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Lung Cancer Detection Using CNN VGG19 + Model

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Abstract: - In the last many years, lung cancer has become a major public health concern. To examine cell breakdown in the lungs in its starting stages, doctors often use imaging modalities such as X-ray chest films, CT scans, MRIs, etc. The timing of diagnosis determines the course of therapy. Artificial intelligence (AI) is a hotspot for developing computational models of human intellect. In this research, we aim to enhance the detection and classification of lung nodules from CT images using a novel deep learning approach. Our study builds upon an extensive review of existing lung cancer detection methods, highlighting their strengths and weaknesses. This LIDC/IDRI dataset has been used in over half of the most recent research on lung cancer diagnosis. While several Convolutional Neural Networks (CNNs) architecture are adequate to process medical field data using technology solutions to discover and diagnose Lung cancer, here we proposed model VGG-19+ model. It is known for its strong feature extraction capabilities. It outflanks the ongoing model on a few exhibition measures, including exactness, accuracy, responsiveness/review, and f1-score.This research using VGG-19+ model could lead to more widespread utilization in cancer diagnosis by enhancing early lung cancer detection and developing the field of medical image analysis.

Keywords: Artificial Intelligence, Deep Learning, Lung Cancer, Machine Learning,VGG-19

I. INTRODUCTION

One of the top killers in recent years, lung cancer (medically known as "Small Cell Lung Cancer (SCLC)" or "Non-small Cell Lung Cancer (NSCLC)" and a third, less prevalent kind called "Carcinoid"), has suddenly become a major public health concern. Cancer of the lung develops when cells in the respiratory epithelium of the bronchial tree multiply uncontrollably and spread to other parts of the lung. Medical obstacles, such as the difficulty in detecting the illness in its early stages, lower the likelihood of patient survival. Additionally, a diagnosis before to the age of 45 is quite infrequent, whereas it is often identified between the ages of 55 and 70. To examine the early stages of cellular breakdown in the lungs, doctors often use imaging modalities such as X-ray chest films, CT scans, MRIs, etc. Using computed tomography (CT), a region of the body may be imaged in a series of cross-sectional views. Due to the massive volume of data that has to be processed, outwardly perceiving and dissecting these photographs for any irregularities is a troublesome and tedious exertion.

The treatment of the illness depends on how early the sickness is recognized with the goal that therapy can keep the infection from progressing (in stage) and spreading to different pieces of the body. The infection can be controlled with great clinical consideration and a few treatments including a medical procedure, chemotherapy, and radiographs, for various reasons including the patient's wellbeing and the illness' movement. The survival rate of five years is however just 21%. To overcome the medical challenges, Image Processing and Artificial Intelligence approaches may be used to process medical field data using technology solutions in order to discover and diagnose the disease at an initial stage which will not only help medical practitioners to deliver effective results but also help to save valuable human lives. Machine and deep learning algorithms are critical in training a computer system to become an expert that can assist in making predictions and taking decisions.

Machine learning is a subfield of AI that makes it possible for computers to automatically learn new skills by analyzing and interpreting data that has already been collected. As a branch of ML, deep learning enables computers to "learn" from data and form perceptions of the environment according to the rankings of their own ideas. These fields imbibe a computer with intelligence, enabling it to extract patterns based on specific facts and then process them for autonomous reasoning. AI is a prominent area for representing human intelligence in a machine as shown in Fig. 1 AI is a subset of simulated intelligence, while Profound Learning is a subset of AI.

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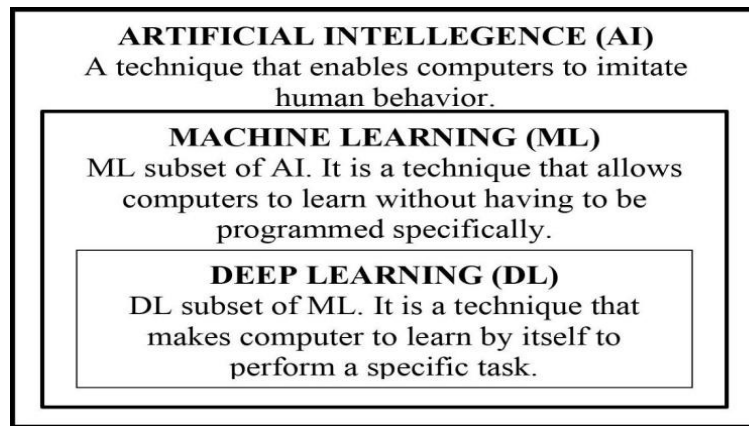
Fig. 1 Domains of AI, ML and DL

II. MATERIAL AND METHODS

A. *Machine Learning Versus Deep Learning*

ML refers to the study of teaching computers to identify patterns in data. These data patterns are then utilized to make predictions or to make conditional evaluations. ML algorithms help to build models which are dependent on training data which is further utilized to make predictions or decisions without the need to be explicitly programmed. These algorithms are based on the depth of supervision they endure during training, as: supervised, unsupervised, and reinforcement learning.

The second branch of machine learning is known as deep learning (DL), and it basically consists of a three-layer neural network. A perception, basic node, is the fundamental unit of any neural network. It is similar to a basic linear classifier. These are utilized to create a complex generalized system capable of taking any form of input and predicting output based on the inputs. DL makes use of a deep graph with a number of different processing levels. Deep learning automates the feature extraction process, thereby minimizing the need for expertise. Data pre-processing is often an integral aspect of machine learning, but our approach removes some of that step. Fig. 2 exercises a brief overview of the techniques while Table. 1 highlights the major difference between them.
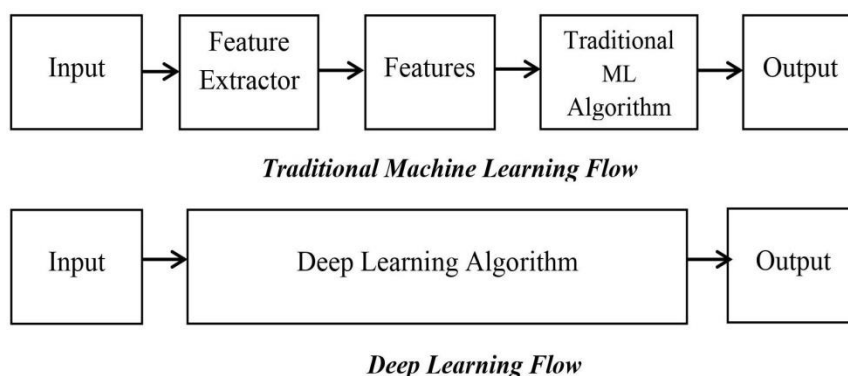

Fig. 2 Machine Learning Versus Deep Learning

Compared to ML, Deep learning algorithms can support any type of information but requires a lot of computational power (GPU) and large dataset to solve complex problems. Also the effective time required to train a model is very large but the accuracy is quiet high compared to ML. A few instances of profound learning techniques incorporate stacked auto encoders, Convolutional Brain Organizations (CNNs), Fake Brain

Organizations (ANNs), Long Transient Memory Organizations (LSTMs), and Intermittent Brain Organizations (RNNs).

Some of the image processing methods discussed in [1] include image acquisition, enhancement, segmentation, and feature extraction. Support Vector Machines (SVMs), K-nearest neighbors (KNNs), decision trees, and artificial neural networks (ANNs) are among the classification algorithms utilized in this system. Sensitivity, accuracy, and specificity are the three main performance metrics. Image preprocessing is improved by noise filtering approaches that use Auto Encoder Systems and segmentation algorithms, such as the OTSU algorithm. With an accuracy of 84.01%, SVM accomplishes the research goals to a satisfactory level.

Table 1 Comparing ML and DL

Factors	Machine Learning	Deep Learning
Data requirement	Can be trained on small amount of data	Requires large amount of data
Accuracy	Gives less accuracy	Provides higher accuracy
Training time	Takes less amount of time to train a model	Takes longer time to train a model
Hardware dependency	Can work on CPU to train model	Requires GPU to train a model

B.   Literature review

Machine learning techniques are used in [2] using K-Nearest Neighbours, Support Vector Machines, Naïve Bayes, Decision Trees, and Artificial Neural Networks. Using principal component analysis (PCA), chest radiograph dimensions are reduced by a factor of 1/8. To compare the efficacy of machine learning methods with and without principal component analysis (PCA), the APR, F-measure, and precision are used. Using an accuracy rate of 93.24%, Decision Tree outperforms all other performance metrics when tested using the actual data.

Methods for segmentation including Region Growing, Marker Controlled Watershed, and Marker Controlled Watershed with Covering have been utilized in [3] Pre-handling. The following kinds of machine learning are used: Support Vector Machine, Neural Network, Naive Bayes classifier, Decision Tree, KNN, Gradient Boosted Tree, and MLP. Compared to previous segmentation approaches, pre-processing marker-controlled watershed with masking segmentation yields more accurate results. An accuracy level of approximately 97% was achieved when image data was segmented using a marker-controlled watershed-based segmentation and a multi-class SVM classifier.

Read about SVMs, Random Forests, and Artificial Neural Networks that rely on machine learning in [4]. When comparing algorithms, In order to select the one that provides the most accurate predictions, it is necessary to compute characteristics such as precision, recall, and accuracy. With a precision of 92% for locale based highlights and 96% for surface based highlights, Artificial Neural Networks outperform the other methods. Image categorization, object recognition, and feature extraction are three areas where the authors predict Deep Learning will eventually surpass machine learning.

The authors presented a four-step process in [5]. The first step is pre-processing, which involves applying morphological smoothening and median filters. The GLCM (Dark Level Co-Event Network) strategy is utilized to extricate the elements from the pre-handled picture. In the second and final stages of lung disease identification and separation, classifications based on multilayer perceptrons (MLP), SVM, and KNN are utilized. The last step is to test how well the classifier performed. Authors may save time and memory by using GLCM to derive a matrix that includes just the characteristics that are required. With MLP, the authors attained 98% accuracy, with SVM reaching 70.45% and KNN reaching 99.2%.

[6] Summarizes current research on using deep learning for medical imaging and medication development. Clinical picture investigation and medication disclosure frequently utilize profound learning methods like

Convolutional Brain Organizations (CNNs), Profound Conviction Organizations (DBNs), Sparse, and Variable Auto Encoders. Because of the reliability of pooling layers and the fact that including dropout into the network greatly reduces overfitting, CNN is the most used design for picture categorization. In comparison to Deep Belief Networks (DBNs), Sparse and Variable Auto encoders, and Convolutional Neural Networks (CNNs), the authors find that CNNs perform better. We urgently want models that can make good use of sparse data.

Survey picture categorization, object identification, pattern recognition, reasoning, and the application of ML and DL to medical images are all discussed in detail in [7]. The authors centre their work on algorithms that have potential applications in the fields of illness research and automated decision-making. According to the authors, a human developer could struggle to reduce complicated illness patterns to a manageable amount of feature descriptors, which is one of the limits of the conventional machine learning technique. In contrast with profound learning calculations, ML programs are frequently less difficult, yet they really do require a lot of preparing information and ceaseless human contribution to deliver results. Conversely, profound learning is a strategy for portrayal discovering that abstracts the information data into different layers and uses a multi-facet brain network plan to learn information portrayals naturally. While DL is more complicated to set up, it needs minimum human interaction and does not require large training data. A unique approach to medical picture analysis has emerged using deep learning methods, notably convolutional networks.

For the Deep Learning method, the authors of [8] suggested the Adaptive Hierarchical Heuristic Mathematical Model (AHHMM). In order to prepare images for DNN's image classification, the authors use the Modified K-means technique to pre-classify them into different parts of the same image. Recognition rate, misclassification ratio, sensitivity, and accuracy were some of the metrics used to assess the suggested AHHMM method's efficacy. The AHHMM method that has been proposed is able to accurately forecast lung cancer using CT scans. The results of the test demonstrated an accuracy rate of almost 90% in picture identification. These results demonstrate that DNN is helpful for cyst diagnosis when it comes to lung cancer classification.

The authors provide a concise overview of CNN knowledge and the reasons why they are suitable for medical image analysis in [9]. A far reaching synopsis of the cutting edge in CNN-based pneumonic knob examination is likewise included. To work on the use of CNN in clinical picture handling and pneumonic knob location, the article dives into the ongoing impediments and possible future ways.

In [10], CNNs were utilized to recognize lung knobs and arrange them as harmless or dangerous, creating noteworthy outcomes. Concentrates on utilizing CNNs comprise 93.8% and 60.5% of the all out distributions, separately, according to figures gathered from the IEEE Xplore and PubMed databases for the period of 2015 to 2018. Also, between 2017 and 2018, there was a remarkable 153.3% rise in the number of research that used CNNs.

Technological differences, size of data, accuracy, and the knowledge of various advantages and disadvantages are all important elements in deep learning are recent success. Several deep learning methods such as DNN, RNN, LSTM, Autoencoders and CNN are listed in Table 2 for this purpose.

Table 2 DL Classification Algorithms

Classifiers	Advantages	Disadvantages
Deep Neural Network (DNN)	In a neural network that is already complicated, more hidden nodes. Might be utilized to do the more unpredictable information calculation.	It is extremely expensive to train due to complex data models. Parameters are prone to over-fitting, fine-tuning.
Recurrent Neural Networks (RNN)	Handles inputs of varying lengths with ease. The model size remains constant regardless of the input size. Using the assumption that each pattern is reliant on earlier ones, RNNs may simulate a set of records (i.e. a temporal collection).	Issues with gradient disappearing and bursting. It is not an easy process to train an RNN.

Long Short Term Memory (LSTM)	Vanishing gradients might be an issue that they could resolve. Lack of sensitivity to the duration of the gap. Updating each weight becomes less complicated.	Require a lot of resources, memory and time to get trained. Prone to overfitting.
Auto encoders	Auto encoder learns continuously using backward propagation. Provides dimensionality reduction. It doesn't have to learn dense layers.	Not very efficient in the process of compressing images.
Convolutional Neural Networks (CNN)	Excellent performance in image recognition tasks. Identifies key traits autonomously, without human intervention. Distributing the load. Powered by increased computing resources and operates efficiently.	A significant quantity of training data is necessary. Inability to maintain spatial independence from the input data. CNNs do not record the object's orientation and location.

C.   *Datasets of Lung Cancer CT images*

With the use of the Public Malignant growth Establishment (NCI), the Food and Medication Organization (FDA), and the Establishment for the Public Foundations of Wellbeing (FNIH), three examination associations had the option to effectively make LIDC/IDRI, a data set of thoracic CT checks. It is open on the web and fills in as a worldwide asset for the turn of events, guidance, and assessment of PC helped symptomatic (computer aided design) ways to deal with cellular breakdown in the lungs conclusion and identification. Seven exploration habitats and eight clinical imaging organizations cooperated to make this information assortment, which incorporates 1018 occurrences.

In addition to the CT scan images, each subject has an accompanying XML file that records the results of a annotation process. Actually, there are only 1,010 unique CT scans since eight instances were accidentally duplicated during collecting the images. The DICOM format is used to store all the collected image data, which is consistently 512×512 in size. The most well-known picture thicknesses are 1 mm, 1.25 mm, and 2.5 mm, but they might be somewhere in the range of 0.5 mm to 5 mm. Over half of the most recent studies on the diagnosis of lung cancer have made use of this LIDC/IDRI dataset. Each case in the LIDC/IDRI collection consists of hundreds of photographs and an XML file that details the lung lesions that have been diagnosed. Based on their diameter, we divided the identified lung lesions into three main categories: knobs (3-30 mm), non-knobs (distance across > or equivalent to 3 mm), and miniature knobs (width < 3 mm) utilizing electronic calipers.

Using CT scan images acquired from the Shandong Provincial Hospital image collection, the authors of [10] used a Densely Connected Convolutional Networks and Adaptive Boosting technique. The lung cancer datasets were processed and classified using dense net. Lastly, in order to increase classification performance, the adaboost method is used to combine several classification outcomes. The proposed model achieved an accuracy rate of 89.85 percent. Transferable Texture Convolutional Neural Network was applied to a collection of CT scan images by Imdad Ali et.al. [11]. There are only three convolutional layers in the model, and the pooling layer is replaced by an EL.In order to focus on the textural characteristics, EL eliminates the general shape information. The amount of network parameters that may be learned was also decreased by the EL. The model's accuracy is 96.69%.

Using the VGG16-T technique, Shanchen Pang et.al. [12] analysed a dataset of CT scan images. As a preliminary step, we implement a classification framework for lung cancer type using enhanced VGG16-T. Step two involves training a boosting based classifier to cut down on false positives (FPs) generated in step one. The model has an accuracy of 86.58%. The CT scan image dataset is analysed using a two-dimensional convolutional neural network (CNN) in [13]. We provide a new automated approach for pulmonary nodule diagnosis using a 2D CNN to aid in the interpretation of CT scans. There are two parts to the model: first, a boosting-based classifier for false

positive reduction; and second, an enhanced Faster R-CNN for nodule candidate discovery. The model has an accuracy of 86.42%.

The CT image dataset used in the tests conducted by Nakrani et.al. [14] was sourced from the LIDC/IDRI collection and trained using ResNet. The identification of lung nodules was accomplished with an overall accuracy of 95.24% using the ResNet architecture of a 2D convolutional neural network. The AlexNet Architecture was used to CT scan pictures by Neal Joshua et.al [15]. Three-layered AlexNet design a three-layered multi-layered convolutional brain organization — had the option to distinguish lung knobs with an exactness of 97.17 percent. Afshar et al. used 3D-MCN to [16] had the option to recognize lung knobs with a precision of 83% on CT pictures taken from the LIDC/IDRI assortment. With an exactness of 93.548%, the creators of [17] utilized Alexnet to analyze a dataset of CT pictures procured from an emergency clinic in Iraq. Using AlexNet architecture and a convolutional neural network approach, the cases of the patients are categorized as normal, benign, or malignant. Utilizing DenseNet on the LIDC/IDRI picture dataset, the creators of [18] achieved a precision of 93.26 percent. DenseNet-NSCR, a sparse, non-negative, collaborative representation classification technique, is described here.

Cheng Wang et al. classified the pulmonary images using multiple classifiers (Softmax, Logistic, and SVM) [19] achieved an accuracy of 85.70 percent for automated feature extraction by employing a transfer learning-tuned Inception-v3 model.

The assignment included of two distinct tracks: Complete nodule detection and False-positive reduction. While various scientists have accomplished agreeable precision involving CNN as of late, the models' presentation break down when there are varieties in picture qualities like turn, tiling, and other unusual directions. Additionally, CNN is unable to detect pose, texture, or deformations in an image. Convolutional neural networks (CNNs) do not remember the relative location of scanned visual features. Although they do not guarantee invariance when rotated, Convolutional Neural Networks remain unchanged when translated. This indicates that they are able to identify items in one visual region that are perpendicular to one another, but they are unable to do so when the objects are in a different orientation. Because of this, when using a CNN for image segmentation or object recognition, you may end up losing certain picture characteristics in the pooling process. Therefore, in order to address problems with the pooling layer in the basic CNN model, modifications must be made.

D.   Proposed CNN VGG19 +

An abbreviation for a typical multi-layered deep CNN architecture is Visual Geometry Group or VGG for short. "Deep" variants of the system are VGG-16 and VGG-19, which feature 16 and 19 convolutional layers, respectively The VGG network is built using incredibly small convolutional filters. The VGG-16 consists of three completely linked layers and thirteen convolutional layers. VGG19 contains three more convolutional layers in comparison to VGG16.

 Limitations of VGG 16:

• The original VGG model involves a period of two to three weeks of training on an Nvidia Titan GPU.

• VGG-16 imageNet weights have a 528 MB size. Therefore inefficient because it uses a large quantity of

   storage space and bandwidth.

• An explosion in gradients issue is caused by 138 million parameters.

The model that is proposed utilizes VGG-19. Fig. 3 VGG19 consist of sixteen convolution layers, three fully linked layers, five MaxPool layers, and one SoftMax layer make up the VGG-19 architecture. Each of the two completely linked layers has 4096 channels, and to predict 1000 labels, another fully connected layer with 1000 channels comes after them. Last but not least, a completely linked layer called the Softmax layer is employed for categorization. Additionally, VGG19 Model makes use of optimizers that import Adamax. This is the system's default optimizer, which it uses to get better results from the dataset. The suggested strategy overcomes pooling layer losses by using picture augmentation to train the model with various locations, angles, and flips.

The VGG-19 model is utilized to classify and recognize objects; Table 3 and Fig. 4 provide the model parameters and classification results, respectively.
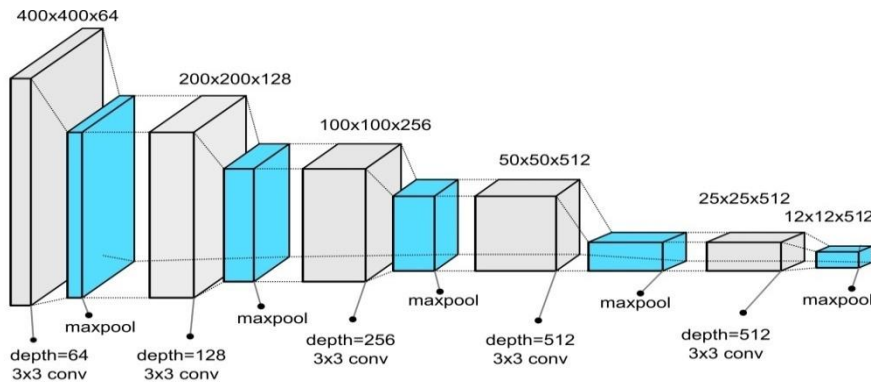

Fig. 3 VGG19 Architecture

III. RESULTS AND DISCUSSION

A.   Performance Analysis

It includes normalization, train and test split of data set, then we have visualized few images (10 CT Scan images) from the split dataset. Then build and visualize the model and train the model after image augmentation, it takes long time to train the present model. Train Test Split the dataset into two parts: one was containing photos that are benign and the other including images that are malignant. There was a 50% split in the dataset for testing, and a 50% split for training. The model is train for 50 epochs.

 The overall eminence of the proposed method is validated by computing the essential measures, such as True-Positive (TP), False-Negative (FN), True-Negative (TN), False-Positive (FP), Accuracy, Precision, Sensitivity, and F1-Score which are calculated in percentages.

TP: Positive samples for which a positive label is correctly anticipated.

FN stands for positive samples that are mistakenly anticipated to have a negative label.

FP: Negative samples that are mistakenly anticipated to be positive.

TN: negative samples for which a negative label is accurately anticipated.

Accuracy: Performance evaluation of the classification algorithm. This computes the subset of labels

forecasted for a sample must completely match the corresponding true label value

$$(TP + TN) / (TP + TN + FP + FN) = Accuracy$$

Sensitivity (Recall): shows the percentage of classes with positive labels that are categorized as having

positive class labels.

$$TP / (TP + FN) = Recall$$

Precision: The percentage of classes that are identified as positive on all positive projected labels is known as
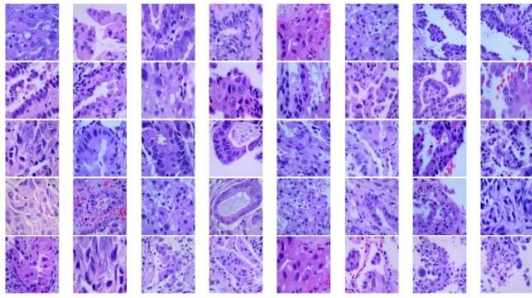
Precision

$$TP / (TP + FP) = Precision$$

The F1 score represents the balance between accuracy and recall
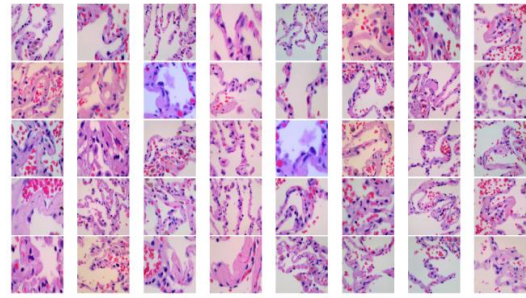
$$2 * ((Precision * Recall) / (Precision + Recall)) = 2 * TP / (2 TP + FP + FN) = F1$$
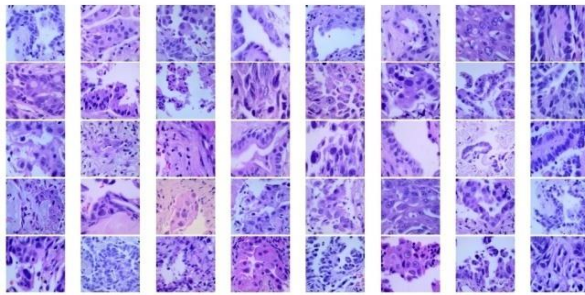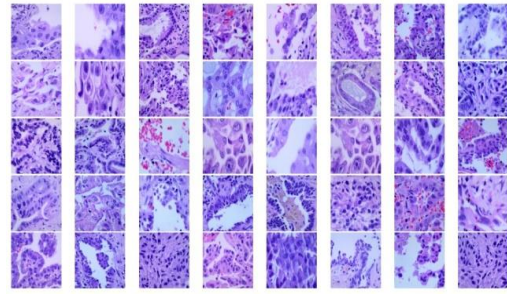
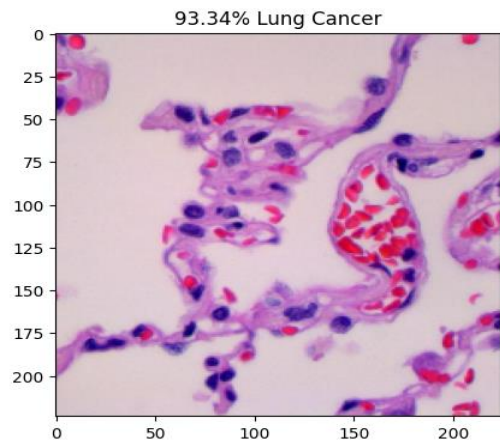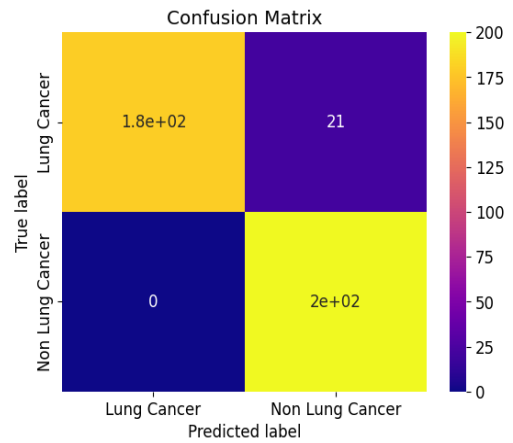Positive Lung Cancer Images
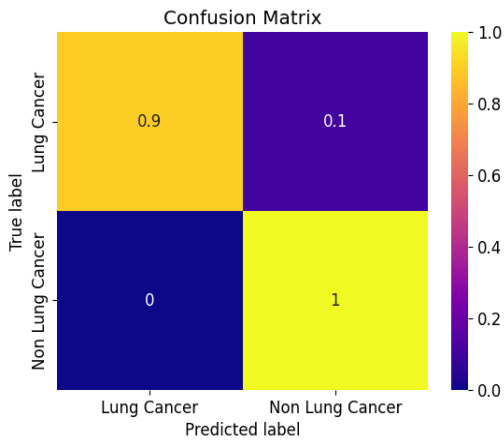

(a)

Negative Lung Cancer Images

(b)

X_train

(c)

X_test

(d)

(e)

(f)

(g)

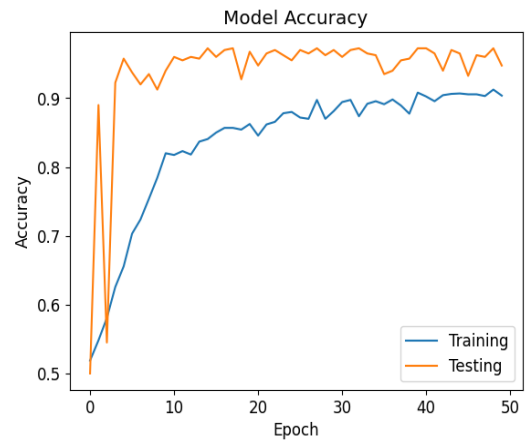(h)

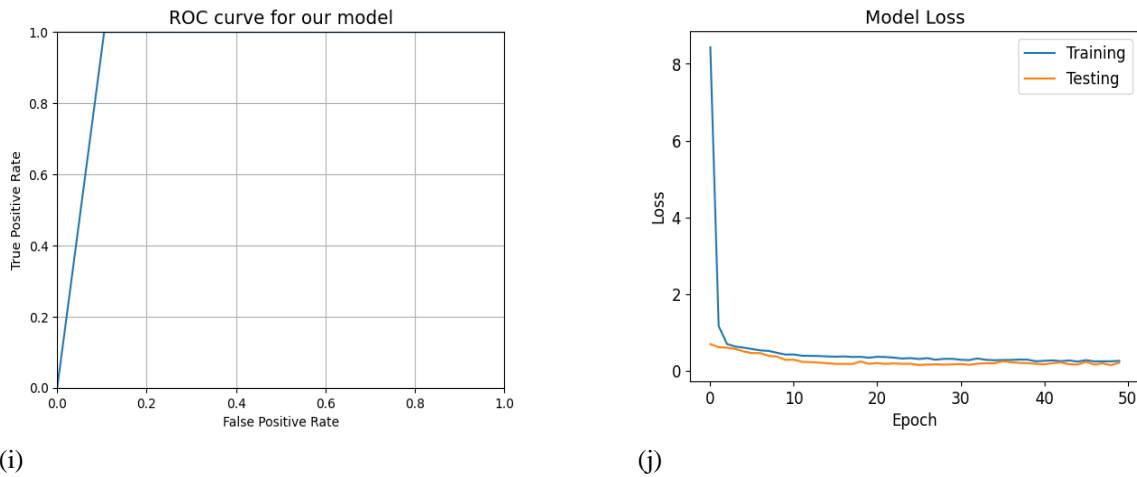(i)   (j)

Fig. 4 Model outputs (a) Positive images, (b) Negative images, (c) Train CT images, (d) Test CT images, (e) Lung cancer in sample image, (f) Confusion Matrix without Normalization, (g) Confusion Matrix with Normalization, (h) Model Accuracy, (i) ROC curve and (j) Model loss

Figure 4a and 4b show sample positive lung cancer and negative lung cancer CT images. Figure 4c and 4d shows train and test CT images from dataset. Figure 4e shows predicated possibility of lung cancer in sample image in percentage. Figure 4f show confusion matrix for predicted label outcomes for model train without normalization. Figure 4g show confusion matrix for predicted label outcomes for model train with normalization. Figure 4h shows model accuracy in terms of training and test dataset here it is observed that test accuracy is improved due to training of model on train dataset. Figure 4i shows roc curve for model's True Positive and False positive rates. Finally Figure j shows model loss curve which reduces with epoch. Table 3 show classification report Precision, Recall, f1-score here the model achieved the accuracy of 95% with precision, recall and f1 score of 100%, 90% and 94% respectively.

Table 3 Classification Report Precision, Recall, f1-score

Label	Precision	Recall	F1-Score	Support
Lung cancer (0)	1.00	0.90	0.94	200
Non Lung Cancer (1)	0.90	1.00	0.95	200
Accuracy	-	-	0.95	400
Macro Average	0.95	0.95	0.95	400
Weighted Average	0.95	0.95	0.95	400

IV. CONCLUSION

Using lung CT scan images as input, the proposed model can classify the output as "benign" or "malignant" using binary classification in the LIDC-IDRI dataset. In terms of accuracy, precision, sensitivity/recall, and the f1-score, the model performs better than the existing model. With nearly 50 epochs the model accuracy approaches 90% during the training phase while it is nearly 95% during testing phase. The model loss during testing phase was below 0.3. Thus the proposed model cannot only predict the "benign" and "malignant" accurately but can also serve as a useful tool for medical image detection.

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