IJFANS INTERNATIONAL JOURNAL OF FOOD AND NUTRITIONAL SCIENCES
ISSN PRINT 2319 1775 Online 2320 7876
Research Paper , UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, 2022

Enhancing Lung Cancer Detection: A Comprehensive Methodology Integrating Deep Learning and Image Processing

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Article History: Received: 09-11-2022 Revised: 18-11-2022 Accepted: 25-12-2022

Abstract
This investigation meets the urgent demand for efficient early diagnosis by presenting a thorough methodology for automated lung cancer categorization utilizing CT scans. The approach starts with the collection of a wide range of CT image databases and uses sophisticated image processing to improve visibility, such as pixel value normalization and Contrast Limited Adaptive Histogram Equalization (CLAHE). The process begins with the Histogram of Oriented Gradients (HoG) for feature extraction. Next, a Convolutional Neural Network (CNN)—more precisely, VGG Net—is fine-tuned to respond to the features of lung cancer. The optimized model is applied in the classification step, and strong generalization is guaranteed by performance assessment measures. Extensive research on the effects of different pre-processing processes complements the results. By providing insights into interpretability and reproducibility and advancing automated lung cancer detection, the research has potential uses for early diagnosis in clinical settings. This multidisciplinary strategy emphasizes how cutting-edge technologies can help solve difficult healthcare problems.
Keywords: Lung Cancer, CLAHE,HoG,Deep Learning,Detection,CNN,VGG Net.

1. Introduction

Since lung cancer causes a sizable number of cancer-related deaths annually, it is a major worldwide health concern. Since prompt intervention and therapy can greatly boost survival rates, early and precise detection of lung cancer is essential to improving patient outcomes. Because it provides precise anatomical information, computed tomography (CT) imaging has emerged as a key tool in the diagnosis and surveillance of lung disorders. However, it takes time and is prone to human error to manually analyse CT scans for the purpose of detecting lung cancer. Combining deep learning approaches with sophisticated image processing techniques presents a viable way to improve the effectiveness and precision of lung cancer detection using CT images [1].

The goal of this research is to create a solid approach for automated CT image-based lung cancer categorization. The suggested approach is a multi-step procedure that begins with the collection of a broad CT image database that has areas of interest (ROIs) tagged to show whether lung cancer is present or absent [2]. The CT scans are preprocessed using Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance the visibility of lung features and anomalies. Consistency in the characteristics retrieved from the photos is further ensured by normalizing the pixel values.

ISSN PRINT 2319 1775 Online 2320 7876
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Finding patterns and edges that are pertinent to the identification of lung cancer requires feature extraction. Because it can capture local variations in intensity, the Histogram of Oriented variations (HoG) approach is used to provide a strong depiction of texture and structure in images. Then, a Convolutional Neural Network [3] (CNN), more precisely the VGG Net, is trained on the dataset to adjust to the subtleties of lung cancer features using the extracted features.

CT scans are divided into classes based on whether they are positive or negative for lung cancer using the refined VGG Net during the classification step. Through softmax activation in the output layer, the resulting probability scores are acquired, allowing for a more nuanced understanding of the model's confidence in its predictions. Based on these probabilities, a threshold is established to create binary classifications.

Standard metrics including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve are used to evaluate performance. To evaluate the model's ability to generalize to new data, the dataset is divided into training and testing sets. Cross-validation and confusion matrices are used to make sure the created lung cancer classification model is resilient and reliable.

2. Literature Review

Deep residual learning was used in the Bhatia et al. work to create a technique for identifying the presence of lung cancer in CT scans. To highlight and extract features from slices of malignant lung tissue, the researchers used a preprocessing pipeline that made use of ResNet and UNet models. The probability of malignancy in CT scans was then predicted using the ensemble of XGBoost and random forest classifiers. The outcomes showed an astounding 84 percent increase in accuracy over conventional methods [4]. Nevertheless, significant biases in the training data and difficulties applying the model to a variety of datasets could be drawbacks.

Joon et al. employed X-ray images and an active spline model to segment lung cancer. During preprocessing, a median filter was used to detect noise, and during segmentation, k-means and fuzzy k-means clustering were used to acquire features. Although their method showed promise in the identification and classification of lung cancer [5], its applicability to other modalities may be limited due to its reliance on X-ray pictures, and image quality differences may have an impact on its effectiveness.

Using a variable level set function, Nithila and Kumar [6] suggested an active contouring approach for lung image segmentation. For effective segmentation of CT lung images, the SBGF-new SPF function was presented, demonstrating computational speed and dependability. The comparison with four active contour models, however, does not fully account for all possible options, and more research is necessary to see whether the suggested algorithm can be applied to different datasets.

The Optimal Deep Neural Network (OODN) was presented by Lakshmanaprabu et al.[7] as a way to classify lung cancer with an emphasis on minimizing the number of characteristics in CT scans. There was an increase in precision and accuracy with the machine learning methods. The outcome of the study, however, can rely on the context, and difficulties with the model's interpretability and possible biases in the labeled data should be taken into account. 14

Deep learning and image processing techniques were highlighted by Talukdar and Sarma for the diagnosis of lung cancer. Although deep learning has great potential, radiologists have pointed out difficulties with false-positive and false-negative results [8]. It was suggested that a computer-aided detection system be developed, however more research needs to be done on the scalability and generalizability of such systems.

Yu et al. concentrated on using machine learning algorithms to forecast lung cancer patients' prognosis using whole-slide histology slides [9]. The results indicated that autonomously generated attributes might be used to predict the prognosis of patients. However, there can be obstacles to acquiring a suitably varied sample and possible biases in the assessment of the survival rate.

Pol Cirueda et al. employed texture aggregation to forecast nodule recurrence from CT scans for non-small cell lung cancer (NSCLC) [10]. In assessing cancer invasion based on morphological tissue features, the approach shown potential. The study's shortcomings, however, include the necessity for additional validation and research into the suggested methodologies as well as possible difficulties in extrapolating results to other datasets and tissue types.

3. Systematic Framework

The process starts with finding a CT image database that is appropriate for lung cancer studies. Notable options include the NSCLC-Radiomics dataset and LIDC-IDRI, which provide a variety of CT scans with annotated areas of interest (ROIs) that show if lung cancer is present or absent. A thorough representation of lung cancer cases is ensured by the dataset's diversity, which is essential for developing a reliable classification algorithm.

As we proceed to the second phase, pre-processing CT scans is essential to improving the visibility of anomalies and structures. The contrast is adjusted using Contrast Limited Adaptive Histogram Equalization (CLAHE), and pixel values are normalized to a standard range. The CLAHE operation can be stated mathematically as follows:

$$I_{CLAHE}\,(x,y) = \frac{I\,(x,y) - I_{min}}{I_{max} - I_{min}} \times L$$

Where I (x, y) is the pixel value, I_{min} and I_{max} are the minimum and maximum pixel values and L is the maximum pixel intensity

The third stage uses the Histogram of Oriented Gradients (HoG) for feature extraction. HoG is used to extract features from the pre-processed CT images by capturing local intensity gradients and highlighting pertinent patterns and edges associated with the detection of lung

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cancer. Each pixel in the image has its gradient's magnitude and orientation determined mathematically as part of the HoG algorithm.

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In the fourth stage, a pre-trained VGG Net—a deep convolutional neural network (CNN)—receives the retrieved features. Using training data from the collected features, the VGG Net is adjusted to the unique characteristics of lung cancer. The process of fine-tuning entails adjusting the weights.

In the fifth stage, the fine-tuned VGG Net is utilized for the classification of CT images into lung cancer-positive and lung cancer-negative categories. The Softmax activation function is employed in the output layer to obtain probability scores P for each class. A threshold is set to categorize CT images based on the probability scores:

$$\text{Prediction} = \begin{cases} \text{Lung cancer Positive,} & \text{if } P > \\ \text{Lung cancer Negative,} & \text{otherwise} \end{cases}$$

The sixth stage involves performance evaluation, starting with the dataset split into training and testing sets to assess generalization. Standard metrics like accuracy, precision, recall, F1-score, and area under the ROC curve are computed. The confusion matrix provides insight into the distribution of true positive, true negative, false positive and false negative predictions. Cross-validation ensures the model's robustness across different dataset subsets, enhancing reliability and generalization.

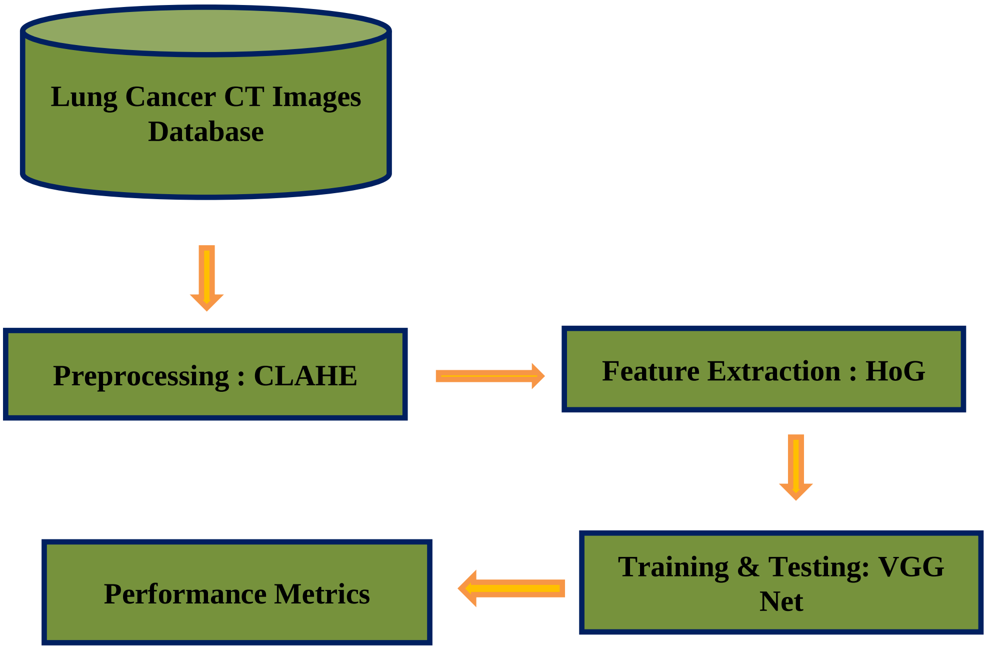

Fig. 1 Proposed Lung cancer detection Method

4. Experimental Investigations

Before any pre-processing, this figure most likely depicts the original CT scan. The raw CT

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 UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, 2022

scan data that displays the anatomical features of the lungs is known as the input lung picture fig 1. This initial raw image serves as the basis for the entire process.

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The output of Contrast Limited Adaptive Histogram Equalization (CLAHE) is shown in this picture fig 2. The improved image shows more contrast, which facilitates the identification of lung anomalies and structures. For the purpose of identifying minute details that may be suggestive of lung cancer, CLAHE is essential.

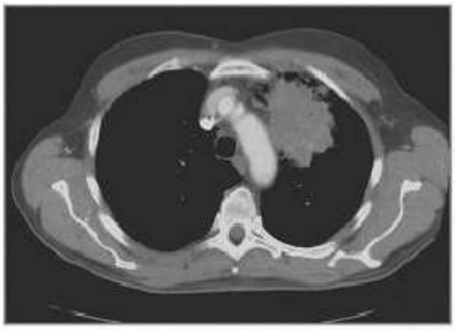

Fig. 2 Input Lung Image

Fig. 3 Enhanced Image

This graphic certainly fig 4 shows the outcome following the application of a threshoulding operation. A popular method for segmenting a picture into sections according to intensity values is threshoulding. Threshoulding may be used to differentiate between possible tumour locations and the surrounding tissue in the context of lung cancer detection.

This fig 5 certainly depicts the image following a filtering process. Image filtering is frequently used to reduce noise or highlight particular features. Filtering may be used to highlight specific patterns or textures that are important for spotting possibly malignant areas in the context of lung cancer diagnosis.

Fig. 4 Threshold output image

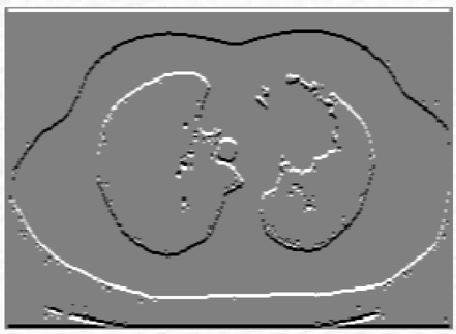

Fig. 5 Filtered image

This fig 6 depicts the image following the process of morphological dilatation, which thickens or enlarges the image's structures. Morphological dilatation is helpful in tying together fractured structures and highlighting certain features. Dilation may aid in ensuring that possible tumor sites are noticeable and well-connected when it comes to lung cancer diagnosis.

This illustration most likely depicts the fig 7 following the use of morphological filling, a technique for completing enclosed areas. It is advantageous to use morphological filling to

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seal off gaps and openings in buildings. Filling may contribute to the creation of more comprehensive representations of possible tumour regions in the context of lung cancer detection, which could facilitate further stages of feature extraction. 14



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Fig. 6 Morphologically Dilated Image Fig. 7 Morphologically Filled Image

This picture certainly shows the results of the methodology's classification stage, which involves classifying CT images into groups that are positive and negative for lung cancer using the optimized VGG Net.

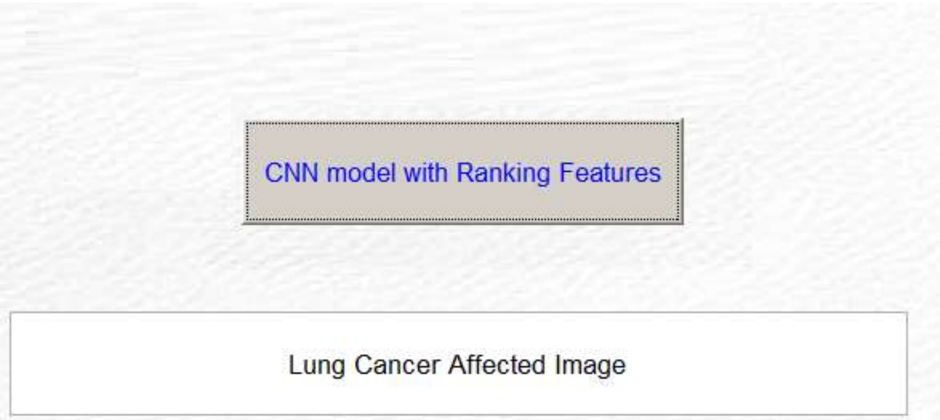

Fig. 8 Lung Cancer detected dialog

5. Conclusion and Future scope

Conclusion: The research concludes by presenting a solid methodology for automated CT image-based lung cancer classification, highlighting the potency of sophisticated image processing and deep learning methods. Promising results are shown in the correct identification of lung cancer from a variety of datasets using a multi-stage technique that includes Contrast Limited Adaptive Histogram Equalization (CLAHE), Histogram of Oriented Gradients (HoG) feature extraction, and VGG Net fine-tuning. The thorough performance evaluation shows that the model can generalize to new data, which lays the groundwork for trustworthy clinical applications. The methodology is further improved by looking into the effects of pre-processing processes. This study adds to the growing body of knowledge in automated medical image analysis, especially in the area of lung cancer diagnosis, and is beneficial to researchers, physicians, and other healthcare professionals.

Future Scope: This research provides opportunities for further investigation and improvement. Firstly, additional research is necessary to determine the wider usefulness of

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, **UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, 2022**

the methodology due to its scalability and flexibility to other datasets and imaging modalities. Classification performance could be improved by investigating ensemble models and incorporating more sophisticated deep learning architectures. The model's sensitivity and specificity may also be further improved by including domain-specific knowledge and continuously enhancing pre-processing methods. An important next step for practical validation would be to investigate real-time applications and implement the model in clinical settings. Additionally, working cooperatively with medical experts may yield insightful information for improving the model in response to clinical input. Future research should focus on integrating explainability techniques to improve the model's predictability and interpretability. This could lead to the creation of automated lung cancer detection systems that are more transparent and have a greater therapeutic impact.

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