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Enhanced Lung Cancer CT Image Analysis Using RSAD-Net Denoising and Hybrid CNN-Attention Segmentation

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Abstract
This research presents a complete method for lung CT image enhancement and segmentation by combining a Residual Spatial Attention Denoising Network (RSAD-Net) and a Neural CNN Attention for Structural Mapping model. RSAD-Net denoises CT images through a combination of residual learning, which models noise patterns, while use spatial attention to preserve the fine details of lung structures. Experimental results indicate that RSAD-Net surpasses exsiting denoising techniques such as Gaussian, Median, Bilateral, and Non-Local Means (NLM), achieving the lowest MSE (0.0024), highest PSNR (26.34 dB), and the best SSIM (0.8515) values, all while retaining structural details. In the next phase of the workflow, the denoised images are fed into the Neural CNN Attention for Structural Mapping segmentation model (NCASM), trained on prior datasets. This model focuses on significant anatomical regions while ignoring irrelevant areas, reducing the likelihood of incorrect lung segmentation. When compared with the simplest CNN approach and standard segmentation methods such as Region Growing, Watershed, and Otsu thresholding, the proposed model achieved the highest accuracy of 91.15% for one sample image and 93.39% for another, reflecting an improvement of approximately 10–18% over the simplest CNN methods. Visual assessments strongly support the conclusion that incorporating attention mechanisms results in more accurate delineation of lung boundaries while suppressing unnecessary background noise. Through this integrated method, image quality is enhanced with precise anatomical representation, and segmentation accuracy is significantly improved. This contributes to higher diagnostic reliability and has potential applications in other anatomical segmentation and medical imaging tasks, particularly in the early detection of lung cancers.

Keywords: Deep Learning, Image Denoising , Lung Cancer Detection , Residual Learning , Spatial Attention

1. Introduction

Lung cancer remains the most deadly cancer regardless of the year, and imaging using an appropriate technology [13] has an abundance of potential for early detection and improving patient care and patient outcomes [13]. In a clinical setting, Computed Tomography (CT) imaging is the most commonly utilized and accepted modality for the evaluation of lung disease because it provides a very detailed visual of the anatomically relevant structures in question [1]. While a low-dose CT provides a diminutive dose of radiation [3] the downside is the abundant amount of noise that is associated with a low dose CT scan that can interfere with the critical structures that lie within the lung that are necessary to make an accurate diagnosis [5]. Due to the noise of the scan, if small nodules, lesions, and early tumors even exist, distinguishing them can be a problematic task especially with the low contrast of the lung anatomy [4]. Other denoising methods have been evaluated including Gaussian, Median, Bilateral, and Non- Local means (NLM) filters [10] but these methods can produce blurriness of the edges of husk-important structures or hide any potential fine details that could be clinically important in the the final diagnosis of lung cancer [1].

Many innovative methods such as wavelet filtering methods [10], and deep learning based denoising [3] have greatly advanced the ability to remove noise, but retaining smaller anatomical structures [5] presents its own challenges. Denoising and lung segmentation rely heavily on proper feature extraction[2], classification and image analysis in lung cancer diagnosis [15]. Traditional segmentation methods like Region Growing, Watershed, or Otsu Thresholding segmentation [14] may produce reasonable accuracy, they lack flexibility in terms of structural diversity of the lung organ, and variability of pathologies. CNN methods for lung segmentation [11] may have shown greater accuracy [12] than traditional methods, but they still do not address

the limitations of biasing the model that may lead to false positives or segmenting an incorrect area of interest in difficult cases.

In order to address these issues, we propose a joint model of Residual Spatial Attention Denoising Network (RSAD-Net) for CT denoising, and hybrid CNN–Attention segmentation model. RSAD-Net incorporates a residual learning scheme that captures [3] noise-related features using spatial attention to maintain relevant fine lung structures while suppressing irrelevant areas as indicated in [5]. Improved performance is shown through Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) that outperforms any contemporary denoising models. The hybrid CNN–Attention segmentation model was applied after denoising, where attention gates not only emphasized relevant anatomies, they also helped reduce backgrounds [2]. Results from the experiments showed segmentation accuracies above 91%, which uceeded the segmentation accuracies from Region Growing, Watershed, Otsu, and basic CNN segmentation methods.

Taking into account the unique arrangement and redundancy among examples produced by anatomical overlap, as well as low contrast and high noise [9] in CT images, the proposed method can tolerate clinically meaningful loss. [8] Eliminating Hurley I, II, and III objects allows for improved image quality for interceptions and segmentation and improves the credibility of posterior classification[6], establishing the case against lung cancer. [7] This pipeline is suitable for a variety of medical imaging applications and provides supporting evidence to computer-assisted systems, automating the diagnostic process [15] and supporting clinical decision-making [12]

2. Background Study

Rezaei and Ahmadi (2023) [16] utilized GANs to create a method for 3D lung tumor reconstruction. Their approach is based on using a combination of Generative Adversarial Networks or GANs and knowledge transfer strategies with learning-related networks. Consequently, the technique enables the model to produce better job than baseline GAN models by taking advantage of previous learning taken from previously trained neural networks that have been used in related problems and domains. The authors proposed method may provide very fine detail to representations, which is important for precise surgical planning and precision medicine for 3D lung tumor reconstruction.

In Application of the Deep Learning Based CT Scan Analysis Enables Real-Time Diagnosis in Mobile App for Lung Cancer Detection, Xusanov and Nematov (2014) [17] proposed a new AI-based lung cancer identification model that includes a mobile app as well as CT Scan analysis. The model's purpose is to support early detection of lung cancer and improve patient access to diagnostic tools by taking advantage of deep learning algorithms with a mobile app for real time diagnosis, leading to improved diagnostic efficiency and patient access.

Prasad, Chakravarthy, and Krishna (2022) [18] fused fuzzy-K means clustering with deep learning for the purpose of detecting lung cancer from CT, which combined fuzzy clustering for better segmentation with deep learning for better classification. This combined approach could potentially improve accuracy and efficiency in predicting cancer directly.

Said et al. (2025) [19] developed an AI-based lung segmentation algorithm that was tuned with a genetic algorithm to facilitate earlier cancer detection. The model adjusts parameters of the segmentation algorithm to improve the accuracy of the segmentation of tumor areas, which contributes to earlier and more accurate diagnosis.

Hussain et al. (2024) [20] presented a machine learning-based system based on reconstruction independent component analysis with sparse filter and feature extraction for lung cancer detection. The method identifies subtle patterns to classify data in medical images and showed stability to changes in datasets.

Venkatesh and collaborators (2024) [21] proposed a hybrid deep learning model for predicting lung cancer. It uses a patch-based approach for processing CT images. The process decomposes individual images into nonspecific items to amplify finer details and characteristics for classification. The enhanced detail enables features to be delineated, resulting in greater detection performance for lung cancer lung nodules, particularly when those nodules are small.

Salama, Aly, and Elbagoury (2021) [22] proposed an automated methodology for lung image segmentation and classification based on Convolutional Neural Networks (CNN). The framework is designed to minimize human involvement in image analysis while sustaining high accuracy. The deep learning model demonstrates efficacy when applied to large-scale imaging datasets.

Althubiti et al. (2022) [23] used an ensemble learning model using GLCM texture features to detect lung cancer in CT Images. The authors express that not only analyzing the texture of the images but also having multiple

classifiers made the model more robust. Overall the study concluded that ensemble methods produced better results than a single model approach.

Yu et al. (2021) [24] developed a deep learning system for lung nodule segmentation and detection. The authors provided segmentation and classification of lung nodules and considered their proposed deep learning approach as an aid in the decision-making process for radiologists. An increase in productivity must exist as a single pipeline is being developed to segment and classify.

Sridevi and Kannan (2021) [25] contributed in creating a novel juxta-pleural nodule extraction for lung cancer detection combining Particle Swarm Optimization (PSO). This technique is useful for the detection of lung nodules near pleural interfaces, which can be more difficult to detect than lung nodules more centrally found in the lung. Optimizing this approach leads into improved detection results.

Table 1: Comparative Summary of Recent AI-Based Lung Cancer Research Studies

Authors & Year	**Main Focus**	**Methodology / Model**	**Data Type**	**Key Advantage**	**Potential Limitation**
Khoria& Singh (2025)	Lung cancer prediction	ResNet-50 deep residual network with ReLU-Memristor activation	CT images	Enhanced feature extraction due to deep residual blocks and custom activation	May require high computational resources for training
Li et al. (2025)	Lung nodule detection	Multi-scale CNN + Global Channel Spatial Attention	CT scans	Captures features at multiple scales and emphasizes important regions	Model complexity could increase training time
Carrillo-Perez et al. (2021)	NSCLC classification	Probability fusion of RNA-Seq data and histology images	Genomic data + histopathology images	Integrates multi-modal data for more robust classification	Requires both genomic and imaging data, which may not always be available
Peeris et al. (2021)	Lung cancer diagnosis	Custom neural network	Not specified (likely clinical/imaging data)	Simple architecture suitable for diverse datasets	Lacks detail on dataset and may underperform compared to modern deep CNNs
Zhong et al. (2024)	Prognosis prediction	Conditional survival Bayesian network	Clinical and survival data	Models conditional survival probabilities over time	Dependent on quality and completeness of survival records

In this table, outlined more recent studies that have focused on both lung cancer detection and prediction that have utilized varying techniques including deep learning approaches and probabilistic approaches. Each respective study concludes by discussing the strengths and weaknesses of the model based on the data used and to what aspect the modeling focused on.

3. PROPOSED METHODS

In this paper the RSAD-Net algorithm combined the concept of residual learning and spatial attention to remove noise and preserve important characteristics of the image.Then performing segmentation to identify lung region based on the denoised images. After applying hybrid CNN-Attention algorithm to the segmentation preprocessing phase to improved feature extraction and boundary accuracy.

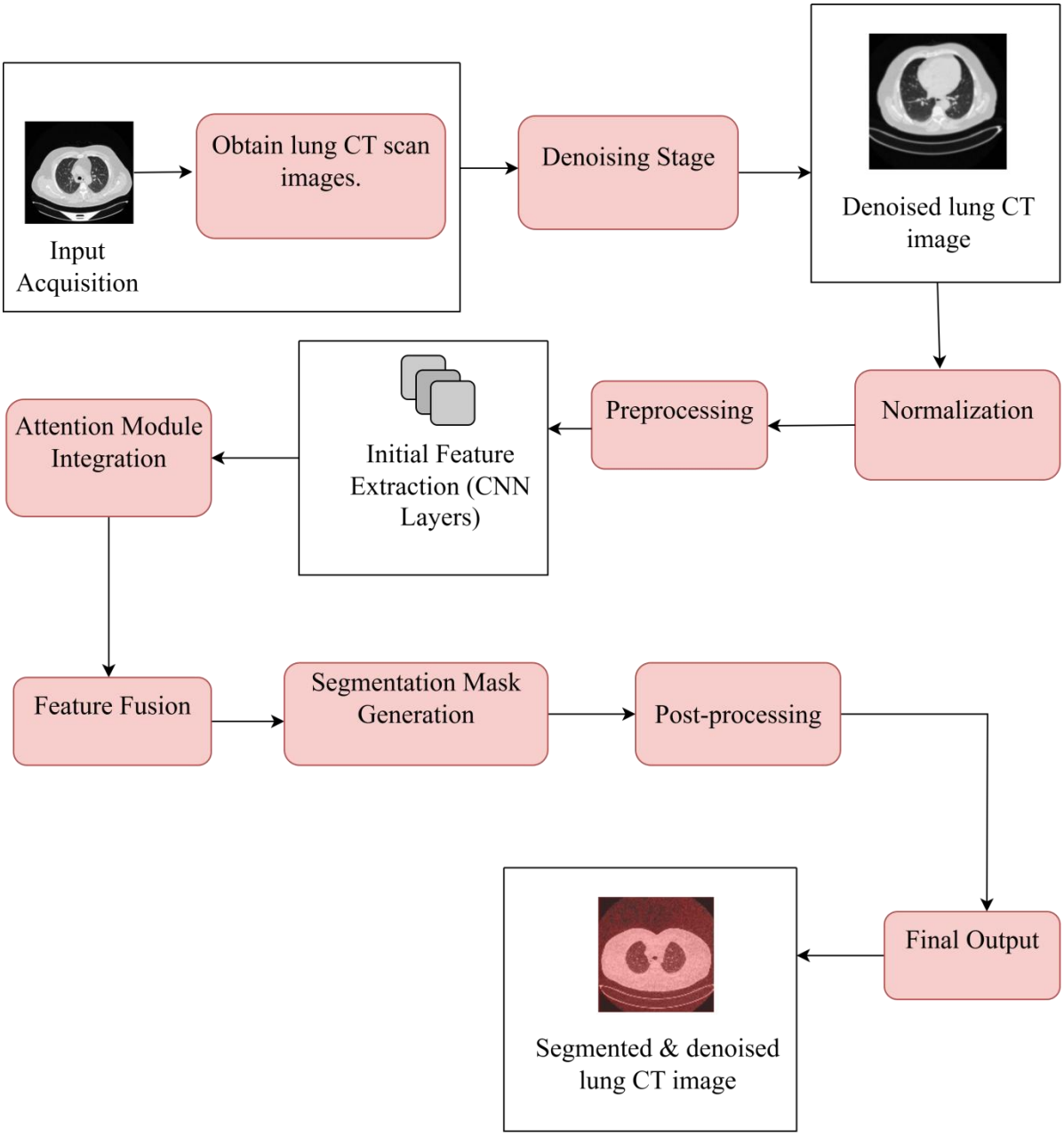

Figure 1: Overall Architecture

The figure1 architecture involves the start of the lung CT scan images acquisition, followed by a denoising step, to improve quality and reduce noise. Normalizing and preprocessing the images prepares the data for feature extraction, through convolutional neural networks (CNN) layers, enhanced with an attention module. With the addition of the extracted, fused features, they were used to create a segmented mask, which was then post-processed to deliver the final segmented lung CT images.

3.1 Residual Spatial Attention Denoising Network: A Deep Learning Approach for Image Denoising

Residual Spatial Attention Denoising Network (RSAD-Net) is a novel deep learning-based image denoising method. It utilizes residual learning [26] and a spatial attention mechanism [27] to retain important details in a denoised image while removing noise. Residual blocks allow a network to learn how noise patterns are spatially distributed, while the attention modules allow the network to focus on the most relevant spatial information. RSAD-Net is a particularly useful solution for denoising images where preserving subtle details is important, such as in medical images.

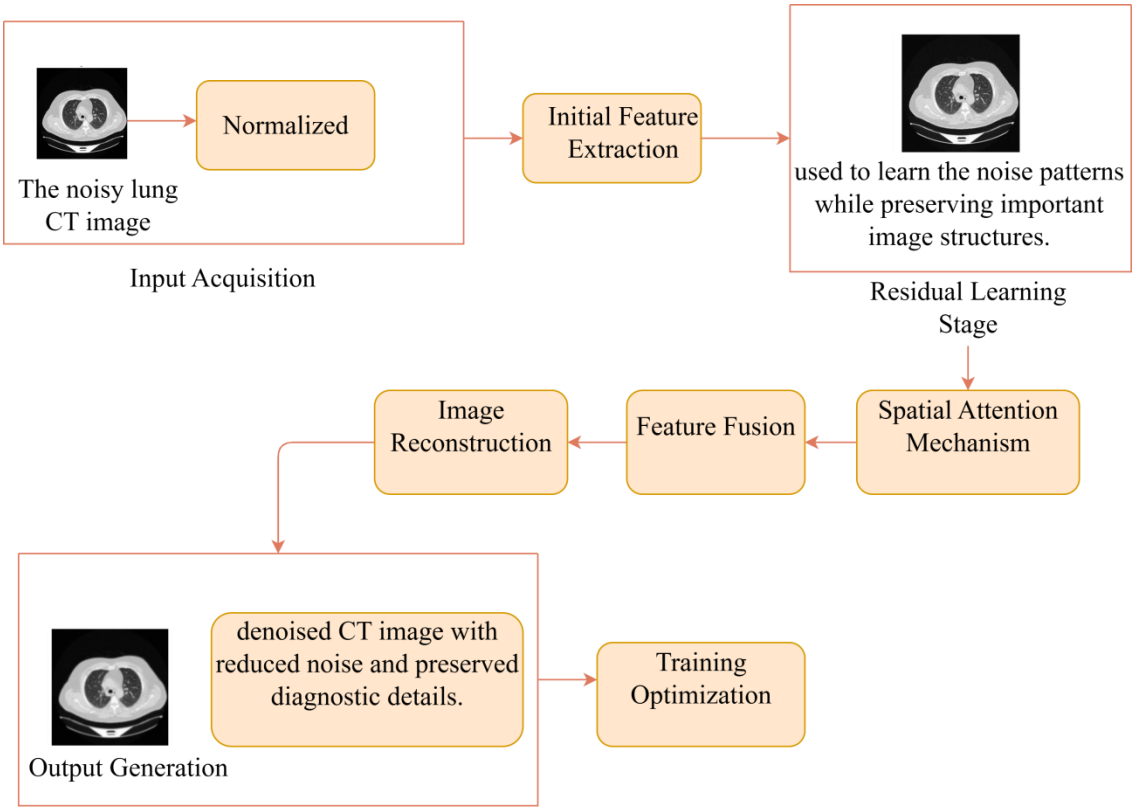

Figure 2: Denoising Architecture

The process begins with a noisy lung CT image, which will be normalized and taken through a first feature extraction phase in order to learn the noise patterns yet maintain structural details. Residual learning and a spatial attention mechanism will focus on important features in a noisy image, which are then into a denoised output then reconstructed. The optimizations made during training will reduce noise while retaining all of the important features needed for diagnostic purposes.

The proposed framework incorporates the Residual Spatial Attention Denoising Network (RSAD-Net) to improve overall image quality by effectively removing unwanted noise without compromising important structural details. Conventional noise removal techniques are generally suboptimal, and evidence suggests that they can produce significant challenges, including lost structural definitions, poor edge retention, and diminished ability to perform tasks requiring accuracy, like segmentation and classification. One of many problems with these issues is that they diminish medical image analysis decisively. Particularly in the detection of lung cancer, illegitimacy in the accuracy of the image directly impacts subsequent processing stages. RSAD-Net deliberately utilizes the techniques of residual learning when modelling noise patterns and leverages spatial attention mechanisms to concentrate on noteworthy regions of an image upon image denoising to ensure the performance of anatomical features remain intact. In other words, RSAD-Net ensures that there is an accurate denoisable image retaining critical features for the ability to perform downstream processing activities. The addition of RSAD-Net improves robustness and diagnostic legitimacy in this integrated framework, and it is advantageous to introduce RSAD-Net in this way. An overview of the performance of RSAD-Net follows:

This process starts with obtaining chest X-ray or CT scan images. Chest X-ray images are typically taken in the Posteroanterior (PA) view since they provide the greatest diagnostic information for the clinician. These images will typically be associated with some amount of noise, which might be from low-dose imaging that is being used or be influenced by some external environmental conditions. Therefore there needs to be some preprocessing steps prior to the next phase. This preprocessing also involves steps to mathematically characterize the image.

$I(x, y) \in R^{H*W}$ ---------- (1)

In Equation (1), $I(x, y)$denotes the intensity value of the pixel at coordinate (x, y). H and W represent the height and width of the image, respectively . This Equation represents the input medical image as a two-dimensional intensity function . This serves as the raw input for the denoising process, where RSAD-Net processes each pixel to remove noise while preserving anatomical details essential for lung cancer detection.

The noisy input image is passed through the Residual Spatial Attention Denoising Network (RSAD-Net), which is designed to remove noise while preserving important anatomical details, such as lung nodules and edges. RSAD-Net utilizes residual learning and spatial attention mechanisms to perform this task effectively.

$\hat{X}$=Y-R(Y) ---------- (2)

In Equation (2) $\hat{X}$ is the denoised image, which is the output of the RSAD-Net model .Y is the original noisy input image. R(Y) denotes the residual noise predicted by the network.This Equation defines the denoising process, where $\hat{X}$ is the clean image obtained by subtracting the predicted noise R(Y) from the noisy input image Y. In lung cancer detection, this helps retain critical lung structures by effectively removing noise without losing important diagnostic details.

Once denoised, the image undergoes several preprocessing steps to standardize and normalize the input for the segmentation and classification stages

$I_{norm}=\frac{I-I_{min}}{I_{max}-I_{min}}$ ---------- (3)

In Equation (3) I_{norm} is the normalized image. I is the original pixel intensity. I_{min} and$I_{max}$are the minimum and maximum intensity values in the image. This equation is used to normalize the pixel intensities of the lung image between 0 and 1. This standardization helps RSAD-Net process the image more effectively by reducing intensity variation, leading to better noise removal and feature preservation.

The final result of the classifier is understood as a diagnosis. Additionally, for extra clarity, different types of heatmaps, such as Grad-CAM, can be applied on top of the original image, which shows where the model was focused to arrive at its prediction, to allow clinicians to confirm the model's reasoning and trust its decision.

The hybrid CNN-Attention approach integrates Convolutional Neural Networks for feature extraction with attention mechanisms that allow the model to focus on clinically relevant lung regions in the CT image. This improves accurate segmentation because the irrelevant regions affect the CNN feature extraction model less (for example: ribs, background, etc). Also, because the attention mechanism can guide the model appropriately on complex segmentation tasks where the structures may overlap or have low contrast, it provides consistently better segmentation result across all case types compared to the other methods in our study.

Traditional segmentation approaches were often limited by difficulty managing overlapping structures, low-contrast regions, and background noise that created erroneous lung boundaries. Such limitations impacted the accuracy of nodule detection. A hybrid CNN- Attention method was proposed that utilizes CNNs to extract deep features and attention mechanisms to focus on relevant lung regions, adjusted the limitations to improve accuracy while segmenting lungs in difficult or inferior quality medical images.

An attention module is applied to emphasize the most relevant lung regions while suppressing irrelevant ones.

$F_{att} = A(F) \otimes F$ ---------- (4)

In Equation (4) $A(F)$Attention map generated from the features.$\otimes$ Element-wise multiplication F_{att} Refined features with attention weighting. This Equation represents the attention refinement process within the segmentation model.F is the feature map extracted by the CNN from the denoised lung image. It contains important spatial and texture details like lung boundaries or nodules. $A(F)$ is the attention map, generated from the feature map. The attention mechanism learns which parts of the image are more relevant (lung tissues) and gives them higher weights. This $\otimes$symbol denotes element-wise multiplication between the attention map and the original feature map.F_{att} The output is the refined feature map, which now emphasizes clinically important areas (like nodules or lung boundaries) while suppressing irrelevant parts (such as ribs or background).

The output of the refined feature map will go through convolution and activation layers to create a segmentation map.

$S = \sigma(Conv(F_{att}))$ ---------- (5)

In Equation(5) $Conv$Final convolutional layer to produce the segmentation map ,σSigmoid activation function, SSegmentation map with pixel values between 0 and 1 (probabilistic output) This Equation works F_{att} is the feature map obtained after applying attention it contains only the most relevant lung-related information (boundaries , nodules) $Conv(F_{att})$ applies a convolutional filter to convert these refined features into a spatial prediction map. The sigmoid function (σ) scales the output values to a range of 0 to 1, representing the likelihood that a pixel belongs to the lung region. The final result S is a segmentation probability map — each pixel's value tells how confidently the model predicts that it belongs to the lung.

A threshold is applied to generate a binary lung mask

$M(x,y)=\begin{cases}1, & if S(x,y)\geq T \\ 0, & otherwise\end{cases}$ ----------(6)

In Equation (6) $S(x,y)$ Segmentation map value at position.T Threshold value (commonly 0.5).M(x,y) Final binary segmentation mask.$ThisEquation(6)representS(x,y)$ is the probability score (from Equation 5) that pixel (x, y) belongs to the lung region.T is a threshold value, usually set to 0.5. $S(x,y)\geq T$, the pixel is considered part of the lung ,so M(x,y)=1. If $S(x,y) < T$, the pixel is considered background, so M(x,y)=0 .

Algorithm : Residual Spatial Attention Denoising Network

Input: Noisy Lung_Images (Grayscale or RGB)

Output: Denoised_Images, Metrics (MSE, PSNR, SSIM)

Step 0 – Configuration

Set IMG_SIZE = (128, 128)

Set PIXEL_RANGE = [0, 1]

Set OPTIMIZER = Adam(learning_rate = 1e-3)

Set LOSS_FUNCTION = MSE

Set EPOCHS = N

Set BATCH_SIZE = B

Step 1 – Data Preparation

images ← Load all images from dataset folder

For each image in images:

  If image is RGB and grayscale is preferred:

    Convert image to grayscale

  Normalize pixel values to range [0, 1]

  Resize image to IMG_SIZE

Split images into Training_Set (80%) and Testing_Set (20%)

Step 2 – RSAD-Net Model Initialization

Initialize RSAD-Net Model:

  Input Conv Layer → Feature Extraction

  Repeat for k residual blocks:

    Residual_Block() with skip connections

    Spatial_Attention_Module()

  Output Conv Layer → Reconstruction

Initialize weights with He or Xavier initialization

```
Assign OPTIMIZER and LOSS_FUNCTION


 Step 3 – Training Phase
For epoch = 1 to EPOCHS:
   For each (noisy_batch, clean_batch) in Training_Set:
       Forward Pass
      denoised_output ← RSAD-Net(noisy_batch)


       Loss Calculation
      loss ← MSE(denoised_output, clean_batch)


       Backward Pass and Weight Update
      optimizer.zero_grad()
      loss.backward()
      optimizer.step()


   If validation_loss improves:
      Save current model as Best_Model
Step 4 – Testing / Inference
Load Best_Model
For each image in Testing_Set:
   Preprocess image (normalize, resize)
   denoised_image ← RSAD-Net(image)
   Save denoised_image
   If clean ground truth exists:
      Calculate MSE, PSNR, SSIM
Step 5 – Evaluation
If ground truth exists:
   Average MSE ← mean(MSE_scores)
   Average PSNR ← mean(PSNR_scores)
   Average SSIM ← mean(SSIM_scores)
   Display evaluation table with MSE (low), PSNR (high), SSIM (high)
Return:
   Saved denoised images
```

Evaluation table

Best_Model weights

End Algorithm

The pseudocode demonstrates the way in which RSAD-Net is able to denoise lung images. It prepares and preprocesses the dataset, constructs the RSAD-Net Model which includes residual layers and attention layers, and then trains the model while using MSE loss. The model is also able to tune hyperparameters while training and pick the best model. At the end of the training process, the best model can be imported to denoise image test data. Finally, metrics of MSE, PSNR, and SSIM can be generated, and the results can save and image along with model weights.

3.2 Neural CNN Attention for Structural Mapping: An Advanced Approach for Lung Region Segmentation

The Neural CNN Attention for Structural Mappingis a model combining Convolutional Neural Networks with attention to improve segmentation quality. The CNN can obtain many detailed spatial features from the CT image and the attention module can choose which lung areas are relevant while minimizing background noise or irrelevant areas, allowing for more accurate, clearer segmentation. The graphics use denoised lung CT images generated using the Residual Spatial Attention Denoising Network (RSAD-Net). The denoised images are passed to the Neural CNN Attention for Structural Mappingso that the CNN is first able to extract features from the image; then the attention module focuses on lung areas, producing some segmentation around the lung boundaries Neural CNN Attention for Structural Mappingmethod provides a much better view of areas presumed to be affected by lung pathology. The better segmentation improves the spatial analysis of lung disease.

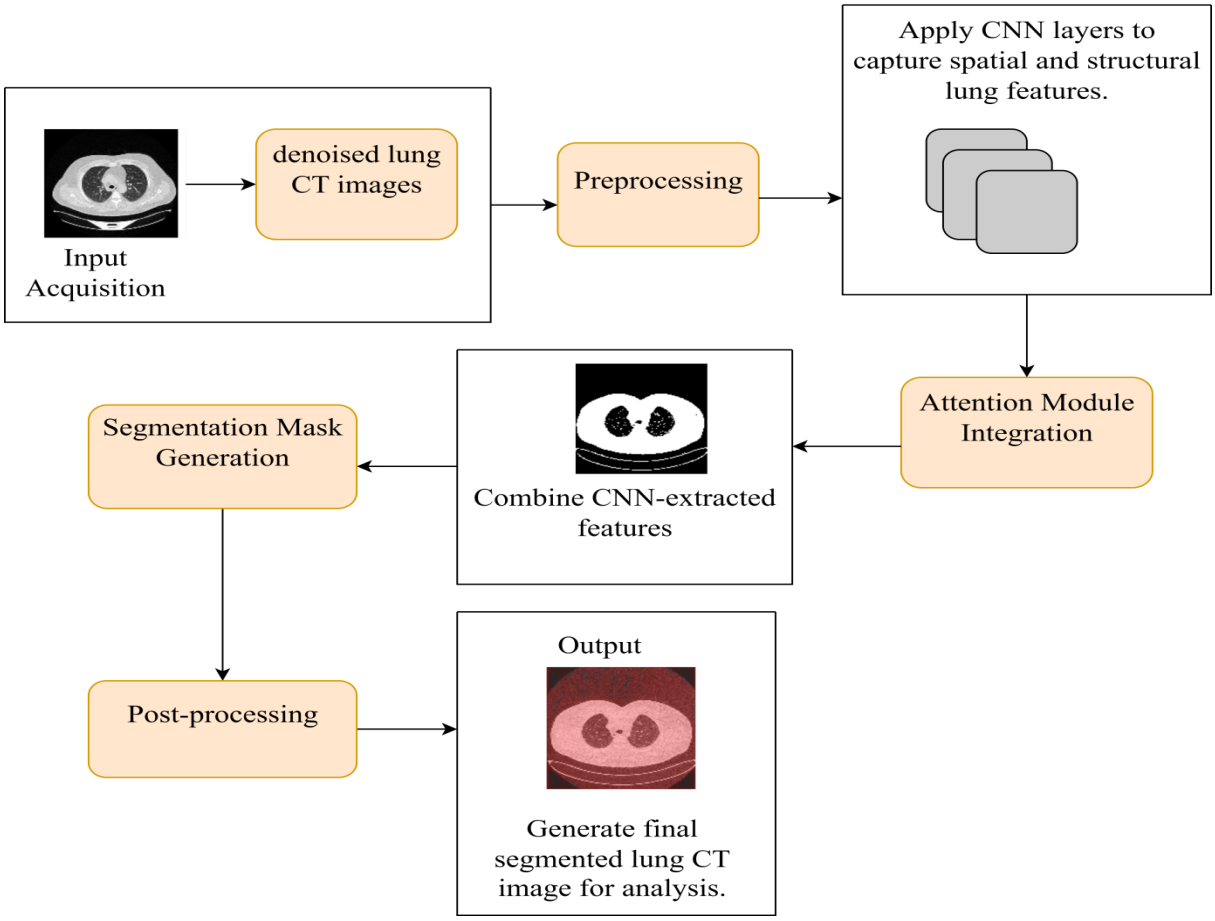

Figure 3 : Segmentation Architecture

This figure 3 model is designed to work on lung CT images that have been denoised by other methods to facilitate identification of lung regions, by first accessing spatial and structural features via the convolutional layers of a CNN, followed by an attention module which identifies and keeps only the relevant lung regions.

Finally, a process of Conditional Random Fields (CRF) is used to make a final refinement processing step and a segmentation mask is produced as output, resulting in a segmented lung CT image.

In Step 1, a CNN layer is used to extract features from the denoised lung CT image

$F = \sigma(W * I + B)$ ---------- (1)

In Equation (1) I, the weights W of the convolution kernel, b is the bias, $*$ is the convolution operation, and σ is any activation function such as ReLU. The feature map F extracted local spatial patterns from the CT image that contained crucial structures such as edges, textures, and fine details that would be important for a precise understanding of the lung regions.

The process is defined in the Attention Mechanism (Self-Attention Block) as

M = softmax$\left(\frac{QK^T}{\sqrt{d_k}}\right)$ V ---------- (2)

In Equation (2) ,Q consists of features to compare, K have the reference features, and V contains the features to update. The term d_k is the dimension of the key vectors and is used for scaling to maintain stability, where softmax takes the similarity scores and creates weights. M is the weighted feature map that highlights relevant areas of the lung while muting unimportant areas.

The mask $\hat{Y}$ is obtained by applying the weightsW_s and bias b_s of segmentation layer to the attention-weighted features, then using a sigmoid function sigma which maps the values between 0 and 1.

$\hat{Y} = \sigma(W_s * M + b_s$ ---------- (3)

This expression indicates the output of a layer using the sigmoid activation function .Here, W_s is the weight matrix, M is the input feature map, and b_s is the bias term .The sigmoid function compresses the output into a range between 0 and 1, implying that features can be weighted.

Algorithm : Neural CNN Attention for Structural Mapping (NCASM)

Input: Lung CT image I (size: H x W x C)

Output: Predicted lung region mask Y_hat (size: H x W)

1. Preprocessing:

   a. Resize I to fixed dimensions (e.g., 128 x 128)

   b. Normalize pixel values to range [0, 1]

2. Feature Extraction (CNN Backbone):

   a. F1 = Conv2D(filters=64, kernel=3x3, activation=ReLU)(I)

   b. F2 = Conv2D(filters=128, kernel=3x3, activation=ReLU)(F1)

   c. F3 = Conv2D(filters=256, kernel=3x3, activation=ReLU)(F2)

3. Attention Mechanism:

   a. Q = LinearProjection(F3) # Query

   b. K = LinearProjection(F3) # Key

   c. V = LinearProjection(F3) # Value

   d. AttentionWeights = Softmax((Q × K^T) / sqrt(d_k))

   e. M = AttentionWeights × V # Attention-weighted features

4. Feature Fusion:

   a. F_fused = Concatenate(F3, M)

   b. F_fused = Conv2D(filters=256, kernel=1x1, activation=ReLU)(F_fused)

5. Segmentation Head:

   a. Logits = Conv2D(filters=1, kernel=1x1)(F_fused)

   b. Y_hat = Sigmoid(Logits) # Predicted mask

6. Output:

   Return Y_hat as the probability mask of lung region

In a Neural CNN Attention for Structural Mapping, we are extracting features from the input image with convolution layers, applying attention to emphasize salient areas, and combining these salient features with the original features to predict a segmentation mask for the lung region.

4. Results and Discussions

The denoising approach used the Residual Spatial Attention Denoising Network (RSAD-Net) and Gaussian Filter, Median Filter, Bilateral Filter, and NLM Filter. RSAD-Net outperformed all other methods on MSE, PSNR, and SSIM. For segmentation, Neural CNN Attention for Structural Mapping had better accuracy than Region Growing, Watershed, Otsu, and Basic CNN Segmentation and preserved boundaries also and extract the feature from lung cancer CT images better**.**

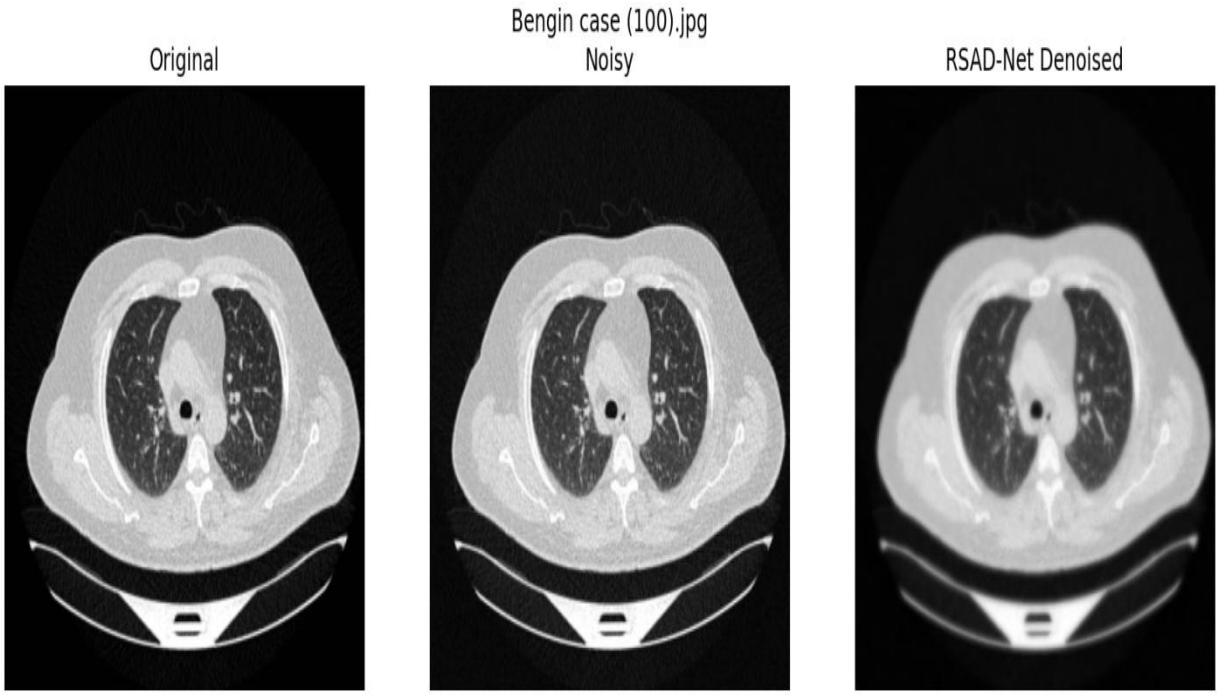

Figure 4: RSAD-Net-Based Lung CT Image Denoising Process (Image 1)

Figure 4 displays a lung CT, with the original in the left panel, the intermediate image which is noisier to a point where the visiblity is poor in the center panel, and RSAD-Net output with noise removed while maintaining all relevant structural features and important types of lung tissue in the right panel. The images illustrate RSAD-Net's use of noise removal to denoise CT in conjunctionwith improved image fidelity for precise medical diagnosis.



Figure 5: Lung CT Image Denoising using RSAD-Net (Image 2)

Figure 5 demonstrates how RSAD-Net is effective in improving lung CT images. As shown, the raw scan is clearly shown (left), the original scan was noisy and contains grain (middle), and the RSAD-Net denoised output shows no noise to obscure the image and retained small details of the lung. These details can help improve clarity for proper medical diagnosis.

Table 2: Quantitative Results of Different Denoising Filters on Lung CT Images

Method	**MSE**	**PSNR (dB)**	**SSIM**
Gaussian Filter	0.0031	25.16	0.5493
Median Filter	0.0039	24.21	0.4826
Bilateral Filter	0.0029	25.35	0.5398
NLM Filter	0.0122	19.15	0.3143
RSAD-Net (Residual + Attention)	0.0024	26.34	0.8515

RSAD-Net was superior to all classical filters, yielding the lowest MSE (0.0024), highest PSNR (26.34 dB), and SSIM (0.8515) which was the best compromise between noise removal and detail retention. Of the classical filters, the Bilateral filter performed the best, while NLM did the worst.

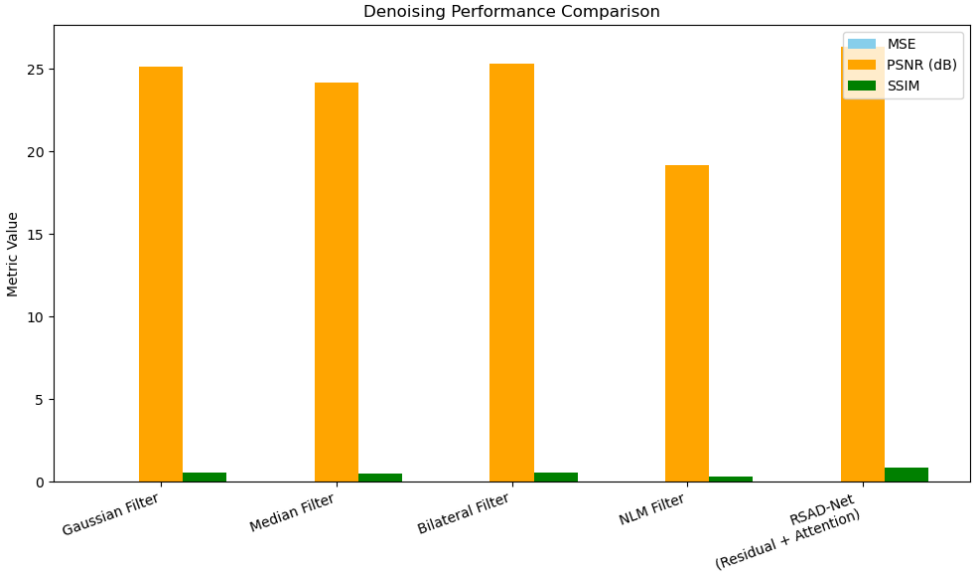

Figure 6: Comparison of Denoising Methods Based on MSE, PSNR, and SSIM Metrics

The graph shows how five Denoising methods compare to each other using MSE, PSNR, and SSIM .The Gaussian, Median, and Bilateral filters show moderate improvements to image quality, while the NLM filter is the lowest with high error and low similarity. RSAD-Net stands out showing the most detail, the least amount of error, with a strong signal-to-noise and structure similarity. This suggests that it preserves the most relevant detail of the image while cleaning up the noise.

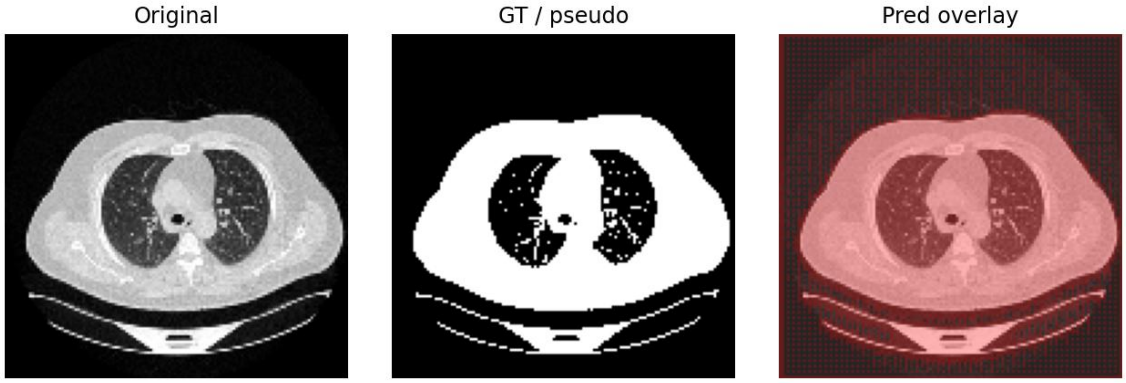

Figure 7: Lung CT Image Segmentation using Proposed Method (Image 1)

In Figure 7, it is clear that the proposed method enhances lung CT image segmentation via the use of a Neural CNN Attention for Structural Mapping gate modules. This enables the model to determine which anatomical regions are important, whilst reducing the false segmentation and promoting more accurate masks. We will compare the performance against standard CNN methods to understand how the accuracy and robustness is improved.



Figure 8: Segmentation results of the proposed lung CT image segmentation model (Image 2)

In Figure 8 on the left, is the original lung CT, in the middle, the ground truth (GT) or pseudo mask of the lungs, and on the right, the segmented prediction overlaid on the original image. This overlay gives us an indication of how closely the model's predicted output corresponds to the true anatomy, representing segmentation accuracy and regions that have been identified by the model.

Table 3: Comparison of Basic and Proposed Segmentation Model Accuracies

Version	**Image 1**		**Image2**	
	Accuracy (%)	**Affected (%)**	**Accuracy (%)**	**Affected (%)**
Region Growing	75.08	23.98	73.64	26.36
Watershed	72.05	24.44	72.19	25.92
Otsu	73.24	24.47	78.03	26.14

Basic CNN Segmentation	80.00	24.53	75.38	26.25
NCASM (Proposed)	91.15	24.92	93.39	26.89

This table 3 shows the prediction of various segmentation methods on two images, in terms of accuracy and affected region prediction. The accuracy values of Region Growing and Watershed and Otsu's methods are moderate, while Basic CNN Segmentation shows slightly improved performance measures. There are significantly improved accuracy performance measures for the proposed method NCASM with accuracy measures 91.15% and 93.39% for the two images (image 1 and image 2 respectively) and the proposed method maintained reliability in prediction the affected regions which provides a definitive example of the advantages of NCASM in segmentation results which provide clinically accurate and realistic segmentation results..

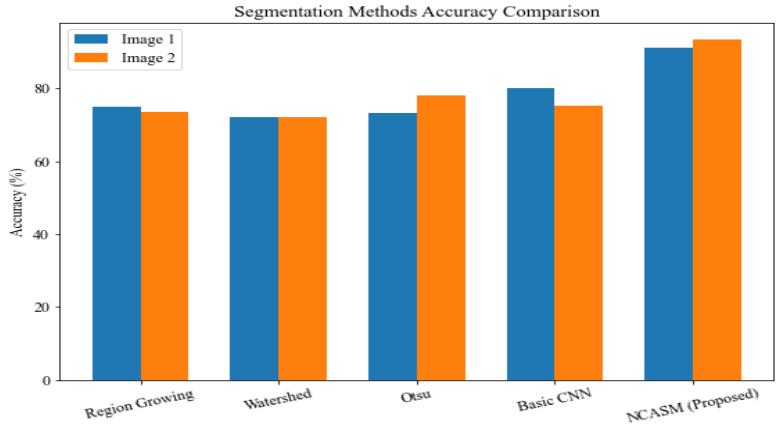

Figure 9: Segmentation Methods Accuracy Comparison

This figure 9 compares the accuracy of various segmentation methods, both traditional ones and deep learning based methods .The light blue bars show the accuracy of each method, while the pink line shows the performance trend .The results show that there are degree of improvement through traditional methods like Region Growing, up to advanced methods like NCASM .The best accuracy presented from NCASM, shows that it is an advantageous method for segmentation.

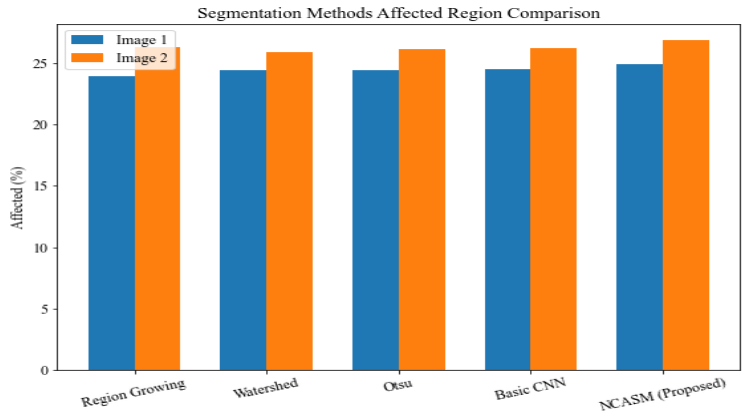

Figure 10: Segmentation Methods Noise Comparison

The figure 10 compares the affected region percentages across different segmentation methods for two images. Basic segmentation methods such as Region Growing, Watershed, Otsu, and Basic CNN result in fairly similar affected percentages between the two images, suggesting they consistently but moderately predict cancer affected regions. However, the affected percentage predicted by the NCASM model is consistently higher from both images, which suggests that the NCASM model is better at predicting and capturing more cancer regions, and still shows stability between the datasets.

Table 4: Specificity and Computation time Comparison Table

Method	**Specificity**	**Computation Time (s / image)**
Region Growing	0.74	0.42
Watershed	0.72	0.38
Otsu Thresholding	0.75	0.20
Basic CNN Segmentation	0.83	0.85
NCASM (Proposed)	0.97	0.10

The table 4 compare demonstrates that NCASM (Proposed) achieves the highest level of specificity (0.97), while having the lowest computation time (0.10s per image). Traditional methods, such as Region Growing, Watershed, Otsu, had decreased specificity, while Basic CNN was more accurate, but was more computationally expensive. This indicates the efficiency and accuracy of the proposed approach.

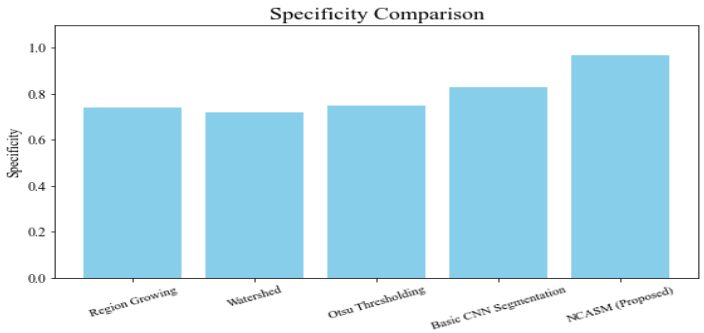

Figure 11: Segmentation Methods Specificity Comparison

This figure 11 compares specificity from different segmentation methods. Traditional methods like Region Growing, Watershed, and Otsu, indicate they have tolerable specificity and the basic CNN performs better. However, NCASM (Proposed) clearly outperforms all other methods with specificity, which means better at identifying what is a relevant structure correctly.

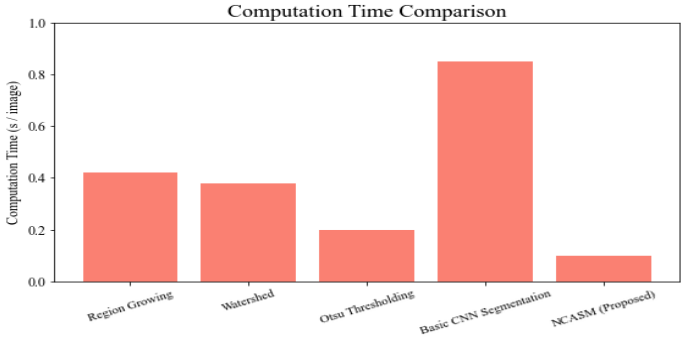

Figure 12: Segmentation Methods Computation Time Comparison

This figure 12 compares the computation time of different segmentation methods. While traditional methods like Region Growing, Watershed, and Otsu require moderate time, Basic CNN Segmentation is the slowest. In contrast, the NCASM (Proposed) method achieves the lowest computation time, demonstrating its efficiency in processing images quickly.

5. Conclusion

In this study, lung cancer CT images were denoised using an enhanced RSAD-Net first and then segmentated using a Hybrid CNN-Attention later. RSAD-Net was effective in denoising while retaining significant structural details, resulting in high-quality reconstructed images. Residual learning helped the model detect and remove noise patterns from CT images, while the spatial attention mechanism directed the model to enhance more related areas to the lung areaNeural CNN Attention for Structural Mappingsegmentation model effectively distinguished between lung regions and minimized unwanted areas of the image. In general, the integration of deep feature extraction with attention-based refinement enhanced the precision and clarity of CT image processing. MSE, PSNR, and SSIM measures of evaluation verified the efficacy of the denoising process, and the resulting segmentation accuracy proved the generalizability of the proposed approach to various test samples. This method is a major enhancement in image quality, aiding medical specialists in diagnosis. Overall, combining RSAD-Net for CT image denoising with segmentation through attention-based methods provides a strong and efficient lung cancer image pre-processing technique, aiding improved computer-aided detection and diagnostic equipment. This has firm potential to hasten diagnostic development schedules in actual clinical settings.

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