A Study on Lung Cancer Detection in CT Images Using Medical Image processing with Deep Learning Techniques

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***Abstract*—Several medical imaging applications have shown success with deep learning, ushering us further into AI technology. For a single activity, the availability of massive amounts of data with annotations, as well as developments in high-performance computing, are widely credited with AI's success. Medical imaging, on the other hand, poses distinct problems to DL techniques. Deep learning algorithms have recently gained traction as the preferred mode for processing medical images. Because of their efficient learning abilities and ability to deal with complex problems relatively rapidly, these algorithms are appropriate for handling certain image processing issues. Lung cancer is the most diagnosed cancer; many people have been infected, and if the disease is not detected early on, the patient has barely any chance of survival. Artificial intelligence methods for early detection are required for the reasons mentioned above and to help in the fight against this terrible disease. This study gives a brief overview of the various Deep Learning technologies utilized in lung cancer detection and their performance. Rather than providing a full literature review, we discuss published research relevant to these case Scenarios. We'll wrap things up with a recommendations and explanation of some successful potential possibilities. Metrics such as sensitivity, accuracy and specificity will be used to evaluate the effectiveness of this strategy.**

Keywords—lung cancer, CT images, artificial neural networks, deep learning, convolutional neural network, support vector machines

I. INTRODUCTION

Cancer is known as the uncontrolled growth of cells, it is called lung cancer when it occurs in the lungs. Most cancer-related deaths occur as a result of lung cancer. [12]. The greatest public health concern is lung cancer in Europe, the United States, Middle East. [14] [15] [10]. To effectively combat the burden of this type of cancer, early detection and treatment are required [10]. Lung cancer seems to be the often-diagnosed cancer and the leading factor in cancer-related fatalities globally. [9]. If not detected in time, tumors in lung cancer form abnormally and spread to other parts of the body, where they might cause invasive consequences. [4]. Professionals can analyze the functions of organs and tissues by using various modalities. CT modalities are frequently used for lung cancer diagnosis because they can clearly visualize body parts and are accurate. As well as detecting lung cancer at an earlier stage, CT imaging can also help diagnose it. In CT lung images the diagnosis of the carcinoma is the most demanding task and the segmented nodule is important in providing information for the diagnosis of the carcinoma. [12].

Lung nodules are most often diagnosed and treated by CT, and automatic 3D segmentation aids in the detection and monitoring of nodules on CT. It can be helpful in determining the location and size of lung nodules, as well as the prerequisites for resecting liver and tumors, with computer-assisted 3D lung nodule segmentation and positioning. [16] [11]. In the past, CT was the best imaging modality for diagnosing tiny pulmonary nodules due to the development of helical technology. [17] [18] [10]. The CT images are high-resolution images that require a lot of storage space. As a result, researchers are working to make it easier for radiologists to analyze these large images and discover probable nodular lung tumours using a computer-aided diagnosis approach (CAD) [19] [10]. By segmenting the lung image, one can remove the extraneous parts and preserve the relevant region for further analysis, which is crucial for accurate nodule detection and characterisation. Frequently employed strategies by researchers are lung segmentation depends on thresholding and region growth. [7].

To aid in the diagnosis of lung nodules and to better describe Imaging features such as segmentation and classification would be trustworthy. [9]. As a result of its effectiveness in a multitude of scenarios, deep learning has lately acquired favour in CAD systems. Deep learning technology has already proven to be successful in a number of medical image processing applications. In recent years, deep learning architecture has been applied in the detection of pulmonary nodules on CT scans. Artificial neural networks and many other heuristic algorithms constitute Deep Learning techniques, are a part of Artificial Intelligence. [20] [2]. The main reason for the tumour severity stage diagnosis process is that researches found the inner boundary of tumour regions in aberrant lung images. In lung CT images, several standard lung tumour detection techniques detect and segment tumour areas. Utilizing machine learning techniques, some researchers have determined the severity level of cancer in lung CT images. [13].

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II. METHODOLOGY

To analyze medical images, different studies employed different approaches. Preprocessing, lung nodule segmentation, classification, and lung cancer detection were the most significant. The following figure 1 illustrates the methodology's block diagram.

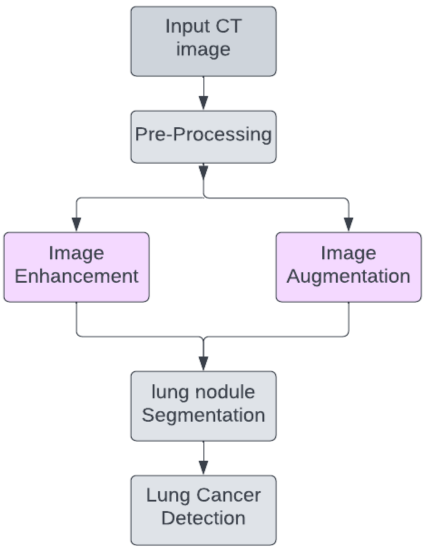

Fig. 1. The methodology's block diagram

A. *Data Collection*

The first phase is to get CT images of lungs. [50] LIDC-IDRI has CT images of labelled lesions for lung cancer detection and screening. This is a global resource for such creation, analysis, as well as training of CAD approaches in lung cancer diagnosis that is able to be accessed. A total of 1018 samples were included in the collection of data, was developed in partnership with eight medical imaging companies and seven academic institutions. Every subject includes images from an XML file and a clinical thoracic CT scan containing the conclusions. The CT scans individually assessed by the radiologist and assigned lesions into categories. ("nodule > or =3 mm," "nodule 3 mm," "non-nodule > or =3 mm") in the early stage.

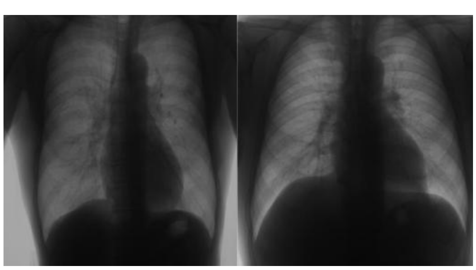

Fig. 2. sample CT images of Lung nodule

B. *CT Scanners*

A computed tomography scan, often known as a CT scan, generates detailed images of the body's internal components. CT scans are painless since they are non-invasive. These CT scans are used to better analyze soft tissues and more complex areas of the image that an x-ray might not be able to distinguish. CT scans are commonly used to examine and image blood arteries and interior organs. [12] [45] CT scans assist medical professionals in making diagnoses such as detecting tumors, inspecting fractured bones, and monitoring the effects of treatment on cancer patients.

C. *Preprocessing*

Image pre-processing is the vital phase. Many pre-processing strategies have been developed, each of which can be employed in a variety of situations. It is critical to use correct pre-processing techniques to maintain image quality. [31] As a result, image preprocessing is frequently the initial step in medical image processing, and it is used to improve image attributes such as quality, contrast, and noise reduction.

The goal of image enhancement [46] is to improve the perception of information from an image by distinguishing between different items in the image. Anything that makes it easier or better to visually understand an image is considered an image enhancement. The enhanced image may appear to be worse in some situations, such as "low-pass filtering," but in reality, it was probably done to make it easier for the interpreter to distinguish low spatial frequency characteristics from the usual high-frequency clutter in an image. In addition, for a given application, an augmentation is conducted. In medical image processing, the quantity of datasets is limited. [47] Data augmentation strategies must be used to address this difficulty. Image augmentation is a useful tactic when we lack the data necessary to train a deep learning model. CT images are unprocessed. In pre-processing CT images are extract the lesion regions effectively by eliminating noise. The phases of pre-processing are as follows, before training, all images were turned into a specific size by lowering the dimensions in the first phase. For retrieving information from images, next edge detection is employed. It is a basic procedure that identifies the shape of an image as well as the boundaries between elements and the surroundings in an image. The intensity values are then normalised in the last step by turning the image back to its original state and applying histogram equalization and smoothing edges.

D. *Lung Nodule Segmentation*

Segmentation is the task of separating an input image into many sections known as segments in deep learning. We can process the input image by dividing it into distinct pieces and utilizing specific segments of the image. For each object in the image, segmentation creates a pixel-by-pixel mask Image segmentation is applied in medical image processing to segment a variety of image modes. Lung nodule segmentation is required for the study of image characteristics in CT of Lung nodule images and the distinction of benign and malignant. Deep learning segmentation methods 3D SegNet and 3D U-Net were utilized. [14] Combined output of segmented images provides a complete image. There have been a number of segmentation techniques developed in recent years.

a) U-NET

U-Net was suggested by Ronneberger et al. (2015) as an object segmentation technique for medical images, and now it is the most widely used segmentation approach in medical images. The difference among FCN and U-Net has been that the information used to code the convolutional image is also used to decode it (Shelhamer et al., 2017). The network model's parameters were optimized using the mini-batch gradient descent approach in this study. A five-fold cross-validation procedure was used. [48] U-Net Segmentation has produced improved outcomes in terms of predicting lung nodule detection and, in turn, the level of malignancy.

b) SEGNET

Badrinarayanan et al. (2017) presented SegNet as a segmentation model for object areas in 2016. The encoder and decoder structures of SegNet are identical to those in U-Net. SegNet uses unpooling instead of convolutional transposition, like U-Net does.

E. Support Vector Machine

Support Vector Machine [1], [7] is a classification algorithm. It is used to analyze data and recognize patterns, as well as classify data by finding distinct patterns. A collection of input data is reviewed first, after which two classes are classified. For detection, these classes are given to the classifier. In this study, SVM is used to classify abnormal images and compare them to normal ones, yielding a result. The SVM classifier was used to determine whether the tumor was benign or malignant based on its characteristics. The outcome reveals the correctness of the chosen classification. For recognising nodules, this approach achieves sensitivity=84.1%, accuracy =90.1% and specificity=91.7%. The following Figure 3 shows the performance measurements of SVM.

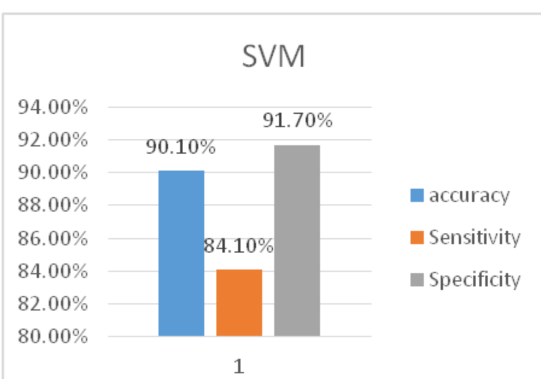

Fig. 3. Performance measurements of SVM

F. Deep Deconvolutional Residual Network

The (DDRN)Deep Deconvolutional Residual Network [5] provides attractive segmentation accuracy for a range of tumours, notably juxtapleural growths, without any post-processing. The deconvolutional and convolutional parts of the network's short and long connections capture full-resolution features and maintain spatial information, as well as assist in faster deep network convergence. With better ANN model, the classification technique achieved 71.18 percent accuracy.

G. Convolutional Neural Network

It accepts an input image and applies biases and trainable weights to various aspects of the image, enabling it to differentiate among them [2], [6]. Furthermore, the amount of pre-processing required for this technique is less when compared to other classification algorithms. The objective of CNN is to transform the images into a format that is safer to work with while maintaining essential characteristics for producing a reliable forecast. Since CNN's became prominent in 2012, applying Deep Learning to medical imaging has been a widely used application.

III. LITERATURE SURVEY

Sunyi Zheng et al. [24] suggested an approach CNN that employs axial section slices with Images from MIP of different slab thicknesses (5mm,10mm,15mm). Based on their morphologies, 2-D CT images are enhanced with spatial information, allowing the differentiation of nodules from vessels. This suggested technique's sensitivity for lung nodule detection was 92.7 percent with one false positive and 94.2 percent with two false positives based on public data collection.The proposed method also demonstrates how combining the clinical procedure with CNNs could improve nodule detection.

Jue Jiang et al. [26] devised a multiscale CNN technique to provide reliable, automated volumetric identification as well as serial measurement by volumetrically segmenting lung tumours. To segment from images of CT scans, two neural networks were proposed that combine several residual streams with differing resolutions. In several datasets, the accuracy of segmentation is greatly improved. This method can be used to follow tumour volumes over time in cancers that have been treated tumors shrink and appear differently on a CT scan after immunotherapy. The approach appears to be promising for additional places, given its success with lung cancers

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K. Vijila Rani et al. [35] proposed a Nanotechnology-based scheme for tumor area detection. The performance of various classifiers used to diagnose is examined. As part of the preprocessing procedure, we take the lung cancer image and perform noise removal and image enhancement. Toboggan-based segmentation is used to distinguish the malignant region from the healthy lung. The cancer is then located using the nanoscale measuring equipment. Applying SVMs, FFNNs, and KNNs, the segmented region is classed as malignant or noncancerous based on the retrieved attributes.98.19% of classifications made by the CNN classifier are correct. In nano CT images, with an innovative nanotechnology-based method, it is possible to precisely segment lung lesions and identify tumour areas

Tiwari Laxmikant et al. [25] developed a strategy on identifying lung cancer using Mask Unit (3FCM) and Target-based Weighted Elman Deep Learning Neural Network (TWEDLNN) according to Deep Learning (DL) algorithms. The method obtained an experimental accuracy of 96%.

You-Wei Wang et al. [41] developed a new deep prediction approach for detection of primary lung tumor in the nodal metastasis (Nmet) using dual-energy computer tomography based on gemstone spectral imaging (GSI). This technique achieves an accuracy of 86 % when trained on the 40 keV dataset. The findings reveal that tumour heterogeneity and size played a role in the proposed model's ability to predict whether nodal metastasis from the original tumour exists or not.

Zhuo Liua et al. [42] introduced a model called deep reinforcement learning that would be useful for detecting lung cancer. To solve a problem in lung tumour localization, this model has likely be beneficial. The localization of the tumour is crucial for both the diagnosis and therapy of lung cancer in deep reinforcement learning. Identifying lung cancer depends on localizing tumour properly, can aid in improving surgical operations and lowering the recurrence rate.

P. Mohamed Shakeel1 et al. [43] employed a new approach for improving the image quality and diagnose. A weighted mean histogram equalization strategy is used to successfully eliminate noise from the image that is included in the data collection while also enhancing the image's quality. The impacted area is divided using the Improved Profuse Clustering Technique (IPCT). An impacted region yields a variety of spectral characteristics. for detecting lung cancer trained neural networks were used. The technique provides 98.42 percent accuracy with such a minimal classification error of 0.038.

Yixian Guo et al. [44] developed Com_radNet and ProNet models are used to detect lung squamous cell carcinoma (SCC), adenocarcinoma (ADC), and small cell lung cancer (SCLC) automatically on Computed Tomography images, respectively It achieved well in distinguishing SCC, SCLC, ADC might be a nonintrusive approach for diagnosing lung cancer clinical variants in the future. SCC, ADC, and SCLC have F1- scores of 90.0 percent, 72.4 percent, 83.7 percent with a 73.2 percent weighted average F1-score, according to the model ProNet used to categorize various forms of cancer in lungs. In SCC, ADC, and SCLC, the F1-scores for com radNet were 83.1 percent, 75.4 percent, and 85.1 percent respectively. Although the average F1-score was 72.2 percent. Accuracy of ProNet model and com radNet was 71.6 percent and 74.7 percent, respectively. Figure 4 and 5 shows the performance of ProNet and radNet. The figure 6 shows the performance measurements of ProNet and radNet.

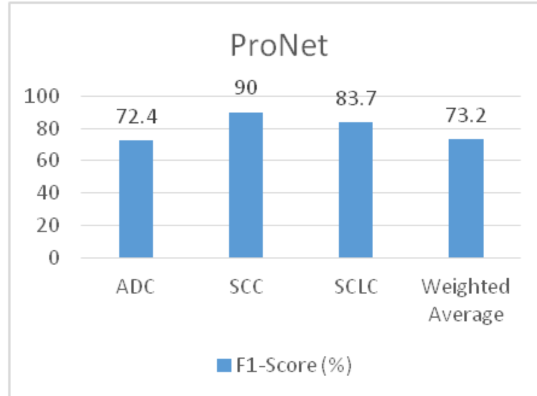

Fig. 4. ProNet Performance

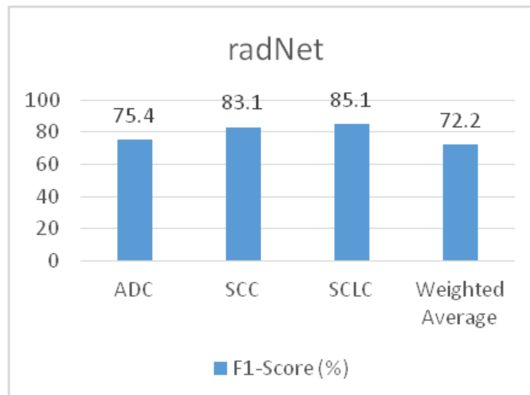

Fig. 5. radNet Performance

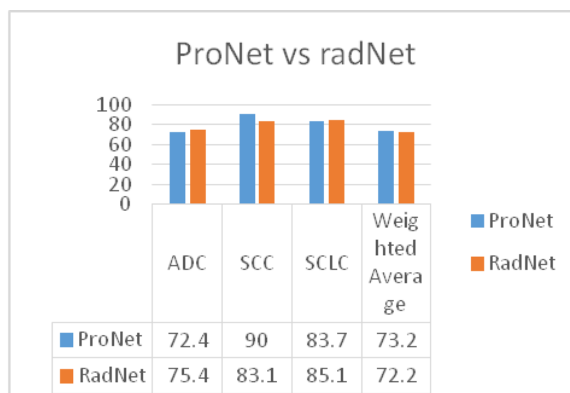

Fig. 6. ProNet vs radNet

TABLE I. Summary of various Lung Nodule detection with Deep Learning Techniques

Authors	Methods	Advantages	Disadvantages
Noor Khehrah *et al.* [1]	Support vector machine (SVM)	Achieved higher sensitivity rate and accuracy.	The running time of this method was high.
Reza Majidpourkhoei	CNN	It increased the overall	However, it failed to

et al. [2]		processing speed.	classify the nodule as cancerous not.
Benita K. J. Veronica [3]	Neural network (NN)	It achieved better classification results.	It failed to increase the classification accuracy by extracting some unique features of lung image.
Amrita Naik, and Damodar Reddy Edla [4]	Deep learning model	It improved the accuracy of lung nodule classification.	It failed to detect the malignant tumors at an early stage.

IV. RESULT AND DISCUSSIONS

In this survey paper, many deep learning models and tasks have been reviewed. It summarizes many methods for identifying lung cancer. The primary intention of survey is compare various models in deep learning for the detection of lung cancer.Initially CT image is given as input into the pre-processing step, when the image is effectively transformed such that the image is passed to the next phase, nodule segmentation separately done using the segmentation model in such a way that the results obtained from the segmentation methods are given to detection module. Comparative analysis of different deep learning models used in medical image processing. We can conclude deep learning models like CNN, Deep Residual Network were found to be more accurate and able to predict the lung cancer nodules.

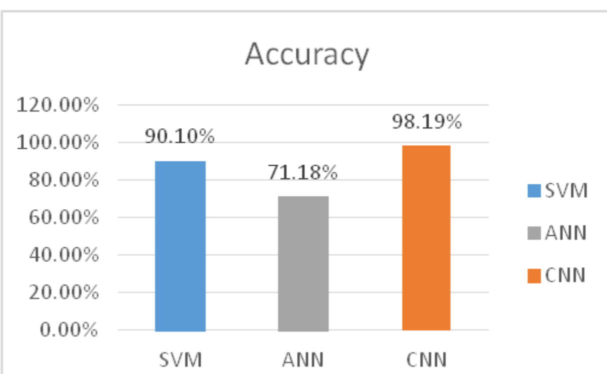

Fig. 7. comparison of various models

V. CONCLUSION

A disease that has a significant impact on people's lives is lung cancer. The disease is frequently only discovered when it has progressed to an advanced stage since the signs of lung cancer are not always apparent in the early stages. We did a comparative examination of various deep learning approaches utilized in medical image processing in this paper. Deep Learning algorithms offer an effective means of early disease prediction. It was discovered deep learning methods like CNN more frequently employed than others. This study summarizes the various ways to detect lung cancer using computed tomography (CT) scans. Convolutional Neural Networks outperform conventional classification techniques, the review's findings show. CNN performed higher in terms of accuracy. CNN outperformed SVM and ANN in accuracy, obtaining a result of 98.19%. In the future, the prediction model's accuracy could be increased by using a CNN model.

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