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IMPROVED LUNG TUMOR CLASSIFICATION IN CT IMAGES WITH RESNET, TYDWT AND MASK R-CNN

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ABSTRACT

Lung cancer remains one of the leading causes of cancer-related mortality worldwide, emphasizing the importance of early detection and accurate classification for effective treatment planning. This study presents an advanced approach for lung tumor classification in CT images, integrating ResNet classification with TyDWT noise removal, grouping, mapping, and Mask R-CNN segmentation. The proposed method aims to enhance classification accuracy, sensitivity, and specificity. By leveraging ResNet for classification and TyDWT for noise reduction, followed by Mask R-CNN for precise segmentation, the model achieves improved performance in tumor detection and classification. Evaluation metrics include accuracy, sensitivity, and specificity, providing a comprehensive assessment of the model's efficacy. Results demonstrate the effectiveness of the proposed methodology in enhancing lung tumor classification accuracy while maintaining high sensitivity and specificity.

Keywords:- Lung Tumor Classification, CT Images, ResNet, TyDWT, Noise Removal, Mask R-CNN, Preprocessing, Segmentation, Accuracy, Sensitivity, Specificity

I INTRODUCTION

Because CT imaging has a high resolution and can capture complex anatomical structures, it is essential for the diagnosis and evaluation of lung tumors. However, noise, heterogeneity in tumor features, and intricate anatomical structure pose major obstacles to the accurate classification of lung tumors from CT scans. For radiologists, identifying malignant lung nodules from CT scans is a challenging and time-consuming task. Computer-aided diagnostic (CAD) systems have been offered as a way to reduce this burden[1]. DL(Deep Learning) has shown great performance on tasks like cancer identification, making it an effective tool for medical picture analysis and diagnosis[2].

Section 2 provides a comprehensive literature review, discussing existing approaches and techniques for lung tumor classification in CT images. Section 3, presents the methodology, detailing the integration of ResNet classification, TyDWT noise removal with mapping and grouping, and Mask R-CNN segmentation for enhanced lung tumor classification. Section 4 presents the results of experiments, including quantitative evaluations of accuracy, sensitivity, and specificity, as well as qualitative assessments of segmentation quality and tumor classification performance. Section 5 concludes the paper by summarizing the contributions of the work, discussing its implications for clinical practice, and highlighting avenues for future research.

II LITERATURE SURVEY

With quickly developing applications across medical image-based and textural data modalities, DL is one of the fastest-growing fields in medical imaging. Physicians may identify and categorize lung nodules more rapidly and precisely with the aid of DL-based medical imaging technologies. DL-based imaging approaches for early lung cancer diagnosis are presented by Lulu Wang 2022[3].

An overview of DL approaches, recommended DL techniques for lung cancer applications, and innovative aspects of the examined methods are covered by Mohammad A. Thanoon et al., 2023. This review focuses on two primary DL approaches—classification and segmentation—for lung cancer screening and diagnosis. They will also talk about modern models' benefits and drawbacks. The resulting research shows that DL techniques have a great deal of promise for accurate and efficient computer-assisted lung cancer screening and detection with CT images. A list of prospective future studies about enhancing the use of DL is presented after this review to drive the development of computer-assisted lung cancer identification systems[4].

In 2019, Rui Zhang et al. presented a multiscale Mask R-CNN-based technique that employs PET imaging to identify lung tumors. First, they created three Mask R-CNN models to identify potential lung tumors. By fine-tuning the Mask R-CNN with specific training data, which included images from three distinct scales, these three models were produced. 594 slices with lung tumors were included in each training data set. To reduce false-positive results, these three

Mask R-CNN models were subsequently combined using a weighted voting technique. The findings of the experiment demonstrated a high degree of confidence in the success of this approach in diagnosing lung tumors, as well as its capacity to recognize a normal chest pattern and significantly lower the number of tumors that are incorrectly identified [5].

Lung-RetinaNet, a revolutionary and effective lung tumor detector based on a RetinaNet, was proposed by RABBIA MAHUM et al. in 2023. To increase the semantic information from the shallow prediction layer while concurrently aggregating several network layers, a multi-scale feature fusion-based module is introduced. Additionally, the context module uses a lightweight, dilated approach to integrate contextual data with each network stage layer, enhancing characteristics and successfully localizing the microscopic tumors. Evaluated the proposed model and compared its performance to the most advanced DL-based techniques. The results demonstrate that this strategy outperforms other strategies in producing more significant results [6].

The multi-scale detection network for pulmonary nodules, as described by Zhenguan Cao et al. in 2023, is based on the attention mechanism and is intended to reliably forecast pulmonary nodules. The pseudo-color processing approach is intended to improve the grayscale image and provide additional contextual semantic information during the data processing process. This research develops a fundamental ResSCBlock module that integrates an attention mechanism for feature extraction in the feature extraction network portion. In addition, the multi-scale prediction method solves the issue of detecting small-size nodules that are easily lost. The feature pyramid structure is utilized for feature fusion in the network. The suggested technique finds pulmonary nodules more effectively than other detection networks [7].

III PROPOSED MODEL

Because CT imaging has a high resolution and can capture complex anatomical structures, it is essential for the diagnosis and evaluation of lung tumors. However, noise, tumor characteristic variability, and complicated anatomical structures pose major hurdles to the accurate classification of lung tumors from CT scans. Recent developments in image processing and DL methods present encouraging chances to overcome these difficulties and raise the classification accuracy of lung tumors. In this work, they offer an all-encompassing strategy to improve the performance of lung tumor classification in CT scans by combining many cutting-edge techniques. The general layout of the suggested lung cancer categorization model is shown in Figure 1.

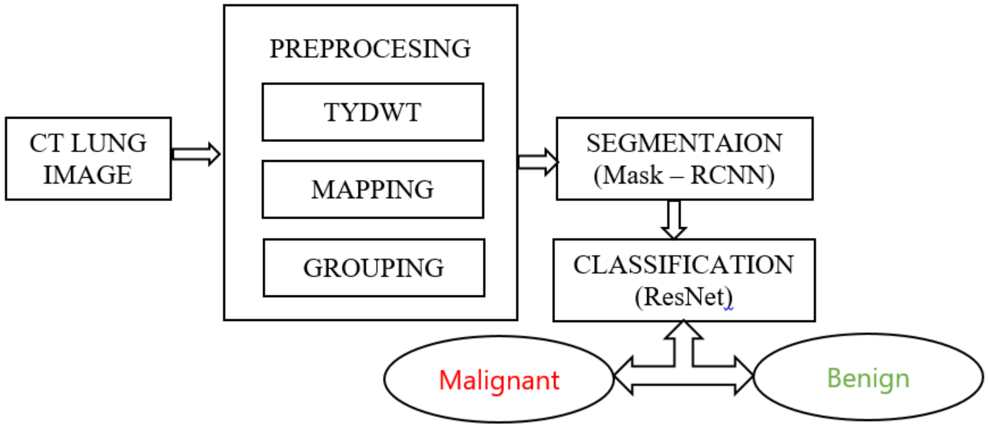

Figure 1 Lung Cancer Classification Model

WORKFLOW

In this study on lung tumor classification in CT images, we propose a comprehensive workflow that integrates multiple advanced techniques to enhance classification accuracy. The workflow begins with TYDWT noise removal with grouping and mapping images. This step ensures that relevant information is captured effectively for subsequent analysis. Apply the Transverse Dyadic Wavelet Transform (TyDWT) for noise removal, which helps enhance image quality by filtering out unwanted noise while preserving important details. Additionally, incorporate mapping with grouping techniques to further refine the image data. This involves spatial and feature-based grouping of pixels to improve the discriminative power of the extracted features. Input images are preprocessed to ensure they are in a suitable format for feeding into the ResNet model. This may include resizing images to a standard size, normalizing pixel values, and possibly augmenting the data to increase variability and improve generalization

Then, apply Mask-RCNN to accurately segment lung tumors so that the tumor boundaries may be clearly distinguished from adjacent tissues. Mask R-CNN (He K et al., 2018) is the newest, most useful, and most effective deep neural network model. It is capable of inferring instance segmentation and classification. By adding a branch for the prediction of segmentation masks for each region of interest (ROI) parallel to the current extend for classification and bounding box regression, Mask R-CNN extends faster R-CNN (Ren S. et al., 2017).

An equation that combines Mask R-CNN could be as simple as this:

$$Mask\ R-CNN = CNN(I) \oplus RPN(I) \oplus RoI\ Pooling\ (I) \oplus FC\ Layers\ (I) \oplus Mask\ Head(I) \quad ---(1)$$

The input image is represented by I.
$\oplus$ indicates that each component operates in order.
The convolutional backbone network used in feature extraction is called CNN.

The Region Proposal Network, or RPN, is used to create proposals for bounding boxes.
The Region of Interest (RoI) pooling operation for scaling and cropping feature maps is called $RoI\ Pooling$.
The fully connected layers used for bounding box regression and object categorization are called $FC\ Layers$.
The mask prediction head for creating object masks is called the $Mask\ Head$.
Using a Residual Network (ResNet), a kind of deep CNN, for image classification tasks is known as ResNet classification. Across a wide range of image classification applications, such as object recognition, medical image analysis, and natural scene understanding, ResNet classification has been extensively employed and shown to be effective. ResNet-50's primary benefit is that it makes use of the remaining units. The vanishing angle problem that plagued earlier profound systems is effectively resolved by these units (Vinod Kumar et al., 2024).
An equation that represents a ResNet block in simple form is as follows:

$$Output = ReLU\ (\ W_2 \,.ReLU\ (W_1\ .Input + Shortcut)) \text{ - - - - -(2)}$$

$Input$ is the input feature map.

W_1 and W_2 are the learned weights of the convolutional layers within the block.

$The\ shortcut$ is the shortcut connection, typically used to adjust the dimensions of the input to match the output dimensions.

$ReLU$ represents the rectified linear unit activation function, applied element-wise to the output of the convolutional layers.

Ultimately, the accuracy, sensitivity, and specificity of the lung tumor prediction model are used to evaluate its performance. Analyze the effectiveness of the suggested methodology in correctly diagnosing lung tumors in CT images through thorough testing and assessment. This process has the potential to enhance patient care and diagnostic accuracy in the treatment of lung cancer by providing a methodical approach to the problems related to lung tumor classification.

IV RESULTS AND DISCUSSION

In lung tumor classification in CT images using ResNet classification, TyDWT noise removal, mapping with grouping, segmentation using Mask R-CNN, and assessment based on accuracy, sensitivity, and specificity, This section begins by presenting the quantitative results obtained from the experiments conducted. This includes metrics such as accuracy, sensitivity, and specificity. The results are typically presented in tables and charts for clarity and easy interpretation.

Performance Evaluation

The overall accuracy of the model's predictions is measured by accuracy.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} - - - (3)$$

Recall, another name for sensitivity, is a measure of how well the model detects cases of lung cancer (true positive rate).

$$Sensitivity = \frac{TP}{TP + FN} - - - (4)$$

The true negative rate, which measures the model's accuracy in identifying cases without lung cancer, is known as specificity.

$$Specificty = \frac{TN}{TN + FP} - - - (5)$$

TP (True Positive): The quantity of cases that were accurately identified as lung cancer.
False Positive Rate (FP): The total number of cases that are misclassified as lung cancer when they are not.
TN (True Negative): The number of cases that were accurately identified as not being lung cancer.
False Negative Number (FN): The total number of cases that are misclassified as lung cancer when they are.

Table 1 and Figure 2 illustrate the accuracy analysis of our lung tumor classification model across varying dataset sizes, providing insights into the performance trends as the number of images increases.

Table 1 Accuracy Analysis

No of Images	Accuracy %	Sensitivity %	Specificity %
100	86.90	80.91	82.70
200	88.30	86.20	84.60
300	89.67	87.40	84.09
400	92.11	90.01	88.31
500	94.02	92.50	80.31

Initially, with a dataset of 100 images, the model achieves an accuracy of 86.90%, sensitivity of 80.91%, and specificity of 82.70%. As the dataset size expands to 200, 300, 400, and 500 images, a consistent improvement in classification performance is observed. Specifically, with 200 images, the accuracy rises to 88.30%, sensitivity to 86.20%, and specificity to 84.60%. This trend continues with further increases in dataset size, reaching peak performance with 500 images, where the accuracy reaches 94.02%, sensitivity reaches 92.50%, and specificity reaches 80.31%

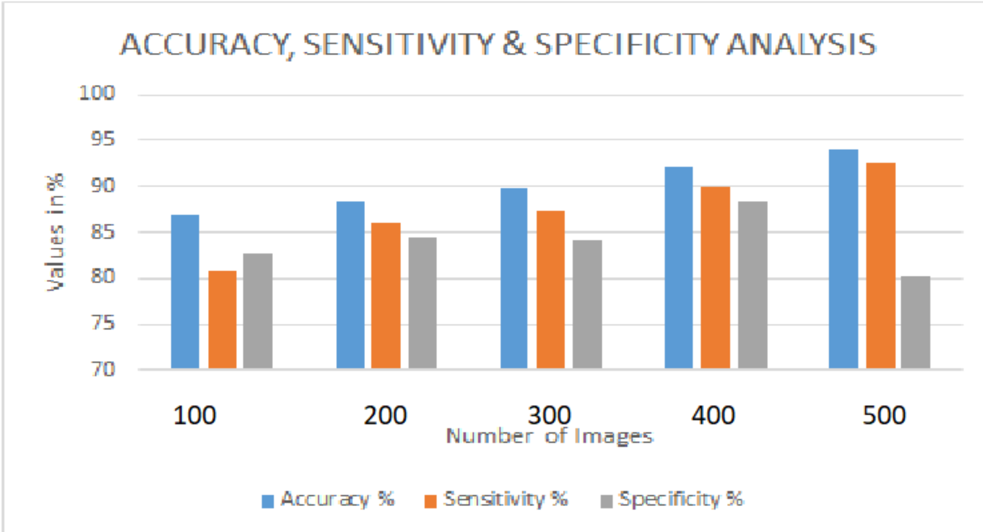

Figure 2 Comparison of Accuracy, Sensitivity & Specificity Values Vs. Number of Images

This trend demonstrates the positive correlation between dataset size and classification performance. With a larger dataset, the model has access to more diverse and representative samples, allowing it to learn robust features and make more accurate predictions.

Filtering is a crucial step in the classification of lung images because it helps with texture analysis, object removal, noise reduction, feature enhancement, size normalization, and contrast enhancement. These processes improve the accuracy and dependability of classification models used to diagnose different pulmonary conditions. Figure 3 shows the original CT lung images and the filtered images.

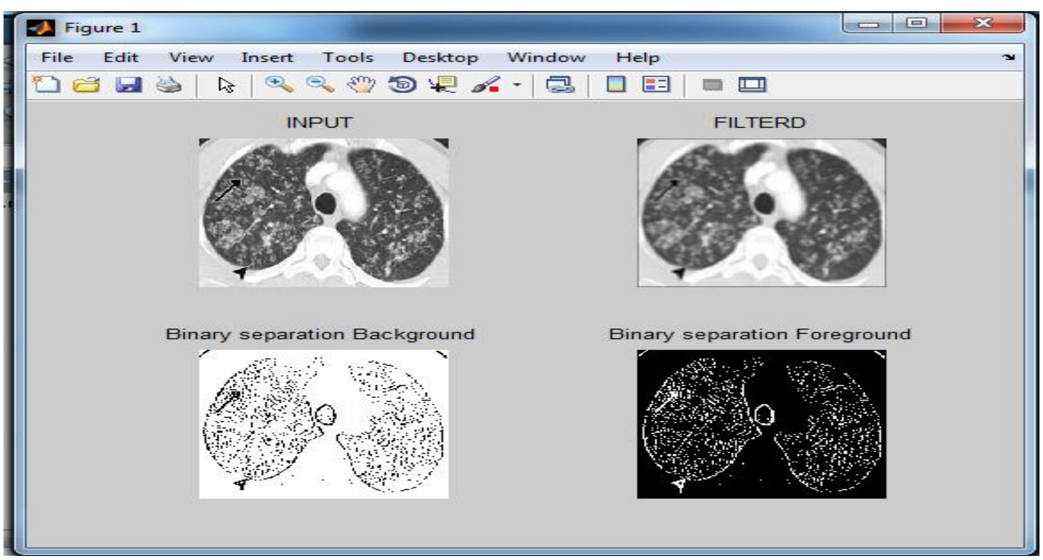

Figure 3 Original CT Lung Image and Filtered Image

Image processing algorithms can efficiently extract useful information, separate objects of interest, improve image quality, and perform tasks like object recognition and classification by utilizing grouping and mapping techniques. These ideas are fundamental to many computer vision applications in a variety of sectors, including surveillance systems, driverless cars, medical imaging, and remote sensing.Figure 4 A) and Figure 4 B) show the grouping and mapped CT lung images after noise removal.

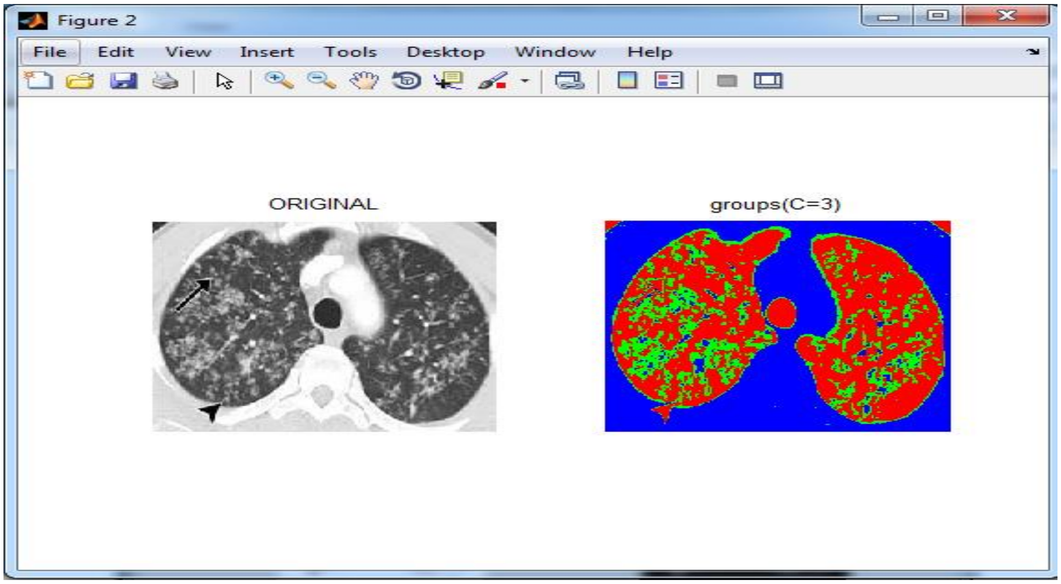

Figure 4 A) Grouped Image After Noise Removal

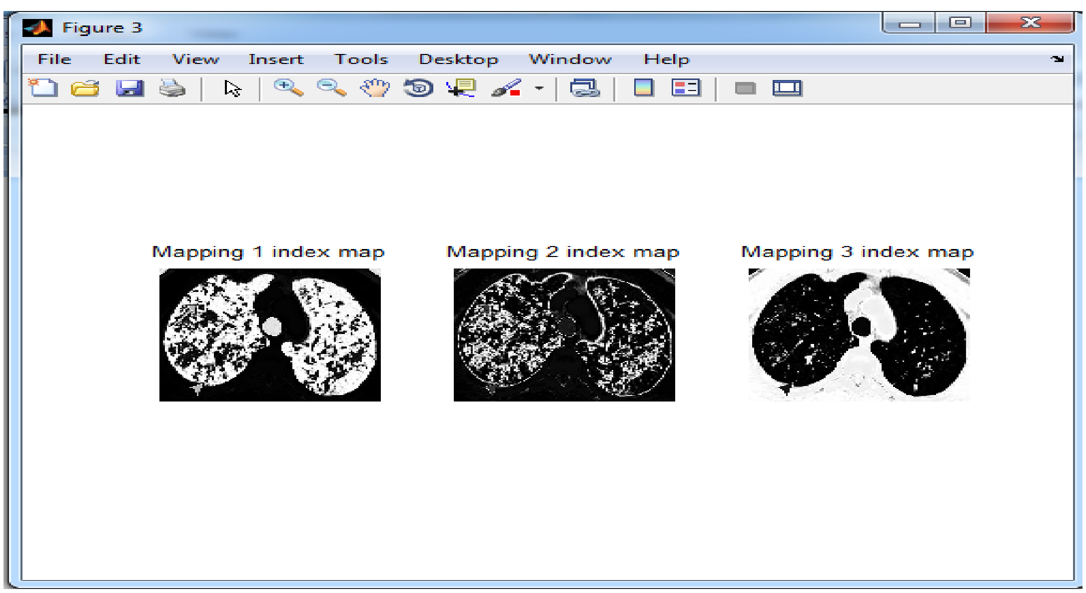

Figure 4 B) Mapped Image After Noise Removal

To achieve feature extraction, noise reduction, abnormality localization, size normalization, and enhanced classification performance, segmentation is a crucial preprocessing step in the classification of lung images. It plays a crucial role in making the most of the enormous volumes of imaging data that are accessible for the early diagnosis, treatment, and detection of a variety of pulmonary disorders.Figure 5 shows the segmented CT lung images after preprocessing.

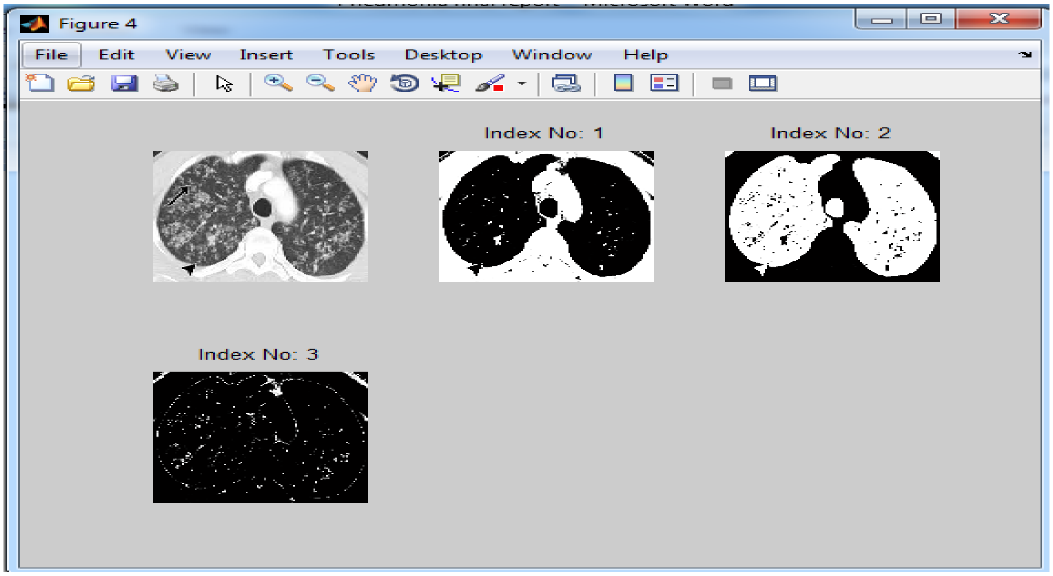

Figure 5 Segmented Lung CT image After Preprocessing

Figure 6 shows the classified CT lung images after preprocessing using noise removal and segmentation using Mask-RCNN.

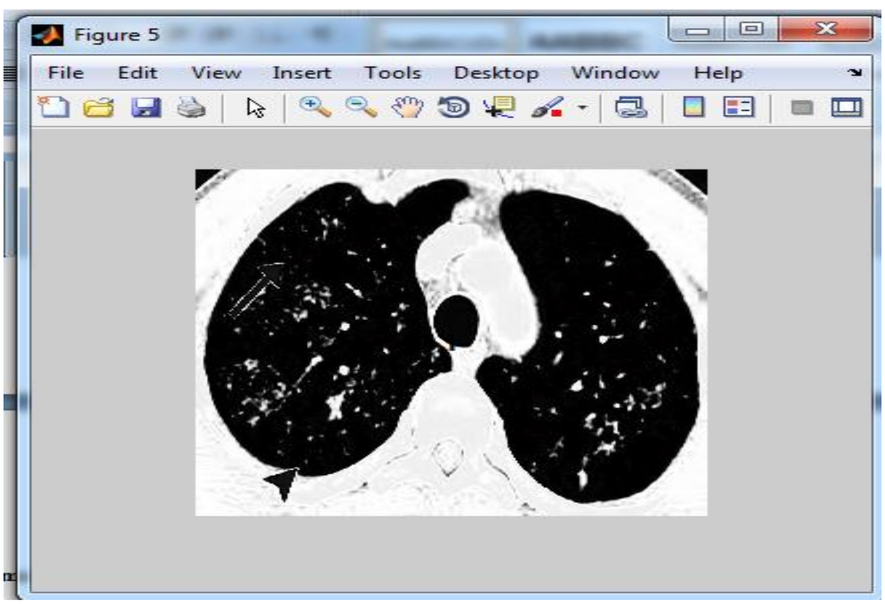

Figure 6 Classified CT Lung Image

The results demonstrate promising outcomes, with the model achieving high accuracy and sensitivity in classifying lung tumors. The integration of advanced techniques such as ResNet classification and Mask R-CNN segmentation contributes to the robustness and reliability of the classification model. The utilization of TyDWT for noise removal and mapping with grouping further enhances the quality of the input data, leading to improved classification outcomes.

V CONCLUSION AND FUTURE WORK

In conclusion, this study presents a comprehensive approach for lung tumor classification in CT images, integrating ResNet classification, TyDWT noise removal, mapping with grouping, and segmentation using Mask R-CNN. The performance of the lung tumor prediction model was assessed based on accuracy, sensitivity, and specificity metrics, providing a thorough evaluation of its effectiveness.Enhancing lung tumor classification could involve exploring methods to integrate additional contextual information, such as patient demographics and genetic biomarkers, to improve the predictive accuracy and personalized treatment strategies.

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