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A Review on Detection and Classification of Lung Nodules using Deep Learning Methods

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ABSTRACT

This paper extensively explores the application of deep learning techniques for early lung cancer detection through medical imaging, specifically CT scans and X-rays. The discussion covers a range of methodologies, including feature recognition, machine learning optimisations and the use of advanced neural networks like CNNs, DenseNet, and YOLOv5. The key findings highlight the effectiveness of innovative algorithms such as adaptive boosting with DenseNet and hybrid CNN-SVM approaches, achieving impressive accuracy rates. These approaches not only enhance precision in distinguishing between cancerous and non-cancerous nodules but also contribute to the overall efficiency of early lung cancer detection. The study underscores the significance of techniques like data augmentation, transfer learning, and pre-processing methods, which play crucial roles in improving the accuracy and computational efficiency of deep learning models. This review signifies the substantial potential of advanced computational methodologies, particularly deep learning algorithms. A comprehensive survey has been carried out, and essential aspects are presented.

Keywords – Lung cancer, Convolutional Neural Networks (CNNs), DenseNet, Deep Learning (DL), Support Vector Machines (SVM), YOLOv5.

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I. INTRODUCTION

Cancer is the second-most frequent cause of death worldwide, trailing behind cardiovascular diseases, where lung cancer stands as second most dangerous disease. The American Cancer Society (ACS) estimates that there were 1.762.450 new cases of cancer in the US in 2019, with lung cancer making up 13% of those cases, out of which 228,150 were new cases [2]. According to US statistics, lung cancer comes in first among cancer-related deaths, responsible for 24% of all cancer deaths [2]. These numbers demonstrate the urgent requirement for more sophisticated lung cancer treatment techniques. Lung cancer claims the lives of over 7.6 million people annually around the globe, according to data from the World Health Organisation (WHO). Predictions suggest that the number of cancer cases may increase and reach roughly 17 million by 2030 [12]. Cancer, accountable for one in six annual deaths, exhibited a particularly grim toll in 2016, with lung cancer topping the charts at 1.76 million fatalities.

The lungs, the primary organs of the respiratory system, are segmented into lobes, with the right lung comprising three lobes, slightly larger than the left lung with two lobes. Separated by the mediastinum, this region houses the heart, trachea, oesophagus, and numerous lymph nodes. Encased in a safeguarding membrane called the pleura, the lungs are shielded from the abdominal cavity by the muscular diaphragm. In Fig. 1 a human lung is depicted.

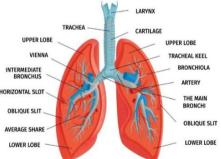


Fig. 1: Human lungs (<u>https://www.vecteezy.com</u>)

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Lung abnormalities can have a substantial impact on one's health. Fig. 2 illustrates how abnormalities in particular anatomical regions can have a noteworthy effect on lung health, encompassing lung cancer.

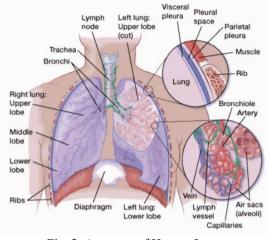


Fig. 2: Anatomy of Human Lungs (<u>https://www.cancer.org</u>)

Lung cancers typically start in the cells lining the bronchi and parts of the lung such as the bronchioles or alveoli, the main air passages leading to the lungs, and can extend to other parts of the lungs, including the bronchioles (smaller airways) and alveoli (tiny air sacs where oxygen exchange occurs). These cancers often arise due to the abnormal and uncontrolled growth of these epithelial cells, forming tumours that can interfere with normal lung function. As the cancer progresses, it may invade surrounding tissues and, in advanced stages, potentially spread to other organs through the bloodstream or lymphatic system. Early detection and understanding the specific cell types involved are crucial for effective diagnosis and treatment of lung cancers.

Deep learning (DL) enables the extraction of abstract representations of data by utilising deep neural networks. The extent to which a cancer has spread is indicated by its stage. Cancer in the lungs is referred to as being in stages I and II, while cancer that has spread to other organs is referred to as being in later stages. Currently used diagnostic techniques include imaging tests like Computed Tomography (CT) and X-ray scans, as well as biopsies.

It is more challenging to identify lung cancer early on because there are fewer symptoms in the early stages of the disease. There is a chance that lung cancer will spread to other organs. Metastases is the term used to describe how cancer cells spread to different organs. Fig. 3 shows the difference between a healthy lung and a damaged lung.

Accurate identification of lung nodules is paramount in medical image analysis. This study

conducted a comprehensive examination of widely recognised deep learning models—CNN, DenseNet, SVM and YOLOv5 to address this critical healthcare concern.

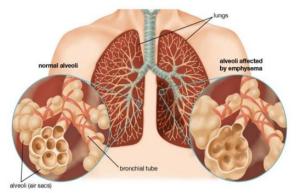


Fig. 3: Normal and affected lungs (https://www.britannica.com)

The demonstration of these models in detecting lung nodules was assessed through metrics such as F1-score, accuracy, precision, and recall. Utilising a dataset reflective of real-world scenarios, the study aimed to discern which machine learning framework excelled in this life-saving task. The results help in the development of methods for accurate and timely lung nodule detection by providing insightful information to the medical community.

II. LITERATURE SURVEY

Lately, deep learning has emerged as a promising avenue for improving identification of lung cancer. Leveraging complex neural networks and sophisticated algorithms, DL models exhibit the capability to enhance the accuracy and efficiency of early detection methods. This literature survey explores the evolving landscape of lung cancer detection, examining key advancements, challenges, and the transformative impact of artificial intelligence in revolutionizing diagnostic approaches for this critical health concern.

In paper [1], using CT scan images, the process of detecting lung cancer consisted of two stages: feature recognition and machine learning application. Relevant features are taken out of the CT scan images in the initial stage. Techniques including feature extraction, segmentation, and image preprocessing might be used for this. During the second stage, the retrieved features are classified as either non-cancerous or malignant by utilizing machine learning techniques. There are several machine learning techniques that have been proposed for identifying lung cancer, including Support Vector Machine (SVM), Naive Bayes, artificial neural networks, and decision trees.

A Computer-Aided Detection (CADe) system for deep learning optimisation in the early detection of lung cancer [2]. Selection, extraction, and preprocessing of features and classification are the four phases of the system. The preprocessing stage enhances the contrast of the Low-Dose Computed Tomography (LDCT) images and removes noise. Convolutional neural network (CNN) is applied to the LDCT images during the feature extraction phase to extract features. A Genetic Algorithm (GA) is utilised in the feature selection stage to identify the most pertinent traits for lung nodule detection. The classification stage makes use of SVM to identify if the LDCT images are malignant or benign. The accuracy, sensitivity, and specificity of the suggested CADe system are 96.25%, 97.5%, and 95%, respectively.

The study suggests a computer-aided system that makes use of deep learning techniques for lung cancer detection in order to lessen this difficulty in [3]. Utilising the AlexNet architecture, a CNN technique is used to analyse the input dataset that was collected from hospitals in Iraq. The introduced model demonstrates high accuracy, reaching up to 93.548%, showcasing its effectiveness in distinguishing between normal, benign, and malignant cases. Further performance metrics highlight the agility of the suggested model, with sensitivity at 95.714% and specificity at 95%. This study represents a significant advancement in the use of AI for early diagnosis, which will increase the survival rates of lung cancer patients.

The method classified lung images as either malignant or normal by using adaptive boosting and DenseNet (Densely Connected Convolutional Networks) in [4]. DenseNet is a deep neural network architecture known for its dense connections between layers. It introduces direct connections from any layer to all subsequent layers, which encourages feature reuse and strengthens feature propagation throughout the network. With a dataset of 201 lung images split for training (85%) and testing (15%), the method achieved an impressive accuracy of 90.85%. This method highlights the capability for cutting-edge AI models to support early detection of lung cancer, which is essential for boosting survival rates and treatment outcomes. It does this by improving detection accuracy.

Used CT images from the Lung Image Database Consortium (LIDC) to classify lung cancer using Deep Convolutional Neural Networks (DCNN) in [5]. Improving the precision of distinguishing between malignant and noncancerous lung nodules was the aim, as this is a critical stage in effective lung cancer therapy. Robust identification of lung nodules was difficult due to their complexity. The study aimed to strengthen the accuracy of lung cancer detection and recognition from CT images by using DCNN to outperform current methods in this regard. This underscores the potential of advanced machine learning techniques.

Employing CADe to process lung CT images for identifying traces of cancer was done in [6]. For image classification, the suggested method presents a hybrid CNN and SVM algorithm. The algorithm uses SVM to weed out irrelevant information and CNN algorithm's training efficiency and parameter reduction capabilities to automatically analyse each lung image for the existence of cancer cells. The study evaluates the algorithm's performance, demonstrating its effectiveness with a remarkable 97.91% accuracy in classifying lung images. These encouraging findings highlight the applicability of the technique and its potential for precise classification of lung cancer using CT scans, highlighting the role that computer-aided techniques play in boosting early identification and raising survival rates.

By making use of CNN, which have emerged as a potent aid for medical image analysis in [7]. CNN algorithms are useful for tasks like diagnosing lung cancer because they are very good at extracting features from images. The deep neural networks included in MATLAB were utilised by the study's authors to estimate the potency of CNN in lung cancer diagnosis. MATLAB provides a comprehensive environment for deep learning research, offering tools and libraries specifically designed for building and training neural networks. For improving the CNN model's accuracy, preprocessing was applied to the input images to remove noise. Because median filtering works so well at maintaining the sharpness and edges of images, it was selected as the noise reduction method. Median filtering replaces each pixel's value with the median value within its local neighbourhood.

Given the difficulty of diagnosing lung cancer at a later stage, [8] is concentrated on the problem of early detection of lung cancer using LDCT images, which is essential for improving survival rates. LDCT scans offer lower X-ray doses but poorer image quality compared to normal CT scans. To address this, the study proposed a methodology leveraging both machine learning and deep learning, specifically employing CNN for attribute selection and categorization. The capability for early cancer identification with LDCT images was enhanced by the CNN technique, which demonstrated promising results in nodule detection and classification. The study also covered available datasets, illuminating potential paths and obstacles in the field, and pointing researchers in the direction of more efficient approaches for early lung cancer identification using LDCT images.

While highlighting the many imaging modalities used in lung cancer detection, it also draws attention to their shortcomings, especially about automatically classifying cancer images and managing patients with coexisting diseases. To address these challenges, [9] focuses on leveraging deep learning, a rapidly growing field in medical imaging. Promising methods for quickly and precisely identifying and categorising lung nodules in medical snapshots include deep learning techniques. The study highlights the latest developments in deep learningbased imaging methods specifically designed to identify lung cancer early on, underscoring their potential to improve diagnostic sensitivity and accuracy.

Acknowledging the significance of precise forecasts, [10] suggests an automated instrument that utilizes ANN to identify anomalous growth in lung tissue. This involves the analysis of lung images from both healthy and malignant individuals, utilizing databases with various views of CT scans. A neural network, leveraging textural characteristics, classifies normal and malignant images. The VGG-16 architecture is used by the CNN and Google Net deep learning algorithms to further increase accuracy. Results from confusion matrix computation and classification accuracy show that the suggested algorithm detects and classifies cancer with an astounding precision of 98%. It offers a promising first step towards the evolution of an automated tool with great reliability for lung cancer early detection.

The proposed method in [11] comprises three stages: preprocessing, segmentation, and classification. To preserve image sharpness for precise segmentation, preprocessing uses a geometric mean filter to eliminate noise from CT scans. In segmentation, lung nodules are identified by pixel similarity using K-means clustering because nodules are generally brighter and more homogeneous than the surrounding lung tissue. Artificial Neural Networks (ANN) are used in classification to categorize lung nodules as benign or malignant. ANN are best for nodule categorization because of their capability to learn intricate patterns from data, which is inspired by the system of the human brain. The approach achieved a 95% classification accuracy for lung nodules when tested on an input dataset of CT scan from patients with lung cancer. Comparing this to conventional diagnostic techniques, which typically yield accuracy levels of 80% or higher, shows a significant improvement.

The six-stage design in [12] involves symptom-based lung cancer identification using a Random Forest (RF) Classifier, CT scan classification with a CNN, and nodule detection making use of a UNet model. Additionally, a RF Regressor predicts medical insurance costs. The web application incorporates interactive Plotly graphs for data analysis and provides a user-friendly interface with four main buttons for different functionalities. The system achieved high accuracies, including 96.9% for symptom-based detection, 92.42% for CT snapshot classification, and 98% for nodule detection. The proposed strategy, encapsulated in a Flask web application, promises accurate results in real-time, making it an organized aid for lung cancer identification and cost estimation. The study also details data processing steps and emphasizes the application's user-friendly design and accessibility.

Leveraging the capability of CNNs to pull out critical attributes from images, the project involves the evaluation of CT scan slices to establish a machine learning model. The 3D CNN are employed in [13] to discover the existence of cancer by evaluating and preprocessing the data. The goal is to identify and address cancerous cells at their earliest stages. The research utilized the "Cancer Imaging Archive" dataset, implementing a pre-processing step to standardize the size and format of CT images before model training. The resulting model demonstrated a high accuracy of 93%, and the analysis metrics, including Precision, Recall, Kappa, and F1 score, further underscore the model's effectiveness in classifying lung nodules as either cancerous or noncancerous. With precision at 0.68669, recall at 0.64384, kappa score at 0.39733, and F1 score at 0.62699, the model exhibits promising performance in lung cancer detection by using 3D CNN.

Employing the LIDC/IDRI dataset from the Lung Nodule Analysis (LUNA16) challenge, the CNN version is built following a successive approach with convolutional loops, max pooling layer, flattening layer, fully connected layer, and the output layer in [14]. The algorithm, named CNN-based Automatic Lung Cancer Detection (CNN-ALCD), is designed for supervised learning, and demonstrates the capability to diagnose lung cancer from newly arrived test samples. The suggested CNN model, trained and tested on an input dataset of 343 lung CT images, exhibits a correctness of 94.11%, surpassing existing designs like ANN (90.24%) and Multilaver Perceptron (MLP) (92.12%) in predicting lung cancer. The study emphasizes performance evaluation using metrics such as accuracy and confusion matrix.

There are limitations in the utility of thoracic radiography, particularly chest X-rays, due to a shortage of skilled radiologists. To prevail over this obstacle, the paper [15] suggests the utilization of a modified model, MobileNet V2, for the classification and prediction of frontal thoracic X-rays. Highlighting the probable life-saving impact of (CT) in detecting tumours early, the study highlights the load on radiologists in analysing a large volume of CT images and the associated observer fatigue. The proposed technique, evaluated using the NIH Chest-Xray-14 database, outperforms contemporary pathology classification algorithms, with an AUC of 0.811 and an accuracy exceeding 90%. Notably, resampling the dataset remarkably improves the model's performance, aiming to outline a model that is easily trainable, requires less computational energy, and hence could be deployed on smaller IoT devices.

To strengthen the training data, the CT-scan snapshots are resized to a standard size and data augmentation techniques are applied in [16]. For picture categorization, 3 deep learning approaches are investigated: the sequential model, the functional model, and the pretrained VGG-16 model. The functional model uses two convolution layers, further by five additional layers, whereas the sequential model makes use of five convolutional loops with increasing filter numbers. A pretrained CNN renowned for its great accuracy is the VGG-16 model.

To prevail over the flaws of prior lung cancer identification, the paper [17] suggested Deep Ensemble 2D CNN model which achieves better accuracy, precision, and recall because it is specifically made for lung tumour identification using CT scan data. The productiveness of the design is attributed to its role to extract relevant information via CNN blocks and merge predictions from numerous deep neural networks, hence augmenting the classification precision overall.

A CNN is constructed using TensorFlow, aiming to predict multiple diseases with a single model in [18]. The CNN undergoes incremental training on an input of 5411 X-ray images, demonstrating its effectiveness in disease prediction. The design is estimated by making use of an Image Data Generator, achieving a correctness of approximately 91% on a test dataset. This study emphasises the need of precise pre-processing and shows how CNN could be used for a diffusion of medical image processing applications outside of lung diseases, such as making predictions using MRI images for early disease detection, such as Lung Cancer and Bronchitis.

To strengthen the overall functioning of DL designs, researchers have made use of an expansion of methods, such as transfer learning, augmentation, and data pre-processing. In the study [19], transfer learning has proven promise in utilising pre-trained designs for lung cancer identification applications. Although deep learning has made immense step, issues like the insufficiency of labelled dataset and the necessity for more broadly applicable models still require additional investigation.

YOLOv5, an advanced object detection system, for identifying lung cancer lesions in chest Xrays. Using a dataset from Kaggle, the design was trained and fine-tuned, optimizing parameters and employing augmentation techniques to enhance accuracy in paper [20]. Results were impressive: the model displayed high proficiency in accurately identifying cancerous areas, surpassing previous methods in a distinct test set. Notably, it exhibited computational efficiency, enabling real-time detection, which could aid in clinical integration. In general, this proposal shows promise in supporting radiologists for early detection, diagnosis, and prompt treatment of lung carcinoma, potentially improving patient outcomes.

In summary, the literature survey emphasizes the significant progress made in deploying deep learning (DL) techniques for the identification of lung cancer through medical imaging, with a focus on CT scans and X-rays. The incorporation of various machine learning strategies and sophisticated DL architectures, alongside the development of computeraided systems, reflects substantial advancements in early detection capabilities. The utilization of innovative methods, including CNNs, SVMs, and ensemble models, showcases promising accuracy rates, indicating the potential to improve patient outcomes through timely identification and intervention. Despite persistent challenges such as limited datasets and the need for enhanced generalizability, the ongoing evolution of these techniques holds great promise in transforming lung cancer diagnostics and enhancing survival rates. The convergence of artificial intelligence and medical imaging marks a significant frontier in healthcare, signifying a crucial shift towards more effective and precise diagnostic tools for lung cancer. The survey notably highlights diverse approaches encompassing attribute recognition, machine learning optimization, and the application of advanced neural networks like CNNs, DenseNet, and YOLOv5.

Table 1: Comparison of methodologies used

Paper	Methodology	Key Findings	Conclusion
[1]	CT Scan + ML	Two stages: Feature Recognition and ML Application	SVM, Naïve Bayes, ANN, Decision Trees
[2]	CADe + Deep Learning	4 Phases: Selection, Extraction, Pre- processing, Classification	SVM, 96.25% Accuracy, 97.5 Sensitivity
[3]	Deep Learning (AlexNet)	CNN analysis of hospital dataset (Iraq)	93.548% Accuracy, 95.714 Sensitivity
[4]	Adaptive Boosting+ DenseNet	Malignant or Normal Classification	90.85 Accuracy
[5]	DCNN on LIDC Images	Distinguishing Malignant vs	Precision in Distinguishing Improved

		Noncancerous	
		Nodules	
[6]	CAD + CNN-	Hybrid CNN-	97.91%
	SVM	SVM	Accuracy
		Algorithm	,
[7]	CNN in	Utilization of	Improved
L' J	MATLAB	MATLAB and	CNN Model
		Median	Accuracy
		Filtering	i ioouiuoj
[8]	LDCT +	CNN for Early	Enhanced
[0]	Machine	Cancer	Early Cancer
	Learning	Detection	Detection
[9]	Deep Learning	Focus on Deep	Potential to
[2]	in Medical	Learning for	Improve
	Imaging	Lung Nodule	Diagnostic
	iniaging	Identification	Sensitivity
[10]	ANN for	Utilization of	98% Precision
[10]	Anomalous	ANN with	in Cancer
	Growth	VGG-16	In Cancer
		VGG-10	
6117	detection	TT:::: 0	0.50/
[11]	Preprocessing,	Utilization of	95%
	Segmentation,	ANN for	Classification
	Classification	Nodule	Accuracy
		Categorization	
[12]	Six- Stage	Random	High
	design	Forest, CNN,	Accuracies for
		UNet for	Different
		Detection	Functionalities
[13]	3D CNN	Utilization of	93%
[]			

[13]	3D CNN	Utilization of	93%
		3D CNN for	Accuracy
		Cancer	
		Detection	
[14]	CNN-based	CNN Model	94.11%
	ALCD	for Cancer	Correctness
		Detection	
[15]	MobileNet V2	Modified	AUC of
	for X-ray	model for	0.812,
	Classification	thoracic X-rays	Accuracy >
51.63		· · ·	90%
[16]	Data	Investigation	Evaluation of
	Augmentations + CNN Models	of three deep	Sequential, Functional
	+ CNN Models	learning	and Pretrained
		Algorithms	VGG-16
			Model
[17]	Deep Ensemble	Improved	Specifically
[1/]	2D CNN	Accuracy,	made for
	2D CININ	Precision and	Lung Tumour
		Recall	Detection
[18]	CNN for Disease	Incremental	Accuracy of
[10]	Prediction	Training of X-	approximately
	1100101011	ray Images	91%
[19]	Transfer	Utilizing Pre-	Promising
. · · 1	Learning	trained Models	results but
	Ŭ	for Lung	Challenges
		Cancer	remain
		Identification	
[20]	YOLOv5 for	Object	Real time
	Object Detection	Detection for	Detection and
		Lung Cancer	Clinical
		Lesions	Investigations

III. PROPOSED METHODOLOGY

Based on the findings of the review, the proposed architecture includes steps which involves, collecting data that is pertinent to the problem to be solved. The data should be cleaned for training the model. The data is divided into three sets: training, validation, and test sets. The training set is used to train the model, the validation set is used to evaluate the performance of the model on unlabelled data, and the test set is used to evaluate the overall performance of the model. If the model is not performing well on the validation data, iterate on the previous steps by varying various parameters. Further, by feeding the data to the model, it's allowed to learn from the data. Once the performance of the model on the validation data is satisfying, it can be evaluated on test data. The overall operations are as shown in Fig. 4.

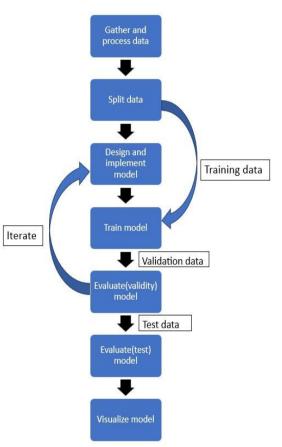


Fig. 4: Proposed Architecture

IV. CONCLUSION

The paper discussed about thorough overview of the great progress made using DL techniques for lung cancer identification from medical snapshots, particularly CT scans and X-rays. The evolution discussed exhibited the probable ease of building DL into diagnostic aids for lung cancer. The studies consistently showcase impressive results, with accuracy rates varying from 90.85% to as high as 98%.

Some of the advantages of this work could be, many of the analysed studies show great accuracy rates exceeding 90%, reflecting the success of DL Suchitra M, et. al. International Journal of Engineering Research and Applications www.ijera.com ISSN: 2248-9622, Vol. 13, Issue 12, December 2023, pp 49-56

models in categorizing between normal and malignant cases. The survey points out a diffusion of methods, along with attribute recognition and the importance of advanced neural networks like CNN, DenseNet, and YOLOv5. The evolution of modern CADe systems, as examined in several papers, specifies a vary towards computerized tools that can aid healthcare professionals in early lung cancer identification.

The major limitation discovered was dataset insufficiency. Despite the betterment made, problems like the lack of labelled datasets remain as a trouble, stressing the necessity for additional research and the designing of more extensive datasets. DL models, mainly CNN, lack interpretability, making it difficult to understand the logic for the predictions.

Early detection is crucial for enhancing survival rates and to give an effective treatment. CADe systems could help as precious tool for healthcare professionals, enhancing diagnostic accuracy.

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