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Lung Tumor Detection and Localization System Using Faster RCNN Algorithm

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Abstract

Lung tumors represent a significant health challenge. Although, their early detection can improve patient outcomes, traditional diagnostic methods often fall short in accuracy and efficiency. Therefore, advanced algorithms are required to facilitate accurate and earlier tumor detection and localization. This study aims to enhance detection efficacy through a systematic methodology that includes image pre-processing, segmentation, feature extraction, classification, and localization. We have invested three CNN models; Our proposed CNN, VGG-16 and RESNET50 integrated with Faster R-CNN to detect and localize lung tumor in computed tomography images from the Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD) dataset. As a result, VGG-16 and RESNET50 attained detection accuracies of 97.66% and 97.20% respectively, while Our-CNN model achieved a detection accuracy of 97.20%, with an average test precision of 97.185 and an F1-score of 0.9737. For localization, ResNet50 and Our-CNN demonstrated accuracy based on Intersection over Union (IoU) at 89.47%, while VGG-16 achieved 73.68%.

Keywords: CNN, Lung tumor, Localization, Faster RCNN, Intersection over Union.

1. Introduction

Cancer is the major cause of death, recording one of six death cases. It can be classified as malignant (cancerous) or benign (tumor non-cancerous) [1]. Cancer can also be classified by its location such as brain cancer, lung cancer, breast cancer, etc. [[2]. The most frequently diagnosed cancer is lung cancer. In 2022, lung cancer accounted for about 2.48 million new cases and 1.8 million deaths [3].

Lung cancer can be cured if it has been detected in early stages. Unfortunately, early-stage lung tumors are difficult to detect as they often lack specific symptoms [4], thereby, around 80% of lung cancer patients are diagnosed only at advanced stages.[5]

Lung tumor can be detected by using several imaging techniques such as X-ray, computed tomography (CT), positron emission tomography (PET), and functional magnetic resonance imaging (fMRI) Despite advancements, radiological images still require analysis by trained radiologists, who face challenges related to experience, fatigue, and increasing workloads due to a growing number of scans. This emphasizes the need for automated machine learning algorithms to assist radiologists in managing their tasks more efficiently. In particular, CT

imaging is faster, effective, and more widely available than other modalities, resulting in lower costs per scan, ability to detect nodules as small as 1 cm, and reduction of radiation exposure [6][7] .
Lung nodules are often asymptomatic and are typically discovered incidentally during imaging for unrelated issues and this diagnostic process results in late-stage cancer detection and complicates the treatment process.[6] Misdiagnoses can occur due to several factors like low image quality, incorrect patient positioning, or to human factors as well. Thus, Computer-Aided Detection (CAD) systems are increasingly used to mitigate these errors and enhance early detection of lung cancer.[4]
In this research, For the detection and localization of lung tumors from CT scans, we proposed an approach based on three Convolutional Neural Network (CNN) models: Our proposed CNN, VGG16, and ResNet50. The most significant contribution in our work lies in the method of localization, which has shown noticeable performance at accuracy of 89.47%.

2. Literature Review

Advancements in artificial intelligence (AI) present significant opportunities for lung cancer detection. Whether for symptomatic or asymptomatic patients, AI techniques became indispensable for detecting cancer and monitoring its progression. As a part of AI, Our investigation into the literature revealed a growing application of deep learning in lung cancer diagnostics, with various innovative approaches being explored for tumor detection, localization, and classification. In this section, we present selected studies to investigate other's potentials for lung tumor detection and classification.
R. Pandian et al. in [8], proposed an automated lung cancer detection approach utilizing the VGG-16 architecture. The study compared the performance of GoogleNet and VGG-16 against Our proposed CNN model, achieving a detection precision of 98%. The evaluation used 100 images per class, with 70 for training and 30 for validation.
The study in [5] introduced VGG16 for diagnosing carcinoma nodules, classifying them as malignant, benign, or healthy. Using the IQ-OTH/NCCD dataset, the model achieved a sensitivity of 92.08% and an accuracy of 91% through Python-Jupyter simulations.
In paper [9], a multi-stage automated detection framework was developed, utilizing 3D CT images. The authors proposed a system based on Faster R-CNN and U-Net with MixNet to evaluate 1200 images and they achieved a sensitivity of 94% and specificity of 90%.
The framework in [4] leveraged the IQ-OTH/NCCD dataset for lung cancer classification. It combined a pre-trained VGG16 model for feature extraction with an Extremely Randomized Tree Classifier, resulting in an accuracy of 99.09% and a sensitivity of 98.33%.
In [10], enhancements to the YOLOv5 model improved its ability to detect small pulmonary nodules in complex CT images. The model achieved a detection average precision of 94.8% and sensitivities of 78.1% and 94.4% under varying false positive conditions.
Akintola et al. [[11] employed Mask R-CNN for integrating localization-to-classification of lung tumor from CT images. The Mask R-CNN delineated nodule boundaries with pixel-wise masks and bounding boxes for tumor localization with 95.6% accuracy, 94.8% precision, 94.3% recall, 97.5% F1-score, and 94.5% AUC.

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Kuo-Yang Huang et al.[12] used the Lung-PET-CT-Dx dataset to investigate YOLO family object detection models for lung tumor detection and localization from CT images. Their approach provided bounding boxes indicating tumor detection and locations with the best performance of YOLOv8 at 90.32% for precision and 84.91% for recall.
Lastly, the study in [13] developed a labeled lung mass database and a deep learning technique for mass classification and detection. The analysis revealed that the RESNET-based approach outperformed VGG16, with an average precision of 52.38%, successfully identifying 41 out of 51 masses.

3. Methodology

The general procedure and methodology of a tumor diagnosis system can be subdivided into five sub-stages: image collection, image preprocessing, image segmentation, feature extraction and classification, then the localization step as shown in Figure **1**.

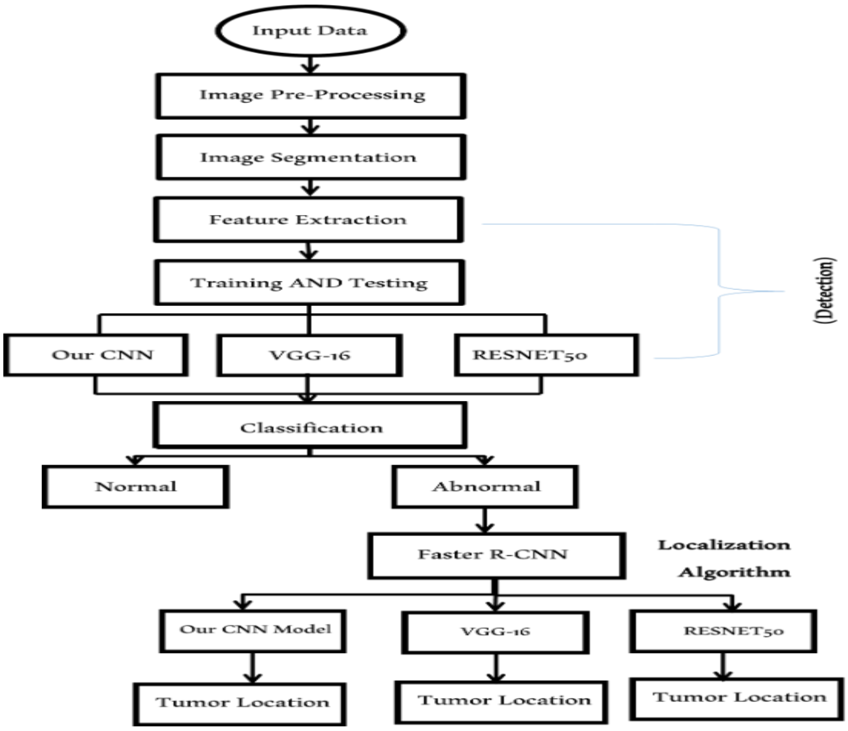

Figure 1: Flow-chart for the Proposed System.

A. Dataset

The dataset used in this research was collected from the Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD)[14], and from Ali Omar Askar Hospital, Alsbaia, Tripoli, Libya. It comprises 1,074 lung CT images, 571 from patients

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diagnosed with lung cancer at various stages and 503 from normal cases. All images have been saved in JPG digital format.

B. Image preprocessing

Image preprocessing aims to reduce noise and redundant information to enhance image quality and highlight key features. The preprocessing stages include input RGB image, gray scale conversion, normalization, noise reduction, image enhancement, binary image. Figure **2** shows the original image and image after preprocessing.

Figure 2: A) Original Image B) Preprocessed Image.

C. Image Segmentation

Image segmentation divides a digital image into segments to simplify analysis and locate objects and boundaries. In this system, morphological operations like dilation (to grow features) and erosion (to shrink features) are used. The opening operation removes some foreground pixels, while closing removes small holes. An inverted image is created for segmentation with the active contour algorithm (snakes), followed by a flood-fill operation to fill holes in the lung areas. These processes produce a mask that separates the background from the foreground, allowing unwanted elements to be removed from the original image. Figure **3**, shows the image after segmentation process.

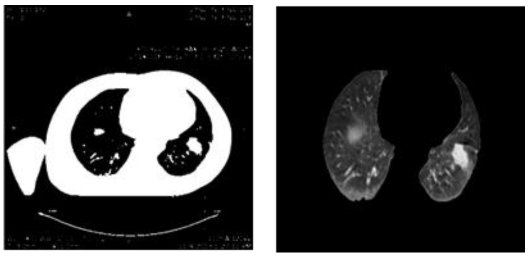

Figure 3 :A) Pre-processed Image B) Segmented Image

D. Feature Extraction and Classification

We employed three deep learning models for feature extraction and classification:

- Our proposed CNN, which has 15 layers tailored for feature extraction and binary classification, 3 convolutional layers for effective feature extraction, each followed by Batch Normalization and ReLU Activation Layers. It concludes with a Classification Output Layer for final results.

- Pre-trained VGG16, which includes 41 layers with 13 convolutional layers for enhancing feature extraction.
- ResNet50, which is more complex, comprising 177 layers, including 50 convolutional layers and residual connections that support training in deep networks.

Utilizing transfer learning, we capitalized on the extensive training of VGG16 and ResNet50 on large datasets, enabling us to extract relevant features efficiently from our limited dataset of normal and abnormal classes. This approach enhances the models' ability to recognize key features while minimizing the need for extensive training from scratch, ultimately improving the accuracy of medical image analysis.

E. Faster RCNN (Faster Region based-Convolutional Neural Network):

The Faster Region Convolutional Neural Network (Faster R-CNN) is an object detection framework that combines deep learning with traditional methods to enhance accuracy and efficiency. It represents advancement over previous models like R-CNN and Fast R-CNN.
Faster R-CNN introduces a Region Proposal Network (RPN) that generates potential object regions, making the entire process trainable. The FR-CNN architecture is illustrated by Figure **4** and includes five stages.

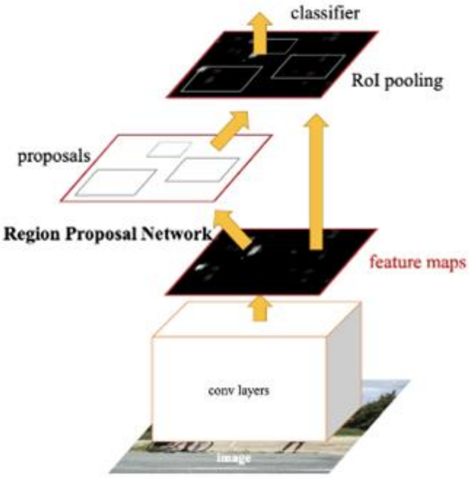

Figure 4: The FASTER RCNN Algorithm's Design.

- **Feature Extractor (Backbone Network)**: it is a CNN, which processes the input image and extracts hierarchical features essential for detecting objects of various sizes.
- **Region Proposal Network (RPN)**: Utilizes the extracted features to predict possible object regions (bounding boxes) using a sliding window approach.
- **Region of Interest (RoI) Pooling**: After obtaining the proposals from the RPN, the RoI pooling layer extracts fixed-size feature maps from the backbone for each proposed region.
- **Classification and Bounding Box Regression**: The fixed-size features from RoI pooling are inputted into fully connected layers. The classification head predicts the

distribution of object classes, while the regression head adjusts the bounding box positions for the proposed regions.

- **Non-Maximum Suppression (NMS)**: After predictions are made, NMS filters out duplicate and low-confidence detections. This process retains high-scoring regions based on their Intersection over Union (IoU) values [15]

The Faster R-CNN algorithm for tumor localization was utilized on three neural networks: VGG16, ResNet50, and Our proposed CNN. It outputs images highlighting tumor locations in the lungs, along with a probability score for each region. The model performance of tumor localization was evaluated by IoU, which can be calculated by comparing the ground truth bounding box to the predicted bounding box. Faster R-CNN has been trained on 25 abnormal images and was tested using 19 images featuring tumors in various locations.

4. Results

A. Detection Results

The dataset was divided into three parts: training, validation, and testing. 604 images have been used for training, 256 images for validation during training, and 214 images (114 abnormal and 100 normal) for evaluating the final trained models on completely unseen data. CNN models' performance was evaluated by several metrics that include precision, recall, F1-score, and accuracy as illustrated in Table **1**. The three models have shown a good performance with almost the same values at .97 for precision, recall, and F1-score, and 97% for accuracy.

Table 1: Metrices Results of Test Data for All Models.

Model	**Average Test Precision**	**Average Test Recall**	**TEST F1-Score**	**Test Accuracy**
our CNN	0.97185	0.97185	.97185	97.20%
VGG16	0.97625	0.97685	0.97655	97.66%
Resnet50	0.9706	0.97360	0.97175	97.20%

B. Tumor Localization Results Using Faster R-CNN

For the localization task, only abnormal images (those containing tumors) were used for training, since the objective was to learn how to detect and localize tumor regions. The same number of training and testing samples was used across all three models to ensure consistency and fairness in evaluation. The model's performance of lung tumor localization is evaluated by their accuracy as shown in Table 2. And sample outputs of tumor localization using our-CNN, VGG16, and ResNet50 are shown in Figure **5**

Table 2: The Performance of Localization Process.

CNN Model	**Number of test images**	**True**	**false**	**Accuracy IoU ≥ 0.3**
Our-CNN	19	18	1	89.47
VGG16	19	17	2	73.68
ResNet50	19	18	1	89.74

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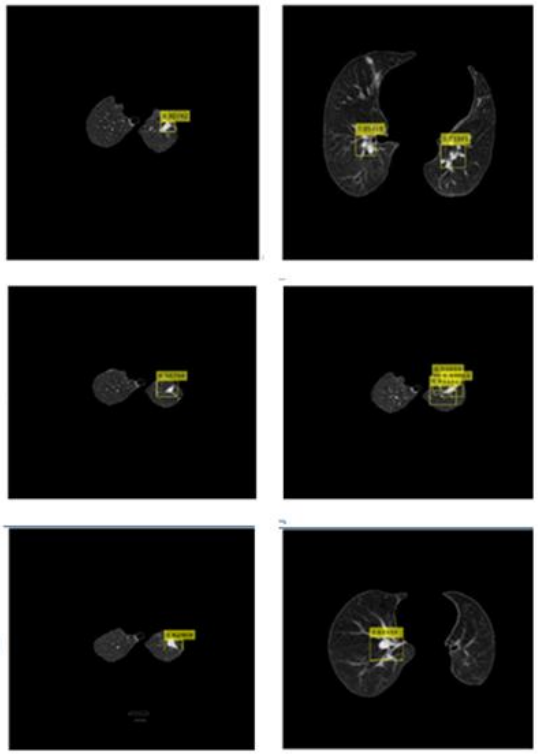

Figure 5: Sample Outputs of Tumor Localization Using A) OUR-CNN, B) VGG16, C) RESNET50

The evaluation of the predicted bounding boxes was based on the Intersection over Union (IoU) metric, which quantifies the overlap between predicted regions and ground truth annotations.

As depicted in the histogram, in Figure **6** the majority of IoU values are concentrated in the higher range, specifically between **0.6 and 0.8**, with several images achieving IoU scores approaching **0.75 to 0.8**. This distribution indicates a high degree of alignment between the predicted and actual tumor regions, suggesting that our-CNN model was effective in capturing the spatial and structural features necessary for accurate localization.

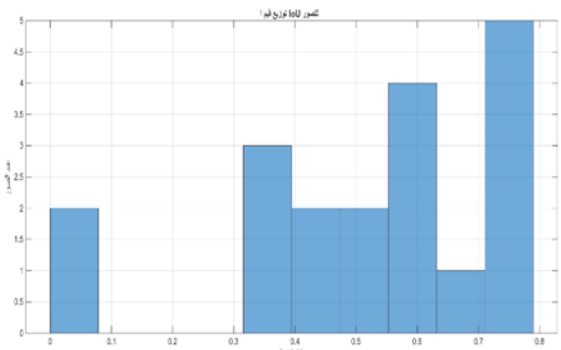

Figure 6: IOU Histogram for CNN Model.

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As shown in Figure 7, represents the IoU histogram for Vgg16 model, most images (approximately 5) achieved IoU scores in the range of 0.5 to 0.55, with the same number extending between 0.6 to 0.8. These values suggest that the model was able to detect tumor regions with moderate accuracy, as many of the predicted bounding boxes overlapped significantly with the ground truth, albeit not perfectly. This indicates that VGG16 can capture general tumor locations but may lack the precision required for exact boundary localization in certain cases. At the same time, the presence of several low IoU values — including some below 0.1 close to 0 and others in the 0.2–0.3 range — highlights cases where the model either failed to detect the tumor accurately or predicted bounding boxes with poor alignment.

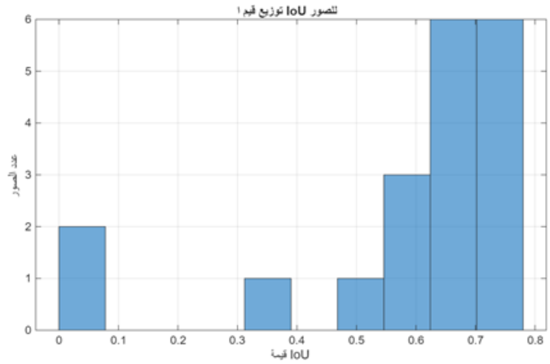

Figure 7: IOU Histogram for VGG16 Model.

As shown in Figure 8, The IoU distribution histogram for ResNet50 further reinforces this result. Most of the predicted bounding boxes achieved IoU scores between **0.5 and 0.8**, reflecting high overlap between the predicted and actual tumor regions. Notably, five of the test samples scored IoU values above **0.7**, indicating highly precise localization that closely aligns with expert annotations. Only a small number of cases fell below the **0.3** threshold, suggesting that the model was able to maintain localization accuracy across most test instances with minimal failure.

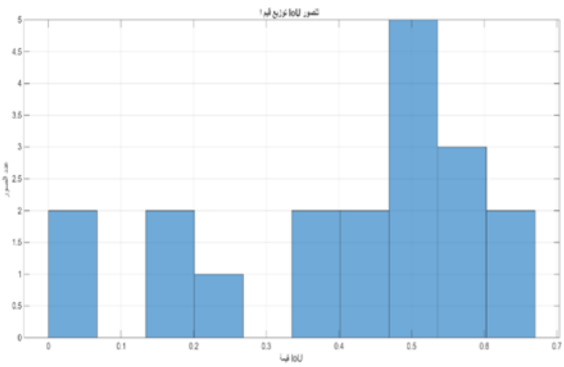

Figure 8: IoU Histogram for ResNet50 Model

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5. Conclusion

This research successfully developed a deep learning-based system for detecting and localizing lung tumors in CT images using the Faster R-CNN framework. The evaluation of three models—Our CNN, VGG16, and ResNet50—demonstrated high classification accuracy, with VGG16 achieving the highest at 97.66%. ResNet50 and our CNN followed closely, indicating that simpler architectures can also provide reliable performance for binary tumor detection. In terms of localization, both ResNet50 and Our proposed CNN achieved a localization accuracy of 89.47%, with high Intersection over Union (IoU) values indicating effective tumor region identification. While VGG16 has lower localization accuracy, the results highlight the potential of diverse architectures for different computational environments. Overall, this study showcases the effectiveness of deep learning models in medical imaging, paving the way for improved diagnostic tools in clinical settings

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