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Lung Tumor Classification and Detection using Deep CNN

Sri P. Anil kumar1, Rachapudi Sai Sruthi[2], Tata Madhuri[3], Rellu Sravani[4]

[1]Assistant professor, Department of Electronics and Communication Engineering, Sheshadri Rao Gudlavalleru Engineering college, Andhra Pradesh, India.

[2,3,4,5] U.G Student, Department of Electronics and Communication Engineering, Sheshadri Rao Gudlavalleru Engineering college, Andhra Pradesh, India

***Abstract*— According to the World Health Organization (WHO), lung tumors are responsible for the highest number of deaths globally. To improve a patient's chance of survival, a practical computer-aided diagnosis (CAD) system has been developed in this study. Early detection of lung cancer through computed tomography (CT) has the potential to save numerous lives annually. Nevertheless, analyzing a vast number of these scans is a daunting task for radiologists who frequently experience observer fatigue, resulting in reduced performance. As a result, there is a need to efficiently read, detect, and evaluate CT scans. This paper proposes a method to detect lung cancer in a CT scan using various models such as Resnet50, Resnet101, GoogleNet, VGG16, and AlexNet. Among these models, AlexNet provided the most accurate results. The author cropped 3D cancer masks on the reference image using the center of the lung cancer provided in the dataset and trained a model with different techniques and hyperparameters. Finally, the author evaluated the result using dice coefficient and confusion matrix metrics, achieving a 94.4% accuracy, 94.5% precision, 94.4% recall, and a score of 94.4% using the AlexNet algorithm on a test set of positive and negative samples.**

Keywords: Deep Learning, Lung Cancer, AlexNet, Computed tomography.

I. INTRODUCTION

Lung cancer is a major global health issue, with lung tumors being a significant cause of this disease. While smoking is often associated with lung cancer, there are instances where non-smokers are diagnosed with the disease. Lung tumors can vary in their location, shape, and intensity. This cancer is one of the most common types, with 225,000 cases and 150,000 deaths in the US alone, costing approximately $12 billion in healthcare expenses. The survival rate for lung cancer is low, with only 17% of people in the US surviving five years after diagnosis. This rate is even lower in developing countries compared to developed ones. Early detection of lung tumors increases the chances of successful treatment, which highlights the importance of effective screening methods. Various approaches can be used to detect lung tumors, including imaging tests, biopsies, and blood tests. Imaging tests are commonly used and may include chest X-rays, CT scans, MRI, and PET scans. These tests can help identify the size, location, and characteristics of a lung tumor. Image analysis of CT scans can be used for early clinical diagnosis, which is useful for treatment planning. Deep learning techniques can be used for the detection of lung tumors, with data acquisition being a crucial step. Large and diverse medical image datasets are required for training deep learning algorithms, including CT or MRI scans indicating the presence of lung tumors. Preprocessing of medical images can help remove noise and normalize the image size, which can enhance the contrast between the tumor and surrounding tissues. Choosing the appropriate network architecture for a specific task is crucial, with Convolutional Neural Networks (CNN), U-Net, and ResNet being some commonly used architectures. The architecture must be able to handle the complexity of the input data, be scalable, and have the capacity to learn the relevant features from the data. Tuning the hyperparameters of the deep learning algorithm is important for achieving optimal performance. The labeled dataset is used to train the deep learning model, and the performance is evaluated on a separate validation set. Hyperparameter tuning involves searching for the optimal combination of hyperparameters that results in the best performance of the model on a given task. The final step is to test the deep learning model on an independent test set and evaluate its performance using appropriate metrics. By using a separate test set and evaluating the performance of the model, we can estimate its

performance on new, unseen data and identify areas for improvement.

II. LITERATURE SURVEY

"Automatic Detection of Lung Nodules in CT Images Using Shape-Based Genetic Algorithm" by Rajendra Singh et al. (2017). In this study, they utilized a shape-based genetic algorithm for automatic detection of lung nodules in CT images. The algorithm demonstrated high accuracy in identifying lung nodules. The authors evaluated the performance of their approach using a CT image dataset, which revealed that the proposed method achieved a sensitivity of 94.28% and a specificity of 98.59% in detecting lung nodules. According to the paper, the shape-based genetic algorithm is a useful technique for detecting lung nodules in CT images and can assist radiologists in diagnosing and managing lung cancer. The authors recommend further research to enhance the performance of the system by incorporating additional features and optimizing the algorithm parameters [1].

"Deep Convolutional Neural Network for Automated Diagnosis of Pulmonary Nodules in CT Images" by Dong et al. (2017). In 2017, Dong and colleagues conducted a research study that utilized deep convolutional neural networks (CNNs) to automate the diagnosis of pulmonary nodules in CT images. Their goal was to create a system that could accurately and efficiently detect the presence of lung nodules and classify them as benign or malignant. Overall, this research study showcases the potential of deep learning in the field of medical image analysis and suggests that using deep CNNs for automated diagnosis of pulmonary nodules could be a valuable tool for early detection and treatment of lung cancer [2].

"Convolutional Neural Networks for Pulmonary Nodule Detection in CT Imaging" by Ardila et al. (2019). In 2019, Ardila et al. presented a novel approach to detecting pulmonary nodules in chest CT images using deep learning techniques. The authors utilized a convolutional neural network (CNN) called CheXNet, which was designed for medical imaging tasks, and trained it on a large set of annotated CT images. The study demonstrated the potential of using deep learning models, such as CheXNet, for automated detection of pulmonary nodules in CT images, which could improve the accuracy and efficiency of lung cancer screening programs [3].

“Computer aided lung cancer diagnosis with deep learning algorithms” W Sun, B Zheng, W Qian - Medical imaging. In 2018, Sun et al. explored the potential of deep learning algorithms for computer-aided diagnosis of lung cancer using medical imaging. They developed a convolutional neural network (CNN) that was trained to categorize CT images of the lungs into three groups: benign nodules, malignant nodules, and normal lung tissue. Overall, the study demonstrated the potential of deep learning algorithms for accurate and efficient diagnosis of lung cancer using medical imaging. The authors suggested that this technology could be integrated into clinical practice to assist radiologists in detecting and diagnosing lung cancer at an early stage [4].

"Automated detection of lung nodules in CT datasets using deep convolutional neural networks" by Ciompi et al. (2017). Ciompi and colleagues published a research paper on the use of deep convolutional neural networks (CNNs) for automating the detection of lung nodules in CT datasets. The main objective of their study was to create a system that could efficiently and accurately identify nodules in CT images and provide diagnostic information for lung cancer screening. To initialize the network, they used a transfer learning approach that utilized pre-trained weights from the ImageNet dataset [5].

"Deep learning-based pulmonary nodule detection in CT images by exploiting both 2D and 3D information" by Shen et al. (2019). In 2019, Shen and co-authors conducted a research study to explore the use of deep learning-based approaches for pulmonary nodule detection in CT images. Their primary goal was to create a system that could effectively utilize both 2D and 3D information to accurately identify nodules in CT scans. The authors trained the system on a large dataset of CT scans. They utilized a transfer learning approach to initialize the network with pre-trained weights from the ImageNet dataset. The proposed approach achieved a high level of accuracy in detecting nodules, with a sensitivity of 95.8% and a false positive rate of 1.6 nodules per scan [6].

“Detection and classification of lung cancer using CNN and Google net” by R. Raj kumar et al. (2022). In the research article titled "Detection and classification of lung cancer using CNN and Google net," R. Raj Kumar et al. propose a method that employs deep learning to detect and classify lung cancer from CT scan images. The authors utilized CNN and GoogleNet, two well-known deep learning architectures, for feature extraction and classification. Additionally, they used data augmentation techniques to enhance their training data's size. The researchers tested their approach on a dataset comprising 302 CT scan images, with 156 malignant and 146 benign images. The authors achieved an accuracy of 96.9% for detecting lung cancer and 93.1% for classification using their proposed technique [7].

"Lung Cancer Detection Using Deep Learning Techniques on CT Images" by S. Sudhakar and S. Prabakaran (2019). The authors stressed the significance of early detection for successful treatment of lung cancer and acknowledged the limitations of traditional image processing techniques. Their proposed approach involved three stages: preprocessing, feature extraction, and classification. The CT images were first preprocessed to eliminate noise and enhance contrast, followed by the extraction of relevant features through a convolutional neural network (CNN). Finally, a support vector machine (SVM) classifier was employed to categorize the images as cancerous or non-cancerous. The authors evaluated their approach on a publicly accessible dataset and achieved a 94.75% accuracy rate [8].

“Lung Cancer Classification and Prediction Using Machine Learning and Image Processing.” By Sharmila Nageswaran et al. In the study "Lung Cancer Classification and Prediction Using Machine Learning and Image Processing" by Sharmila Nageswaran and colleagues, the authors investigate the application of machine learning and image processing for the classification and prediction of lung cancer. They introduce a novel approach that combines image processing techniques with machine learning algorithms to automatically classify and predict lung cancer. The study provides evidence of the potential of combining machine learning and image processing techniques for the automatic classification and prediction of lung cancer. The proposed approach presents a promising direction for future research in this field and has the potential to enhance the accuracy and efficiency of lung cancer diagnosis [10].

III. PROPOSED METHOD

A. End to End Process of CNN

Convolutional network is a deep learning technique, this convolutional network is most often applied to image processing problems, CNN is more effective for processing and classifying the images, this CNN is used to predict the end-end prediction, In this the CNN extracts features from the dataset after training them from the training dataset the convolutional neural network extract the features after that test dataset is compared with the training CNN model then output is in two types normal and cancer.

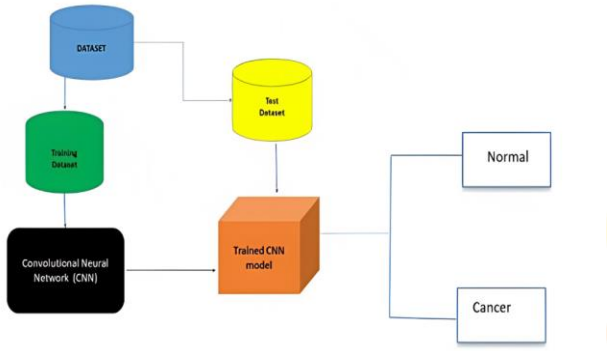


Figure 1: End to End process of CNN

B. Dataset

The dataset used in this project is luna 16 dataset, this dataset consists of two types of datasets one is training dataset and another one is testing dataset, the training dataset is 80% and test dataset is 20%,in training dataset it consists of 1218 and testing dataset consists of 305 and the total images in the dataset is 1523. This dataset is labelled as x_train, y_train, x_test, and y_test.

In this project we use the python programming language to implement the code to execute this python code we use google collab this google collab is easy to execute the implementation to upload dataset in the google collab is:

1.open and create a new file and name it.

2.we have to import or install libraries required for our Project.

3.load the luna 16 dataset.

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2) #split dataset into train and tesrt
print("Dataset train & test split as 80% dataset for training and 20% for testing")
print("Training Size (80%): "+str(X_train.shape[0])) #print training and test size
print("Training Size (20%): "+str(X_test.shape[0]))
```

```
Dataset train & test split as 80% dataset for training and 20% for testing
Training Size (80%): 1218
Training Size (20%): 305
```

Figure 2: Splitting dataset into training and testing datasets

C. Creating the Deep CNN Model

Until the previous step we implemented the required libraries and load the dataset after loading the dataset we split the data to training and testing data After that the architecture will be developed by using keras software , keras libraries is very versatile library in this CNN architecture it consists of so many layers in our project the presented layers are such as convolutional layers, max pooling layer, batch normalization , flatten layer, dense layer, dropout.layer we need a training algorithm to identify the kernel weights and dense layer weights. The used algorithm is alexnet algorithm is used to train the data. this are the following required libraries to define the layers.

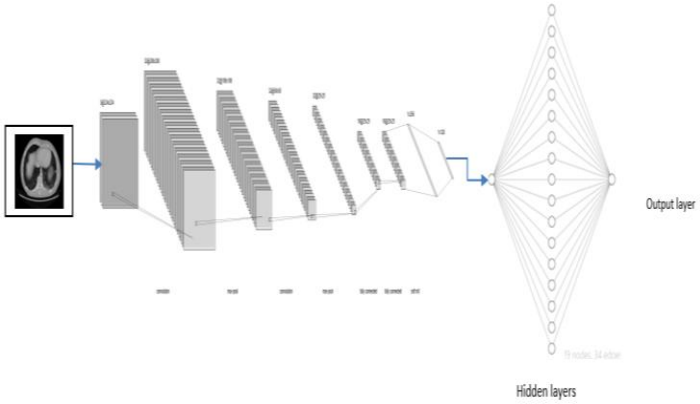


Figure 3. Deep CNN model of Lung tumor Classification and detection by using deep CNN

In this project the alexnet model is declared as sequential since, in a CNN the data flows from input layer to the output layer sequentially.

Convolutional layer 1:

In this convolutional layer 1 the total filters or kernels is equal to 96 with the kernel size 11x11,strides is equal to 4x4,the activation layer is 'relu' .From the definition of kernels, it is found that for each digit 96 feature maps are collected using the 96 kernels.

Pooling layer 1:

The kernel size for the pooling is 1x1 and strides is equal to 2x2 and in this max pooling is considered.

Convolutional layer 2:

In this convolutional layer 2 the total filters or kernels is equal to the 256 with the kernel size of 5x5, strides is equal to 1x1, activation layer is 'relu'. From the definition of kernels, it is found that for each digit 256 feature maps are collected using the 256 kernels.

Pooling layer 2:

The kernel size for the pooling is 1x1 and strides is equal to 2x2 and in this max pooling is considered.

Convolutional layer 3:

In this convolutional layer 3 the total filters or kernels is equal to the 384 with the kernel size of 3x3 , strides is equal to 1x1,activation layer is 'relu'.From the definition of kernels, it is found that for each digit 384 feature maps are collected using the 384 kernels.

Convolutional layer 4:

In this convolutional layer 4 the total filters or kernels is equal to the 384 with the kernel size of 3x3 , strides is equal to 1x1,activation layer is ‘relu’.From the definition of kernels, it is found that for each digit 384 feature maps are collected using the 384 kernels.

Convolutional layer 5:

In this convolutional layer 5 the total filters or kernels is equal to the 256 with the kernel size of 3x3 , strides is equal to 2x2,activation layer is ‘relu’.From the definition of kernels, it is found that for each digit 256 feature maps are collected using the 256 kernels.

Pooling layer 3: The kernel size for the pooling is 1x1 and strides is equal to 2x2 and in this max pooling is considered.

Dense layer 1:

In this model The dense layer 1 is a fully connected network with 256 units(neurons) and the activation function ‘relu’ is chosen.

Dropout layer 1:

In this model the dropout layer has a dropout rate of 0.5.

Dense layer 2:

In this model The dense layer 2 is a fully connected network with 256 units(neurons) and the activation function ‘relu’ is chosen.

Dropout layer 2:

In this model again the dropout layer has a dropout rate of 0.5.

Dense layer 3:

In this model the dense layer 3 is the final layer in this CNN architecture activation function ‘softmax’ is chosen. The reason for choosing 'softmax' over 'ReLu' is in the output we need probabilities.

Figure 4. Layers of deep CNN model.

The summary of the CNN architecture is displayed

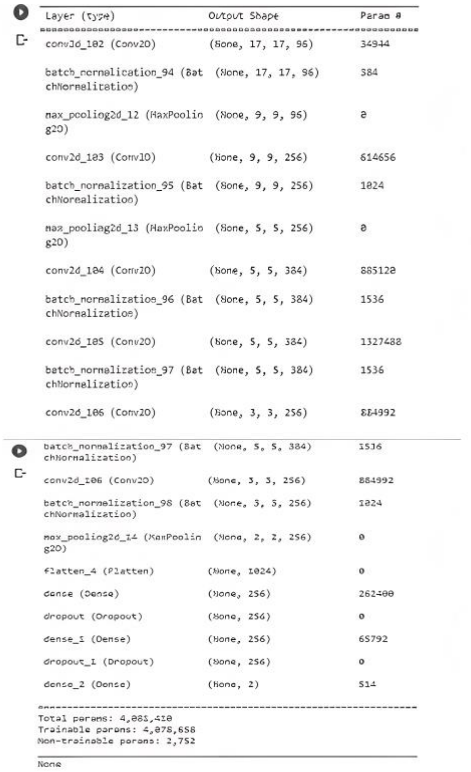


Figure 5. Summary of CNN model

D. Training of the Deep CNN Model

Training in deep learning refers to the process of optimizing the weights and biases of a neural network to minimize the loss function on a given training dataset. The goal of training is to enable the neural network to learn the underlying patterns and relationships in the data, so that it can make accurate predictions on new, unseen data. The training dataset is 80% and test dataset is 20%, the training dataset consists of 1218 images. Now we will train the CNN using the function 'model.fit ()'. Here we taken 10 epochs and one verbose.

Figure 6. Training of deep CNN

E. Testing of the Deep CNN Model

In this after compilation of training the model we will calculate the precision, recall, f score, accuracies. During testing, the neural network takes in the test data as input and produces output predictions, which are then compared with the actual target values to compute the evaluation metrics. The test results can then be used to assess the overall performance of the neural network and identify any areas for improvement.

```
#prediction on test data using Alexnet
predict = alexnet_model.predict(X_test)
predict = np.argmax(predict, axis=1)
testY = np.argmax(y_test, axis=1)
calculateMetrics("Alexnet", predict, testY)

10/10 [==============================] - 2s 134ms/step

Alexnet Accuracy    : 94.42622950819673
```

Figure 7. Testing of the deep CNN

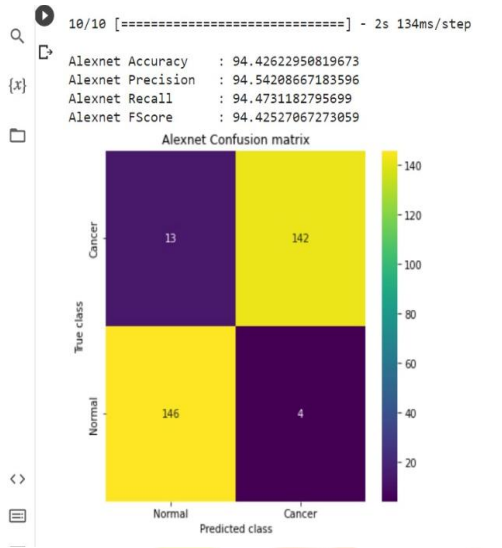


Figure 8. Testing of Alex net model

IV. RESULTS AND ANALYSIS

The developed model predicts the presence or absence of cancer in lung. For this we trailed different models and selected the highly accurate model. Those are Resenet50, Resenet101, GoogleNet, VGG16,Alexnet algorithms. Among those Alexnet predicted the tumors or non tumors with high accuracy compared to other algorithms. The Resenet50 gives accuracy of 49.1%, with 24.5% precision. The Resenet101 doesn't give much better accuracy compared to Resnet50. The GoogleNet algorithm has accuracy of 3.9%, with 1.6% of precision. The Alexnet algorithm has accuracy of 94.4%, with the precision of 94.5%. so the Alexnet algorithm predict accurately compared to other models.

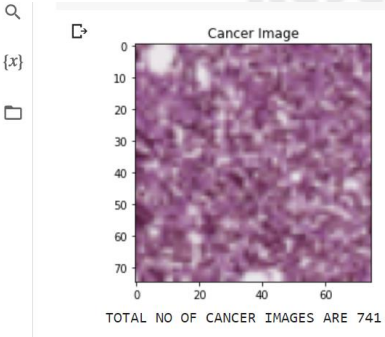


Figure 9. Classification of cancer images

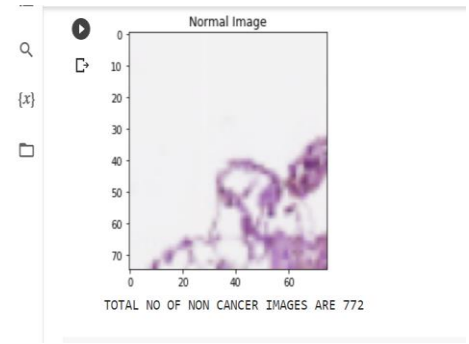


Figure 10. Classification of non-cancer images

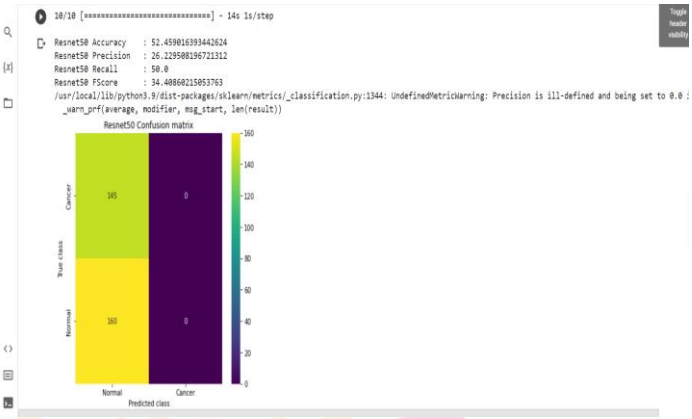


Figure 11. ResNet50 model results.

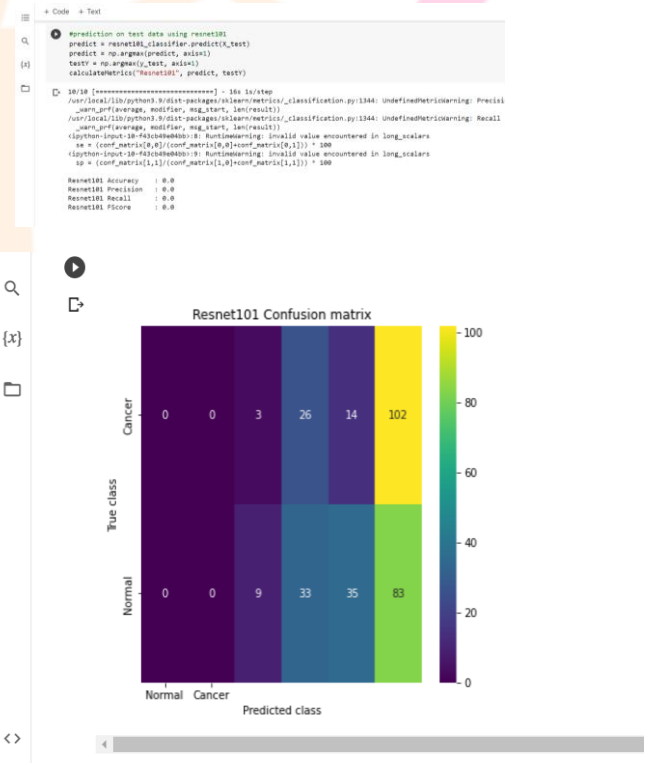
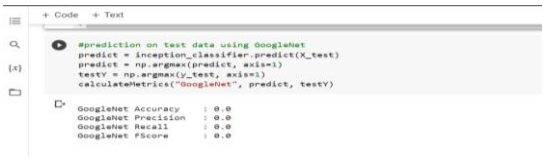


Figure 12. ResNet101 model results.



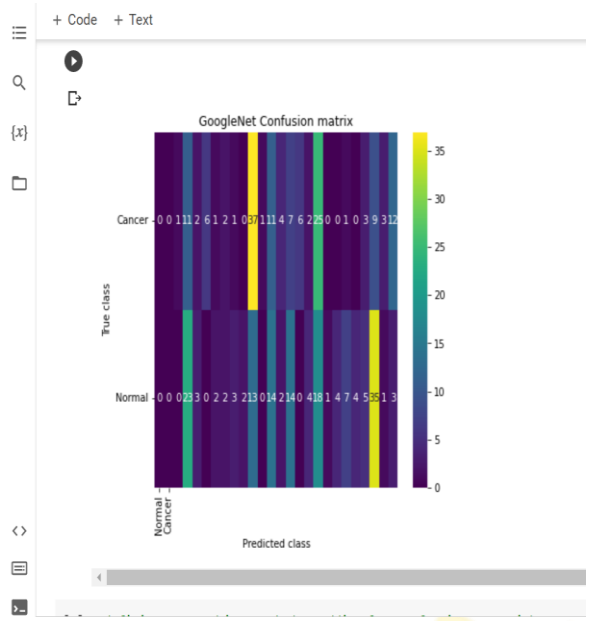


Figure 13. GoogleNet model results.

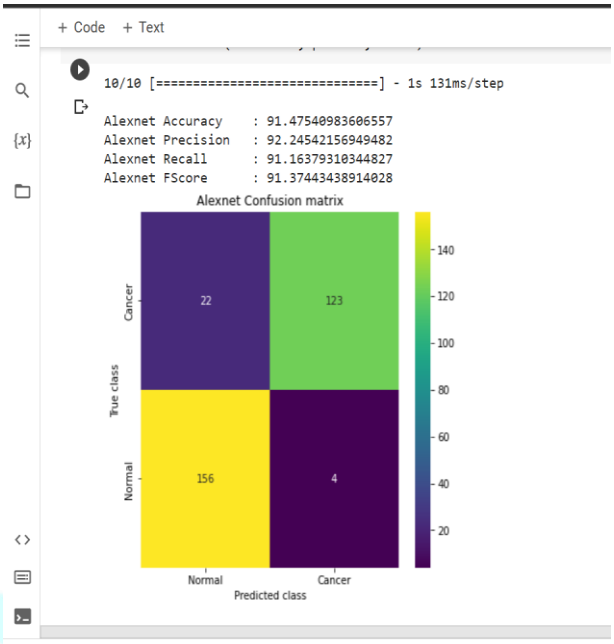
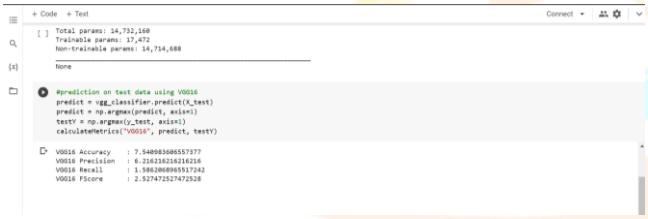


Figure 15. AlexNet model results.



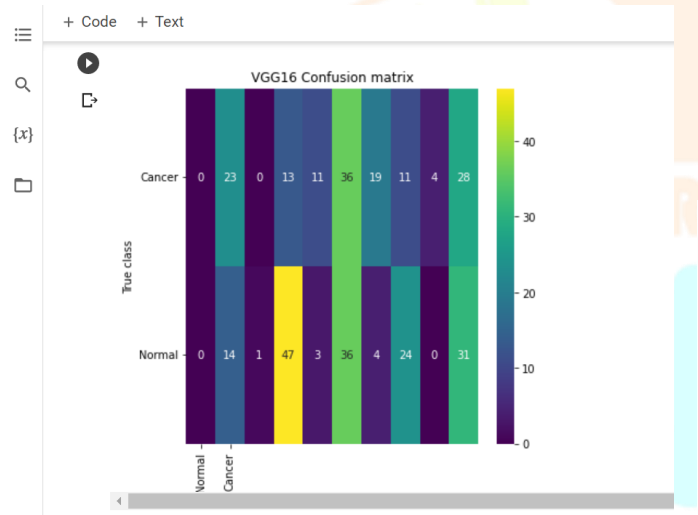


Figure 14. VGG16 model results.

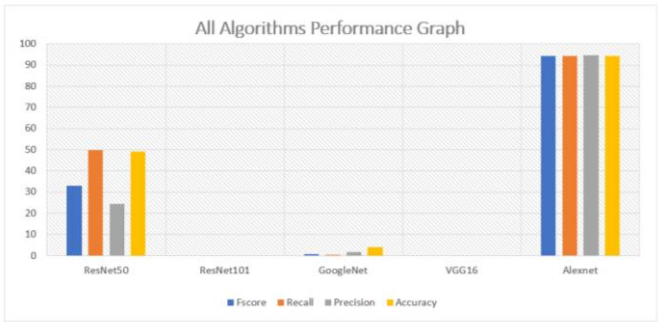
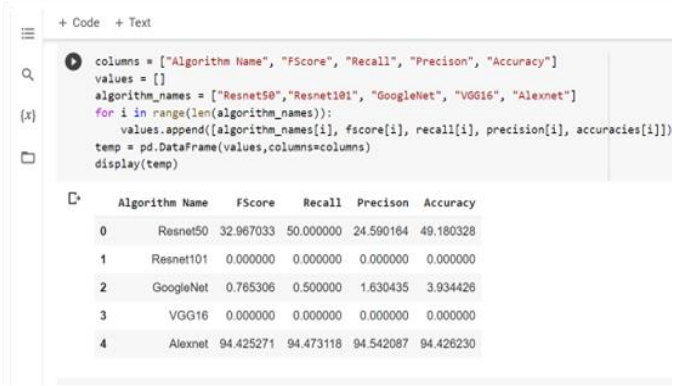


Figure 16. All Algorithm Performance Graph



```
+ Code  + Text

columns = ["Algorithm Name", "FScore", "Recall", "Precison", "Accuracy"]
values = []
algorithm_names = ["Resnet50","Resnet101", "GoogleNet", "VGG16", "Alexnet"]
for i in range(len(algorithm_names)):
    values.append([algorithm_names[i], fscore[i], recall[i], precision[i], accuracies[i]])
temp = pd.DataFrame(values,columns=columns)
display(temp)
```

	Algorithm Name	FScore	Recall	Precison	Accuracy
0	Resnet50	32.967033	50.000000	24.590164	49.180328
1	Resnet101	0.000000	0.000000	0.000000	0.000000
2	GoogleNet	0.765306	0.500000	1.630435	3.934426
3	VGG16	0.000000	0.000000	0.000000	0.000000
4	Alexnet	94.425271	94.473118	94.542087	94.426230

S.No	Algorithm Name	FScore	Recall	Precision	Accuracy
0	ResNet50	32.967033	50.000000	24.590164	49.180328
1	ResNet101	0.000000	0.000000	0.000000	0.000000
2	GoogleNet	0.765306	0.500000	1.630435	3.934426
3	VGG16	0.000000	0.000000	0.000000	0.000000
4	Alexnet	94.425271	94.473118	94.542087	94.426230

Figure 17. Algorithm Performance Table

V. CONCLUSION

The timely identification of lung cancer is crucial for successful treatment and improved patient outcomes. Various imaging tests, such as CT scans and MRI, can be used for its detection. Several studies have explored the use of AI and machine learning algorithms, such as CNNs like AlexNet, for lung cancer detection, which have yielded promising results. However, it's important to note that these algorithms should be considered as an aid to medical professionals, rather than a replacement for them. Regular screening for lung cancer is especially important for high-risk individuals, such as smokers and those with a family history of the disease. If you experience symptoms of lung cancer, such as chest pain, coughing, or shortness of breath, it's crucial to seek advice from a healthcare provider. Essentially, deep learning algorithms are utilized to analyze images to detect the presence of lung cancer. The future of lung tumor detection based on deep learning looks bright, as it has the potential to improve the accuracy, efficiency, and speed of diagnosing and treating lung cancer.

VI. REFERENCES

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