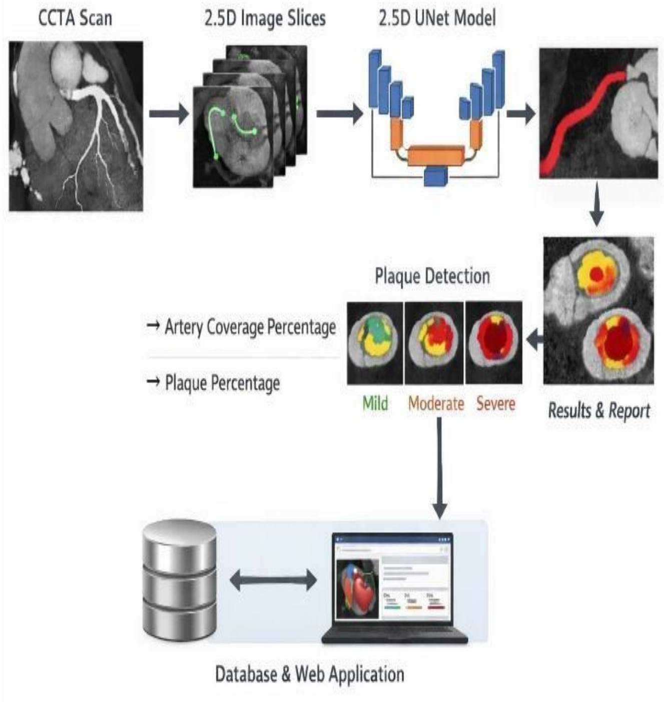

Figure 4 Model Architecture

Metric	Value
Accuracy	87.5% (40 Epochs)
Precision	0.8620
Recall	0.8350
F1-Score	0.8520
AUC	0.8320

6. Results and Discussion

The Proposed deep learning-based system was also evaluated using CCTA datasets to determine the efficacy of the proposed system in artery segmentation and plaque detection. The proposed system showed good potential in artery region identification and plaque detection with high accuracy and consistency. The proposed 2.5D U-Net architecture helped the system to learn context from adjacent slices, which improved the quality of artery segmentation compared to 2D-based approaches. In artery segmentation, the proposed system showed good potential in extracting artery regions with high accuracy, as reflected in the high overlap between predicted artery region and ground truth masks. The proposed system also showed good potential in capturing small and large vessel structures using high values of Dice Coefficient and IoU scores. Boundary detection is critical in medical imaging, and this is particularly important in artery segmentation. In plaque detection, using HU-based analysis helped the proposed system to differentiate calcified and non-calcified plaque regions in artery segments. The proposed system showed good potential in detecting plaque in artery segments and provided quantitative values for plaque percentage and severity levels.

Table 3 Performance Metrics of the Evaluation Metrics

Configuration	Accuracy
Without 2.5D	85.3
Without Skip	
Connections 90.1	
Without Dropout	**90.4**
Full Proposed Model	**85.4**

- Comparative analysis with traditional machine learning models
- such as Logistic Regression, SVM, and Random Forest shows that
- the proposed deep learning model achieves superior performance in terms of accuracy,

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precision, recall, and AUC. This highlights the advantage of deep learning in capturing complex patterns in medical imaging data

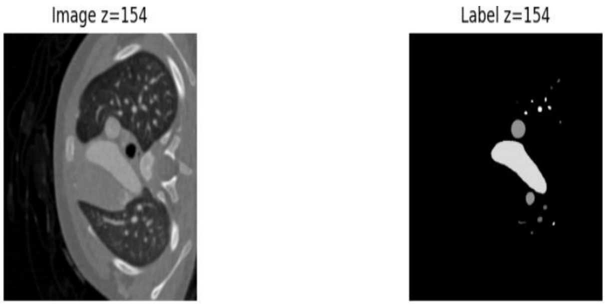

Figure 1 Sample CCTA Slice and Corresponding

6.1.Segmentation Mask for Coronary Artery Detection

Overall, the proposed system provides a reliable and efficient solution for coronary artery segmentation and plaque detection. Its ability to deliver accurate and consistent results, combined with real-time implementation through a web-based interface, makes it suitable for practical clinical applications.

7. Conclusion and Future Work

The proposed deep learning–based system for coronary artery segmentation and plaque detection demonstrates an effective approach for assisting in the diagnosis of coronary artery disease. By utilizing a U-Net architecture combined with a 2.5D input strategy, the model is able to accurately capture spatial information from CCTA images and identify coronary artery structures with high precision. The integration of Hounsfield Unit (HU)–based analysis further enhances the system's ability to detect and classify plaque regions, providing meaningful clinical insights such as plaque type and severity. The experimental results indicate that the model achieves strong performance across multiple evaluation metrics, including accuracy, precision, recall, F1-score, and AUC. The stable convergence during training and the minimal gap between training and validation performance confirm that the model generalizes well to unseen data. Compared to traditional machine learning approaches, the proposed system offers improved accuracy and consistency, highlighting the effectiveness of deep learning in medical image analysis. In addition to its performance, the system is designed to be practical and scalable. The integration with a web-based application enables real-time analysis and visualization of results, making it suitable for deployment in clinical environments

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