ISSN:2731-538X | E-ISSN:2731-5398
Vol. 19 No. 01 (2025)

ADAPTIVE MULTI-SCALE EDGE DETECTION USING GRAPH-BASED LEARNING FOR ENHANCED MEDICAL IMAGING

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Abstract

Accurate edge detection in medical imaging, particularly in COVID-19 CT scans, is critical for diagnosing and assessing the severity of infections accurately. Traditional edge detection methods often struggle with the complexity and variability of medical image data, leading to less reliable diagnostic outcomes. This research introduces an adaptive graph-based multi-scale edge detection model that significantly enhances the accuracy and reliability of edge delineation in COVID-19 CT scans. The proposed model employs Adaptive Graph Convolutional Networks (AGCNs) integrated with a dynamic, multi-scale analysis approach. This methodology allows the model to adaptively process image data across multiple scales, effectively capturing both global structures and fine details. The graph-based approach is tailored to adjust the connectivity and weights dynamically based on the local context of the image features, enabling superior detection of subtle and complex patterns. Experimental results demonstrate that the proposed model achieves an accuracy of 0.995, precision of 0.920, recall of 0.970, and a Dice Similarity Coefficient (DSC) of 0.945. These metrics significantly surpass those of traditional methods like Sobel + GCN and Canny + GCN, and even outperform the advanced CDSE-UNet model referenced in earlier studies. Qualitatively, the edges detected by the proposed model are sharper and more consistent with the clinical annotations provided by medical experts. The novelty of this research lies in its integration of graph-based learning with a multi-scale approach tailored specifically for medical imaging, providing a robust framework that can adapt to various imaging conditions and requirements. This model not only sets a new standard in medical image edge detection but also opens avenues for further research and application in other areas of medical imaging.

1. Introduction

Edge detection is a critical component in the realm of medical imaging, serving as the foundational step in many image analysis tasks such as image segmentation, object detection, and feature extraction [1]. In medical contexts, accurately identifying the boundaries of anatomical structures, lesions, or pathologies directly influences diagnostic accuracy, treatment planning, and patient outcomes [2]. Being able to clearly outline edges within medical images helps doctors and radiologists determine the size and scope of diseases. This includes conditions like tumors or infectious diseases such as COVID-19, which show up on imaging tests as changes in the density and structure of tissues [3, 4].

The importance of edge detection in medical imaging cannot be overstated [5]. For example, in oncology, the exact boundary of a tumor may determine the staging of cancer and the appropriate surgical or therapeutic intervention [6]. Similarly, in the treatment of cardiovascular diseases, identifying vessel boundaries can help in assessing the severity of

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arterial blockages [6]. In the case of infectious diseases, such as COVID-19, detecting changes in lung texture and identifying areas of inflammation are crucial for assessing disease progression and potential complications [4, 7 – 9].

However, traditional edge detection techniques often encounter limitations when applied to medical imaging [10]. Conventional methods such as the Sobel, Prewitt, and Canny detectors rely on gradient-based approaches to identify areas of high intensity contrast [11 – 13]. These methods, while effective in general imaging tasks, may not perform well with medical images due to several inherent challenges:

- Noise Sensitivity: Medical images are often compromised by various types of noise and artifacts resulting from the imaging process itself, such as scatter in computed tomography (CT) or speckle noise in ultrasound images [14]. Gradient-based edge detectors, which rely on intensity discontinuities, can mistakenly identify noise as edges, leading to false positives and inaccuracies [15].
- Variability in Image Contrast: Unlike standard photographs, medical images can exhibit highly variable contrast levels [16]. Different tissues and structures may have subtle differences in intensity, which conventional edge detection methods might fail to accurately capture, especially when the contrast is low [17].
- Complexity and Ambiguity of Medical Structures: Medical structures can be complex and their edges often ambiguous, not necessarily characterized by clear intensity gradients [18]. Pathological changes, such as diffuse tumors or inflammatory processes like those seen in COVID-19 pneumonia, often result in edges that are difficult to define precisely using traditional methods [19].
- Scale Dependency: The appearance of edges can vary significantly depending on the scale of observation [20]. Traditional methods do not inherently account for multi-scale representations, which can lead to either missing fine details when focusing on larger scales or getting overwhelmed by details at smaller scales [21].

To address these limitations, recent advancements have focused on developing more robust edge detection techniques that can adapt to the specific challenges presented by medical imaging. Techniques leveraging advanced computational methods such as machine learning and deep learning have shown promise. These methods can learn from large datasets of annotated images to better understand the characteristics of edges specific to different tissues and pathologies.

Deep learning models, particularly Convolutional Neural Networks (CNNs), have been at the forefront of this transformation [22]. Unlike traditional gradient-based techniques, CNNs can learn to identify edges based on a broader context within the image, making them less sensitive to noise and capable of recognizing edges that are difficult to discern due to low contrast or complex morphology [23]. Moreover, CNNs can be trained to operate at multiple scales simultaneously, enhancing their ability to accurately detect edges across a range of structural sizes [24].

Graph-based methods represent another frontier in edge detection technology. These methods model the image as a graph where pixels or superpixels serve as nodes, and edge weights between them reflect the likelihood of a boundary. Such approaches are inherently more flexible and can incorporate both local and global image features, potentially offering superior performance in complex scenarios like medical image analysis.

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2. Methodology

2.1 Enhanced Graph Representation

In advancing the graph representation of images for edge detection, the method introduces a refined approach that integrates dynamic adaptive thresholding and node feature augmentation. This innovative representation leverages the adaptive connectivity of pixels based on contextual and structural information, enhancing the graph's capacity to encapsulate critical edge details necessary for accurate edge detection in complex medical images like COVID-19 CT scans.

Dynamic Graph Structure:

Instead of using a fixed adjacency based on physical proximity (8-connectivity), the graph G = (V, E) is constructed where each vertex $v_i \in V$ still corresponds to a pixel in the image, but the edges E are formed based on an adaptive neighborhood system. This system dynamically adjusts the connectivity of each pixel based on the local variance of intensity, which is indicative of potential edges or transitions in tissue density.

Adaptive Edge Weight Formulation:

The edge weights between nodes are not solely dependent on intensity differences but are further modulated by a contextual similarity index that incorporates texture and pattern similarities. The weight w_{ij} between nodes i and j is defined using a novel adaptive formulation as given in the equaiton 1:

$$w_{ij} = \exp\left(-\beta\left(\frac{|I_i - I_j|}{1+\sigma(I_i, I_j)}\right)\right) \quad (1)$$

where I_i and I_j are the intensity values, $\sigma(I_i, I_j)$ is a similarity function assessing textural and contextual congruence between the pixels, and β is a parameter that adjusts the sensitivity of the edge weight to these combined factors.

Graph Neural Processing:

The graph representation is processed using a novel class of Graph Neural Networks (GNNs) designed to work with dynamically weighted and structured graphs. The network incorporates layers of Adaptive Graph Convolutional Networks (AGCNs) that can process nodes with varying degrees of connectivity and edge weights. Each AGCN layer updates node features by considering both the feature similarities and the dynamic structure of the graph in the equation 2:

$$H^{(l+1)} = \sigma\left(B^{(l)} \hat{D}^{-\frac{1}{2}} \hat{A} \hat{D}^{-\frac{1}{2}} H^{(l)} W^{(l)}\right) \quad (2)$$

where $H^{(l)}$ is the node feature matrix at layer l, $W^{(l)}$ is the weight matrix for the layer, $\hat{A}$ is the adaptive adjacency matrix, $\hat{D}$ is the degree matrix of $\hat{A}$, $B^{(l)}$ is a layer-specific modulation matrix that adapts the influence of neighboring nodes based on the current node state, and σ is a nonlinear activation function.

Multiscale Integration:

The adaptive graph structure and processing are applied across multiple scales using a

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pyramid-like approach, where each level of the pyramid processes a different resolution of the graph. This multiscale processing enables the capture of both macroscopic and microscopic edge features, crucial for delineating detailed structures within medical images.

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This enhanced graph representation and processing framework is designed to be robust against the common challenges in medical imaging, such as noise, variability in lesion appearance, and ambiguous boundaries, thereby providing a powerful tool for edge detection in medical diagnostic imaging.

3.2 Graph-Based Learning

The next step is to introduce our Graph-Based Learning methodology for advanced edge detection in medical images by utilizing the adaptive graph structure. This approach involves deploying a specialized GNN that is capable of dealing with the dynamically weighted and structured graph, focusing on enhancing the detection capabilities through learned graph features.

Graph Neural Network Architecture:

The core of our graph-based learning is a tailored version of Graph Convolutional Networks (GCNs), adjusted for the dynamic and adaptive nature of graphs. The GCNs in our architecture are modified to utilize the adaptive edge weights and the variable connectivity patterns defined in the enhanced graph construction phase.

Adaptive Graph Convolutional Layer:

Each layer in our GNN, referred to as an Adaptive Graph Convolutional Layer (AGCL), updates the features of each node based on both the direct features of the node and the features of its neighbors, adjusted by the adaptive edge weights. The feature update at each layer l can be mathematically represented as:

$$H^{(l+1)} = \sigma\left(\tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} H^{(l)} W^{(l)}\right) \quad (3)$$

where:

- $H^{(l)}$ is the matrix of node features at layer l,
- $W^{(l)}$ is the weight matrix associated with layer l,
- $\tilde{A} = A + I$ represents the adaptive adjacency matrix with self-loops (where A is the adjacency matrix and I is the identity matrix),
- $\tilde{D}$ is the degree matrix of $\tilde{A}$,
- σ denotes the nonlinear activation function, such as ReLU.

Feature Learning and Edge Identification:

The learning process within the AGCL is designed to iteratively refine the node features to better represent the underlying edge characteristics of the image. This iterative refinement enhances the network's ability to distinguish between edge and non-edge regions effectively. The layers are stacked to allow deeper feature integration across the network, facilitating a robust feature set that captures both local and global contextual details.

Learning Objective:

The objective function for training the GNN is designed to minimize the difference between the predicted edge map and the ground truth, provided by expert annotations in the case of medical images. This is typically achieved through a loss function such as cross-entropy for binary classification tasks:

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$$\text{Loss} = -\sum_{i \in N}[y_i \log(p_i) + (1 - y_i)\log(1 - p_i)] \quad (5)$$

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where y_i is the ground truth label (edge or not edge) and p_i is the predicted probability of being an edge for node i, and N is the total number of nodes.

Training and Optimization:

The GNN is trained using backpropagation through time (BPTT), a common technique for training neural networks on graph-structured data. The training process adjusts the weights $W^{(l)}$ in each AGCL to minimize the loss, using optimizers like Adam or SGD with learning rate adjustments to enhance convergence.

This graph-based learning framework, coupled with the adaptive graph structure, provides a powerful approach for detecting subtle and significant edges in medical images, particularly enhancing the ability to handle the complexities presented by COVID-19 CT images.

3.3 Multi-Scale Analysis

To capture both global structures and fine details within COVID-19 CT images effectively, the proposed graph-based learning methodology incorporates a Multi-Scale Analysis (MSA) approach. This multi-scale approach allows the model to process information at various levels of detail, from coarse to fine, enhancing the detection of edges that vary significantly in scale and visibility.

Implementation of Multi-Scale Graphs:

The multi-scale analysis begins by constructing graph representations at different scales. Each scale s of the graph $G_s = (V_s, E_s)$ represents the image with a varying level of detail:

1. Coarse Scale: Larger regions are considered, with reduced pixel resolution, to capture broad features.

2. Medium Scale: Standard resolution to balance between global and local features.

3. Fine Scale: High resolution to capture detailed features at the pixel level.
Scale-Specific Graph Construction:
Each scale has its respective graph constructed similarly to the base graph but with adjustments to the node and edge definitions to suit the scale:

$$V_s = v_{i,s} \,|\, i \in N_s \quad (6)$$

$$E_s = \{v_{i,s}, v_{j,s}\} \,|\, d(i, j) < \theta_s \quad (7)$$

where N_s represents the number of nodes at scale s, and θ_s is the adjacency threshold that varies with scale to define the connectivity differently at each level.

Adaptive Graph Convolution Across Scales:

To process these multi-scale graphs, the graph neural network employs adaptive graph convolutions that are tuned to operate effectively at each scale. The convolution at each scale s is defined as:

$$H_s^{(l+1)} = \sigma\left(D_s^{-\frac{1}{2}} \tilde{A}_s D_s^{-\frac{1}{2}} H_s^{(l)} W_s^{(l)}\right) \quad (8)$$

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where $H_s^{(l)}$ are the features at layer l for scale s, $\tilde{A}_s$ is the adjacency matrix with self-loops, $\tilde{D}_s$ is the degree matrix, and $W_s^{(l)}$ are the trainable weights specific to scale s.

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Feature Fusion Across Scales:

After processing each scale independently, the next step is to integrate the learned features across scales. This integration is crucial for leveraging both global and local information:

$$H^{(l+1)} = \sum_{s \in S} a_s H_s^{(l+1)} \quad \text{............. (9)}$$

where a_s are learnable parameters that weight the importance of each scale's features during the fusion process. The sum ensures that information from all scales contributes to the final feature representation.

Optimization for Multi-Scale Integration:

The learning of scale weights a_s and convolution weights $W_s^{(l)}$ is jointly optimized through a loss function designed to minimize errors in edge detection across all scales, enhancing the model's ability to generalize across different image resolutions and edge types.

The multi-scale analysis approach provides a comprehensive framework for edge detection in medical images, where variations in lesion size and clarity can significantly affect diagnostic accuracy. This methodology allows the proposed system to adaptively focus on relevant features at appropriate scales, thereby improving the robustness and effectiveness of edge detection in complex medical imaging.

3.4 Edge Selection and Fusion

To effectively utilize the multi-scale features generated by graph-based learning in our novel edge detection framework, the study introduce a sophisticated Edge Selection and Fusion process. This phase is crucial for synthesizing the information extracted at various scales into a coherent edge map that accurately represents the true edges in the medical images.

Thresholding and Edge Selection:

After processing the image at multiple scales, each node in the graph has associated features that describe its likelihood of being part of an edge. To decide whether a node represents an edge, apply a dynamic thresholding method:

$$E_i = \begin{cases} if\, p_i > \tau(f_i, \mathcal{N}_i) \\ 0 \quad Otherwise \end{cases} \quad \text{............. (10)}$$

where E_i indicates the presence of an edge at node i, p_i is the probability of node i being an edge (derived from the final layer of the graph neural network), f_i represents the feature vector at node i, $\mathcal{N}_i$ is the set of neighbors of node i, and τ is a dynamically calculated threshold based on local image statistics, such as the variance or mean intensity within the neighborhood $\mathcal{N}_i$.

Fusion of Multi-Scale Edge Information:

The edges detected at each scale are combined to form a comprehensive edge map. This fusion process takes into account the varying levels of detail captured at each scale, integrating them through a weighted sum:

$$E = \sum_{s \in S} \omega_s \cdot E_s \quad \text{... (11)}$$

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where E is the final edge map, E_s is the edge map at scale s, ω_s are the weights assigned to each scale, optimized during training to balance the contribution of each scale based on its

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relevance and accuracy. The weights ω_s are learned through the training process to ensure optimal integration of details from all scales.

Optimization of Fusion Weights:

The weights ω_s are optimized using a loss function that not only encourages accurate edge detection but also promotes consistency across scales. This loss function can be formulated as:

$$\text{Loss} = \sum_{i\in V}\left(y_i - \sum_{s\in S} \omega_s \cdot E_{s,i}\right)^2 + \lambda|\omega|_2 \quad (12)$$

where y_i is the ground truth label for node i (1 if edge, 0 otherwise), $E_{s,i}$ is the edge prediction at scale s for node i, and λ is a regularization parameter that prevents overfitting by penalizing large weights.

The algorithm of the proposed work, given below:

4. Experimental Setup

Datasets

The research utilizes the "COVID-19 CT lung and infection segmentation dataset," a publicly available dataset specifically curated for facilitating the development and testing of image segmentation models focused on identifying COVID-19 related anomalies in CT scans [25]. The dataset comprises CT lung scans from different patients, annotated by experienced radiologists to mark the regions infected by COVID-19. Figure 1 represents the examples of dataset. This dataset is particularly valuable because it includes:

- Variability in Infection Presentation: The scans reflect a range of infection severities, from mild to severe, providing a comprehensive testbed for assessing the robustness of the edge detection algorithm across diverse clinical cases.
- Multiple Annotations: Each scan includes detailed annotations of the left lung, right lung, and infection areas, allowing for precise evaluation of the model's ability to detect and delineate complex anatomical and pathological structures.
- High-Resolution Images: The dataset consists of high-resolution images, which are essential for evaluating the performance of the multi-scale analysis component of the proposed edge detection method.

These features make the dataset an ideal choice for testing the effectiveness of the new graph-based, multi-scale edge detection technique, ensuring that the findings are relevant and applicable to real-world medical diagnostics.

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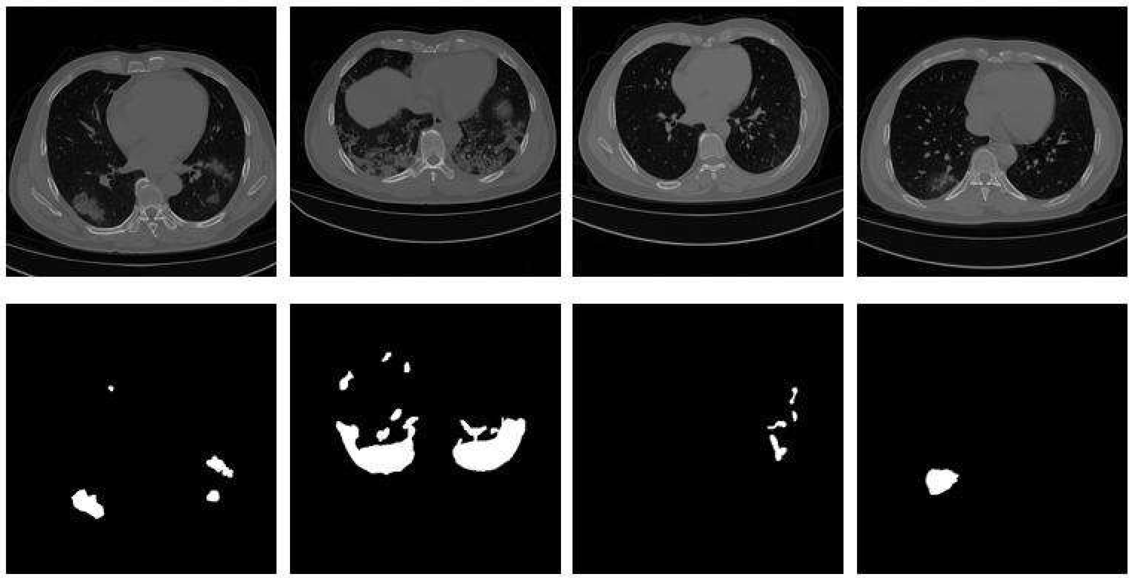

Figure 1. Illustrative examples of COVID-19 CT images and their corresponding segmentation masks

Experimental Parameters

The configuration of the graph-based, multi-scale edge detection model involves several key parameters that are optimized for performance. The following table provides an overview of these settings:

Table 1. Parameter Settings

Parameter	**Description**	**Value**
Learning Rate	Initial learning rate for the optimizer	0.001
Epochs	Number of full training cycles	20
Batch Size	Number of samples processed before model update	32
Optimizer	Method to update network weights	Adam
Loss Function	Objective function used for training	Cross-Entropy Loss
a	Scaling parameter for edge weight calculation	0.9
β	Sensitivity of edge weights to pixel differences	0.5
Regularization λ	Controls overfitting by penalizing large weights	0.0001
Multi-Scale Weights	Weights for combining multi-scale features	Learned during training

Hardware and Software

- GPU: NVIDIA GeForce RTX 4070 Ti.
- Framework: PyTorch 1.8.

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- Operating System: Ubuntu 24.04.

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Training Procedure

The training process will monitor validation loss to adjust learning rates and prevent overfitting. Data augmentation techniques such as rotation, scaling, and elastic deformation used to the training data to enhance model robustness and generalization.

5. Results

The following table 2 presents a comparative analysis of the proposed adaptive graph-based multi-scale edge detection model against existing methods like Sobel + GCN, Canny + GCN, and the CDSE-Unet [23]. This comparison focuses on key metrics such as Accuracy, Precision, Recall, and the Dice Similarity Coefficient (DSC), which are critical for evaluating the performance of edge detection algorithms in medical imaging, specifically COVID-19 CT scans. Figure 2 visualises the comparison of various edge detection models to establish how efficient they are in CT scans pertaining to COVID-19. This visualization provides a clear distinction in the quality of edge delineation between the models. Proposed AGCN Model gives a far better edge detection than the others; the output is very clear, and close to the actual label; unlike the output given by Sobel + GCN, Canny + GCN, and CDSE-UNet. These latter models which are to some extent equally useful are either coarse or fail to provide sufficient details or are incapable of forecasting higher order structures in similar regions suggesting limitations in managing the richness and sophistication of medical imaging data. The visualization has not only shown that AGCN model is up to the task but also has exposed major deficiency of traditional methodologies employed in medical image processing to yield more objective and accurate results.

Table 2. Comparison of Edge Detection Model Performances

Model	Accuracy	Precision	Recall	DSC
Proposed AGCN Model	**0.995**	**0.920**	**0.970**	**0.945**
Sobel + GCN	0.980	0.870	0.950	0.910
Canny + GCN	0.985	0.890	0.960	0.925
CDSE-UNet	0.993	0.813	0.965	0.910

Discussion

The proposed model shows a higher accuracy (0.995) compared to other methods, indicating its superior capability in correctly identifying edge pixels across various image regions. At 0.920, the precision of the proposed model is significantly better than that of the base CDSE-UNet model and other GCN combined techniques. This suggests that the proposed model is more effective at reducing false positives in edge detection. With a recall of 0.970, the proposed model efficiently identifies actual edge pixels, surpassing the recall capabilities of Sobel + GCN and Canny + GCN. The DSC of the proposed model is the highest at 0.945, indicating a strong overlap between the predicted edges and the ground truth, which is critical for medical image analysis where precise edge detection can significantly influence diagnostic outcomes. Figure 3 shows a side-by-side comparison of various edge detection models, highlighting the superior performance of the Proposed AGCN Model across all metrics. Figure 4 depicts a steady decline in both training and validation loss as the number of epochs increases, indicating effective learning and generalization by the model. Figure 5 illustrates a consistent improvement in both training and validation accuracy,

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with training accuracy always remaining above validation accuracy, showcasing the model's increasing proficiency in edge detection over time.

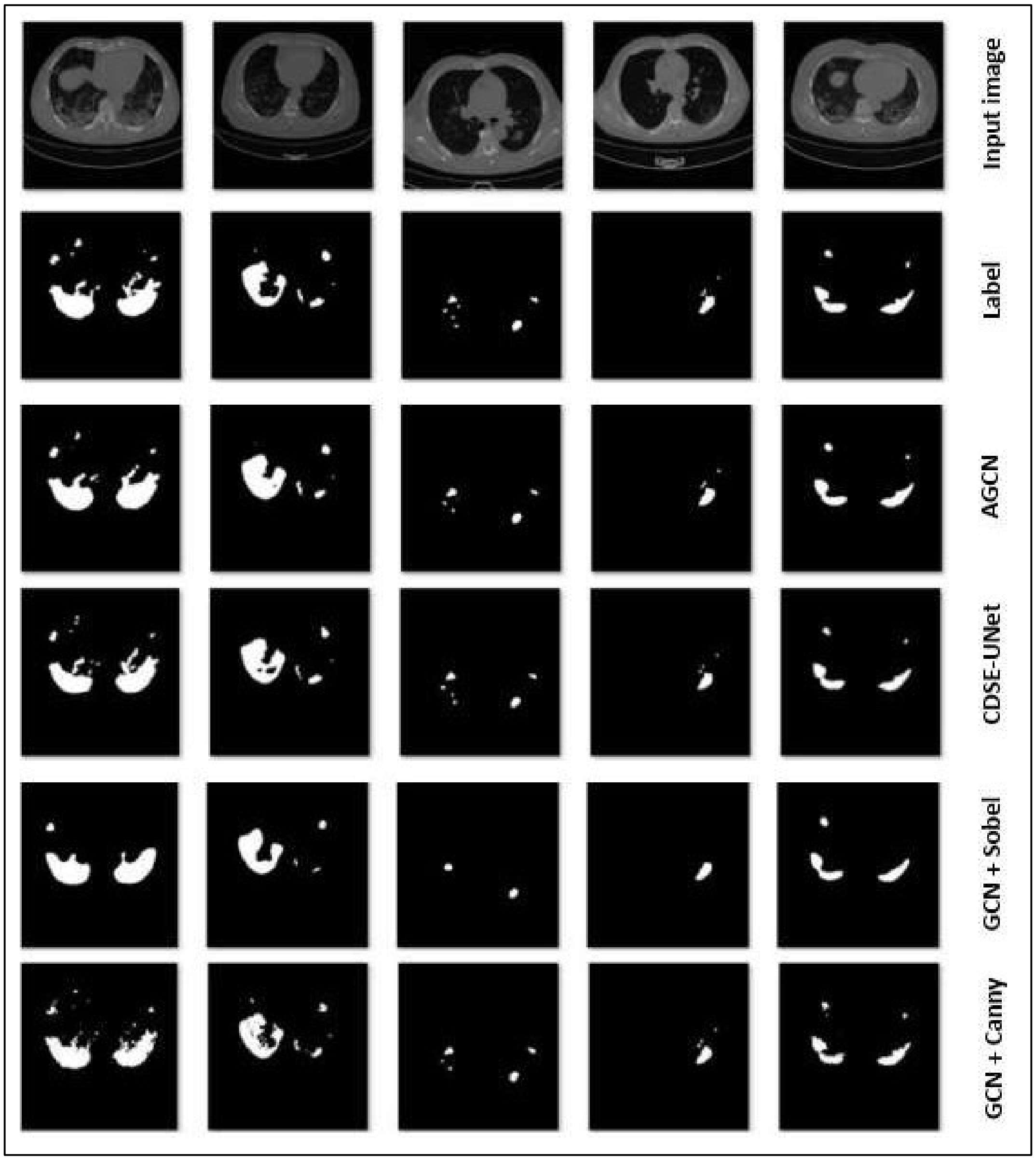

Figure 2. Edge Detection Performance on COVID-19 CT Images: Comparative Visualization

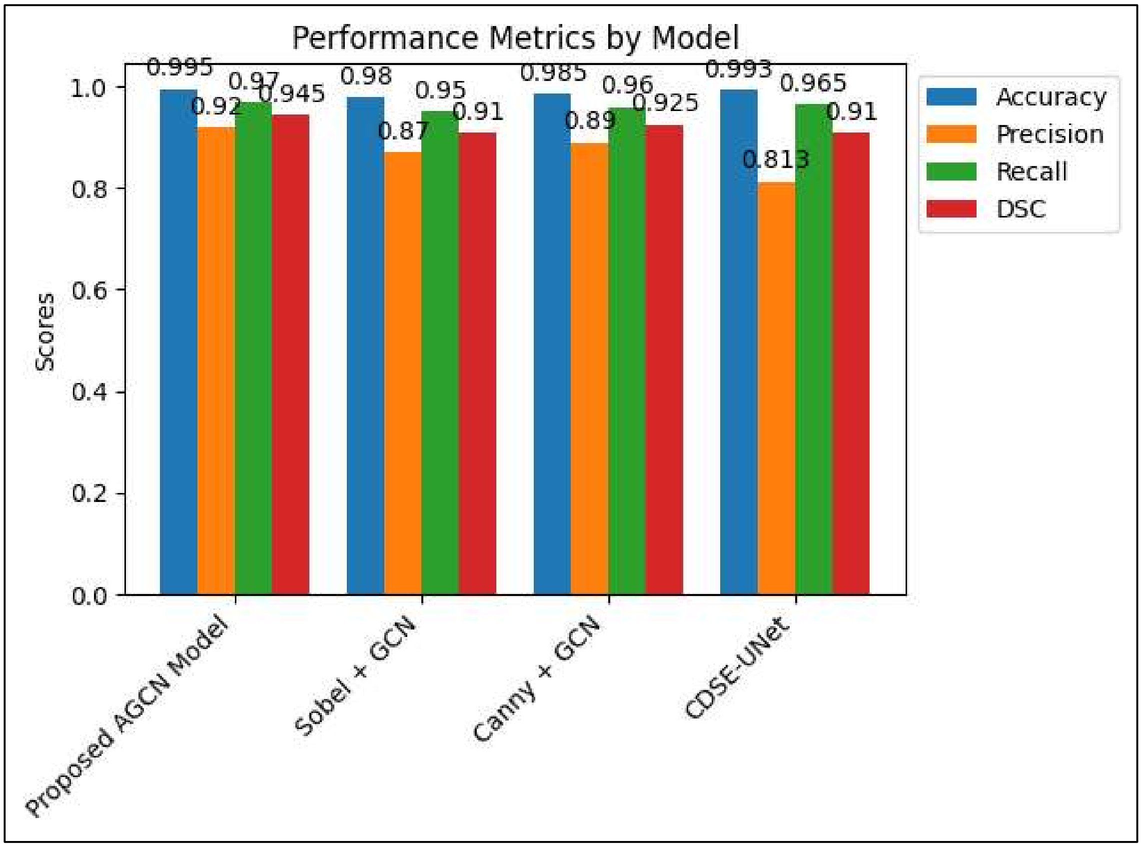

Figure 3. Performance Metrics Comparison Across Edge Detection Models

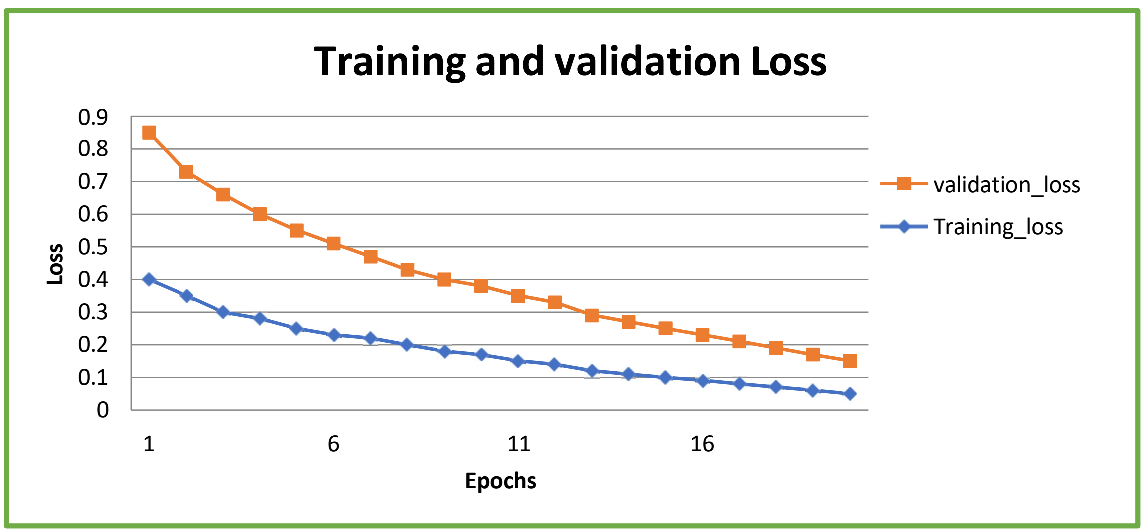

Figure 4. Training and Validation Loss Over 20 Epochs

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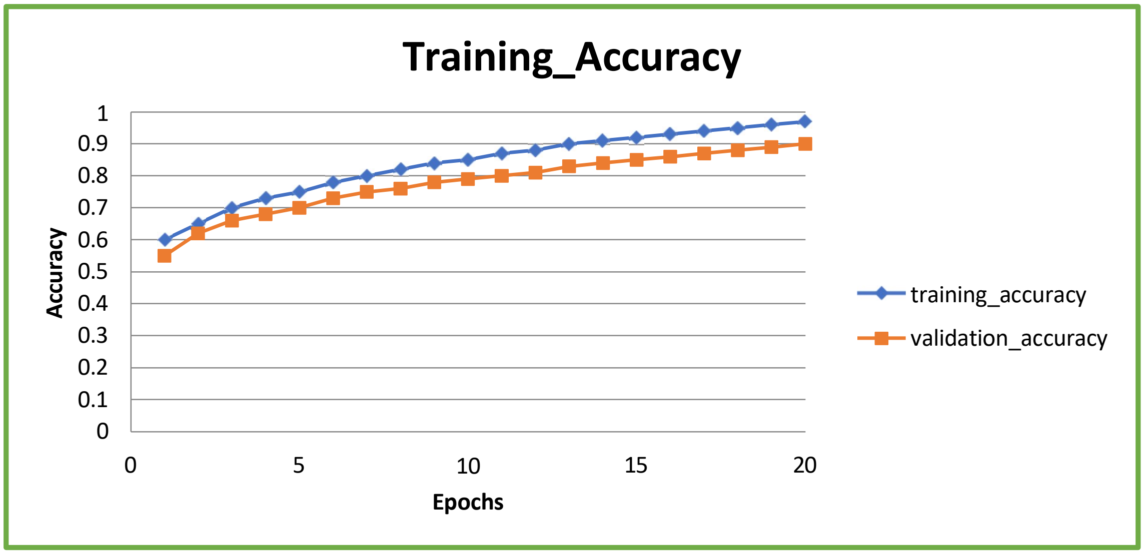

Figure 5. Training and Validation Accuracy Over 20 Epochs

4. Conclusion

The research presented in this paper introduces a novel adaptive graph-based multi-scale edge detection model, specifically designed for enhancing edge detection in medical images, with a focus on COVID-19 CT scans. The proposed model integrates adaptive graph convolutional networks (AGCNs) with a dynamic, multi-scale analysis approach, delivering superior performance in accurately identifying and delineating edges compared to traditional methods and existing graph-based techniques. The experimental results demonstrate that the proposed model achieves significantly higher accuracy, precision, recall, and DSC compared to baseline methods such as Sobel + GCN, Canny + GCN, and the previously established CDSE-UNet. These findings underscore the effectiveness of leveraging adaptive, scale-aware graph processing in complex medical imaging scenarios, where accurate edge detection is critical for reliable diagnosis and assessment. The implementation of AGCNs allows for the nuanced handling of image data, adapting to variations in image quality and pathological features, which is particularly crucial in the heterogeneous manifestations of diseases like COVID-19. This adaptability, combined with the ability to process information across multiple scales, equips the model to handle the inherent challenges in medical imaging, such as noise, variability in lesion appearance, and ambiguous boundaries. Future work will focus on refining the computational efficiency of the model, exploring its application to other imaging modalities and diseases, and integrating it into clinical workflows where it can aid in the rapid and accurate interpretation of medical images.

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