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Deep Learning-Based Detection of Lung Nodules in CT Scans for Cancer Screening

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Abstract: Lung cancer is one of the major killers, hence early cancer identification is crucial to improve survival chances. The most popular option for early screening and identifying lung illnesses is a computed tomography (CT) scan. However, even for seasoned radiologists, manual lung disease detection and labeling requires a lot of time and effort since a sophisticated CT scanner generates a lot of CT images. An automated Computer-Aided Diagnosis (CAD) of pulmonary CT scan to aid the Radiologists is a workable answer to this. The primary topic of this paper is the development of deep learning algorithm-based methods for the early prediction of lung malignancies, which are carried out in three stages: (a) lung segmentation; (b) classification of interstitial lung disease (ILD); and (c) classification of lung cancer. The strength of the overall CAD system for diagnosing lung disorders depends on precise lung segmentation throughout the multi-stage process of automatic evaluation of the lung CT image.

Keywords*: Computed Tomography (CT), Computer-Aided Diagnosis (CAD), Lung Segmentation, Interstitial Lung Disease*

1. Introduction

Lung cancer is a leading killer worldwide. Recent data from the American Cancer Society estimates that 228,000 new cases of lung cancer are diagnosed annually, including 135,000.When detected early, lung cancer may be successfully treated in a minority of cases, according to studies. While most of the time, death results from a delay in diagnosis and treatment. Consequently, increasing the patient's chance of survival requires early detection of lung cancer. When looking for lung problems, a CT scan is the gold standard diagnostic tool. However, due to the high volume of CT pictures produced by a modern CT scanner, even experienced radiologists must expend considerable effort to manually identify and diagnose lung illness. A feasible solution to this problem is the use of automated Computer-Aided Diagnosis (CAD) of lung CT scans to assist the Radiologists. In the numerous phases of self-assess of the lung CT scan, accurate lung segmentation is a vital step towards the robustness of the entire CAD system to detect lung illness.

Interstitial Lung Disease (ILD)

Continuous accumulation and fast proliferation of differentiated fibroblasts in locations of repetitive epithelial damage and greater resistance to apoptosis [16] are hallmarks of interstitial lung disease (ILD). Tumor suppressor gene mutations, oncogene activation, and apoptotic gene transformation are only some of the genomic modifications that result from chronic inflammation [21]. There seems to be an elevated risk of developing lung cancer in those with interstitial lung disease, as shown by a recent research [8]. Therefore, even in the presence of chronic obstructive pulmonary disease, interstitial lung disorders have a significant risk of progressing to lung cancer..

In this study, we create an efficient method for separating the lungs from the rest of the chest by using a conditional Generative Adversarial Network (c-GAN). The provided lung CT slices are sent via a chain of encoders in the suggested segmentation method, where they are converted into a series of feature maps. The collection of encoded feature maps is then used as input to a multi-scale feature extraction module. Last but not least, multi-scale characteristics are fed into decoders to extract the lung segmentation. Through the use of Multi-Scale Feature Extraction (MSFE), the network is trained to recognize anomalies in dense data. However, the dense abnormality's magnitude is irrelevant because of the repetitive down-sampling and up-sampling. Selecting an appropriate architecture of c-GAN and fine-tuning the parameters of this network to improve lung segmentation performance is illustrated using a Taguchi-based technique. The effectiveness of the suggested technique is proven for a variety of ILD designs with varying dimensions, orientations, and surface textures.

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Segmentation performance of regular CNN networks suffers for these kinds of pattern deviations. By experimenting with various MSFE module configurations and fine-tuning the network with the fundamental parameters Learning Rate (LR), gradient decay factor (), L1, and, the performance of the proposed c-GAN is maximized using the Taguchi approach, as measured by Dice Similarity Coefficient (DSC) and Jacquard index (J). Finally, the best designed network's performance in lung segmentation is compared to that of existing networks in the literature while dealing with dense anomalies caused to ILD patterns in lung CT images. Screening for ILD using CT imaging may improve the standard of medical treatment significantly. To deploy the deep learning classification technique, most previous ILD classification studies required time-consuming human identification of the area of interest (ROI) from the lung CT image. In this research, we create a two-tiered deep learning strategy for ILD classification. The first step involves extracting the lung region from the CT scans using an optimized c-GAN algorithm. After the lung pictures have been segmented, Resnet50 has been used to extract the deep features. Additionally, segmented lung pictures from various ILD classes are utilized to fine-tune the training of a pre-trained Resnet50 through a transfer learning technique. Support Vector Machine (SVM) is then utilized to categorize the deep learning characteristics into six distinct ILD types. Without having to manually remove the ROI, the proposed two-level method may classify a CT image into an ILD category using just the input picture.

2. Deep Learning: Overview

Some of the many scientific disciplines that have benefited from the advent of deep learning (DL) include: voice recognition; picture recognition; gaming technology; image-related technologies; music; and so on. When compared to other computational approaches, deep learning's success in solving some issues was previously thought to be unattainable. Thus, the rising trend of publications in this sector is indicative of the growing importance of this technology for medical imaging. To really grasp deep learning, one must first have a firm grasp on the underlying concepts. Machine learning, pattern recognition, and Neural networks are three such areas..

Machine Learning and Pattern Recognition

In this method, a system is created to make judgments automatically, such as classifying fruits such as apples and pears. Figure 1 depicts the pre-processing of the training dataset for feature extraction during the training phase. Noise reduction and picture rectification are two examples of the pre-processing techniques used in conventional image processing. Additionally, the feature extraction method is an algorithm that draws out a unique and comprehensive feature representation. In the pattern recognition method for classifying fruits, for instance, the traits that set them apart can be their color, the length of the semi-axes of an enclosing ellipse, etc..

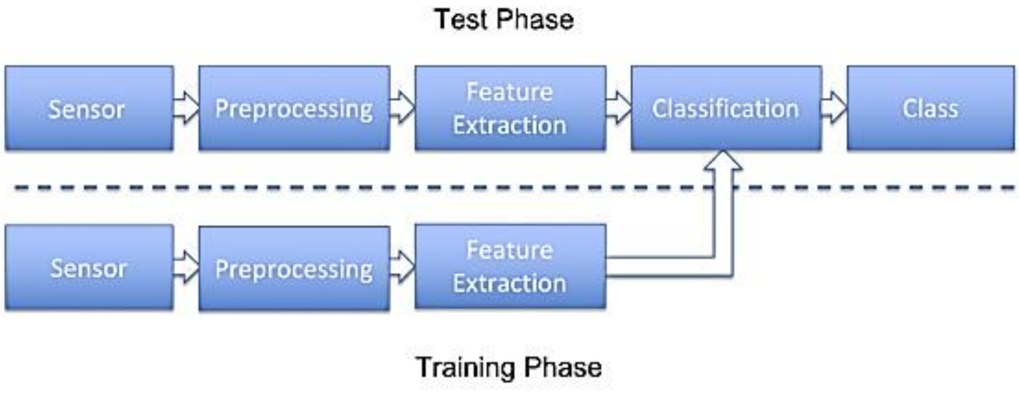


Fig 1: Typical example of traditional Pattern Recognition approach

Image Detection and Recognition

For the purpose of locating a certain feature in a medical picture, we create image detection and recognition issues. Figure 2 depicts a common instance of this kind. Some medical imaging applications provide volumetric data that must be efficiently parsed. One well-liked method that has proven effective and reliable in organ identification is called "marginal space learning." The deep learning implementation improves upon the effectiveness of the boosting cascade by replacing the bayesian boosting trees with a neural network. By substituting the search mechanism with an artificial agent, we were able to efficiently scan the whole volume and correctly recognize anatomical features. This method of searching is based on anatomy and uses deep reinforcement learning to identify anatomical features. The approach can quickly and accurately recognize hundreds of landmarks over an entire CT volume.

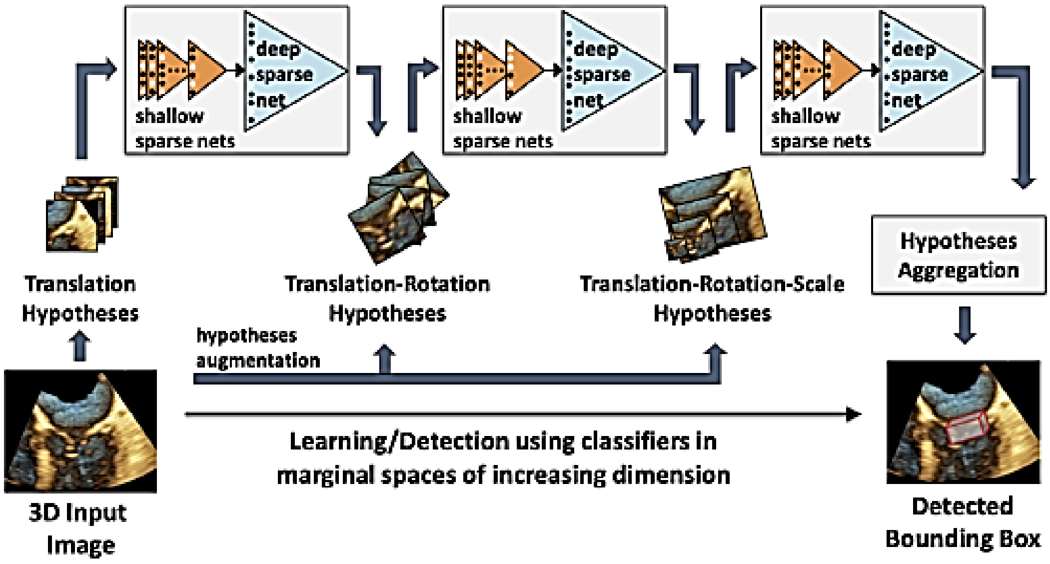


Fig 2: Typical example of medical image detection and recognition

Computer-Aided Diagnosis

When it comes to medical image processing, this is one of the more difficult applications of deep learning. This method incorporates the prediction process and serves as supplementary evidence in the quantification of the diagnosis. In this method, deep learning is used for each of the operations that make up the whole, including picture segmentation, feature extraction, classification, and so on. The specific purposes and uses that determine how these jobs are combined in a given area.

3. Literature Survey

In Paper [1] When it comes to malignant tumors, lung cancer poses the greatest risk to human health since it has the highest fatality rate. Doctors' capacity to identify and understand lung cancer may be aided by the wealth of data currently available thanks to ongoing studies into the improvement of imaging techniques. A lung nodule is often the first symptom a person notices when lung cancer is present. About a third of pulmonary nodules, which may be spherical or irregular in appearance, are malignant lung tumors. Therefore, detecting pulmonary nodules is crucial for detecting lung cancer at an early stage.

In Paper [2] A significant source of mortality and sickness across the world, malignant tumors of the lung are the most common kind of lung cancer. The incidence of lung cancer is on the rise, according to studies. The histology of a lung cancer patient is crucial to effective therapy. Artificial intelligence systems have the potential to dramatically improve lung cancer diagnosis. In this study, we provide a deep learning strategy for diagnosing lung cancer by modifying neural networks based on convolution (CNN) to make them more portable and effective. In this approach, the CNN model is utilized to identify lung cancer after the input histopathological images have been normalized. Using a publicly available collection of histopathology images, we compare our method to the current standard of excellence in cancer detection. Compared to previous methods, the suggested deep model for detecting lung cancer has an accuracy of 0.995%, as shown by the results analysis. These findings validate our method's computational efficacy.

In Paper [3] Lung cancer historically has a high mortality rate compared to other cancers. Improving prognoses, decreasing mortality, and stopping the spread of lung cancer all depend on early detection. Despite the high sensitivity of many current technologies for diagnosing lung nodules, they are often impractical because of the large number of false-positive suggestions they bring. In this research, we propose the MHSnet—a multi-head identification and spatial attention network—to deal with the critical problem of false positives. We begin by collecting multi-scale characteristics from nodules of varying sizes, shapes, and kinds using multi-head detectors and skip connections. After being taught with a spatial attention module, the network can now properly differentiate nodules in noisy tissues on CT scans, much as human doctors do. In order to reduce the amount of false-positive proposals, we built a lightweight yet effective false-positive reduction module that imposes no limits on the front network. Extensive experiments reveal that our MHSnet outperforms state-of-the-art models in terms of average FROC and false finding rate by 2.64 percentage points and 6.39 percentage points, respectively. The false discovery rate dropped by 14.29% after the erroneous-positive reduction module was implemented, suggesting that it has the potential to lessen the number of distracting suggestions made in subsequent tasks that depend on detection outcomes.

In Paper [4] According to a study conducted by the World Health Organization in the year 2020, pulmonary cancer (which is caused by abnormal cell development in the lungs) is the second most lethal disease in the world. Rapid metastasis to other organs, including the brain, is a hallmark of lung cancer, which in most instances originates in a single lymph node in the lungs. The potential improvement in diagnosis and treatment offered by earlier tumor detection might save millions of lives annually.

In Paper [5] If cancer is detected at an early stage, treatment is more likely to be effective. Multiple studies have shown a link between the growing cancer rate and improving life expectancy. Recent studies in India as well as across the globe have indicated that lung cancer is the second leading cause of mortality, behind heart disease. Early detection of cancer using machine learning and neural networks has being studied because it has the potential to improve therapy and save lives. By fusing a biological image processing approach with knowledge detection in data, a number of novel approaches have been created and put to use. In this study, we used several machine learning algorithms to a dataset characterizing lung cancer and analyzed their performance in terms of accuracy, sensitivity, specificity, F1 score, and precision. Our study's overarching purpose is to identify the best machine learning algorithms for early lung cancer detection. A data set predicting lung cancer was analyzed using multinomial naive Bayesian logistic regression, a random forest, a ridge classifier, and a support vector machine.

Lung Cancer Detection

The medical field has made extensive use of image processing techniques for the purpose of disease diagnosis. In order to use CT scans for diagnosing lung cancer, four steps must be taken. There is no one test that can reliably diagnose lung cancer, rather a battery of them[11]. To begin, noise is removed from the lung CT image, and then the image is segmented to provide a Region of Interest (ROI). In the third and final step, features including entropy, energy, etc variance are retrieved by feature extraction. Characteristics of lung tissue are extracted from the CT image and fed into algorithms for further analysis. Figure 1 shows all the steps involved in making a cancer diagnosis**..**

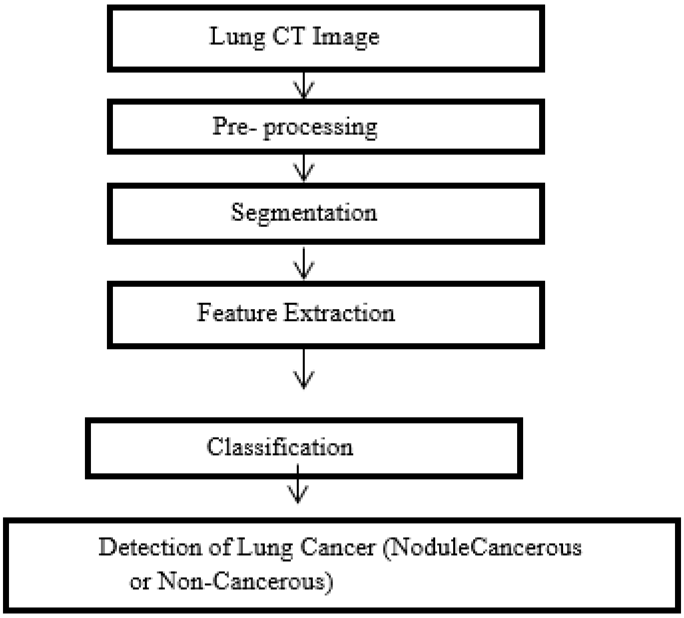


Fig 1 Steps involved in detecting Lung Cancer

Pre-Processing of Lung Cancer

In pre-processing, image data is cleaned up by removing noise or improving other qualities so that further processing is easier. Additionally, the blue hue must be removed, which calls for the mitigation of image distortions such light tremors. In order to divide photos into their needed and undesired parts, it enhances features like lines, borders, and textures..

Image Segmentation

Segmenting an image is a crucial step in the analysis of a picture and often leads to more work. In particular, the findings' dissection is the basis for many of the presentday techniques we employ for describing and identifying pictures. Thresholding and watershed segmentation methods are utilized, however thresholding is the most efficient method for dividing a picture into distinct sections. The segmented picture produced by thresholding requires less storage space, processes quicker, and is simpler to deal with than the gray level image, which typically includes 256 levels. As a result, well-known methods like Thresholding continue to be studied extensively. The seeds may be extracted via watershed segmentation by determining the locations and presence of items in the image's background[13-15]. The watershed procedure is implemented once the markers are relocated to the local minima of the topological surface.

Feature Extraction

It can locate and isolate certain visual characteristics for further processing. As before, this is a crucial stage in establishing whether or not the picture is normal. In order to properly classify anything, the following features must be retrieved. Area, perimeter, eccentricity, and mean intensity are used to quantify them. Following the defining of the characteristics as a standard:

First, its surface area, which is a scalar value that specifies the number of the nodule's final pixel. The picture does this by summing the areas of its individual pixels, which are represented as 1s in the resultant binary representation.

Classification:

This is an example of supervised machine learning, in which an algorithm draws inferences about the world based on a labeled data sample. Convolutional neural networks (CNNs), backpropagation, and support vector machines (SVMs) are just a few examples of classification techniques that make use of picture features[16, 17].

Machine Learning Techniques in Lung Cancer

The two phases of machine learning (ML), a branch of artificial intelligence concerned with deducing previously unknown information from current data samples, are (i) the estimation of unknown dependencies from a given dataset, and (ii) the prediction of future outputs in the system using estimated associations. The ability to apply acceptable generalization to collections of biological data is what has made ML such an interesting area of biomedical research, and it has done so with the assistance of a wide range of techniques and algorithms. In the context of supervised learning, input data is mapped or approximated to the desired output using a labeled collection of training data. In contrast, unsupervised learning does not need labeled examples or the creation of a fixed notion before it can be used. So it's up to the learning model to spot patterns or find new sources of incoming data. One possible interpretation of this as a classification issue in the context of supervised learning is as follows. The act of learning may be seen as a classification problem that sorts the given information into categories[18]. Common applications of machine learning include classifying data and doing regression. A learning function is then used to convert the input into a variable with numerical values. A predictive variable for each new sample may be estimated using this technique as a starting point. Clustering, in which groups of data points that share characteristics are grouped together and given meaningful labels, is a common unsupervised data analysis approach. Each subsequent sample may be assigned to one of the established groups according to their shared characteristics. The ultimate aim of machine learning is to create a prototype that can help with classification, prediction, estimation, and similar tasks.

Another form of machine learning method is semi-supervised learning, which combines features of both supervised and unsupervised approaches. In order to build a good learning model, we blend labeled and unlabeled data. This method of training is often used when there are more unlabeled than labeled datasets available.

The data samples themselves are the primary constituents; these samples are then aggregated using a number of features, each of which may initially have several values. In addition, being familiar with the data's structure beforehand enables for the selection of useful analytic tools. Some data-related difficulties provide insights about the quality of the data, while pre-processing methods make the data more amenable to machine learning. Data problems may be caused by things like outliers, noise, duplicate or missing records, and skewed, unrepresentative samples.

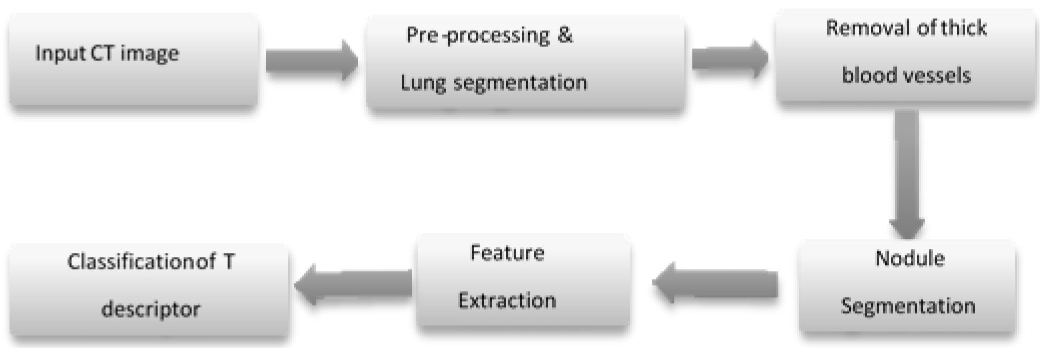
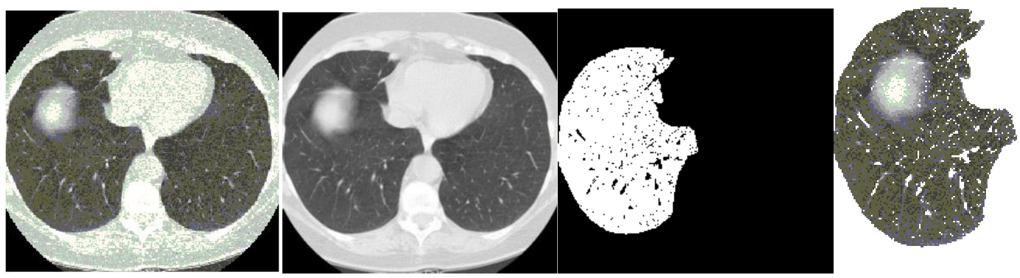


Fig 2 Flow Diagram of the Proposed System

Preprocessing is necessary because of the potential for noise in the provided image. A median filter was used to get rid of the background noise. A multi-level, single-click region growth strategy is used to extract the Lung region and segment nodules. Morphological operators are used in the removal of blood vessels. After calculating statistical features, the T descriptor for the nodule is arrived at. Figure 2 illustrates how the suggested CAD system was developed. Nodule segmentation reduces the size of the search space from which various picture characteristics are extracted, which speeds up the computations. It is possible to calculate some relevant metrics by using the located region. The key measure of interest is tumor size, hence the area and diameter are being calculated after segmentation.



(a) (b) (c) (d)

Fig 3 Preprocessing results (a) Original Gray Scale image (b) MedianFiltered Image(c) Segmented left lung (d) Masked lung

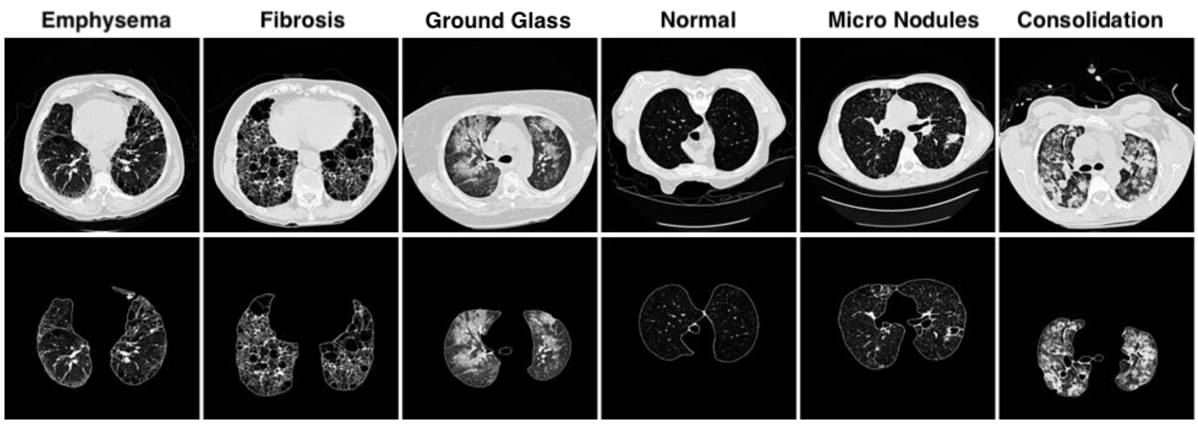


FIG 4: Examples of CT of six ILD

(First Row shows original CT images and second row show respective segmented image)

Performance of c-GAN for the Segmentation of Lung

The Cancer Imaging Archive (TCIA) is used for testing and training the suggested algorithms. There are CT scans of people who have lung cancer in the database, and the pictures have been annotated to show where the tumors are. These CT scans have a resolution of 512 pixels by 512 pixels. Five academic thoracic radiologists who specialize in lung cancer have annotated the database. TNM labels have been applied to the patient data for easy reference. In this investigation, researchers choose between 10 and 20 CT scans from each patent based on the available annotations. Here is a quick explanation of what each TNM class really means in terms of physics:

Table 1: Comparative performance assessment of average DSC and J for cGAN and existing methods for lung segmentation

Tumor	Performance	Present Study	NMF	UNet	Resnet
T1	DSC	0.9921	0.8575	0.9632	0.9694
	J	0.9846	0.8006	0.9365	0.9490
T2	DSC	0.9850	0.9291	0.9796	0.9848
	J	0.9707	0.8725	0.9795	0.9701
T3	DSC	0.9826	0.9113	0.9618	0.9768
	J	0.9661	0.8396	0.9601	0.9556
T4	DSC	0.9756	0.8794	0.9505	0.9763
	J	0.9528	0.8035	0.9076	0.9541
Average	DSC	0.9838	0.8943	0.9638	0.9768
	J	0.9685	0.8291	0.9459	0.9572

Performance of Deep Learning-based TNM Classifier

Tumors (T), nodes (N), and metastases (M) were classified using three distinct Resnet50 networks, each of which was then supplemented by a unique SVM method (T1, T2, T3, and T4). Although there will be three TNM class labels for each divided picture,

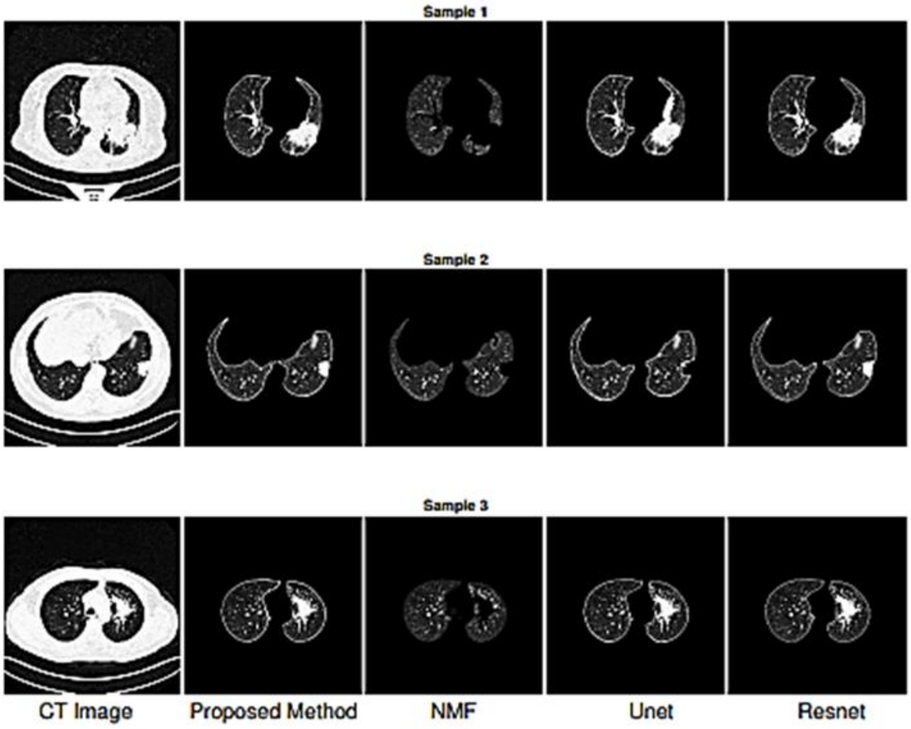


Figure 5.: Qualitative segmentation performance comparison of T class CT images.

4. Conclusion

In order to forecast the stage of lung cancer, a multilayer deep learning strategy is created in this study using the TNM coding system. The multilevel deep learning strategy employs several deep learning networks operating at different depths to address difficult issues. This research provides the TNM classification, which aids in diagnosing the stage of cancer, while previous studies on lung cancer classification concentrated on determining if a certain nodule was benign or malignant. When compared to the current binary cancer classification method, the suggested classifier performs much better, and its performance is quite similar to that of the newly created TNM classifier. Another benefit of the proposed method is that it classifies the provided CT image into TNM classes automatically, without the need for a human expert to manually pick or copy the ROI region.

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