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Automated Coronary Artery Disease Severity Grading Using Deep Learning

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Abstract

Coronary Artery Disease (CAD) is a common cardiovascular disease worldwide and requires accurate and early detection to avoid serious complications such as heart attacks and cardiac arrests. Invasive Coronary Angiography (ICA) remains the most reliable method for assessing the degree of arterial stenosis; however, its interpretation is often subjective and prone to human error. This project aims to overcome these limitations by utilizing a deep learning-based framework for automated CAD classification using ICA images. The classification of image patches into lesion and non-lesion categories across different lesion severity ranges is performed using five Convolutional Neural Network (CNN) architectures: DenseNet, ResNet, LeNet, AlexNet, and VGGNet, after implementation and evaluation. High-quality model training is achieved by preprocessing the dataset through vessel segmentation, patch extraction, class balancing, and data augmentation. Measurement of performance is done by using accuracy, precision, recall, F-measure, and area under the ROC curve (AUC). The experimental results demonstrate that DenseNet and ResNet perform better, with an F-measure that exceeds 90% and an AUC that exceeds 98%, effectively identifying severe lesion regions. By using the proposed framework, CAD diagnosis can be improved through the use of a robust, automated, and clinically applicable solution that improves diagnostic precision and reduces manual workload for cardiologists.

Keywords: *Coronary Artery Disease (CAD), Deep Learning, Convolutional Neural Networks, Invasive Coronary Angiography, DenseNet, ResNet, LeNet, AlexNet, VGGNet.*

1. Introduction

Deep Learning is a subset of Artificial Intelligence (AI) and a specialized branch of Machine Learning (ML) that focuses on using artificial neural networks to model and understand complex patterns in data. Inspired by the human brain, deep learning systems consist of multiple layers of interconnected nodes (neurons) that can automatically learn hierarchical feature representations from large amounts of data. Unlike traditional machine learning algorithms that rely heavily on manual feature extraction, deep learning models learn features directly from raw data such as images, audio, or text. This ability to perform end-to-end learning makes deep learning exceptionally powerful in handling complex tasks like image recognition, natural language processing, speech recognition, and autonomous systems. In traditional machine learning, humans must manually choose which features or patterns to focus on. But in deep learning, the system can automatically learn important features from raw data such as images, videos, sounds, or text. This makes it very effective for complex tasks like image recognition, speech processing, natural language understanding, and medical diagnosis. This work focuses on developing a deep learning-based automated system to classify coronary artery lesions from Invasive Coronary Angiography (ICA) images. Coronary Artery Disease (CAD) is a major cause of death globally, and accurate lesion detection plays a critical role in diagnosis and treatment planning. However, manual interpretation of angiograms is subjective and time-consuming, often varying among cardiologists. To overcome this, the work applies Convolutional Neural Networks (CNNs) such as LeNet, AlexNet, VGG16, ResNet50, and DenseNet201 for binary classification of image patches into lesion and non-lesion categories. The ICA images from the CADICA dataset were preprocessed through vessel segmentation, patch extraction, and data augmentation to enhance model learning. Among the

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tested architectures, DenseNet201 achieved the best performance, with a validation accuracy of 92.7% and AUC of 0.981, demonstrating superior capability in detecting high-severity lesions. The system also visualizes the lesion probability map on the original ICA image, providing interpretability for medical professionals. This work supports computer-aided diagnosis (CADx) systems, helping clinicians in faster and more consistent coronary disease detection and enabling future real-time clinical applications.

2. Literature Review

Iyer et al. (2021) introduced AngioNet, a convolutional neural network designed specifically for vessel segmentation in X-ray coronary angiography. The network achieves Dice similarity of 0.864 and pixel accuracy of 0.983, successfully delineating coronary vessels comparable to Quantitative Coronary Angiography (QCA). The study demonstrates that accurate vessel masks are essential for downstream tasks such as lesion detection, highlighting the model's suitability as a preprocessing module in automated lesion detection frameworks. Alskaf et al. (2022) provided a comprehensive survey of deep learning techniques applied to coronary imaging, including ICA, coronary computed tomography angiography (CCTA), and intravascular ultrasound (IVUS). The review outlines tasks such as vessel segmentation, stenosis detection, plaque characterization, and Fractional Flow Reserve (FFR) estimation. The authors conclude that CNN-based models outperform traditional image processing methods but face challenges like dataset heterogeneity and limited clinical validation. The study provides valuable context, emphasizing the growing trend toward fully automated coronary analysis and the importance of robust, generalizable networks for clinical use. Wang et al. (2024) proposed an end-to-end architecture that simultaneously localizes and classifies coronary artery narrowings. Unlike traditional two-step systems, their integrated model jointly optimizes bounding-box regression and stenosis severity classification, achieving superior accuracy and computational efficiency. This approach provides evidence that combined learning of localization and classification improves model performance and could serve as an upgrade path for transitioning your project from patch-level detection to region-based lesion identification. Arefinia et al. (2024) developed a CNN-based framework for predicting Fractional Flow Reserve (FFR) directly from angiographic images, enabling non-invasive evaluation of stenosis severity. The model extends lesion detection into functional assessment, representing a clinically meaningful progression from visual lesion classification. The work demonstrates the potential to combine anatomical lesion detection with physiological prediction, aligning with the future vision of integrating lesion detection and hemodynamic estimation in one automated workflow. Lalinia et al. (2024) proposed a hybrid edge-based and tracking-assisted segmentation model to improve robustness against non-uniform illumination, image noise, and compression artifacts in angiographic imaging. The model employs probability mapping for vessel boundaries and path-tracking refinement to preserve vessel continuity. Testing on real-world angiography datasets shows improved Dice coefficients and smoother vessel topologies under challenging imaging conditions. This study underscores the need for artifact-resilient preprocessing to ensure reliable input for lesion patch generation and classification, which is vital for real-world clinical applications. Jiménez-Partinen et al. (2024) presented a comparative evaluation of multiple CNN architectures—LeNet, AlexNet, VGG, ResNet, and DenseNet—for lesion classification in ICA images. The authors analyze the influence of patch size, learning rate, and data augmentation techniques on model accuracy. Results show that ResNet and DenseNet outperform shallow networks, achieving higher precision and generalization across folds. The paper also recommends stratified cross-validation and balanced datasets for fair model comparison. This work validates your project's approach of evaluating various CNN models for patch-based lesion detection, offering empirical guidelines for optimal training configurations.

3. Methodology

The problem of automated detection of coronary artery lesions from invasive Coronary Angiography (ICA) images is addressed by this work. The purpose

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of the proposed method is to develop a reliable and easily implementable deep learning framework that can accurately categorize lesion and non-lesion regions while also delivering clinically interpretable results. Preprocessing, feature extraction, classification, and visualization stages are part of the patch-based CNN approach that the system follows.

3.1 Proposed Method

The method involves breaking up preprocessed ICA images into 32x32 image patches and using a CNN to categorize each patch as either a lesion or a non-lesion. Deep feature extraction is carried out by DenseNet201 due to its dense connectivity, which improves feature reuse and learning efficiency. The efficiency of computational efficiency can be improved by pooling and normalizing layers, while fully connected layers perform final decision-making. Probability scores for each lesion are generated by a sigmoid activation function. To visualize affected vessel regions, lesion probability maps are generated by mapping these patch-level predictions back onto the original ICA image. Both mild and severe lesions can be detected through this design while ensuring high accuracy, efficiency, and interpretability.

3.2 Algorithm Used Dataset

The proposed model's training and validation are ensured by using a dataset that is clinically relevant and well-annotated in this study. For coronary lesion analysis, the CADICA dataset is utilized, which comprises ICA videos collected from 42 patients. Each frame has a resolution of 512x512 pixels, and the images are captured in real clinical conditions. Lesion severity levels that range from less than 20% to 100% occlusion can be found in the dataset's ground-truth lesion annotations. The precise localization of lesion regions can be done using bounding box coordinates. The dataset is suitable for supervised deep learning experiments and comprehensive model evaluation because it includes both selected and non-selected videos, as well as clinical metadata. Figure 1 represents the dataset images.

3.3 Preprocessing

Enhancing vessel visibility and standardizing input data for CNN models involves performing preprocessing. The OpenCV library is used to read ICA images and convert them from RGB to grayscale, which reduces computational complexity while maintaining essential vessel information. To enhance arterial structures while suppressing noise and improving vessel contrast, histogram equalization is used, followed by other morphological operations. To isolate arterial regions, vessel masking techniques are employed, and background pixels are eliminated using thresholding. Patch-based processing that captures localized vessel features is made possible by splitting the preprocessed images into 32x32 patches. To improve model generalization and robustness, data augmentation techniques are applied, and pixel values are normalized to the range [0, 1].

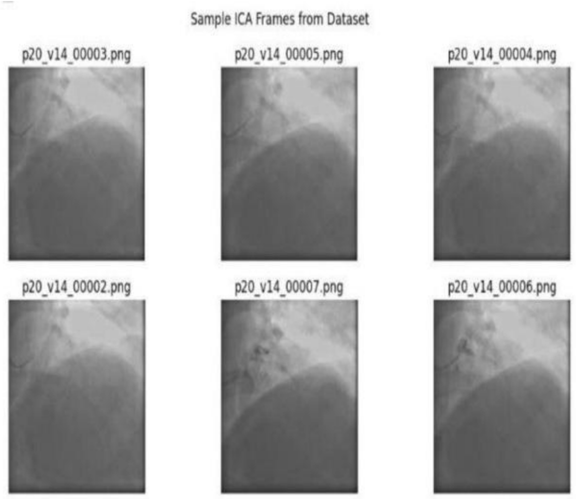

Figure 1 **Dataset**

4. Implementation

The process (Figure 2) begins with ICA image acquisition, where coronary angiography frames are collected from the dataset for analysis. These images are then passed to the preprocessing stage, which removes noise, enhances contrast, and generates vessel masks using OpenCV to clearly highlight coronary arteries. Next, the enhanced images undergo patch extraction, where each image is divided into 4×4 grids and resized to 32×32 patches for uniform CNN input. In the patch labeling stage, each patch is annotated as a lesion or a non-lesion based on the presence of coronary abnormalities. The VGG16

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feature extraction network uses the marked patches to learn hierarchical vessel and lesion features through multiple convolutional blocks with ReLU activation and max-pooling. Effective classification is achieved by passing the extracted features through fully connected layers with dropout and softmax. The classification output gives a clear indication of whether the region is a lesion or not through a binary decision. The evaluation stage involves evaluating model performance using metrics such as accuracy, AUC, loss, and F1-score. Finally, lesion visualization makes it possible to clearly interpret clinical findings by highlighting detected lesion regions in red and normal regions in green.

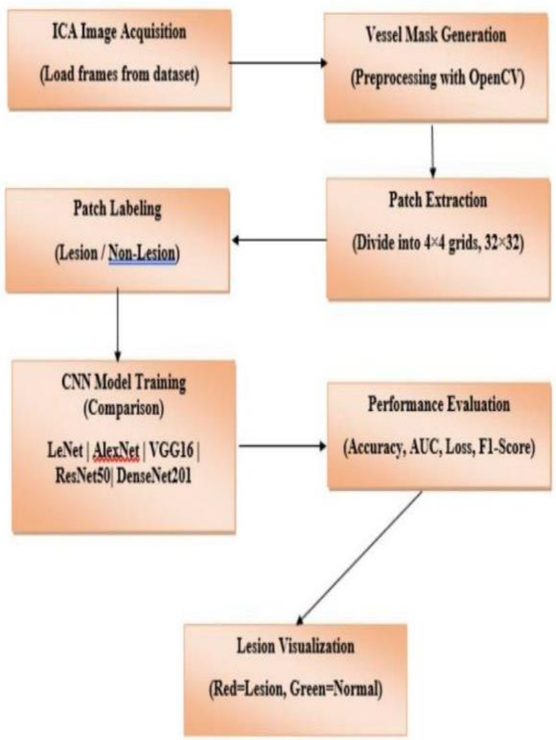

Figure 2 Block Diagram

4.1 ICA Image Acquisition

In the first step, angiographic frames are collected from the CADICA dataset. These ICA images contain visual representations of coronary arteries, which are used as the primary input for the system. Each frame is read and loaded into the program using the OpenCV library in Python for further processing.

4.2 Vessel Mask Generation (Preprocessing With OpenCV)

The acquired ICA images often contain noise, uneven illumination, and background regions. Therefore, preprocessing is performed using OpenCV functions to enhance vessel visibility. A vessel mask is generated through techniques such as histogram equalization, morphological operations (opening and closing), and thresholding. This mask isolates the coronary vessel regions from the background, allowing the model to focus only on diagnostically relevant features.

4.3 Patch Extraction

Once the vessel mask is created, each preprocessed image is divided into smaller patches using a 4×4 grid, resulting in 16 patches of size 32×32 pixels each. This patch extraction method allows the CNN models to analyze localized vessel structures more effectively, helping them identify lesion patterns in small regions rather than entire frames.

4.4 Patch Labeling (Lesion / Non-Lesion)

Each extracted patch is manually or semi-automatically labeled as either Lesion or Non-Lesion based on the presence or absence of arterial blockage. This labeling serves as the ground truth for supervised learning, enabling the CNN models to learn the distinguishing features of diseased and healthy vessel regions.

4.5 CNN Model Training (Comparison)

The labeled patches are used to train and compare multiple CNN architectures — LeNet, AlexNet, VGG16, ResNet50, and DenseNet201.

Each model processes the patches through convolutional, pooling, and fully connected layers to extract relevant features and perform binary classification (Lesion / Non-Lesion). This comparative analysis identifies which CNN model provides the highest accuracy and reliability for CAD image classification.

4.6 Performance Evaluation

After training, each CNN model is evaluated using performance metrics such as Accuracy, AUC, Loss, and F1-score. The evaluation results are visualized using plots (accuracy and loss curves), allowing a clear comparison of how effectively each model generalizes to unseen data. Among all models,

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DenseNet201 achieved superior validation accuracy (92.7%) and AUC (0.98), indicating its effectiveness for CAD lesion classification.

4.7 Lesion Visualization

In the final stage, the system overlays the classification results on the original ICA image for interpretability. Each patch is marked using a color-coded system:

- Red boxes indicate Lesion (diseased) regions.
- Green boxes indicate Non-Lesion (normal) regions.

This visual representation allows cardiologists to easily identify areas with possible blockages and assess lesion severity.

Conclusion

The proposed research project, "Coronary Artery Disease Classification Using Deep Learning," successfully developed and evaluated an intelligent system capable of detecting and classifying coronary artery lesions from Invasive Coronary Angiography (ICA) images. Through a comparative analysis of multiple deep learning architectures — LeNet, AlexNet, VGG16, ResNet50, and DenseNet201 — the study established that DenseNet201 provides the most accurate and reliable classification performance. Key outcomes of the project include:

- Implementation of automated vessel segmentation and patch-based image preprocessing to enhance feature clarity.
- Comparative training of five CNN architectures under consistent conditions to ensure fairness and reproducibility.
- The DenseNet201 model achieved superior results with a validation accuracy of 92.7%, F1-score of 0.93, and AUC of 0.98.
- Effective lesion visualization overlays were generated, highlighting affected artery regions for clinical interpretability.
- The system demonstrates potential as a Computer-Aided Diagnostic (CADx) tool, aiding cardiologists in early detection and treatment planning for coronary artery disease.

In conclusion, the proposed deep learning framework provides a highly accurate, efficient, and interpretable solution for CAD lesion detection, proving the feasibility of AI-driven diagnostics in cardiovascular imaging.

Future Enhancement

The ICA dataset will be expanded with clinically annotated images for better generalization through future enhancements. To identify levels of lesion severity, the model can be extended to multiclass classification. Preprocessing quality can be further improved with the use of advanced vessel segmentation and noise reduction. To enhance interpretability, it is possible to integrate explainable AI methods such as Grad-CAM. Using temporal ICA information is an option for video-based models such as CNN-LSTM. Inference speed can be improved through the use of model compression techniques. Clinical use can be improved through the enhancement of real-time web and mobile deployment. Exploration is possible for optimizing the GPU and edge devices. Reliability can be enhanced through clinical validation with cardiologists. Real-world adoption can be supported by integrating with hospital systems.

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