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MASK-RCNN on the diagnoses of lung cancer in Kurdistan Region of Iraq

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ABSTRACT

Cancer is one of the danger diseases in our life, especially lung cancer is one of the most effected organs by cancer and causes death. The early detection of the tumor is very important issue for staging the cancer phases, usually the shape and size of the tumor are considered for classify the cancer type, calculation size of the tumor area and detecting it in accurate way will help to save patient life, this paper uses Mask-RCNN to analyze and detect malignant and benign tumor with real dataset of CT scan lung cancer images in (Kurdistan Region of Iraq) KRI, also develop calculating area size of tumor in cm^2. After training and testing the system accuracy 96.59%, sensitivity 95%, specificity 95% and F_1 score 99.65% have been achieved. The study concludes that Mask-RCNN is a very good model for diagnoses cancer tumors and can help radiologists to detect and stage the cancer.

1. Introduction

Lung tumor is one of the most fatal diseases, with a high fatality rate both globally and in Kurdistan region of Iraq (KRI). Survival and enhanced standard of living of lung cancer patients are highly rely on prompt treatment and diagnosis. Patients who receive an early diagnosis have a roughly 54% five-year survival rate, compared to only 4% for those who receive an initial stage four cancer diagnosis. According to table 1, lung cancer is the second most common malignancy in the KRI area, and since the Corona Virus directly affects the lungs, they anticipate that the prevalence will rise (Barzingi et al., 2020).

Since imaging technology can help with early diagnosis and therapy for such malignancies by essentially identifying tumors at an early stage, it is of utmost importance for the evaluation of lung tumors.

Clinicians find it difficult to interpret and identify cancer from CT scan data, despite it being the best imaging way in the healthcare field. Because of this, practitioners may find computer assisted diagnosis helpful in accurately identifying the cancerous cells. There have been numerous studies and application *Barzingi et. al.*, 2020s of computer-aided approaches using image processing and machine learning.

Despite the progress made in lung cancer screening and diagnosis methods, several limitations exist in traditional approaches, traditional screening methods such as chest X-rays, computed tomography

CT scans, and bronchoscopy have limited sensitivity, leading to false-negative results, these methods have a high risk of false-positive results, these limitations highlight the need for automated methods that can overcome these challenges and improve lung cancer detection and diagnosis.

Deep learning performs well in classification and recognition because to its vast volume of data and thorough feature extraction (van Ginneken et al., 2010). The identification of lung nodules using deep learning is a growing area of research. A common deep learning model called the Convolution Neural Network (CNN) is very helpful for categorizing images. Mask R-CNN is a target detection technique based on CNN. a thorough, flexible, and conceptually simple framework for object instance segmentation.

Our method in this paper effectively detects objects in images while also producing a top-notch segmentation mask for each instance. “By adding a branch for object mask prediction in tandem with the current branch for bounding box recognition, Mask R-CNN expands Faster R-CNN” (He et al., 2016).

This study's accomplishments include developing and applying a genuine dataset of KRI patients, achieving the highest accuracy of 96.59% to date, and estimating the tumor area, which is also a very good point and aids in determining the stage of the malignancy.

Table1 :Distribution of cancer cases by Tumor site (2015-2019) (Barzingi et al., 2020)

Site	Count
Breast	2701
Lung and bronchus	1030
Colon and rectum	964
Skin	732
Lymphoma	730
Prostate	609
Bladder and ureter	559
Head and neck	527
Acute leukemia	511
Sarcoma	427
Stomach	419
Thyroid gland	381
Kidney	354
other organs	2793
total	12737

2. Related Work

Deep learning and lung tumor diagnosis have aided in the advancement of lung tumor diagnosis. “In lung cancer diagnosis, AI is primarily employed in image recognition, medical image segmentation, lung nodule extraction and recognition, pathological diagnosis, and tumor marker search” (Wang et al., 2022), Table 2 is the comparison of seven studies on their results and problems, and the following are the goals and findings of the studies that are most similar to this study in terms of how to identify lung cancer tumors using various methodologies.

For accurate diagnosis and treatment of pulmonary nodules, it is essential to differentiate between benign and malignant nodules utilizing CT imaging. To overcome the difficulties of a small-scale medical picture library and the small size of the nodules, a novel Agile convolutional neural network (CNN) framework is provided. It enhances the performance of pulmonary nodule classification using CT images. Since they give the system the entire image and the accuracy is insufficient between 0.822 and 0.877, it is challenging to determine which sort of tumor is present (Zhao, 2018).

Present a unique Fuse-TSD lung nodule classification method that classifies lung nodules based on texture, shape, and deep model-learned information at the decision level. Our findings indicate that combining traditional visual features with the image representation learned by deep models at the decision level enhances nodule classification performance and yields more accurate results than three state-of-the-art methods currently in use. The results are accuracy 89.53%, sensitivity 84.19%, and specificity 92.02%. They don't just concentrate on CT pictures; they also employ deep features, texture, and forms to classify objects (Xie, 2018).

The aim of the study was to investigate the prevalence of pulmonary nodules (PNs) in China and to develop and evaluate a deep learning (DL) algorithm for PN recognition on LDCT. The effectiveness of the algorithms and radiologists was assessed using the FROC score, ROC-AUC, and average time consumption. Both our study's data and the LUNA data missed key fundamental details, like smoking history, and there was no gold standard for lung nodule detection rather than only a reference standard (Cui, 2020). The results of the assessment of the agreement between the reference standard and the DL algorithm in detecting positive nodules are accuracy 90%, sensitivity 82%, and specificity 82%.

Deep learning has been proved as a popular and effective technique in numerous medical imaging diagnosis fields. In this research (Song, 2017), three types of deep neural networks (e.g., CNN, DNN, and SAE) are designed for lung cancer calcification. The results are accuracy 84.15%, sensitivity 83.96%, and specificity 84.32%. The classification is only done for two categories, and the accuracy is not that good.

To ensure early identification of lung cancer and the distinction between benign and malignant tumors, a comprehensive Computer Aided Diagnosis (CAD) system has been created using CT images. They use the Self-Organizing Maps (SOM) method for detection, and their results are good in terms of sensitivity and specificity more than accuracy (Dandil, 2014). The developed CAD method ensures categorization of benign and malignant nodules using ANN and neural networks model of Self-Organizing Maps (SOM) for nodules on the lobes (Artificial Neural Network).

Table 2 : Studies Comparison related to Lung cancer detection and classification

No	Paper	Dataset	Result	Problem
1	(Zhao , 2018)	(LIDC-IDRI)	Accuracy between 0.822 and 0.877	The accuracy is not much enough between 0.822 and 0.877, and they give the whole image to the system which make it difficult to decide its which type of tumor
2	(Cui , 2020)	LUNA	Accuracy 90 sensitivity 82 specificity 82	Accuracy 90 sensitivity 82 specificity 82
3	(Xie , 2018)	(LIDC-IDRI)	Accuracy 89.5 Sensitive 84.1 Specificity 92.02	The study doesn’t focus on CT images only, they use deep feature / texture / shapes to for the classification.
4	(Song , 2017)	LIDC-IDRI	accuracy of 84.15%, sensitivity of 83.96%, and specificity of 84.32%.	The classification is only with DNN and CNN that didn’t record high result, detecting method doesn’t mentioned

3. The Proposed Work

Based on the classic CNN structure, the spatial pyramid pooling convolutional network (SPPNet) adds a ROI pooling layer before the support vector machine (SVM) classifier, allowing the network input picture to be any size while maintaining a constant output size.

The SPPNet only needs one operation and is faster in terms of speed and map than R-CNN. Instead of using support vector machine (SVM) classifier, Fast R-CNN, which is based on SPPNet, classifies data using neural networks. This increases speed by simultaneously training feature extraction, judgment category, box regression, and neural networks(He, 2014).

3.1 Mask R-CNN

Mask R-CNN, also known as Mask RCNN, is the most effective method for object detection and a state-of-the-art Convolutional Neural Network (CNN) for image and instance segmentation. It was enhanced to Mask R-CNN (He et al., 2016) with better outcomes after being extended on Faster R-CNN (Girshick, 2015).

Additionally, it is the best option for the majority of studies based on medical image analysis. Figure 1 depicts the Mask R- CNN structural layout. There are two sections to the model. The first stage scans the picture and produces region suggestions. The proposals are categorized in the second section, which also creates bounding boxes and masks. We initially extract the feature and create a feature map from the convolutional backbone when we input the image into the network (CNN).

Mask-RCNN evaluation metrics contains two models, resnet50 and resnet101, that are used in the experiment (He et al., 2016), but we train on model restnet101 and then input the feature map into Region Proposal Network (RPN) to construct Region of Interest (RoI). Then, two networks compute the head component simultaneously: The mask head completes the pixel-level two categorization of RoIs after the box head alters the bounding box and category information, 50 epochs have been used during training data for three hours.

In Figures 2 and 3, we present an overview of the suggested strategy and a sample training model for identifying diseased sections. As seen in Figure 2, the model's parameters are first set up as given in Table 2, the model is then trained using pathological lung cancer sections, and the test image is fed into the inference model to provide a predicted image that has been masking applied to it as well as an AP value. Once the model has been retrained and detection has been made, the parameters are adjusted based on the results, various data improvement techniques are used, and the optimal parameter configuration and data annotation technique is then selected.

Table 3. Parameters of Configuration

Parameter Value	Value
BACKBONE	resnet101
BACKBONE_STRIDES	[4, 8, 16, 32, 64]
BATCH_SIZE	64
DETECTION_MAX_INSTANCES	100
DETECTION_MIN_CONFIDENCE	0.95
GPU_COUNT	1
IMAGES_PER_GPU	1
IMAGE_CHANNEL_COUNT	3
IMAGE_MAX_DIM	1024
IMAGE_META_SIZE	15
IMAGE_MIN_DIM	800
LEARNING_MOMENTUM	0.9
LEARNING_RATE	0.001
MASK_POOL_SIZE	14
MASK_SHAPE	[28,28]
NUM_CLASSES	3
STEPS_PER_EPOCH	70
USE_MINI_MASK	TRUE
WEIGHT_DECAY	0.0001

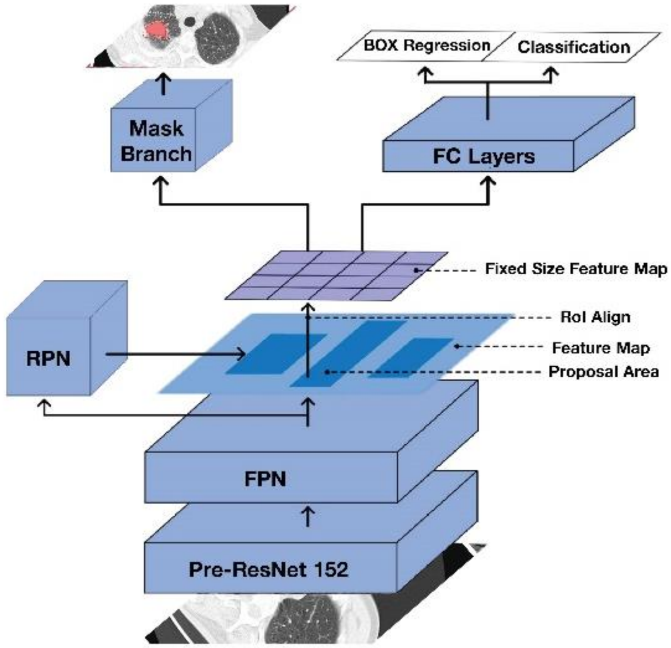

Figure 1. Segmentation using the Mask R-CNN framework. CNN, RPN, feature maps, and Rol Align are all included in the first section. The second section includes mask branches, FCN, classification, and bounding box regression.

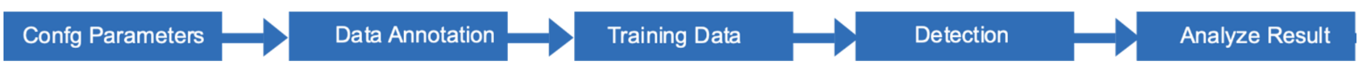

Figure 2. Overview of the proposed method

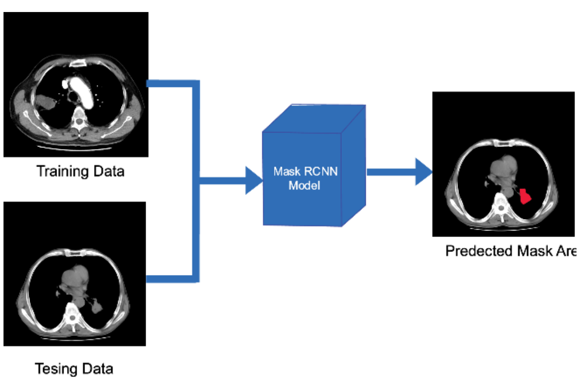

Figure 3. Example of lung cancer pathology parts detection and training model. To obtain the masked pathological sections, first input the pathological sections with labels training model.

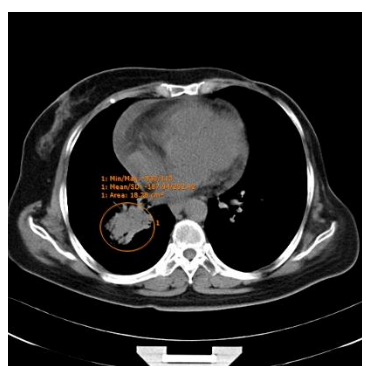

Figure 4. An example of segmented malignant tumor by doctors with low contrast

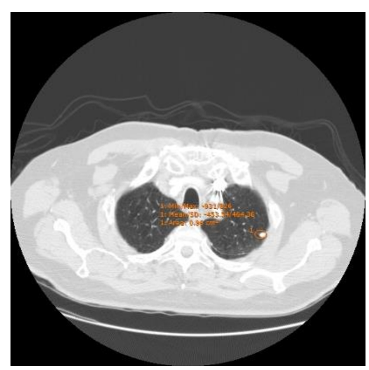

Figure 5. An example of segmented benign tumor by doctors with high contrast

4. Dataset

In this study we able to collect 600 CT scans images with cancer tumors after visiting the cancer-focused two hospitals in KRI (Awat and Rzgari Hospitals). After acquiring the CT scans, the radiologists of the hospital segmented the CT scans images and divide the tumors into two classes, malignant and benign. The thickness of each CT scan slice was different from patient to patient depending on the size of the tumor they had, and the amount of the drug that was given to patient was different from one to another, which helps us to have a good range of image contrasts.

Data acquisition process achieved by visiting the hospitals daily, patient by patient then archiving the CT scan files from their machine, because data only remain for one month and collecting these CT scan images takes more than six months.

We use SanteDicom viewer to view CT scans and save them as 512x512 size images, in two classes for benign and malignant tumors. For labeling process Visual Geometry Group (VGG) image annotation uses to identify tumors before converting them into JavaScript Object Notation (JSON). The radiologists segment the tumor and label it with SanteDicom, then for the use of VGG to distract the RIO the CT scan converted to a JSON file. The region of interest has been segmented with the label of the class name as shown in Figure 6.

The position, size, and shape of lung tumors were noted by radiologists. Typically, the large, irregular shapes that are closer to the outer part of the lung are malignant, while the small, rounded shapes are benign. The dataset will aid the model in locating and detecting the position, size, and shape of the tumor. In addition to the determination of whether it is benign or malignant, we can also assume that the tumor should be confirmed via biopsy.

Because each patient's body responds differently to the amount of the drug that enters the lung and produces different contrast of the images, we use a lot of different images with different contrast and brightness that will improve the dataset. Rotating, flipping, and scaling are not as important as being aware of the brightness of the image.

In this study we utilized the Keras and Tenser flow package training model, and we divided the dataset into training, testing, and validation as follows: 70% for training, 20% for validation, and 10% for testing.

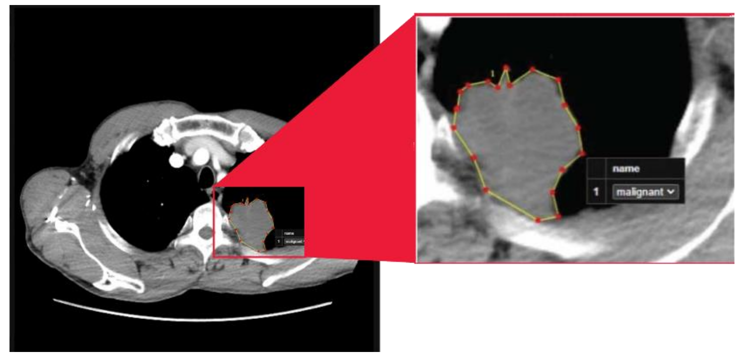

Figure 6. An example of labeled tumor

5. Results and Discussion

Our study yields the greatest findings in comparison to relevant prior research, which is detailed above. The outcomes of our work are as follows: Precision 96.59% sensitivity The Mask RCNN is the best model for detecting the position of the tumor, but as expected the Mask RCNN is best model for detection, with 95% specificity 95% f-1 score 99.65%, the highest accuracy from previous models going for(Zhao , 2018) which is 94.56%, calculating the area of the tumor is very useful for radiologist and doctors. detecting small benign tumors is one of the hard parts for any researchers, most of previous works have only work on malignant tumors but this study has good results in benign tumors too, the results are acceptable and good, future works can focus on extending the dataset from KRI region, and it will be better if each patient among of his CT scan have other information like their (age, place of living, smoking state) more information will bring more success and accuracy, Figures 7 and 8 describe the image segmentation for both a benign and malignant nodule and calculating the area of the nodule, The error between the output of our algorithms and the specified target value is calculated using loss functions. The loss function, to put it simply, expresses how far off from the target our computed output is. The classification, localization, and segmentation mask losses are combined by the multi-task loss function of the

Mask R-CNN: $L=L_{cls}+L_{box}+L_{mask}$, where L_{cls} and L_{box} are same as in Faster R-CNN, Figures 9 and 10 shows the loss function plotting for 50 epochs for both objects malignant and benign

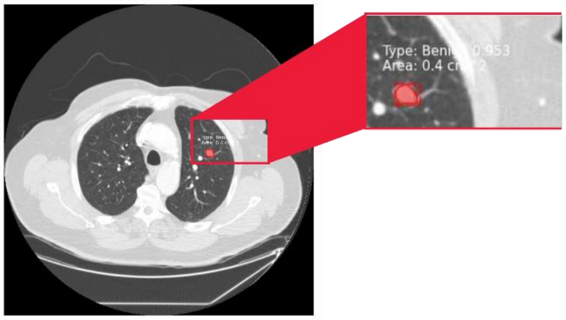

Figure 7. Image of the results after training the dataset, which shows type of benign nodule with 95.3% and the area of it which is 0.4 cm^2

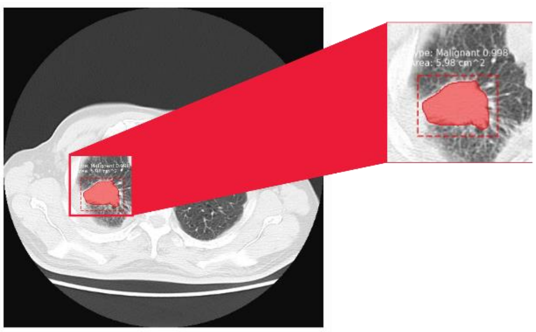

Figure 8: image of the results after training the dataset, which shows type of malignant nodule with 99.8% and the area of it which is 5.98 cm2

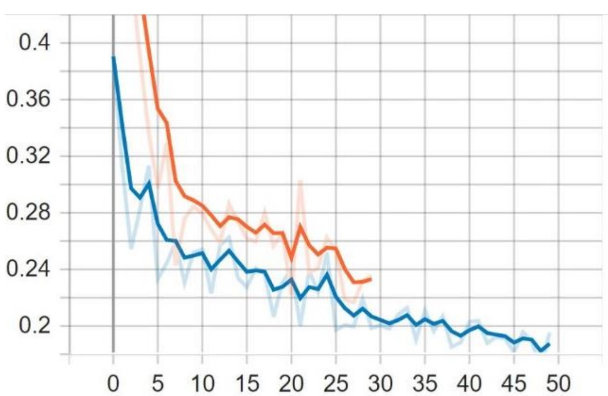

Figure 9: main loss function plot

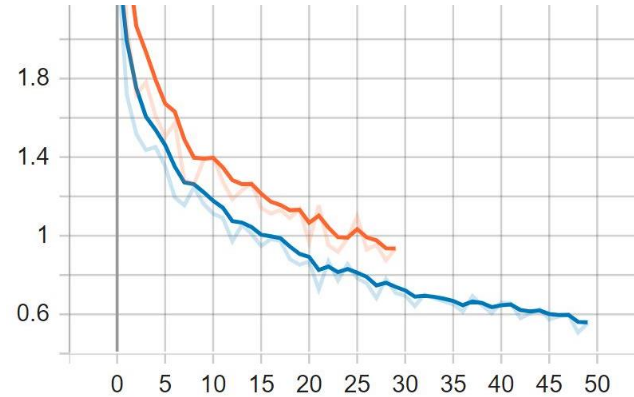

Figure 10. Mask R-CNN loss function plot

List of abbreviations

KRI	Kurdistan Region of Iraq
MASK-RCNN	Mask Region-Based Convolutional Neural Network
CT SCAN	Computed tomography Scan
CNN	convolutional neural network
DL	Deep Learning
PN	Pulmonary Nodules
LDCT	Low-dose computed tomography
FROC	Free-Response ROC Curve
ROC-AUC	Area under the ROC Curve
LUNA	Laparoscopic uterine nerve ablation
DNN	Deep Neural Network
SAE	Convolutional Neural Network
CAD	Computer-aided diagnosis
SOM	Self-Organizing Map
SPPNET	Spatial Pyramid Pooling Convolutional Network
ROI	Region of Interest
SVM	Support Vector Machine
RPN	Region Proposal Networks
VGG	Visual Geometry Group
JSON	JavaScript Object Notation

6. Conclusion

The accuracy in the healthcare industry is very focused and should be within an acceptable range, Image segmentation and recognition had assist doctors in their works a lot, and still researchers are trying to improve the techniques, one of the fields that deep learning can help is diagnosing tumors in lung cancer, In this paper, we try to create a dataset for KRI lung cancer patients including their CT scan images then train and test the dataset on one of the best deep learning models that is Mask-RCNN, results for detecting benign and malignant tumors with high accuracy 96.59% sensitivity 95% specificity 95% f-1 score 99.65%, has been achieved, another good points of this study were calculating the area of tumor.

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