Detection of Lungs Cancer through Computed Tomographic Images using Deep Learning

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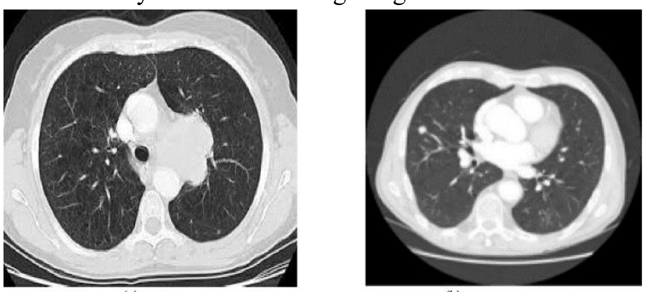
***Abstract*— Lung cancer has become a particularly lethal disease in the last decade. Lung cancer is the second most common cause of death for women and the primary cause of death for men. Therefore, early detection of lung knobs is one of the most effective ways to treat lung infections. Similarly, computer-aided diagnosis (CAD) of lung knobs has gotten a huge interest over the last decade. As a result of the broad variety of lung knobs and the complications of the entire environment, developing a robust knob detection approach is extremely difficult. A convolutional neural network (CNN) based framework is proposed to detect tumors that are identified as risky or benign in lung disease screening using CT images. Two publicly available datasets LUNA-16 and LIDC are employed to detect lung cancer. The dataset is augmented to maximize the volume of images in it. Also, preprocessing is done on CT images for better noise removal. Additionally, segmentation is performed to specify the infected area. Three pre-trained architectures, DenseNet, AlexNet, and VGG-16, are utilized to classify the cancerous and normal images. The DenseNet classifier achieved 98% classification accuracy, 98.93% sensitivity, and 99% specificity, which exhibits outstanding performance than other classifiers. The efficient results of the proposed framework show better performance than existing state-of-art studies.**

Keywords—computed tomography, deep learning, lung cancer, convolutional neural network, chest CT images

I. INTRODUCTION

According to statistics from the American Cancer Society, about 235,760 patients with lung cancer were projected to die, with 131,880 deaths due to lung cancer, including 69,410 men and 62,470 females. In older people, cellular breakdown in the lungs occurs more frequently. The vast majority of people found to have a cellular breakdown in the lungs are 65 or older. However, just a small proportion of people examined are younger than 45.

CT imaging is beneficial for the detection of lung cancer. Moreover, CT images are used to perceive the tainted locales. The significant difficulties while capturing and analyzing the CT images include low visibility of cancer districts, and negative rates [1]. Several image processing and artificial intelligence methodologies have been developed to successfully diagnose lung cancer. Moreover, for lung cancer detection, convolutional deep learning-based algorithms such as convolutional neural network (CNN), capsule network, and visual neural network are being used. Lung cancer is the most dangerous cancer of the last decade around the globe. Fig. 1 (a) represents the healthy lung image and (b) represents the unhealthy or cancerous lung image.



(a) (b)

Fig.1. Lung CT images (a) healthy (b) cancerous.

As per the latest statistics of world health organization, lung cancer is the second major reason of death around the globe [2]. Lung cancer is classify into three categories; small cell lung cancer (responsible for 13% of all lung cancers), adenocarcinoma, and non-small cell lung cancer (responsible for 84% of all lung cancers). Cigarette smoking and the use of alcohol raise the risk of a cellular breakdown in the lungs significantly. Tobacco smoke contains tar, which contains 3500 cancer-causing chemicals [3].

The following are the significant contributions of this research; in this research, an advanced method is presented for the classification of lung cancer. After retrieving the image database from the repository, the median filter is used to pre-process it. Following this, CT images are segmented using the thresholding technique. Subsequently, data augmentation is done to refine and get different angle views of an image. Moreover, feature extraction is performed. DenseNet, AlexNet, and VGG-16 classifiers were modified as per the need for the detection of lung cancer. The proposed approach outperformed current state-of-the-art approaches in terms of results.

The remaining part of paper is arranged as follows: Section II describes the researches carried out in the past and a critical review on it. Section III goes over the proposed framework. Section IV describes the results and discussion of

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the proposed methodology. In section V, a conclusion has been described.

II. Related Work

The detection of lung knobs ordinarily includes two phases: firstly, identification of competitor lung knobs; secondly the decrease of false-positive lung knobs. As of late, numerous pieces of literature had been proposed. Generally, these strategies are partitioned into machine learning techniques and the CNN approaches which are given below.

Tekade et al. [4] proposed a method for lung cancer detection. In this research, the authors took CT scan image from two datasets LIDC and IDRI which contains 1000 images. Preprocessing was done in the first phase using the backpropagation approach, followed by feature extraction. In the next step, the images were classified as healthy or normal. The proposed method attained 96% classification accuracy.

Cao et al. [5] designed architecture with the addition of two layers of pooling in the convolutional neural networks. In the first step of their proposed methodology, they attained rough nodule detection using U-Net segmentation based on the ResNet architecture. After the estimation, the authors perform fine segmentation on small reign and achieved 96% accuracy.

Nithila, et al. [6] fostered a fully automatic system for secluded lung knob detection that utilizes molecule grouping computation for network improvement and achieved 97.2% classification accuracy.

Zhang et al. [7] put forward a technique to magnify the computational complexity and results. A dataset of 50 CT images was employed for testing and training the model.

Asuntha & Sirinvasan [8] utilized a robust Deep Learning-based framework for lung cancer detection. An FPSOCNN architecture was proposed which decreased the computational complexity of CNN. This work utilized the best feature extraction methods. An extra valuation was performed on another dataset obtained from the Arthi Scan Hospital. According to the experiment results, the original FPSOCNN performs better than other existing literature.

Sori et al. [9] discussed an approach using de-noised computed tomography images to detect biological degradation inside the lungs. To acquire the best results for diagnosing biological degradation inside the lungs, many approaches were explored. As a result, the methodology focused on model accuracy. The authors proposed that this methodology be employed in supplemental detection research whenever there was situation regarding class imbalance.

Tarjanovski, et al. [10] proposed a lung cancer disease classification technique by utilizing several private and publically available datasets. The framework attained an area under curve (AUC) value of 94%

Sreekumr, et al. [11] designed a method to deal with destructive lung knobs. Their endeavor utilizing the C3D engineering has expanded the affectability of malignant lung nodule detection to 86%, which is 10% more than the existing research. This advancement was accomplished through advanced preprocessing, and better detection strategies.

Elnakib et al. [12] designed an fully-automated framework for the diagnosis of lung knobs. They trained a classification model through low dose computed tomography (LDCT) images. Furthermore, recommended a framework to work on the difference in the low portion images. Subsequently, the refined images were separated by utilizing diverse deep learning models AlexNet, VGG-19, and VGG-16. To get the best outcome to upgrade the segmented images, a genetic algorithm (GA) was prepared to choose the significant components for early diagnosis. This design accomplished an accuracy of 96.25% that is more promising than the previous research.

Bharati et al. [13] developed a fully automatic framework VDSNet for diagnosing infections in the lung using X-beam imaging dataset. The framework was tested on the NIH chest X-beam imaging dataset, which was obtained from the Kaggle library. After the several series of experiments, VDSNet exhibits the prime accuracy of 73%.

Rahane et al. [14] proposed a framework utilizing distinctive image processing and AI techniques that are, grayscale transformation, and image binarization. These images were utilized for the pre-processing of the given CT filter image. Furthermore, these features were useful for characterizing the lungs malignant growth at prior stages.

TABLE 1. Summery of Previous Studies.

Authors	Year	Datasets	Parameters	Accuracy
Tekade et al. [4]	2018	LIDC and IDRI	Accuracy	96%
Cao et al. [5]	2020	LUNA16	False-positive, Sensitivity, Specificity	90%
Nithila et al. [6]	2017	LIDC-IDRI,	Sensitivity, Specificity	97.2%
Zhang et al. [7]	2019	LUNElnakib A16	Sensitivity and Specificity	79.6%
Asuntha & Sirinvasan et al. [8]	2020	LIDC	Sensitivity and Specificity	95.6%
Sori et al. [9]	2021	Bowl 2017 challenge (KDSB) and LUNA 16.	Recall and Specificity	96.6%
Tarjanovski et al. [10]	2021	Lahey Hospital, Medical Center	AUC	94%
Sreekumr et al. [11]	2020	LIDC-IDRI, LUNA 16	Sensitivity	86%
Elnakib et al. [12]	2020	I-ELCAP	Accuracy	96.25%
Bharati et al. [13]	2020	NIC, LIDC	Accuracy	73%
Rahane et al. [14]	2018	LUNA16	Performance	-

III. Proposed Methodology

In clinical practice, correctly characterizing lung cancer regions is far more significant than determining whether cancer occurs in the CT scan, segmenting the lung cancer region can help with clinical assessment and treatment planning, such as effective surgical treatment. This study proposes a CNN-based framework for CT image-based lung cancer diagnosis. In the process of image pre-processing, CT images are enhanced to get a clearer CT imaging database. To get more accurate results, the lung tumor area is segmented through the area thresholding technique. To compare the performance of the proposed technique to publicly known state-of-the-art approaches, statistical evaluation parameters are used.

Two publicly available databases LUNA-16 and LIDC have been utilized and the no. of images are increased using the augmentation technique. This method seeks to expand the database of CT images, which is necessary for training DCNN. Fig. 2 depicts the proposed classification and segmentation framework for lung cancer disease detection.

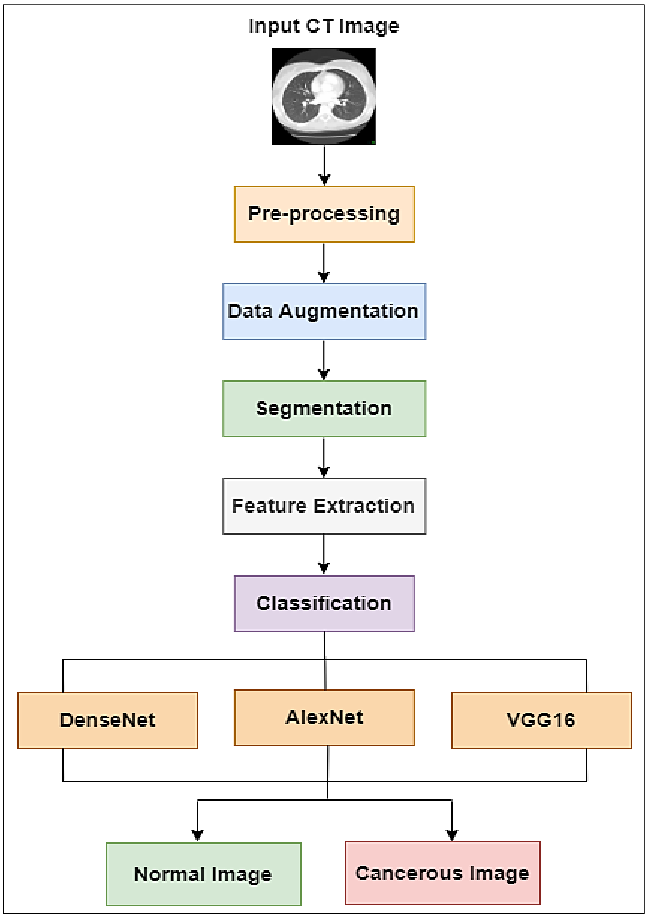

Fig. 2. Functionality Diagram of Proposed Method.

A. Database

Two publically available datasets LIDC-IDRI and LUNA16 were imported from [5] for testing and training the models.

B. Preprocessing

Data pre-processing is viewed as a significant stage in image processing techniques for disease detection. Images are enhanced by applying a median filter. Chest CT classification involves large raw images that require substantial preprocessing to detect and categorize the lung knobs. Productive preprocessing techniques are important to discover the area of interest which comprises minuscule zones. The publicly available LIDC-IDRI dataset contains 1018 DICOM images weighing around 124 GB that require some preprocessing.

C. Augmentation

Data augmentation is used to increase the number of images in a database. It includes flipping and rotation of the images. Therefore, this helps to attain the best accuracy. A variety of pre-dispositions, including lighting, obstacle, scale, foundation, and many more, can be avoided through data augmentation. Data augmentation prevents overfitting by transforming small datasets into those large datasets. Therefore, overfitting is not as much of a problem with an excessive number of images in the dataset.

D. Segmentation

CT images include a variety of statistics, finding it challenging to separate the insights of the image. However, an effective segmentation algorithm may contribute to enhance diagnostic performance. On that account, Otsu's thresholding method is utilized to segment the normal and malignant images. It is a thresholding approach that is dynamic and used for image binarization. Therefore, the variance methodology was conducted to identify the threshold at which the difference weighted between the background and foreground pixels seems to be the smallest. This technique chooses the appropriate threshold level for a given image by testing with all alternative threshold values scale from 0 to 255. Segmentation is a critical approach for identifying the area of interest to improve the performance of the classifier.

Thresholding is the essential strategy for splitting the image into the background and the foreground area, in which one limit esteem is utilized to change a greyscale image into a binary image. This method's significant thing is to pick the limit esteem, pixels with power far beyond the frontal area district's edge worth, and any remaining pixels in the background region.

E. Feature Extraction

The least demanding and most regularly utilized technique in image classification is the primary request measurement registered from the histogram. Rather than mirroring the article in the image and spatial connection between pixels, the histogram only includes the distribution of low-light pixels. More than 1000 pneumonic knobs utilize the further developed gray level co-occurrence matrix (GLCM) evaluate to extract the surface attributes of the area of interest. Extraction of features is the main stage in acquiring the sample data of the sectioned knob. In this stage, the elements are separated utilizing GLCM. Also, it has high separation performance and less computational speed.

F. Classification

AlexNet [15], VGG-16 [16] and DenseNet [17] are separately used for the classification of CT images. AlexNet is a pre-trained deep CNN architecture, that was developed by Krizhevsky and Sutskever in 2012 and first presented in the ImageNet LSVRC-2010 challenge and achieved remarkable results. AlexNet is trained over 1000 classes and therefore, called and transfer learning model. Since AlexNet contains 60 million parameters, re-training the entire structure takes a significant amount of time and effort. Additionally, there is no compelling reason to tune each parameter in AlexNet [15].

VGG-16 architecture is mainly used to resolve the issue of speed and space. VGG-16 models pack the prior highly effective structure and improve the following perspectives: small model size, quick speed, utilizes remaining learning for quicker combination, better speculation, and tackles the issue of worth, and it corresponds to the non-compacted model's accuracy [16].

DenseNet has several compelling advantages: It promotes the reuse ability and eliminates the disappearance of slope issues. Conversely, it has weaknesses as well. In the first place, each layer joins maps obtained from going before layers by linking activity disregarding the interdependencies between various channels. In request to tackle the issues in DenseNet, we have utilized a novel architecture called Multiple Feature Reweight DenseNet with pre-processed CT images [17].

The image with a huge size contains dynamically semantic information about nature around the target, however, the smaller one is progressively focused on the actual target and contains less semantic information. At this point, the extracted features are then utilized to construct a deep learning model to diagnose lung cancer. Therefore, a DenseNet classifier is employed to evaluate whether an image is healthy or cancerous.

IV. Experiment and Results

Technologies based on artificial intelligence (AI) are rapidly integrating into our daily lives. Additionally, several initiatives for run-time evaluation are being made in the fields of science and artificial intelligence breakthroughs. [19-21].

The diagnosis of several diseases through artificial intelligence techniques such as hypertensive retinopathy [22-23], Papilledema [24-25], Brain Tumor [26-29], Glaucoma [30], Alzheimer's disease [31], and CSR [32] can be conduct using artificial intelligence techniques.

There are numerous algorithms available for diagnosing the lung cancer. The most recent technology, however, is a convolutional neural network. It has given the good results in contrast to all other techniques in the literature. In Table II, some of the most recent algorithms are described for detecting lung cancer and compared their results with the proposed method. CT images are pre-processed and found more effective than the other available technologies. This refinement of the lung image achieved good results through the proposed method.

In the proposed method, images are pre-processed to achieve better results. In the first step, pre-processing of raw CT images has been performed using median filter techniques. Subsequently, the segmentation technique has been performed through Otsu thresholding. The proposed methodology attained the best accuracy which is higher than the previous techniques. The major problem in detection is the divergence in lung images. The main issue in detecting lung cancer is the divergence in CT images of the lungs. The fundamental goal of our proposed methodology was to outperform other state-of-the-art methodologies.

A. Evaluation Parameters

After the experimentation, the output results are evaluated using the evaluation parameters that are: accuracy, sensitivity, and specificity. Moreover, a ratio of 70 and 30 was set for training and testing images respectively.

1) *Accuracy*: The correctly predicted data of testing set in percentage is called accuracy. It can be found by the division of correct predictions by total predictions.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{(TP+FN+TN+FP)}} \times 100 \quad (1)$$

Using the above-mentioned equation, the accuracy was calculated by dividing the number of correctly predicted samples by the total number of samples.

2) Precision: It is the true values from all predicted values.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (2)$$

3) *Sensitivity:* It is a percentage of actual positive findings that are projected to be true positives. It implies that there is another actual positive observation proportion that can be predicted as incorrect as negatives. [18].

$$\text{Sensititivity} = \frac{\text{TP}}{\text{TP+FN}} \quad (3)$$

4) *Specificity:* It is a percentage of actual negative findings that are projected to be true negatives. It implies that there is another actual negative observation proportion that can be predicted as incorrect as positives [31].

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \quad (4)$$

Table II compares the proposed method to other existing advanced approaches.

TABLE II. Comparative Analysis of Proposed Methodology with state of art Methods.

Ref No.	Classifiers	Accuracy	Sensitivity	Specificity	Precision
[21]	FPSOCNN	95.6%	-	-	-
[22]	CNN	96.6%	-	-	-
[25]	Genetic algorithm	96.25%	-	-	-
Proposed Method	**DenseNet**	**98%**	**98%**	**98%**	**97%**
	AlexNet	**97%**	**99%**	**87%**	**98%**
	VGG-16	**96%**	**92%**	**99%**	**97%**

In the testing phase, dataset is tested on three models that are: AlexNet, VGG-16, and DenseNet with augmentation. It improves the accuracy as compared to the previous algorithms as we attain the accuracy of 98%, the sensitivity of 98%, specificity of 98%, and precision of 97% for DenseNet. In addition, AlexNet achieved 97% of accuracy, 99% of sensitivity, 87% of specificity, and 98% of precision. Furthermore, VGG 16 achieved 96% of accuracy, 92% of sensitivity, 99% specificity, and 97% of precision. It is to be observed that, DenseNet achieved outstanding performance among AlexNet and VGG-16.

The spatial relationship of information is successfully handled by the neural network infrastructure. Furthermore, a CNN's convolution layer generates a fragment map by mixing undeniable image sub-regions. A detailed analysis has been made of literature containing deep learning models for the detection of lung cancer. Determined that, a single CNN model is increasingly beneficial to develop that can efficiently detect the lungs cancer through CT images as early diagnosis is the only way to save the life of a patient. Since the time delay in detection makes the life of a patient at more risk.

There are various obstacles to effectively diagnosing the disease. One major problem is divergence in lung CT scan images. We also prioritize reducing calculation time since many calculations provide high precision but require a significant amount of computational time. The more complex the architecture, the more difficult it will be to comprehend and research. Therefore, focus on the complexity of the structure was included in the priority.

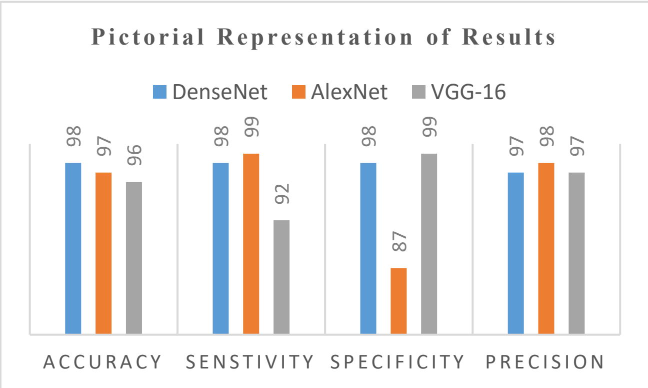

Fig. 3. Graphical Representation of Results.

V. Conclusion

This research work presents a robust deep learning-based approach for cancer detection that has high results. Figured out that, the proposed method outperforms physicians' manual evaluation procedures. Nevertheless, despite the unavoidable errors it may make, a deep learning system will never be able to replace doctors. Deep learning algorithms, in any case, can be a decent aid in CT evaluation with a similar demonstration with the radiologist. When it comes to dealing with the massive scale dataset, this research endeavor meets a few challenges. While the usage of small datasets gives high precision. However, it is not practicable in real world applications for a variety of reasons. As a result, in the future, other new deep learning algorithms will be used with larger datasets that are publicly available. Future research advancements will also comprise the execution of image information expansion techniques, for example, shading space increases, component channels, space expansion, and so on, to improve the accurateness in the fully automated chest CT scan decision framework. The proposed technique is suitable to diagnose lung cancer in different parts of the body accurately and efficiently at the early stage.

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