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# A Deep Learning Approach to Detect and Classification of Lung Cancer

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***Abstract*—Cancer is a name of fear to people in the world. Every year millions of people dead of cancer in the world and lung cancer is one of them. Lung cancer is classified by our research. Non-small cell lung cancer (NSCLC) is the most common of the two main types of lung cancer. Here we have classified our model NSCLC into 2 subtypes Adenocarcinoma and Squamous Cell Carcinoma and non-cancerous benign tumors. The CNN model is utilized here for classification (VGG19, ResNet50, EfficientNetB7 and MobileNetV2). We used 15 thousand image data. The Augmentor package was utilized to enhance to 15 thousand from 250 benign lung tissue, 250 lung adenocarcinomas, and 250 lung squamous cell carcinomas. In comparison to other models, ResNet50 has the best accuracy of 98% among our proposed models. By putting this model into practice, medical experts will be able to create an accurate, automatic method for diagnosing different forms of lung cancer.**

***Index Terms*—Lung Cancer, ResNet50, Deep Learning**

## I. Introduction

The most important organ of our body is the lung. That helps us breathe. Lumps or lumps appear in different parts of the body when cells in the body continue to grow uncontrollably because cancer-suppressor genes are inactive. What we call a tumor. This tumor can be benign or malignant. Malignant tumors are known as cancer. That is, neoplastic or tumor cells with a high rate of aggressiveness, metastasis and the ability to spread elsewhere in the body are called malignant tumors or cancer. Difficulty breathing, coughing with blood, weight loss, air pollution, genetic factors, chest pain, vomiting with blood are among them. Also various chemicals like arsenic, nickel, silica etc, increase the risk. Lung cancer is classified into three categories. – non-small cell type, small cell type and carcinoid. Of these, the small cell type is the worst, growing and spreading throughout the body very quickly. Small particles or fibers of inorganic materials such as asbestos, nickel, chromium and organic materials such as benzene, benzopyrene etc. Enter the lungs with the air and cause lung cancer. Constant torture on the lungs is responsible for this. 85% of lung cancer cases are attributed to tobacco use and the remaining 10%-15% are those who have never smoked or used tobacco products. Lung cancer is the greatest cause of illness and fatality in males around the world. Women's deaths are the second biggest cause of death. Every year, 1.3 million people worldwide pass away from lung cancer. According to GLOBACON 2020 data, the risk of this cancer increases with age to 1 in 101 people in the population up to the age of 74 years, 1 in 68 in men and 1 in 201 in women. Apart from this, the risk of lung cancer also increases in diseases like silicosis, interstitial lung disease, cystic fibrosis, chronic bronchitis etc. The presence of radon gas in the air and unwanted radioactivity are also significant causes of lung cancer.

The study's purpose was to accurately and efficiently diagnose lung cancer. That's why in this paper we have implemented four Deep Learning models. ResNet50, VGG19, EfficientNetB7, MobileNetV2. We got the highest accuracy from ResNet 50 and VGG19.

The remainder of the research study is structured as follows. Section 2, it is outlined earlier research on lung cancer detection. The dataset utilized is narrated in Section 3. In Section 4, we describe the various backdrop strategies used. Section 5 goes over the proposed technique, pre-processing operations, feature extraction, and classification. In Section 6, the outcomes are further discussed. In Section 7, we finish with directions for the future.

## II. Literature Review

Bhatia et al. [1] used Tree-based classifiers such as XGBoost, Random Forest as deep learning models. They got an accuracy of 84% using an ensemble of UNet+RandomForest and ResNet+XGBoost which separately have accuracies respectively 74% and 76%.

Yiwen Xu et al. [2] analyzed time series CT images of advanced non-small cells. They performed CNN with RNN and single seed localization on pre-treatment and post-treatment patients. END showed that deep learning predicts survival and cancer-specific outcomes and that the CNN model improved model performance with additional follow-up scans.

Riquelme et al. [3] aimed to detect malignant lung nodules from computed tomography and for this they proposed computer-aided diagnosis (CAD) systems. They used deep learning's CAD algorithm and split its architecture into 2 parts and analyzed the performance.

Ibrahim et al. [4] used multi-classification to diagnose pneumonia, covid-19, X-RAY, lung cancer and CT images of the chest were used for this. VGG19 +CNN model gave better results than other models and their accuracy was 98.05

Asuntha et al. [5] Their main aim was to detect cancerous lung nodules and classify lung cancer and its acute stage. They used various feature extraction techniques such as Histogram of Oriented Gradients(HoG), Local Binary Pattern (LBP), wavelet transform-based feature, and Zernike Moment and Scale Invariant Feature Transform (SIFT). and then they used Fuzzy Particle Swarm Optimization (FPSO), geometric, volumetric, and intensity features algorithm to obtain good results in FPSOCNN.

Kriegsmann et al. [6] studied the potential and limitations of different models of CNN images. They used CNN to detect 4 subtypes of cancer and An optimized InceptionV3 CNN architecture detected the most accurately.

Lei Cong et al. [7] For the diagnosis and treatment of primary or metastatic malignancies, the recognition and features of malignant cells are crucial. Applications of deep learning for lung cancer research, progress, future and problems were discussed.

Machine learning techniques are utilized in biomedical applications to forecast and categorize different kinds of signals and pictures. Deep learning (DL) techniques have made it possible for machines to handle large-scale data sets such anatomical multidimensional films and photographs. Machine learning includes deep learning that develops methods to create an artificial neural network modelled after the structure and operations of the human brain [8]. The bulk of earlier studies used DL to concurrently classify images of colon and lung cancer. Others focused on lung cancer detection, while some authors were more concerned with colon cancer.

Masud et al. [9] used a deep learning-based algorithm to categorize lung and colon histology pictures. To create four feature sets for image categorization, they applied two different sorts of domain alterations. To reach the final classification result, they combined the two categories' attributes. Their accuracy rating was 96.33

Mangal et al. [10] was successful in classifying colon and lung tumors based on histology pictures by using a shallow neural network design. They achieved classification accuracy for lung and colon cancers of 97% and 96%, respectively.

Deep learning based on CNN was proposed by Hatuwal et al. [11] Only lung tissue samples from the dataset are shown in the approach. This method could only distinguish between two benign and one malignant lung tissue, and no classification of colon cancer was provided. Their proposed categorization model for lung tissue achieved 97.20% accuracy, 97.33% recall, and 97.33% precision.

A classifier of K-Nearest Neighbor with features obtained for colon cancer tissues using a pretrained DenseNet121 network was proposed by Sarwinda [12]. Their method searches the data for colon tissues and separates benign from cancerous colon tissues. Their model had a recall of 98.63% and an accuracy of 98.53% for colon classification. However, the inability of their model to collect lung cancer tissues and offered no data regarding lung cancer classification.

The DenseNet-121 captures more meaningful properties than other convolutional neural network pre-trained networks, according to Kumar [13]. This is due to the network's utilization of tiny links to increase its accuracy and effectiveness.

Wang et al. [14] developed a deep learning-based Python library to identify cancer image types. They merged the CNN model and the SVM algorithm in their suggested approach. The total accuracy of the Support Vector Machine model was 94

Chehade et al. [15] distinguished between subtypes of In terms of accuracy, recall, and precision, the XGBoost model has the highest classification rate for colon and lung cancer. XGBoost scored 98.8% F1 and had 99% accuracy.

Convolutional neural networks were used by Hlavcheva [16] to assess medical photos were used deep learning methods. Their dataset was utilized to evaluate the classification accuracy of various convolutional neural network designs. Statistical mathematical techniques and neural network theory were used to attain the accuracy of 94.6

A spatially limited neural network was suggested by Sirinukunwattana et al. [17] for identifying the nucleus in colon cancer histopathology images. Using a unique nearby group predictor, cell nuclei were categorized. The highest level of accuracy was 97.1%. Despite producing positive results, their model's computational efficiency fell short because it often took Fifty minutes to execute only one presentation.

Sun et al. [18] created a Machine Learning algorithm to determine whether a lung nodule was malignant. characteristics from lung nodule CT images have been used numerous times. were extracted using max-pooling, and feature maps were cropped using a pooling method. This method is unique in that it utilized the CT scan pictures without using any segmentation or feature extraction techniques. They achieved an accuracy of 87.14 percent for identifying lung nodules using only their machine-learning model. They used three deep structured algorithms to autonomously extract information from a lung nodule's CT pictures in this study: SDAE (stacked denoising autoencoder),deep belief network (DBN), and CNN. Using CNN, the greatest degree of a result obtained was 89%.

To identify lung cancer, Selvanambi et al. [19] used RNN (Recurrent Neural Network) with the DLS (Damped Least-Squares) method, and the GSO (Glowworm Swarm Optimization) technique, with an accuracy of 98%.

Image segmentation was utilized by Filho et al. [20] to preprocess CT images of lung nodules. By combining to distinguish between benign and malignant tumors, index fundamental taxic weights with standard taxic weights patterns classification using CNN, the authors were able to identify patterns with 92.6 percent accuracy.

Masood et al. [21] introduced with an accuracy of 84.5 percent, Using a deep CNN as its foundation, the DFCNet model, can classify CT scan pictures of pulmonary nodules show the four stages of lung cancer. False-positive results are produced by using multiple data sets with different scan parameters which were faulty when it comes to malignant tumors. Utilizing same scan parameters across all datasets yields the best categorization results. polyp can be found utilizing colonoscopy videos.

Mo et al. [22] achieved 98.5% average accuracy using a Faster R-CNN ( Region-Based Convolutional Neural Network ) was developed in four different datasets.

Deep CNNs were created and put into use by Urban et al. [23] for the detection of polyps in images collected from more than 2000 colonoscopies that had been expertly tagged. Their model managed to achieve 96.4% accuracy. The categorization of colonoscopy frames using the model proposed in [24] with an accuracy of 90.28%. applied binarized weights with convolutional neural networks to minimize the network size. Wolf heuristic features with the least amount of recurrence were chosen in [25] to decrease dimensionality and complexity. Lung structures that are both diseased and normal were distinguished with exceptional accuracy of 98.42% using a combined neural network: a learning comprehensive developed for AdaBoost.

An eight-layer CNN architecture was suggested by Suresh and Mohan [26] for classifying a lung lesion's CT picture to one of three categories. To extract the interesting nodule regions from pictures, segmentation was used in consultation with specialists. In addition, the dataset was expanded using generative adversarial networks. Their suggested model has a classification accuracy rate of 93.9%. for the purpose of finding pulmonary nodules.

A simple deep learning approach using only four convolutional layers in the CNN architecture was proposed by Masud et al. [27]. For each convolutional layer, made up of a connecting convolutional block, two convolutional blocks that follow one another, non-linear activation functions, and a pooling block. Due to the fact that it contains less flops and parameters than cutting-edge CNN architectures, the authors determined that their suggested model is appropriate for real-time CT image interpretation. The accuracy of the suggested model was 97.9%.

[28] used a method to preprocess lung cancer CT scans that preserves image brightness at multiple levels and eliminates noise. For feature extraction and segmentation of the affected regions, an improved neural network was used. To classify an ensemble classifier was applied to the features. The model's classification accuracy was 96.2

Bukhari et al. [29] achieved 96.4% accuracy by using data from two different databases, three pre-trained CNNs( ResNet-34, ResNet-50,and ResNet-18) were used to assess histopathological pictures of colonic cancer.

## III. Methodology

### A. Description of the dataset

Datasets are required for any machine learning or deep learning approach. The quality of the data at hand aids in the creation, training, and improvement of the algorithms. The accessible data in medical imaging applications must be validated and labeled by professionals in order to be used in any development. The datasets utilized in current research on deep learning for lung cancer diagnosis are presented in this section.

TABLE I
Dataset of Lung Cancer

| Disease | Class | Total Image |
|---|---|---|
| Lung Adenocarcinoma | lung_aca | 5000 |
| Lung Squamous Cell Carcinoma | lung_scc | 5000 |
| Lung Benign | lung_n | 5000 |

There are 3 classifications and 15,000 histopathology pictures in this collection. Each image is a jpg file with a resolution of 768 by 768 pixels. The 750 lung tissue images were produced from a sample of original sources that were HIPAA compliant and confirmed (250 cases of benign lung tissue, 250 cases of adenocarcinomas, and 250 cases of squamous cell carcinomas in the lungs). used the Augmentor package to augment to 15,000. The dataset consists of three categories, each containing 5,000 images:

- Lung Adenocarcinoma
- Lung Squamous Cell Carcinoma
- Lung Benign Tissue

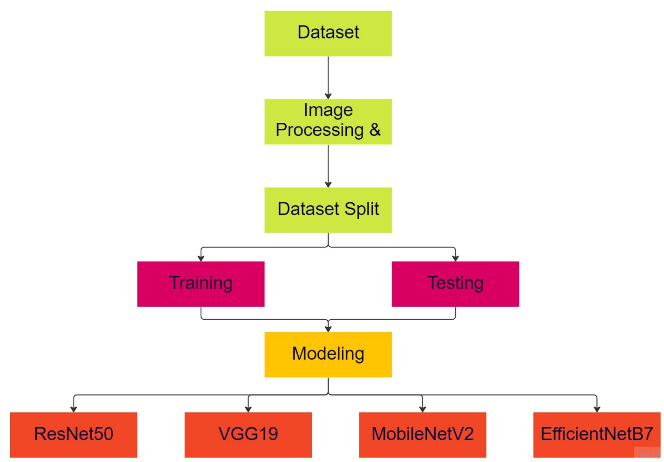


Fig. 1. Proposed Diagram

## IV. Model Implementation

Many different types of supervised deep learning algorithms are used in this research study to generate the four suggested categorization models. ResNet50, VGG19, EfficientNetB7, and MobileNetV2 are the names of these models. The following subsections provide details on each of the four developed models.

### A. Proposed Model

- ResNet50: ResNet is a Convolutional Neural Network where ResNet50 is fifty neural network layers of ResNet-50. In these 50 layers, 48 layers are convolutional layers and Two layers are the MaxPool layer and average pool layer. ResNet50 classifies the new images.
- VGG19: The Visual Geometry Group is known as VGG. VGG is used for image recognition or classification.

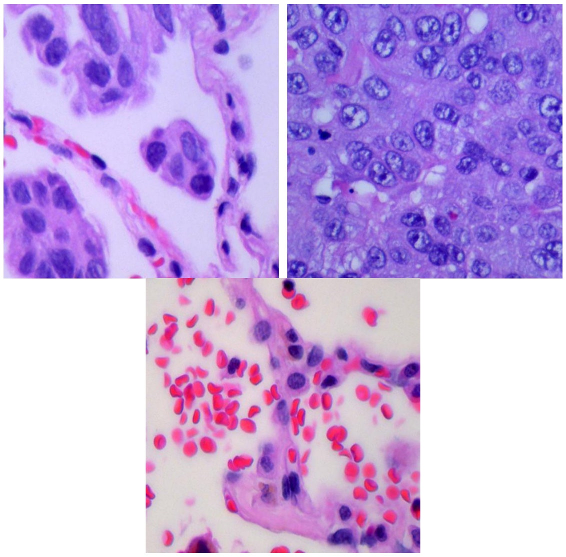

Fig. 2. Lung Adenocarcinoma, Squamous Cell Carcinoma, and Benign Tissue of the Lung

TABLE II
CLASSIFICATION REPORT OF RESNET50

| Cancer type | Precision | Recall | F1 score |
|---|---|---|---|
| Lung Adenocarcinoma | 0.98 | 0.96 | 0.97 |
| Squamous Cell Carcinoma | 0.96 | 0.96 | 0.97 |
| Lung Benign | 1.00 | 1.00 | 1.00 |

VGG19 is a convolutional neural network with 19 deep layers which when compared to other state-of-the-art models, consistently achieves greater performance.

TABLE III
CLASSIFICATION REPORT OF VGG19

| Cancer type | Precision | Recall | F1 score |
|---|---|---|---|
| Lung Adenocarcinoma | 0.97 | 0.96 | 0.97 |
| Squamous Cell Carcinoma | 0.97 | 0.96 | 0.97 |
| Lung Benign | 1.00 | 1.00 | 1.00 |

- EfficientNetB7: EfficientNetB7 is one of the most powerful convolutional neural network (CNN) models available today.

TABLE IV
CLASSIFICATION REPORT OF EFFICIENTNETB7

| Cancer type | Precision | Recall | F1 score |
|---|---|---|---|
| Lung Adenocarcinoma | 0.91 | 0.99 | 0.95 |
| Squamous Cell Carcinoma | 0.99 | 0.91 | 0.94 |
| Lung Benign | 1.00 | 0.99 | 1.00 |

- MobileNetV2: MobileNet-v2 is a 53-layer deep convolutional neural network. The pretrained network can classify photos into 1000 different object categories, including laptops, tables, pens, and a variety of birds.

TABLE V
CLASSIFICATION REPORT OF MOBILENETV2

| Cancer type | Precision | Recall | F1 score |
|---|---|---|---|
| Lung Adenocarcinoma | 0.92 | 0.83 | 0.88 |
| Squamous Cell Carcinoma | 0.86 | 0.94 | 0.90 |
| Lung Benign | 0.99 | 0.99 | 0.99 |

### B. Evaluation of Performance

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{1}$$

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

$$Recall = \frac{TP}{(TP + EN)} \tag{3}$$

$$F1 - Score = \frac{(2 * Precision * Recall)}{(Precision * Recall)} \tag{4}$$

where, TP denotes True Positive, TN is True Negative, FP denotes False Positive, and FN denotes False Negative. The accuracy, Precision and recall of ResNet50, VGG19, EfficientNetB7, MobileNetV2 are shown in Fig.4 The highest accuracy is ResNet50. So the accuracy of ResNet50 is better then the others model like VGG19, MobileNetV2 and EfficientnetB7.

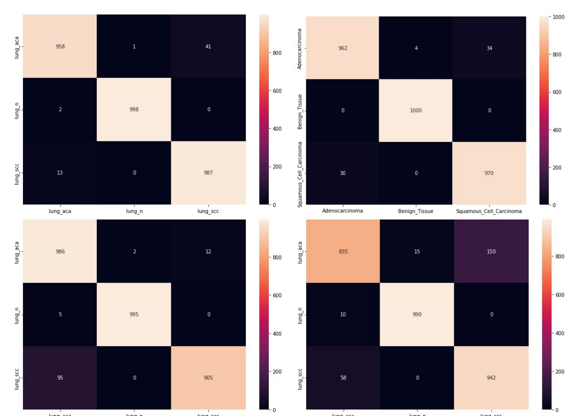

Fig. 3. Confusion Matrix of ResNet50, VGG19, MobileNetV2, EfficientnetB7

## V. RESULTS AND DISCUSSION

Our dataset contains 15000 photos that are equally split among 3 classifications. We divided the dataset so that 20% of the images in each class were utilized for testing, while the other 80% were used for training. Precision, f-1 score, recall, and accuracy were all taken into account throughout the performance analysis. The highest accuracy achieved by the ResNet50 models is 98% and VGG19 models is 97% then EfficientNetB7 and MobileNetV2 are 96% and 92% respectively.

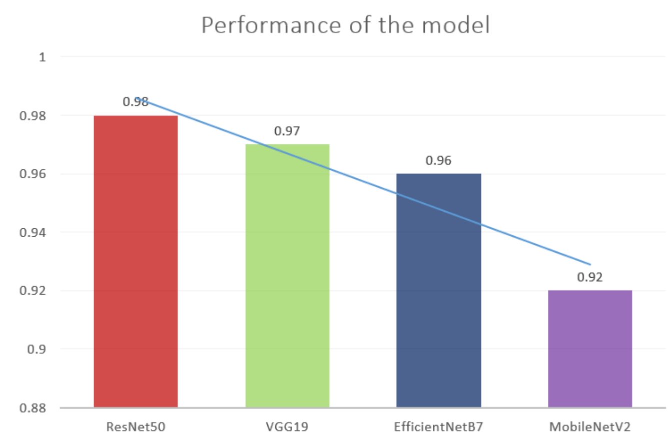


TABLE VI
COMPARISON OF FOUR DEEP LEARNING ALGORITHMS

| Algorithms | Class | Precision | Recall | F1-Score | Accuracy |
|---|---|---|---|---|---|
| **ResNet50** | aca | 0.98 | 0.96 | 0.97 | 0.98 |
| | n | 1.00 | 1.00 | 1.00 | |
| | scc | 0.96 | 0.99 | 0.97 | |
| **VGG19** | aca | 0.97 | 0.96 | 0.97 | 0.97 |
| | n | 1.00 | 1.00 | 1.00 | |
| | scc | 0.97 | 0.96 | 0.97 | |
| **EfficientNetB7** | aca | 0.91 | 0.99 | 0.95 | 0.96 |
| | n | 1.00 | 0.99 | 1.00 | |
| | scc | 0.99 | 0.91 | 0.94 | |
| **MobileNetV2** | aca | 0.92 | 0.83 | 0.88 | 0.92 |
| | n | 0.99 | 0.99 | 0.99 | |
| | scc | 0.86 | 0.94 | 0.90 | |

## VI. CONCLUSION AND FUTURE WORK

Lung cancer is a leading cause of death worldwide.The therapy results and survival rates of various malignancies can be considerably increased with an early and appropriate diagnosis. We think that our suggested approach can be utilized to accurately detect a number of diseases. Lung cancer is a dangerous disease that must be combated with all available resources. Many previous technologies and research shows some gaps in which they did not achieve high-accuracy detection results. However, the proposed model ResNet50 is useful in lung cancer detection because of its high accuracy and helps in improving the accurate results of tumor cells, which reduces the death rate.

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