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A Review on Lung Cancer Detection and Classification using Shallow Learning and Deep Learning

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***Abstract*— Out of all cancers, lung cancer is a leading cause of deaths worldwide. Accurate detection and classification are crucial for better care of patients. In this survey, lung cancer detection and classification has been studied. Out of all the techniques used, learning based techniques are frequently used. It also provides more accurate result than other method. In this survey, shallow learning and deep learning based study has been carried out. Most of the techniques discussed are deep learning techniques and it has more accurate rate of detection than other methods.**

Keywords—Lung cancer, deep learning, CT scans, diagnosing, classifying.

I. Introduction

Lung cancer is a deadly disease among humans, poses a substantial threat to human survival and responsible for more than 25% of all cancer-related deaths every year. In the past, lung cancer was diagnosed based on the expertise and experience of radiologists who examined CT images. However, radiologists could sometimes generate imprecise findings when manually analyzing these images. In recent years, computer-aided diagnosis has been used to detect lung cancer earlier [1]. These systems use artificial intelligence (AI) to analyze CT images and identify suspicious lesions. Deep learning is particularly well-suited for image analysis tasks. Deep learning models can be trained on large datasets of CT images to learn to identify lung cancer lesions with high accuracy. In contemporary time, numerous deep learning methods has been used to detect lung cancer with promising accuracy.

In this study, various lung cancer detection and classification methods has been discussed. The paper continues as follows: Section II outlines the shallow learning methods. Section III outlines the deep learning methods used. Section IV covers the deep learning framework while section V concludes the study.

II. Shallow Learning approaches

This section examines various machine learning models for lung cancer detection. Makaju et al. [2] introduced a novel method for lung CT scan cancer nodule detection, achieving 92% accuracy using watershed segmentation and SVM, replacing Gabor filters with Median and Gaussian filters in pre-processing. Soni et al. (2020) [3] developed a lung cancer detection model that relies on Histogram Equalization, Prewitt Filtration, and Morphological Dilation techniques, achieving an impressive 95.83% accuracy rate. SVM has been used for classification purpose using lung cancer. A simple architecture of SVM is shown in Fig.1. In Swain et al. [4], histogram oriented gradient features are extracted from the image and used as input to detect cancer. The input features are then presented to SVM classifier identifying the cancer.

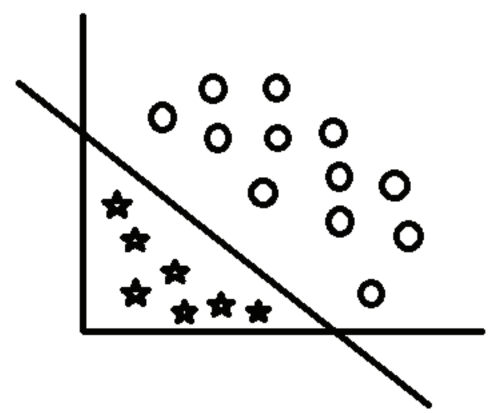

Fig. 1. SVM architecture [4].

Naqi et al. [5] proposed a hybrid methodology that combined the geometric texture, HOG and PCA features. This methodology used the LIDC database and different classifiers such as kNN, Naive Bayesian, SVM and AdaBoost for lung nodule detection. As a comparative study, the performance with SVM found more than kNN and Naive Bayesian. The AdaBoost classifier performed best than other classifiers with accuracy 99.2%. In Saba (2019) [6], an automated method for lung nodule detection outperformed state-of-the-art techniques. It outperformed with voted perceptron classifiers with accuracy nearly 100%. In Astarak et al. (2019) [7], a dataset of 30 patients with 31 tumors, primarily in stage III NSCLC, was used. SALoP proved to be a superior prognostic tool compared to radiomics ($AUROC_{SALoP} = 0.90$ vs. $AUROC_{radiomics} = 0.71$). The research conducted by

Naqi et al. [8] centered on implementing stacked autoencoder and softmax algorithms to optimize features and classify nodules. This approach substantially improved the accuracy rate of 95.83%. Table I outline the methodology, data-set used and performance of the machine learning method used.

TABLE I. ANALYSIS OF SHALLOW LEARNING BASED METHODS

Authors	Methodology	Data-set	Performance statistics (%)
Makaju et al. (2018) [2]	Machine Learning, Watershed algo, SVM	LIDC-IDRI dataset	Accuracy : 92%
Soni et al. (2020) [3]	Machine learning, Histogram Equalization, Prewitt Filtration and Morphological Dilation.	NCI dataset	Accuracy : 95.83 %
Swain et al. (2023) [4]	SVM using HOG features	TCIA database	Accuracy : 96%
Naqi et al. (2019) [5]	HOG-PCA for feature extraction and AdaBoost classifier used for lung nodule detection	LIDC database	Accuracy: 99.2% Sensitivity: 98.3% Specificity: 98.0%
Saba (2019) [6]	Multiple classifiers voting used for nodule detection	LIDC dataset	Max. Accuracy: 100%
Astarak et al. (2019) [7]	A novel feature set called Size-Aware Longitudinal Pattern (SALoP)	NCI dataset	$AUROC_{SALoP}$ = 0.90
Naqi et al. (2020) [8]	Stacked autoencoder	LIDC–IDRI dataset	Accuracy: 96.9%

III. DEEP LEARNING APPROACHES USED

This section examines deep learning models for lung cancer detection. The analysis identifies key challenges and development of framework. In [9], VGG-16, resnet-50 and inception v3 has been used for classifying cancer. In their study, Wankhad et al. [10] introduced a hybrid deep learning approach that blends 3D-CNN and RNN for the early detection. They harnessed the LIDC-IDRI dataset to extract CT scan images, yielding impressive results: 95% accuracy, 90% specificity, and 87% sensitivity. Heuvelmans et al. [11] introduced a deep learning approach for distinguishing between benign and malignant nodules, showcasing notably high sensitivity rates.

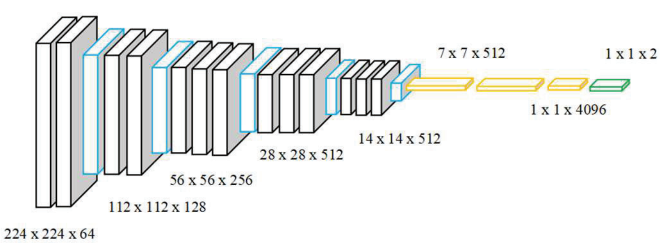

Fig. 2. VGG-16 architecture [9].

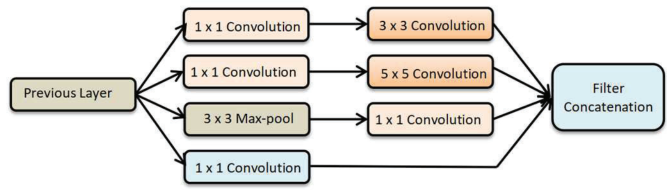

Fig. 3. Inception module [9].

Tian et al. [12] processed lung CT scan images, utilizing an optimized fuzzy possibilistic c-ordered mean method with CSAR. The final diagnosis employed Enhanced Capsule Networks (ECN) and outperformed ResNet, KE-CNN, and CNN. Dodia et al. [13] conducted a review on recent lung cancer detection advancements. The paper concludes by addressing clinical and technical challenges and outlining future directions in the field. In their work, Rajasekar et al. [14] introduced a methodology demonstrating improved performance metrics using deep learning algorithms.

Brunese et al. [15] introduced a three-step method: distinguishing healthy from pulmonary disease in chest X-rays, discerning generic pulmonary disease from COVID-19, and detecting the region of interest. Their approach utilized VGG-16 network for COVID-19 detection, attaining an impressive 97% accuracy. In the study conducted by Tekade et al. [16], lung patient Computer Tomography (CT) scan images were employed to identify and categorize lung nodules, while also determining the alignancy level associated with these nodules. The CT scan images underwent segmentation using the U-Net architecture. These images were sourced from the LIDC-IDRI dataset. In Sahu et al. [17] paper it introduced a streamlined multi-view CNN model. It captures a nodule's cross sections from various angles, condensing the volumetric data via a view pooling layer. The study utilized LIDC-IDRI datasets and achieved an impressive 93.18% classification accuracy, setting a new performance benchmark. Kalaivani et al. [18], suggested a deep learning method for lung cancer. This approach yielded an impressive 90.85% accuracy rate. In the research paper Sait et al. [19] implemented segmentation with the top of UNETR network and Classification with deep neural network that used ReLU activation function with a promising accuracy 98.77%. In [20], a method is introduced to classify and detect lung nodules. Evaluation on the LIDC-IDRI dataset shows reduced False Positive Rate (FPR) and improved accuracy. Table II summerises all the deep learning method used.

IV. DEEP LEARNING FRAMEWORK FOR LUNG CANCER DETECTION

In this section, a frame work that involves several sequential steps, has been outlined below. Fig. 4 illustrates the flowchart of the framework for lung cancer detection approach. The deep learning based framework for lung cancer detection includes various steps as discussed below.

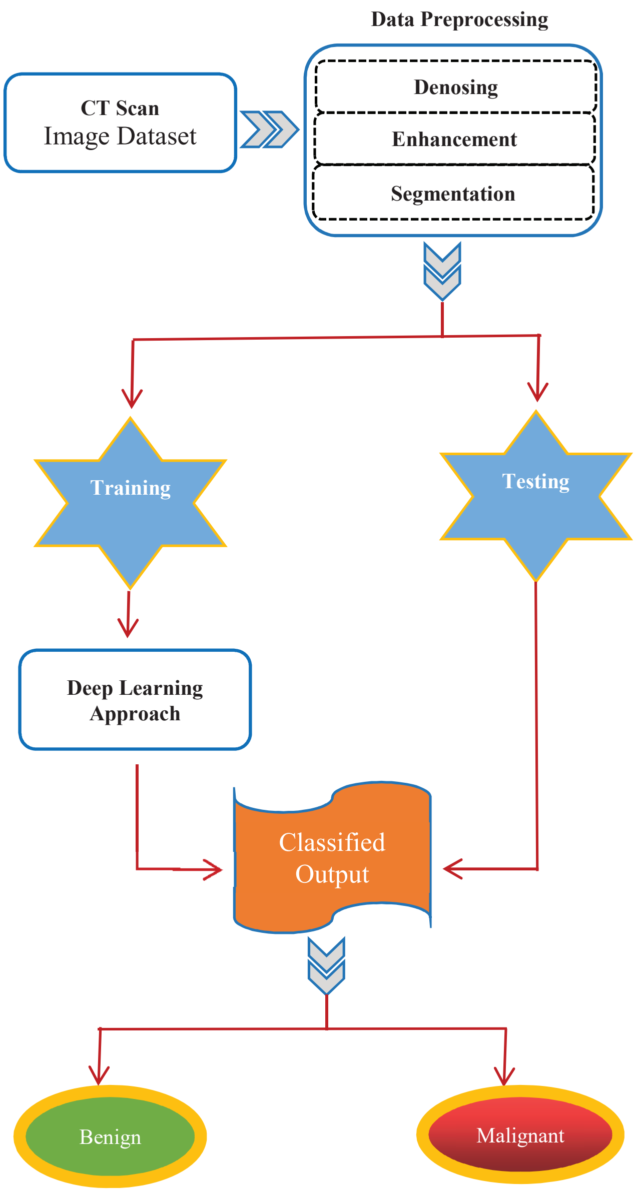

Fig. 4. The architecture of the lung cancer detection system using deep learning.

A. Dataset

The chest CT images, PET images are mostly used for lung cancer detection. Different lung cancer dataset has been used by reserchers such as LIDC-IDRI, TCIA [21] etc.

B. Pre-processing

Pre-processing enhances lung CT scan clarity by reducing noise and artifacts, improving pulmonary nodule visibility.

i. Denosing

Denoising methods reduce data noise in input lung images and enhance resolution. This study employs spatial filtering for denoising.

ii. Enhancement

It improve the quality of an image as perceived by a human being. Also it is used to give better input to other automated image processing methods.

iii. Segmentation

Image segmentation is the technique used to partition an image into its fundamental components or entities. The primary purpose of dividing an image into its constituent parts or entities is to enable in-depth analysis of each of these components or objects once they have been identified and separated. Consequently, the output of image segmentation is a set of segments extracted from the entire image.

TABLE II. ANALYSIS OF DEEP LEARNING METHODS

Authors	Methodology	Data-set	Performance statistics (%)
Wankhadet al. (2023) [10]	Combining 3D-CNN and RNN for image classification.	LIDC-IDRI dataset	Accuracy: 95 % Sensitivity: 87% Specificity: 90%
Heuvelmans et al. (2021) [11]	CNN	NLST	Accuracy: 94.5 %
Tian et al. [2021) [12]	ResNet, CNN	Lung CT-Diagnosis database	Accuracy: 96.65%
Brunese et al. (2020) [15]	CNN, VGG-16 for COVID-19 pulmonary disease detection.	ChestX-Ray 14, CoVID-19 2020 image dataset	Accuracy: 97 %
Tekade et al. [16]	U-Net architecture	LIDC-IDRI dataset	Accuracy: 95.6 %
Sahu et al. (2018) [17]	A streamlined multi-view CNN model	LIDC-IDRI dataset	Accuracy: 93.18 %
Kalaivani et al. (2020) [18]	DenseNet	.A dataset of 201 lung images	Accuracy: 90.85 %
Said et al. (2023) [19]	Segmentation with the top of UNETR network, Classification with deep neural network with ReLU activation function	Decathlon dataset	Accuracy: 98.77 %
Ahmed et al.(2022) [20]	Faster-RCNN, YOLOv3, and SSD, for lung nodule detection	LIDC-IDRI data set	Less FPR

C. Deep Learning Approach for detection

Different deep learning models has been used for classification such as VGG-16, resnet-50, inception, CNN etc. VGG Net excels in feature extraction, enabling the categorization of unseen objects. Increasing CNN depth was the key innovation behind VGG, aimed at enhancing classification accuracy.

D. Matrices used for performance analysis

Confusion matrix is used to examine classification in detail. The values of metrices are computed as follows.

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

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

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

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

$$\text{FPR} = \frac{\text{FP}}{\text{TN} + \text{FP}} \quad - (5)$$

$$\text{F-Score} = \frac{2 \text{ x TP}}{2 \text{ x TP} + \text{FP} + \text{FN}} \quad - (6)$$

Accuracy serves as a metric to evaluate the overall correctness of a model's predictions. Precision represents the model's positive predictive value and assesses its ability to accurately classify positive instances. Sensitivity gauges the model's capability to correctly identify instances of a specific class, which is particularly useful in applications like cancer detection. Specificity correctly reject instances. The false positive rate (FPR) is an indicator of the expected rate at which the model incorrectly classifies instances as positives. F1-score, derived from the harmonic mean of precision and recall. Recall, in the context of cancer detection, reflects the model's sensitivity in identifying cases of a specific cancer type.

V. CONCLUSION

In this survey, lung cancer detection and classification based on CT scan data using shallow learning and deep learning has been discussed. Different shallow learning techniques such as SVM, random forest, neural networks has been used for lung cancer detection along with various feature extraction techniques. Deep learning techniques such as CNN, VGG-16, Resnet-50, LSTM, inception network has been used for lung cancer detection and classification. Major shortcomings of most of the work is that it uses only one data-set to validate the method. The future scope of the work can be extracting lung cancer features and classifying lung cancer with less complex network structures.

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