Lung-Retina Net: Lung Cancer and Stage Detection Using a Retina Net with Multi-Scale Feature Fusion and Context Module

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***Abstract:** Early identification of lung cancer is crucial yet difficult, and it continues to pose a serious danger to global health. Conventional techniques like CT scans and blood tests take a long time and involve a lot of human labor. In order to lower mortality, this study suggests Lung-RetinaNet, a unique automated approach for identifying lung cancers and determining their severity. The model uses a dilated lightweight approach in the context module to improve tumor localization, especially for tiny tumors, and incorporates a multi-scale feature fusion module to augment semantic information. In comparison to current deep learning-based techniques, Lung-RetinaNet achieves good accuracy (99.8%), recall (99.3%), precision (99.4%), F1-score (99.5%), and AUC (0.989), proving its efficacy in lung cancer detection.*

***Keywords:** RetinaNet, lung cancer, early detection of artificial intelligence*

I. INTRODUCTION

With a fatality rate of 19.35%, lung cancer is among the most deadly illnesses in the world. To find lung cancer, radiologists usually employ methods including sputum cytology, CT scans, X-rays, and MRIs. There are two types of tumors: benign, which are not cancerous, and malignant, which are cancerous and grow out of control. The survival rate is substantially higher when lung cancer is detected early, but it is significantly lower when lung cancer is diagnosed at an advanced stage. The accuracy and speed of early-stage detection might be increased with the use of image processing tools.

However, manual lung cancer diagnosis is hampered by two significant issues. First, radiology resources are frequently insufficient to meet the enormous demand, which hinders the capacity to make prompt and precise diagnosis. Second, the shortcomings of the present detection techniques lead to a large number of false positive instances. To overcome these obstacles, it is essential to improve radiologists' training and keep improving image processing methods to increase the accuracy of lung cancer identification and categorization.

Lung cancer diagnosis has moved toward computer-aided detection (CAD) systems due to recent developments in deep learning (DL) and machine learning (ML). Conventional machine learning methods such as K-Nearest Neighbour. Lung cancer has been detected using Random Forest (RF) and Support Vector Machine (SVM), which need human feature extraction prior to classifier training. Nevertheless, this procedure takes a long time, and because there is a lack of training data, ML models frequently have problems with generalization. Furthermore, several strategies use segmentation techniques to help diagnose lung cancer.

The region of interest (ROI) in segmentation-based methods for lung cancer diagnosis is chosen from the original image based on its texture, color, or grayscale. Thresholding, Atlas, and Region Growing are examples of popular segmentation techniques. The precision of the retrieved characteristics and the segmented region are key factors in these approaches' efficacy. Even though these methods have yielded noteworthy outcomes, they frequently have trouble with unknown samples and need to be improved in order to reduce false positives.

As deep learning has advanced, DL-based methods have shown better results in identifying a wide range of illnesses, including those that impact the knee, eyes, brain, and even plants like potato leaves. The capacity of DL models to automatically extract pertinent features, whether for segmentation or classification tasks, is their main benefit. To extract representative features and lower complexity, these models make use of layers such as batch normalization, convolutional, fully connected layers, and pooling. Many of the DL-based models that have been presented for the detection of lung tumors rely on basic categorization techniques.

In order to collect the most representative feature maps while reducing information loss from input data, we suggest using a feature fusion block in place of RetinaNet's conventional feature pyramid network (FPN). We use dilated convolution to extract potent features at shallow levels in order to improve the detection of small lung cancers. For better localization, we also combine features from the lower layers with those from the upper layers, which provide high classification accuracy. A contextual block that incorporates elements from lower layers is used to use contextual information.We use a k-means clustering technique, akin to YOLO-v3, to provide more accurate anchors because the default anchors in RetinaNet were not efficient in identifying lung cancers with irregular shapes.

Our work's main contribution is a multi-scale feature fusion module that improves semantic information in shallow prediction layers by combining different network layers. In order to incorporate contextual information and enhance feature localization for tiny tumors, we present a simplified and dilated approach inside the context module. The Lung-RetinaNet model greatly improves lung tumor detection capabilities by utilizing adaptive anchors and integrating the dilated context module with lateral connections at each network level. When compared to established benchmarks, our model regularly performs better than current lung tumor detection techniques.

II. LITERATURE SURVEY

In order to increase accuracy and lower death rates, this study assesses the application of convolutional neural networks (CNN) for lung cancer detection. In underdeveloped nations, lung cancer is still a significant problem, and early, accurate detection is essential. With a higher accuracy than earlier techniques, the suggested CNN model presents a viable way to diagnose lung cancer more accurately. [1]

The goal of this effort is to improve the identification of lung cancer by classifying CT scans from the Lung Image Database Consortium (LIDC) using Deep Convolutional Neural Networks (DCNN). Because of their intricacy and variety, lung nodules must be accurately identified as either malignant or noncancerous. The model uses DCNN to improve classification accuracy, surpassing current techniques and helping to diagnose lung cancer more accurately. [2]

With the limits of current clinical methods like X-rays, this study focuses on the need for precise and affordable lung cancer prediction models. It emphasizes how crucial machine learning is to medical diagnosis, particularly for the early detection of lung cancer. ANN, Random Forest, KNN, and SVM, a hybrid voting classifier, are among the models that are compared in the study classifier, assessing their accuracy-based performance. By offering a dependable technique for early identification, these models hope to lessen the effects of the disease and enhance patient outcomes. [3]

The potential of plasma metabolites as diagnostic biomarkers for the early identification of lung cancer in Chinese patients is examined in this study. The study intends to find biomarkers that may reliably differentiate between healthy people and those with early-stage lung cancer by examining particular metabolic profiles. This will ultimately improve diagnostic techniques and patient outcomes. Six metabolic biomarkers were found by integrating metabolomics and machine learning, and they were highly accurate (specificity = 100%, sensitivity = 98.1%, AUC = 0.989) in differentiating stage I lung cancer patients from healthy people. For the early prediction of lung cancer, Naïve Bayes is advised. In addition to supporting blood-based screening, this multidisciplinary approach may help discover other malignancies-early.[4]

Radiation therapy (RT) is the main treatment option for lung cancer, which is the largest cause of cancer-related death. Accurately segmenting the gross tumor volume and surrounding organs-at-risk (OARs) is crucial for efficient radiation therapy planning. The labor-intensive nature of manual segmentation highlights the need for automated methods to lessen radiation oncologists' workload. Atlas-based automatic segmentation is widely used, however its efficacy may be limited because it mostly relies on how comparable the atlas and the images being analyzed are. Recent developments in deep learning hold promise for enhancing medical imaging's automatic segmentation. While deep learning achieves excellent accuracy for major organs like the heart and lung, there are still difficulties in segmenting smaller structures, according to this review that compares deep learning techniques to atlas-based methods the esophagus, for example. [5]

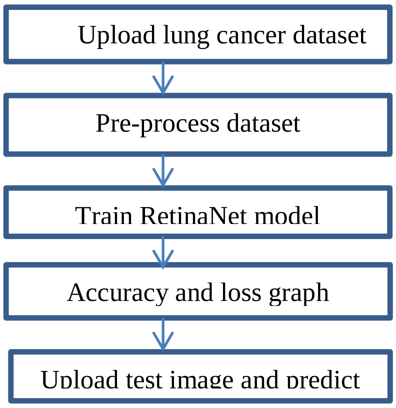
The early diagnosis of glaucoma, a progressive eye condition that can cause vision loss owing to elevated intraocular pressure, is the main emphasis of this study. The suggested model evaluates retinal fundus pictures for precise screening using deep learning-based feature extraction. To extract the region of interest (ROI), the images first go through preprocessing and segmentation. characteristics of the optic disc and hybrid descriptors, such as CNN, speeded-up robust features (SURF), local binary patterns (LBP), and histogram of oriented gradients (HOG), are then used to create the optic cup. While SURF and LBP are used to gather texture features, HOG captures low-level features. CNN is used to extract high-level features, while the MR-MR approach is used to choose the most pertinent features. Support vector machine (SVM), random forest (RF), and K-nearest neighbor (KNN) are three multi-class classifiers used in the study to categorize photos as either healthy or unhealthy. The outcomes show how effective the RF algorithm-based model is for early glaucoma detection, achieving up to 99% accuracy on benchmark datasets and 98.8% accuracy during k-fold cross-validation when integrated with SURF, LBP, CNN, and HOG. [6]

Features from the optic disc and optic cup are then derived using hybrid descriptors, including histogram of oriented gradients (HOG), speeded-up robust features (SURF), local binary patterns (LBP), and CNN. Low-level features are captured by HOG, while texture features are obtained through SURF and LBP. High-level features are extracted using CNN, and the most relevant features are selected using the MR-MR technique. The study employs multi-class classifiers— support vector machine (SVM), random forest (RF), and K-nearest neighbor (KNN),—to classify images as healthy or diseased. The results demonstrate that the model based on the RF algorithm, combined with SURF, LBP, CNN, and HOG achieves an accuracy of up to 99% on benchmark datasets and 98.8% through k-fold cross-validation, indicating its effectiveness for early glaucoma detection. [6]

III. PROPOSED METHOD

The proposed Lung-Retina Net method aims to detect lung cancer and its stages using a RetinaNet model enhanced with multi-scale feature fusion and a context module. By leveraging deep learning techniques, the model is trained to efficiently analyze lung cancer images for accurate predictions. The following steps outline the process.

1. Upload lung cancer dataset,
2. Pre-process dataset,
3. Train RetinaNet model,
4. Accuracy and loss graph,
5. Upload test image and
6. Predict Cancer Model



3.1 Upload Lung Cancer Dataset:

- Compile and submit a labeled lung cancer dataset that includes CT scans of malignant and non-cancerous conditions along with the appropriate stage classifications.

3.2 Pre-process Dataset:

- To increase the robustness of the model, do image normalization, resizing, and augmentation (such as rotation, scaling, and flipping).
- Divide the dataset into training, validation, and test sets after converting the photos to the proper format.

3.3 Train RetinaNet Model:

- To identify lung cancer and its stages, use the RetinaNet model with context modules and multi-scale feature fusion.
- Enter the training dataset that has already been processed.

- Use an optimizer (like Adam or SGD) to improve model weights and apply loss functions (such focal loss to correct class imbalance).

3.4 Accuracy and Loss Graph:

- During training, plot accuracy and loss graphs to monitor model performance.
- Performance indicators such as F1-score, recall, and precision should be evaluated.

3.5 Upload Test Image and Predict Cancer:

- For testing, upload a fresh CT scan of the lung.
- Predict the existence and stage of lung cancer using the RetinaNet model that has been trained.

3.6 Cancer Model Prediction:

Based on the context-aware feature fusion, the model will produce the detected stage and the probability of cancer occurrence.

III. RESULT

To run project double click on ‘run.bat’ file to get below screen

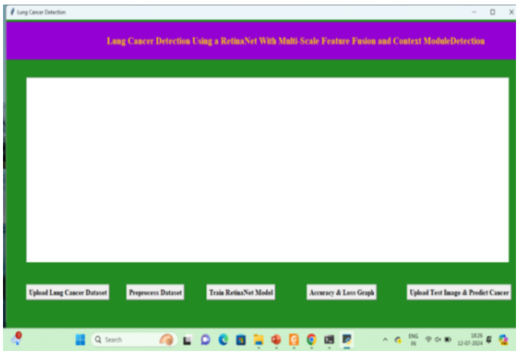


Fig 5.1 Overall GUI for Proposed Method

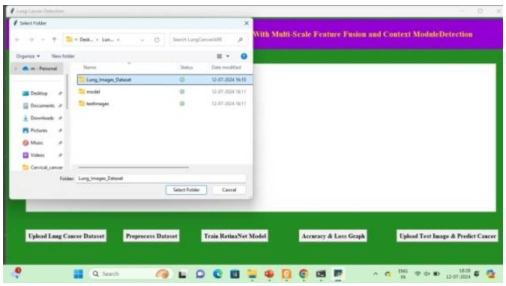


Fig. 5.2 Dataset Selection

In above screen dataset loaded and now click on ‘Preprocess Dataset’ button to convert all images into colour format and resize them into equal sizes so CNN can accept those images

Fig. Sample Preprocessed image

In above screen application process all images and then I am displaying one sample image to confirm all images loaded properly

Fig. Performance of RetinaNet Model

In above screen we can see dataset contains total 138 images and now click on ‘Build CNN Model’ button to train CNN algorithm on above images and then calculate prediction accuracy

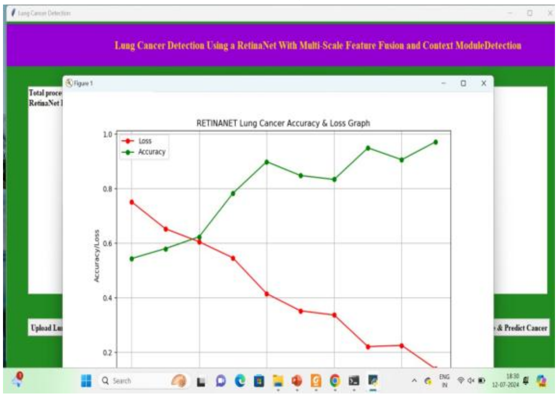


Fig. Accuracy and Loss Graph for RETINANET

The x-axis in the graph above represents the epoch, while the y-axis shows the accuracy and loss values. We can observe that in order to train CNN, we used 10 epochs, and that as the epoch increased, the accuracy increased and the loss values decreased. The red and green lines in the graph above indicate accuracy and loss, respectively. To upload a test image, click the "Upload Test Image & Predict Cancer" button.

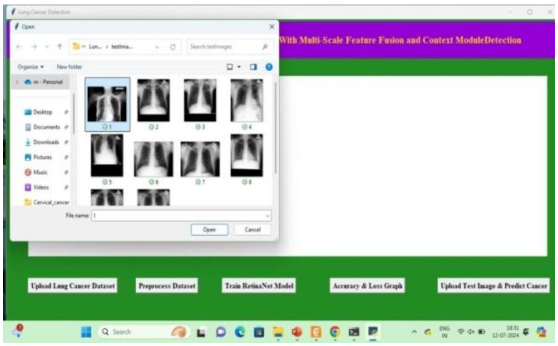


Fig. Select Test Image for Lung Cancer Detection

In above screen selecting and uploading '1.png' file and then click on 'Open' button to get below result

Fig. Predicted Results of Lung cancer and stages detection

The first image in the above screen shows the projected outcome since CT-SCAN contains abnormality in blue text. The second image shows the locations where abnormality was found, and the third image extracts all abnormality patches from the original image before showing them.

Fig. Predicted as 'Normal Scan'

In above screen CT-SCAN is predicted as NORMAL. Similarly you can upload and test other image

V. CONCLUSION

Early prediction of Lung cancer may reduce the deaths per year in india or globally. Lung- RetinaNet has higher accuracy compare to state of art techniques. Successfully implemented lung cancer detection and stages identification using python software

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