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A Review of Deep Learning Techniques for the Detection of Lung Cancer on Medical Images: Current Advancements and Challenges

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Abstract
Lung cancer is a prevalent global ailment characterized by the uncontrolled proliferation of aberrant cells within the lungs. Frequently, it happens within the airway cells, particularly in the bronchi, which serve as the main conduits for air to reach the lungs. While it is not possible to completely avoid lung cancer, it is indeed possible to mitigate the risk associated with it. The occurrence of cancer has resulted in an increase in death rates for both males and females. Patients have a far better chance of surviving if lung cancer is detected early. Computed Tomography (CT) is a commonly employed imaging modality for distinguishing between malignant and benign lung nodules. However, the cost of a CT scan was prohibitively high, making it unaffordable for many people in remote areas. In addition, the process of analysing those scans require a significant amount of time and a team of highly qualified radiologists. Lung cancer detection and classification using CT images has seen a proliferation of Deep Learning (DL) frameworks in the last several decades. These algorithms have the capability to identify dubious nodules or lesions at an early stage, which could potentially result in earlier identification and enhanced patient outcomes. Furthermore, the insights derived from those frameworks might assist clinicians in making informed decisions and achieving early diagnosis, therefore mitigating the likelihood of adverse patient outcomes. This research provides an extensive analysis of various DL frameworks that have been built for the purpose of identifying and classifying lung cancer based on CT images. Firstly, a brief study is conducted on various lung cancer categorization systems developed by multiple researchers, which are based on DL algorithms. Afterwards, a thorough evaluation is carried out to determine the shortcomings of current algorithms and provide a fresh strategy for precise lung cancer classification, with the goal of reducing global mortality rates.

Keyword: Lung Cancer, Computed Tomography, Deep Learning, Earlier Diagnosis Global Morality Rate

1. INTRODUCTION

In order to sustain life, the lungs are vital respiratory organs that allow for the exchange of carbon dioxide and oxygen. This process allows cells to take in oxygen and eliminates waste products from metabolism [1]. The airway epithelial cells are a common location of tumor development in lung cancer. Pulmonary carcinogenesis is characterized by the occurrence of cellular abnormalities in the lungs, resulting in unregulated proliferation and division. Cancerous cells have the ability to develop tumors that disrupt the regular functioning of the lungs, including the capacity to breathe adequately and supply oxygen to the body's tissues [2]. In terms of overall cancer mortality, it accounts for 18%, making it the leading cause of death across all cancer types. Approximately 10% to 20% of people diagnosed with lung cancer will still be alive after five years [3]. Figure 1 shows the difference between a normal lung and a cancerous lung.

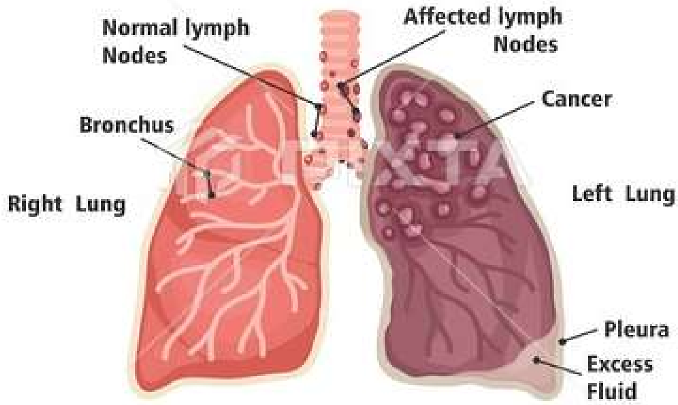

Figure 1 Healthy Lung (left) vs. Lung cancer (right)

Two primary subtypes of lung cancer are Small Cell Lung Cancer (SCLC) and Non-Small Cell Lung Cancer (NSCLC) [4].

NSCLC: It is the predominant form of lung cancer. NSCLC exhibits a faster growth rate and wider dissemination compared to this condition. The three primary subtypes of NSCLC are classified based on the particular cell type present in the tumor.

- Adenocarcinoma is the most common lung cancer. It usually starts in the outer parts of the lungs. Also, among people who have never smoked, it is the most common type of lung cancer.
- Large cell carcinomas refer to a collection of malignancies characterized by the presence of very large and aberrant cells. These tumors can originate from any location within the lungs and have a tendency to proliferate rapidly.
- Squamous cell carcinoma is a synonym for epidermoid cancer. The illness usually starts in the bronchi, located in the middle of the lungs.

SCLC: The overwhelming majority of small cell lung cancer cases can be attributed to cigarette smoking. It is a deadly cancer that grows and spreads far more quickly than any other kind of lung cancer. SCLC can be classified into two distinct subtypes.

- Among lung cancers that affect tiny cells, the most prevalent is small cell carcinoma, sometimes called oat cell cancer.
- Combined small cell carcinoma refers to a type of lung cancer that includes both small cell carcinoma and another type of cancer.

Figure 2 illustrates the visual representation of NSCLC and SCLC. The main factors contributing to the development of lung cancer are tobacco smoking, exposure to asbestos, radon gas, air pollution and a family history of the disease. Still, cigarette smoking is still the leading cause of lung cancer, and in many nations, the rate of smoking has either peaked or is rising. The results show that lung cancer will likely continue to be more common for at least a few more decades. [5]. Common symptoms of lung cancer include a persistent cough, chest pain, shortness of breath, blood in the mucus, lethargy, lack of appetite and recurrent infections. However, these symptoms may not manifest in the earliest stages, making the diagnosis process more difficult [6]. Timely identification and precise diagnosis of lung cancer can greatly enhance patient prognosis.

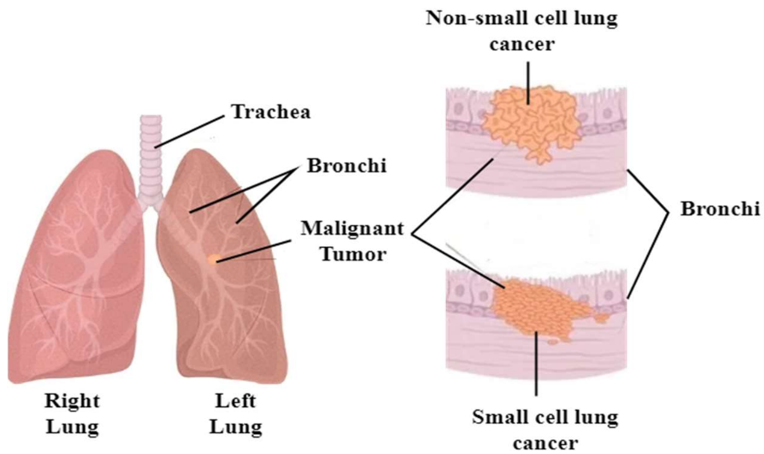

Figure 2 NSCLC vs. SCLC

In previous years, lung cancer was identified using many methods including a skin test, biopsy, sputum sample test, Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), Chest X-ray, and CT scans [7]. The primary function of CT scans in the detection of lung cancer is the identification and classification of anomalies pertaining to the lungs [8]. The CT imaging module provides highly accurate and detailed cross-sectional pictures of the lungs with high resolution. CT imaging enables radiologists to visually examine and describe lung nodules, which helps in detecting them early and arranging appropriate therapy. CT imaging is a non-invasive and patient-friendly procedure that enables several imaging sessions without causing any discomfort or harm to the patient. It can be integrated with other imaging modalities such as PET to achieve a more thorough assessment of lung cancer [9].

1.1 Lung Cancer Prediction using Image Processing Techniques

Advances in CT and image analysis techniques have greatly improved the capacity to identify lung cancer. Capturing images, pre-processing them, extracting features and finally classifying them are the several steps involved in using CT imaging to identify lung cancer. [10].

Image Acquisition: The first step is to gather CT scans from several sources, such as hospitals, online image databases, or picture libraries. Subsequently, the images were saved in MATLAB software and presented as a grayscale image. The image database has the capability to store CT-Scans in several formats, including JPEG and PNG image standards [11].

Image pre-processing: Before further processing, the CT scans will be pre-processed to improve image quality by removing unwanted distortions and boosting certain image aspects. It reduces the impact of distortion in imaging devices, such as fluctuations in light, to eliminate blueness. Additionally, pre-processing is necessary to remove undesired areas from the images. Sometimes, it is also employed to enhance specific features of the image, such as lines, boundaries, and textures. This allows for easy differentiation between the desired and undesired contents of the image [12]. Spatial domain, linear (Wiener or mean filter), non-linear (median filter) and frequency domain (wavelet transform) filtering are some of the methods used by researchers to remove noise from images. The kind of noise determines the filtering strategy to be used. Additionally, there are several image improvement techniques such as Gabor Filter, Fast Fourier Transform, Wiener Filter, and others that improve the quality of image pixels.

Image Segmentation: The process of segmentation involves dividing a picture into smaller, more manageable pieces that stand in for important features or objects, enabling their subsequent identification and categorization. The input photos undergo segmentation, when they are divided into separate components and certain regions of the image are utilized. Segmentation generates a mask for each object in the image, delineating the boundaries of each object on a pixel-by-pixel basis. In order to distinguish both benign and malignant instances, it is essential to segment lung nodules before studying their unique characteristics in CT scans. The process of partitioning the image into two components, namely the desired and undesired parts. The main objective in lung cancer diagnosis is to accurately detect and identify the tumor within the lung picture, while excluding any irrelevant areas [13]. Two popular methods exist for picture segmentation: region-based segmentation and edge-based segmentation. Some of the methods used in edge-based segmentation include zero crossing detection, gradient approaches, and region growing. Region-based segmentation, on the other hand, utilizes methods like thresholding, region growing, and clustering in feature space.

Feature Extraction: An essential facet of image processing is feature extraction, which is picking out individual elements or traits from a picture. After the lung area has been segmented, the features can be extracted and the analysis rule may be computed to reliably detect lung nodules that are cancerous. This approach utilizes CT images to extract quantitative data, gathering essential information regarding the shape, texture, and intensity attributes of the nodules. These characteristics function as distinctive indicators for differentiating between benign and malignant nodules. Image processing involves three distinct categories of features: structural features, texture features, and spectral features [14].

Structural features refer to the examination and analysis of anatomical structures such as organs, tumors, or anomalies, focusing on their shape, size, and content. Additionally, it explores the analysis of the distribution of intensity along lines within the image, as well as the identification of boundaries between various tissues or structures.

The texture characteristics analyse the spatial correlations among pixel intensities, yielding insights on texture patterns such as smoothness, coarseness, or regularity. It identifies adjacent pixels that have the same gray-level value, providing information about the uniformity, regularity, and characteristics of lung tissue textures. Spectral characteristics are used to assess the composition of materials and tissues by determining various energy levels [15]. The prominent features include Gabor, Local Binary Pattern (LBP), texture descriptor, color and edge descriptors, Hu moments, edge histogram descriptor, shape characteristics, orientation, dimension, bounding box, autocorrelation, Scale-Invariant Feature Transform (SIFT), Speeded-Up Robust Feature (SURF) and others. Unlike other methods, Convolutional Neural Network (CNN) has the ability to autonomously acquire and comprehend features, eliminating the need for manual extraction of properties.

Classification: Classification is the fundamental procedure in image processing. After extracting the features from the photos, it is possible to detect the cancer stages (malignant or benign) or levels. After the cancer stage is identified, medical professionals, such as doctors or radiologists, carefully determine the most suitable course of action for therapy based on the severity of the cancer [16]. The classification process consists of two distinct phases: training and testing. The training phase entails training the classifier by employing image processing techniques on a training image. Picture capture, pre-processing, feature extraction, and categorization are all part of this. The uploaded image is then subjected to the same tests as the training image during the testing phase, which includes acquiring a test CT scan, pre-processing the image, extracting features, and finally, classifying the results. In general, Machine Learning (ML) and DL are branches of Artificial Intelligence (AI) that can be used to automatically predict and categorize lung cancer. These models are highly beneficial in making decisions for medical systems, as well as aiding in early diagnosis and treatment planning [17]. Figure 3 illustrates the operational module of ML ML\DL utilizing image processing techniques for the identification of lung cancer.

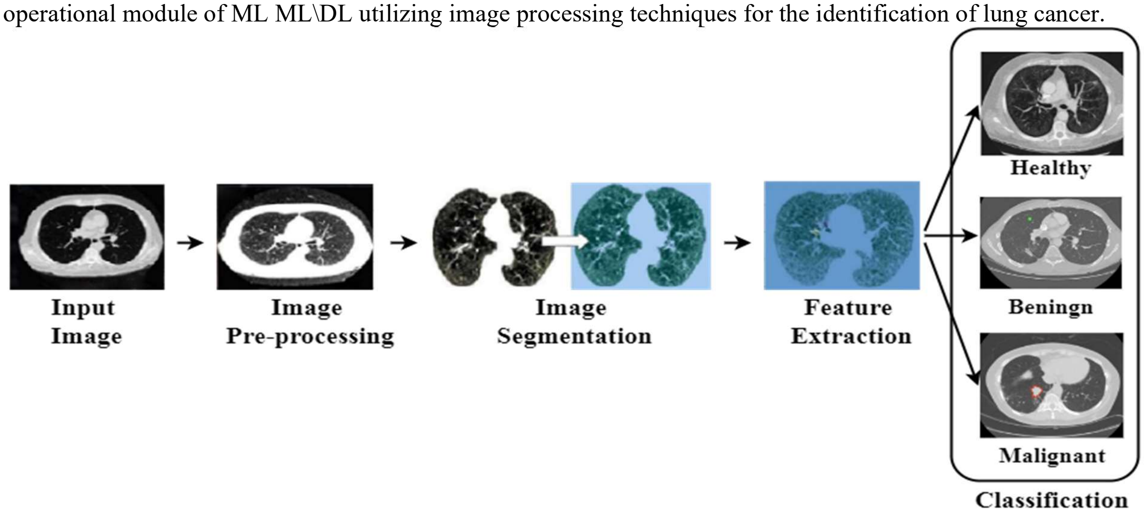

Figure 3 Pipeline of image processing techniques for lung cancer detection

1.2 Lung Cancer Prediction using ML model

ML techniques are employed to forecast lung cancer by means of CT image processing. ML models have the ability to integrate data from various sources in order to detect and classify potentially abnormal growths or masses in CT images, therefore enhancing the likelihood of successful treatment. It aids in the identification of new biomarkers and supports the creation of new diagnostic tools, treatment approaches, and predictive models to improve patient care in the diagnosis of lung cancer [18]. Machine learning methods encompass a variety of models such as Support Vector Machines (SVMs), Genetic Algorithm (GA), K-Nearest Neighbour (KNN), Random Forest (RF), Navies Bayes (NB), Artificial Neural Networks (ANNs), Decision Tree (DT), Bayesian Networks (BNs), and others. These strategies have been commonly employed in lung cancer research to develop predictive models, leading to more precise and timely predictions for controlling mortality rates [19]. Nevertheless, the primary constraints of these algorithms [20] are demonstrated below.

- **Imbalanced data:** Imbalance in the distribution of classes in medical data can cause machine learning algorithms to be biased, leading to subpar performance in identifying minority classes such as lung cancer. This is because the number of negative cases typically outweighs the number of positive cases.
- **Data Quality and Quantity:** ML algorithms necessitate substantial quantities of high-caliber data in order to train with optimal effectiveness. Furthermore, it is unable to ascertain the annotated medical imaging data (CT scans) and hence cannot assess the quality and consistency of the data, thereby impacting the performance of the model.
- **Inadequate results on large dataset:** Certain ML methods may encounter difficulties when processing huge image datasets, resulting in the need for significant CPU resources, extended training durations, and potential uncertainty problems.
- **Overfitting and Underfitting**: ML models can be prone to overfitting, where they capture irrelevant noise present in the training data, or underfitting, where they fail to catch the fundamental patterns in the data. These issues can lead to suboptimal performance when the models are applied to new, unseen data.

- **Feature Selection and Extraction:** Undoubtedly, ML is unable to identify the important characteristics from intricate medical data. Feature selection has a substantial impact on the performance of machine learning models.

1.3 Lung cancer detection DL model

DL models have high efficiency in predicting and classifying lung cancer. DL algorithms can automatically extract meaningful features from CT scans, catching intricate patterns and delicate details that can indicate the presence of malignant lesions. This eliminates the requirement for manual feature extraction, as demonstrated in [21]. DL algorithms have the ability to extract patterns from extensive datasets, seamlessly incorporate cancer detection systems into clinical workflows, and effectively analyse voluminous CT scans. It can be enhanced for processing in real-time or near-real-time, allowing for quick analysis of CT images and timely detection of problematic lesions [22]. Several DL algorithms, such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long-Short Time Memory (LSTM), and Deep Belief Network (DBN), are commonly used.

CNN models are extensively utilized in lung cancer prediction among various types of DL algorithms. This is primarily because CNN models possess the capability to directly learn distinctive features from the data and can easily adjust to differences in imaging techniques and clinical circumstances. CNNs leverage spatial hierarchies inherent in images. The model utilizes convolutional layers to extract features at several spatial scales, allowing it to detect both local patterns like edges, textures, and forms, as well as global patterns that may suggest the existence of tumors [23]. It is common practice to use convolutional, max-pooling and fully connected layers in a CNN-based architecture when extracting features. Features from CT images are extracted using the convolutional layer. The shallow convolutional layer is used to extract basic edge and texture features, the mid-level layer is used to extract more sophisticated texture and some semantic characteristics, and the deep layer is used to extract high-level semantic features. After the convolutional layer, a max-pooling layer is used to keep the image's key features. In the end, the high-level semantic data is sorted into different categories using the classifier, which is made up of completely linked layers (cancer). The development of CNNs has resulted in a more efficient and automated detection of lung cancer [24]. The diagram in Figure 4 illustrates the hierarchical organization of the CNN model used for classifying lung cancer.

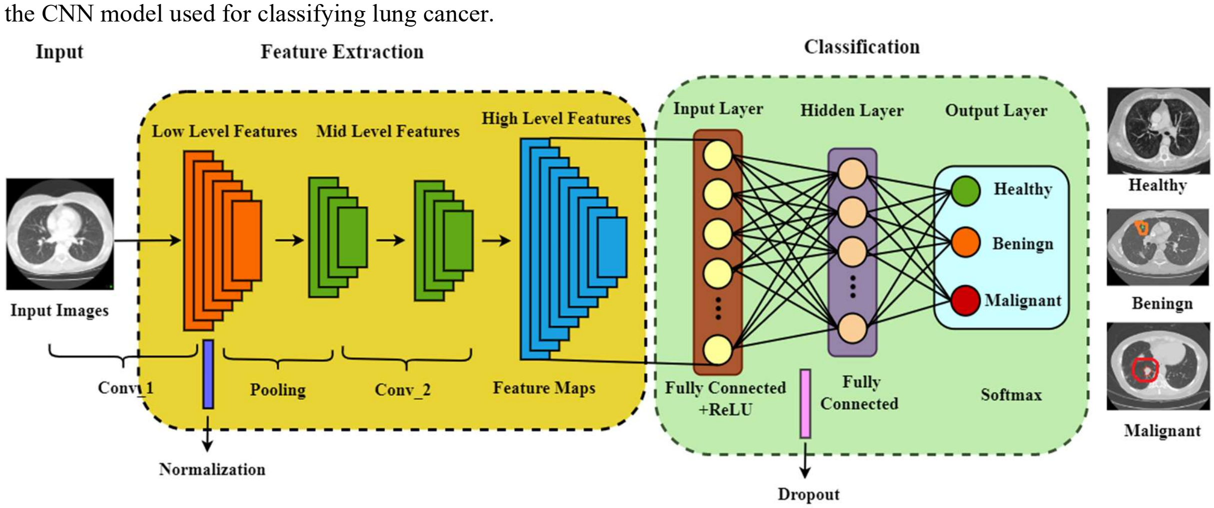

Figure 4. Structure of CNN for Lung cancer Detection

However, simple CNNs that primarily concentrate on local patterns and features may have difficulties in understanding the overall context of larger and more intricate images. This is because they have a restricted comprehension of spatial relationships. Pre-trained CNN models such as AlexNet, VGG19, DenseNet201, EfficientNet, XceptionNet, InceptionV3, MobileNetV2, ResNet, and ShuffleNet are employed to address the limitations of the basic model [25]. These pre-trained models are usually trained on high-performance computing infrastructure and can be used on devices or environments with limited resources, such as hospital workstations or edge devices, without requiring a large amount of processing capacity. These models of pre-trained CNNs may improve treatment results, shorten training times and aid in the early detection of lung cancer. These algorithms allow radiologists to accurately detect distinct characteristics, ensuring the reliability and comprehensibility of clinical applications [26].

This paper aims to present a thorough review of various CT-based lung cancer prediction and categorization frameworks. Additionally, a comparison analysis is provided to examine the merits and weaknesses of these frameworks in order to propose potential future opportunities. The remaining sections are organized in the following manner: Section II examines various DL methods specifically designed for the prediction and categorization of lung cancer from CT scans. Section III presents a comparative examination of the frameworks. Section IV provides a comprehensive overview of the full survey and offers suggestions for future areas of focus.

2. LITERATURE SURVEY

Shakeel et al. [27] created the Improved Profuse Clustering Technique (IPCT) and DL Immediately Trained Neural Networks (DLITNN) to detect cancer of the lungs from CT data. The Weighted Mean Enhancement approach was employed to eliminate the noisy images in this method. Subsequently, the IPCT approach was employed to partition the afflicted area while preserving all original and normal pixels. The damaged region was analyzed using DITNN to identify lung cancer, and several spectral features were extracted and studied.

A CNN model was suggested by Al-Yasriy et al. [28] to detect and diagnose lung cancer from CT scans. The dataset was processed and normalized to remove noise and improve image quality. Next, the pre-processed photos were inputted into the AlexNet model to classify lung cancer.

A study conducted by Ahmed et al. [29] introduced a Three-Dimensional CNN (3DCNN) for the purpose of detecting lung cancer through the analysis of CT images. The obtained CT Lung images were pre-processed and segmented using the thresholding technique in this procedure. Subsequently, a vanilla 3D CNN classifier was employed to categorize a lung CT scan as either malignant or non-cancerous.

Chaunzwa et al. [30] developed a CNN-SVM model for classifying lung cancer histology based on CT scans. In this approach, the CT scans that were gathered underwent pre-processing, which involved manually identifying tumors, rescaling them to have equal dimensions in all directions, and normalizing their density. The tumor areas were localized using seed-points identified by clinicians. The features were then extracted from the already processed images using the CNN model. Ultimately, the SVM model was employed to forecast and classify lung pictures of patients as either cancerous or non-cancerous.

Automatic detection of lung cancer was shown by Shakeel et al. [31] utilizing an Ensemble (ELM) Classifier and an Improved Deep Neural Network (IDNN). For the purpose of detecting lung cancer, this model makes use of a dataset consisting of CT scans for NSCLC. Subsequently, the Multilevel Brightness-Preserving (MBP) technique was employed to eliminate noise and enhance pixel quality. The IDNN approach was utilized to partition the regions and extract characteristics. The HSOIGRS technique was utilized to choose the features, which were subsequently classified using an ELM for predicting lung cancer and non-cancer cases.

Balannolla et al. [32] developed a multi-strategy approach for the identification and categorization of lung nodules. This methodology consists of two stages: nodule detection and categorization into three categories - benign, malignant, and non-cancerous. The lung CT scan pictures are processed to create a mask and generate image annotations. Subsequently, the U-Net model was employed to perform segmentation on CT scans in order to identify nodules from the annotated images. Ultimately, the VGG Net model was employed to extract intricate characteristics such as nodule size and forms. These extracted features were then inputted into a softmax layer for the purpose of detecting lung cancer.

Shafi et al. [33] introduced a CNN -SVM model for the purpose of classifying lung cancer. This method employed Computer-Aided Design (CAD) models to detect physiological and pathological alterations in the soft tissues of lung cancer lesions. The CT pictures were pre-processed to eliminate extraneous objects. Next, the process of lung segmentation was carried out using a capsule network. The data received from the collected dataset was used to determine the ROI after the segmentation process. The CNN algorithm was employed for feature selection, whereas the SVM algorithm was utilized for cancer classification.

Ramana et al. [34] introduced a Saliency-based Capsule Networks (SCN) and Optimized Pre-trained Transfer Learning TL (OPTL) approach for accurately identifying and categorizing lung tumors in CT images. The obtained CT scans were pre-processed using Histogram Equalization (HOE) to normalize the picture intensities and contrast. After that, the images were processed using the Adaptive Median Filter (AMF) to eliminate any noise. The SCN was utilized for the purpose of segmenting, while OPTL was employed for the prediction of lung malignancies. Another step used to improve the accuracy rate was training the features obtained from the saliency map and capsule network hybrid using the Whale Optimization Algorithm (WOA).

Pandian et al. [35] developed a Hybrid Lung Cancer Detection Model (HLCDM) by utilizing VGG-16 and

GoogleNet. This method included pre-processing and augmentation of the collected CT lung cancer pictures to make them better. The VGG-16 model was utilized as the foundational network to extract profound characteristics and distinguish between normal and unhealthy lung images using successive layers. GoogleNet was utilized to predict and classify lung cancer.
A Cat Mouse Optimizer with Machine Learning Driven Lung Cancer Classification System (SCMO-MLL2C) for CT scans was presented by Ragab et al. [36]. Before further processing, the acquired CT images were subjected to Gaussian filtering (GF) in order to reduce noise. As a hyperparameter optimizer, the DenseNet-201 architecture was then used to extract features from the slime mold method (SMA). For lung cancer classification, the Elman Neural Network (ENN) approach was used, alongside the SCMO system for better ENN parameter tuning. Using this method, the CT images were classified as either benign, malignant, or normal.
Mamun et al. [37] developed a lung cancer diagnosis model called LCDctCNN, which utilizes CT scans and a CNN model. In this approach, the gathered CT scans underwent preprocessing, augmentation, and segmentation to minimize noise, enhance data quality, and anticipate the masks, respectively. In order to detect lung cancer, the CT scans were trained, tested and validated using the custom CNN model.
In order to diagnose lung cancer, Muñoz-Aseguinolaza et al. [38] presented a CNN model-based three-dimensional perspective technique. The obtained photos were segmented using the 3D Slice method in this study. Subsequently, the 3DCNN model was employed to forecast and categorize the cancer segments derived from the segmentation images. Ultimately, 3D image encoders were utilized to compress the preceding and subsequent picture slices in a comparable fashion to enhance the detection of lung cancer.
Utilizing CT scan and histology data, a CNN model for lung cancer prediction was suggested by Rajasekar et al. [39]. In this approach, the acquired CT scans underwent pre-processing and augmentation to enhance the quality of the image pixels and remove any unwanted noise. Afterwards, the features from the pre-processed images were extracted using the pre-existing convolutional neural network (CNN) models, which included CNN GD, VGG-16, VGG-19, Inception V3, and Resnet-50. In the end, softmax layers were used for cancer in the lungs prediction and categorization. But compared to other models, VGG-16 and VGG-19 perform better in detecting lung cancer.
The Modified Extreme Inception Model (MEIM) was proposed by Bhattacharjee et al. [40] to identify chronic renal illness and early lung cancer from CT scans. The CT pictures were pre-processed to decrease the intricacy. Next, the "Imagenet" dataset was inputted into the original XceptionNet and processed through the designated convolutional layers. The Sep Conv 2D layers with residual connections address the limitations of traditional CNNs and offer improved convergence speed. Ultimately, the lung cancer diagnosis utilized the modified Extreme Inception model.
Combining CNNs with the Ebola Optimization Search Algorithm (EOSA), Mohamed et al. [41] automated the detection and classification of lung cancer CT scans. This approach used a linear filter procedure for image processing that is based on Gaussian blur. This technique utilizes blurring and smoothing effects to remove noise. After that, a CNN model was used to classify the pre-processed images as either cancerous or non-cancerous based on their unique features. In an effort to optimize the CNN's parameters for reduced complexity and increased accuracy, the EOSA model was created.
Shah et al. [42] introduced a Deep Ensemble 2D CNN (DE-2DCNN) method for detecting lung cancer. At first, the gathered CT scans underwent pre-processing to remove any noise and extraneous data. Subsequently, the images underwent augmentation in order to mitigate the problems caused by class imbalance. Ultimately, the DE-2DCNN model was utilized to identify and categorize the Lung Nodules found in CT Scan pictures.
Kumar et al. [43] created an Enhanced U-Net model to automatically identify lung cancer nodules. In order to reduce noise and improve picture quality, the collected photographs were normalized and pre-processed with a thresholding model in this method. Next, the CT images were subjected to Dilated Convolutional U-Net (DC-U-Net) to extract profound characteristics and enhance information extraction without modifying picture parameters. Ultimately, the lung cancer prediction was made using the CNN model.
The authors Venkatesh et al. [44] presented a combined approach to lung cancer prediction using CNNs and patch processing applied to CT) scans. The image quality of acquired CT images was enhanced and noise was reduced using Median Filtering (MF) and patch processing in this method. The pre-processed images undergo a clustering segmentation procedure, which divides the image into segments and inputs it into a CNN classifier. The Convolutional Neural Network (CNN) was employed for the purpose of extracting features and performing classification.
A model for segmenting and classifying lung cancer was developed by Naseer et al. [45] using AlexNet-SVM. The procedure consists of three steps: lobe separation, candidate nodule extraction, and nodule categorization (malignant or non-cancerous). The lobes were precisely segmented and a mask was generated using the CT scan images by utilizing the altered U-Net architecture during the lobe separation process. Afterwards, an altered U-Net based on the projected mask was used to locate the candidate nodule mask using a candidate nodule extraction model. Ultimately, the adapted AlexNet-SVM model was utilized to categorize the potential nodules as either cancerous or non-cancerous.

3. COMPARATIVE STUDY

This section delves into a comparison analysis that aims to assess the pros and cons of several DL methods for lung cancer classification and prediction using CT images. Table 1 provides the technical specifications. Based on this research, the most optimal approach is given to address the limitations in cancer diagnosis, hence providing improved recognition and accuracy rates.

Table.1 Comparison of Different DL Frameworks for Lung Cancer Classification using CT data images

Ref No.	Techniques	Merits	Demerits	Dataset	Performances
[27]	Weighted Mean Enhancement IPCT DITNN	Enhanced the efficacy and feasibility of classification in real-time medical systems.	The presence of poor image quality in certain samples hindered the ability to make accurate predictions, and no attempts were taken to resolve this issue because to the imbalanced nature of the datasets..	Cancer imaging Archive (CIA) dataset	Accuracy = 94.5%; Precision = 94%; Recall = 96.8%; F1-Score = 95.4%
[28]	AlexNet	This model overcomes the challenges of small sample sizes and sparse, high-dimensional features	It struggled to discover an adequate search space for excellent classification due to a lack of prior knowledge of datasets.	Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD)	Accuracy = 93.55%; Sensitivity 95.714%; Specificity = 95%
[29]	Thresholding technique, vanilla 3D CNN	Increased rate of detection and reduced computational complexity	This model has lesser accuracy when used to larger datasets.	LUNA 16	Accuracy = 80%
[30]	Isotropic rescaling and density normalization. CNN SVM.	Classify histological phenotypes in lung cancer and present visually interpretable explanations for its predictions.	The parameters were inadequately tuned, resulting in worse performance of this model on larger datasets	NSCLC tumor histology database	Accuracy = 68.6% Area Under Curve (AUC) = 71%
[31]	MBP, IDNN, ELM, HSOIGRS	Reduce misclassification error and dimensionality by utilizing spiral settings and approximation methods to choose optimum features.	The system experiences challenges with scalability and has a slower rate of convergence	CIA dataset	Accuracy = 96.2%; Precision = 97.4%; Recall = 98%
[32]	U-Net, VGG-16	It accurately classifies CT images as either healthy or unhealthy, reducing the workload for radiologists.	Further experimentation was required to distinguish between various characteristics of cancer, a task that is impractical for extensive databases.	LIDC-IDRI, LUAN16	Accuracy (LUNA 16) = 97.1%; Accuracy (LIDC-IDRI) = 88.1%
[33]	CAD, Capsule network, CNN, SVM	Even in large dataset the features space characters were stable and robust	The local regions were hard to segregate while there was a huge number of opacities	LUAN16	Accuracy = 94%
[34]	HOE, AMF SCN and OPTL- WOA	Models parameter were well optimized which enhances the prediction accuracy and eliminates the uncertainty issues.	The considered database was limited, and the restrictions of hardware conditions were not solved.	LUNA-16	Accuracy = 98.5%, Precision = 99.0%, Recall = 98.8%;

[35]	VGG-16 and GoogleNet	This model enhances clinical decision-making and aids in early prediction of cancer and its types.	The database was not sufficient and the accuracy outcomes was not efficient	Lung Cancer CT images from different hospitals	Accuracy = 83%; F1-score = 89%.
[36]	GF, DenseNet-201, SMA, ENN SCMO	Each models' parameters was fine-tuned with optimization algorithms to reduce complexity.	Hinder convergence and finds difficult to destabilize training, especially on hardware architectures	LIDC-IDRI dataset	Accuracy = 99.3%; Sensitivity = 98.95%; Specificity = 99.47%
[37]	Customized CNN	This model results in better convergence rate provides generalization abilities for the diagnosis of lung cancer.	This model was only suitable for a limited number of samples and the restrictions of hardware conditions were not solved.	Publicly available "Kaggle" source lung cancer Dataset (CT scan Images)	Accuracy = 92%; AUC = 98.21%, Recall = 91.72%
[38]	3D Slice 3DCNN, 3D image	It offers 3D imaging capabilities, reducing healthcare professionals' workload and lowering the time and resources needed for diagnosis	Classification was difficult while few similar slice of CT images have multiple disease tags.	Lung-Pet-Ct-Dx, MosMedData	Accuracy = 89%
[39]	Various pre-trained CNN models	Data interpretation was efficient with low computational issues.	Trained with little data and not sufficient for full practical application	CIA and histopathologica l images	Accuracy = 97.86%; Precision = 96.39%; Sensitivity = 96.79%. F-Score = 97.96%
[40]	Residually connected Sep Conv 2D CNN, Modified Extreme Inception	Training is completed more quickly and computational complexity is decreased using this model.	This model fails to learn about the inner-slice depth so advanced segmentations model was necessitated to increase models performance.	IQ-OTH/NCCD and NCTS dataset	Accuracy = 99.39%;
[41]	Gaussian blur based linear filter-type technique CNN EOSA	The models parameters were optimized well, eliminating thhe uncerta9nitry issues and has high generalizability	Because of resource constraints, the sample size is too small, and possible data imbalances and time complexity are not taken into account..	IQ-OTH/NCCD lung cancer dataset	Accuracy = 93.21%; F1-score = 92.72% Recall = 90.71%
[42]	DE-2DCNN	This model works well on both large and smaller datasets	The issue of overfitting persisted due to a lack of consideration for a sufficient number of scans.	LUNA 16 Data set	Accuracy = 95%; Precision = 93%; Recall = 80%
[43]	DC-U-Net, CNN	It was more efficient to categorize High-intensity energy-spectral CT images for real-time medical systems.	When performing on few CT samples, this model provides lower results due to class imbalance data and poor image quality.	Publicly available "Kaggle" source lung cancer Dataset (CT scan Images)	Accuracy = 93.4%; Sensitivity = 98.4%; Specificity = 97.1
[44]	Median filtering and clustering	Flexible and effective in selecting relevant features from a training dataset for	The models results in high localization error, and in some cases generazability	LIDC	Accuracy = 98.86%

	segmentation, CNN	predicting the target variable.	error was high		
[45]	Modified U-Net and AlexNet-SVM	Reduced false positive and efficiently leverages the discriminative area detailed information to categorize lung disorders.	This model was highly efficient to train single dataset (LUAN16), but lacks the performances to train on other validated datasets	LUAN16 dataset	Accuracy = 97.98%; Sensitivity = 98.84%; Precision = 97.53%; F1-Score = 97.70%

4. RESULT AND DISCUSSSION

The performance evaluation of the existing DL approaches, as presented in Table 1, demonstrates the accuracy of overall prediction and classification in the context of lung cancer prediction. Most of the publications used the 888 CT scans that made up the LUAN16 dataset. There are 589 CT scans that were determined to be cancerous and 299 that were determined to be non-cancerous. Subsequently, further models employed the benchmark dataset to predict the occurrence of lung cancer. This section assesses the precision of various DL based models for predicting lung cancer by utilizing the LUAN16 dataset and other benchmark datasets. The visual depiction demonstrates the efficacy of these models in identifying and categorizing lung cancer using CT images.

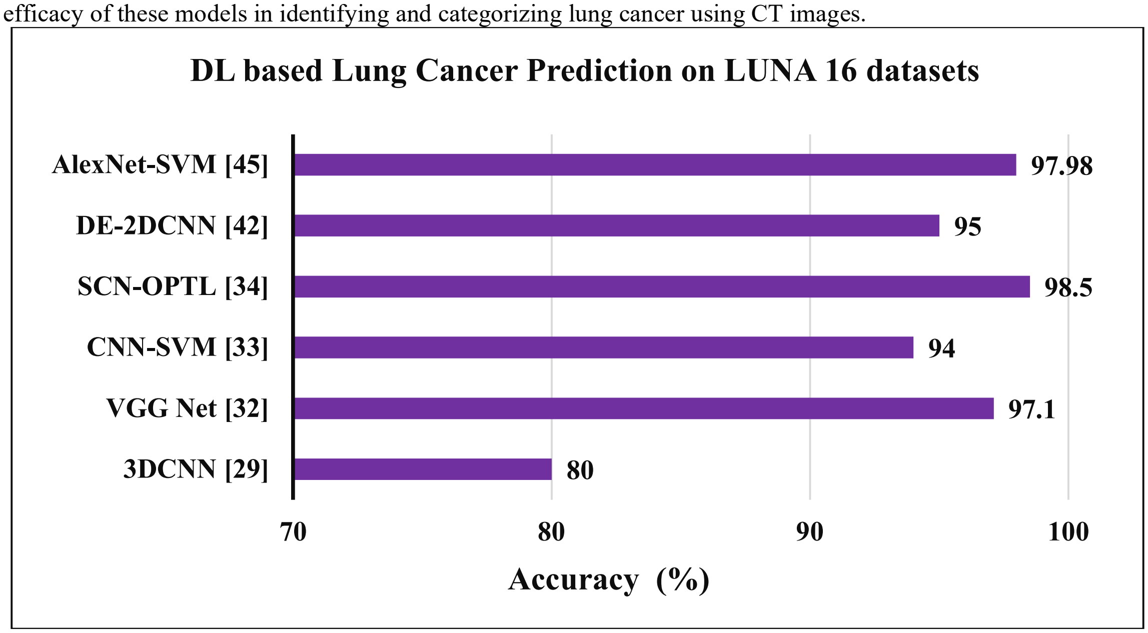

Figure 5 DL based Lung Cancer Prediction using LUAN 16 datasets

Figure 5 illustrates the utilization of DL for predicting lung cancer using a dataset called LUAN 16. Based on this investigation, it is evident that the SCN-OPTL [34] and AlexNet-SVM [45] models demonstrate high efficacy in predicting and classifying lung cancer. AlexNet-SVM demonstrates superior model performance compared to SCN-OPTL due to the limited database used for training SCN-OPTL and the unresolved hardware constraints. Additionally, our approach identified a significant number of false positive instances and was unable to accurately categorize lung illnesses based on the distinguishing areas. The limitations of SCN-OPTL are overcome by using the AlexNet-SVM modified U-Net architecture for lobe segmentation and CT scan image mask generation. Next, in order to distinguish between the expected and candidate nodule masks, the candidate nodule is identified by employing a modified U-Net. The candidate nodules were classified as malignant or non-cancerous using the Modified AlexNet-SVM model. Additionally, AlexNet-SVM effectively minimizes the occurrence of false positive cases and optimally utilizes the detailed knowledge of discriminative areas to classify lung illnesses without any loss of information.

Figure 6 illustrates the utilization of DL for predicting lung cancer utilizing alternative benchmark datasets. Based on this investigation, it is evident that the MEIM [40] models outperform other existing models when employing different benchmark datasets (IQ-OTH/NCCD and NCTS) for lung cancer prediction and classification. The original XceptionNet was applied to the Imagenet dataset by passing it through the designated convolutional layers, as shown in [40]. The Sep Conv 2D layers address the inherent problems of traditional CNNs and offer a higher rate of convergence. Ultimately, the lung cancer diagnosis utilized the modified Extreme Inception model.

Additionally, this model offers accelerated training time and decreased computing complexity. This makes it a valuable tool for radiologists and nephrologists in the early diagnosis of lung cancer and chronic kidney disease, respectively.

According to the results of the two aforementioned analyses, MEIM [40] models operate effectively on the IQ-OTH/NCCD and NCTS datasets, while AlexNet-SVM works better on the LUAN 16 datasets. Nevertheless, the MEIM model lacks the ability to acquire knowledge about the depth of the inner-slice. Therefore, an advanced segmentation model was required to enhance the performance of the models. AlexNet-SVM demonstrated efficiency in training a single dataset (LUAN16), however it lacks the capability to effectively train on additional verified datasets for the purpose of lung cancer diagnosis.

The drawbacks of these models will be addressed in future proposed models by incorporating models that can be trained on diverse lung cancer detection datasets, introducing advanced segmentation models, improving detection speed, and reducing computational complexity. Additionally, the upcoming model aims to train by merging CT scans from LUAN 16 and other established lung cancer datasets. Through comprehensive training on diverse datasets, the future model improves the performance of real-time applications by accurately recognizing distinct characteristics of lung cancer nodules and providing tailored treatment options. By analyzing extensive medical picture datasets, this technology offers researchers valuable insights into the characteristics, development, and potential treatment approaches for lung cancer.

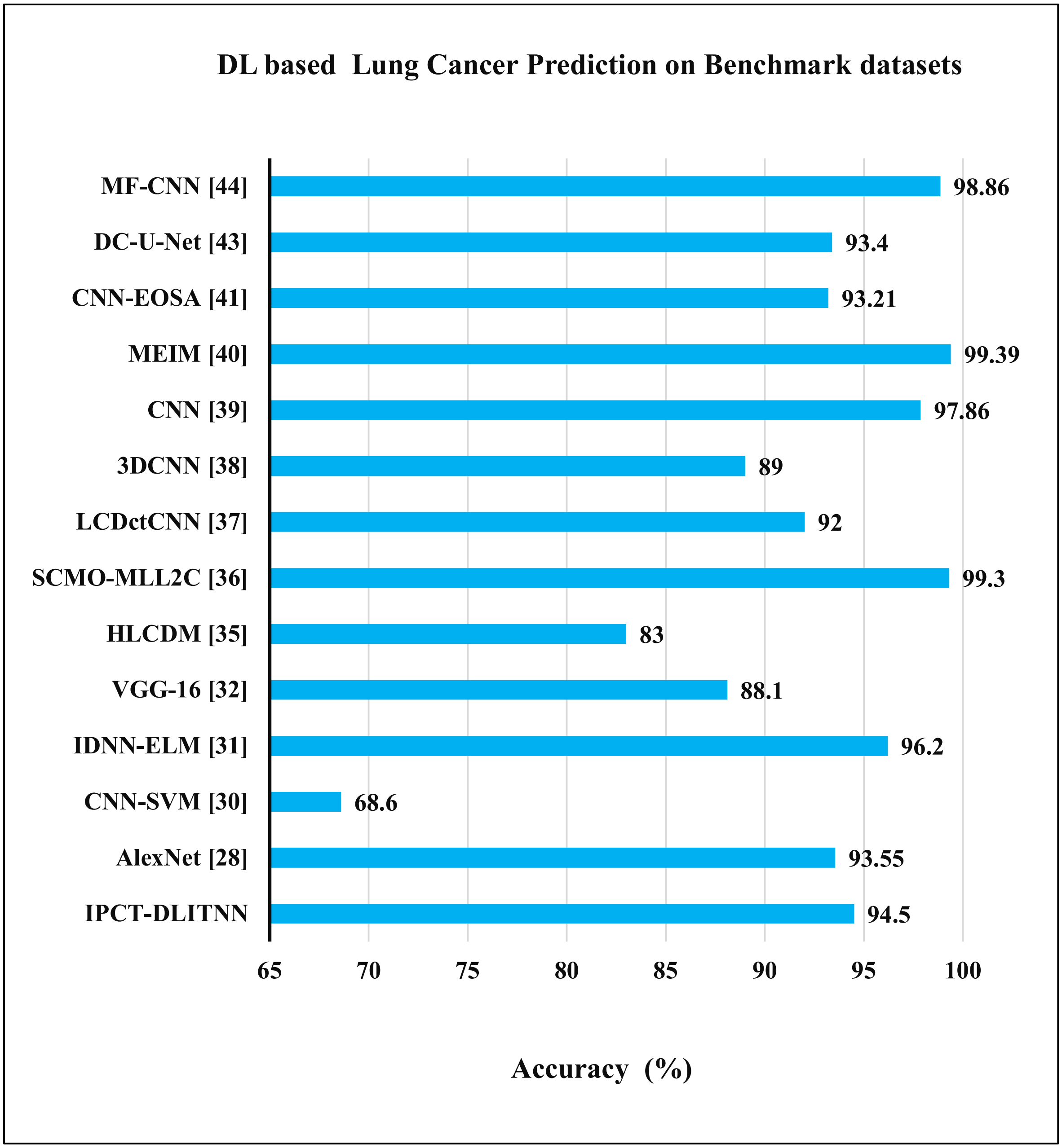

Figure 6 DL based Lung Cancer Prediction on other benchmark datasets

.5. CONCLUSION

Lung cancer is a perilous and demanding illness that impacts both males and females, requiring prompt and precise evaluation of nodules. Reducing mortality rates requires early identification of cancer. Recently, DL algorithms have found widespread use in the early diagnosis of lung cancer. This research investigates different DL methods for predicting lung cancer, analysing their strengths, weaknesses, and performance effectiveness. The problems and successes that have been found provide researchers with important starting points for creating models that can be used to identify and prevent lung cancer. The problems and successes that have been found provide researchers with important starting points for creating models that can be used to identify and prevent lung cancer. This facilitates decision-making and precise prediction of outcomes from a vast picture library. In order to improve lung cancer therapies, future studies will investigate how to train complex models on various datasets, how to locate nodules, and how to analyse large medical image databases.

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