



LUNG CANCER DETECTION AND PREDICTION USING DEEP LEARNING

Rameshwari Anand, Nandan A Rao, Sumukh DS
Department of Electronics and communication BNMIT, Bangalore
Karnataka State, India

Abstract — Lung cancer is a malignant tumor of the lungs that is characterized by uncontrolled cell proliferation. Early identification of lung cancer can improve lung cancer patient's chances of survival and save many lives. Because cancer diagnosis is one of the most difficult tasks for radiologists due to the shape of cancer cells, a computer- aided diagnosis method can be beneficial. As a result, early detection and prediction of lung cancer should play a critical role in the diagnosis process, as well as increase patient survival rates. This project presents lung cancer detection based on CT images using efficient lung cancer classification and prediction using deep learning models for improved accuracy. The architecture is trained using pre-processed CT images. The patient input photos are then tested using deep learning models. The primary goal of this research is to determine whether a patient's lung contains a cancer tumor. By creating a handcrafted CNN model and using Transfer Learning-based VGG-16 and Inception V3 architectures to train the model, we present a convolution neural network-based classification technique. The performance of these models is compared in this study. To achieve the best outcomes, hyper parameter optimization was performed.

Keywords— tumor detection and prediction, machine learning approaches, convolution neural network, vgg16, inception v3, web page building, flask framework.

I. INTRODUCTION

Lung cancer is a disease that develops as a result of uncontrolled cell development. Lung cancer is the most frequent cancer, and its high mortality rate has a significant impact on patients. The lungs' overall job is to assist us in breathing, that is, to take in air from the atmosphere and provide oxygen to the bloodstream. Each of the lungs is now surrounded by a sac-like substance known as the pleural sac, which contains a fluid known as pleural fluid; the function of this fluid is to allow the outer and inner layers of the lung to glide over each other; cells present in the lung have the potential to mutate, and thus cannot perform the same functions as those of a normal healthy lung. As a result, tumours develop. Small cell lung carcinoma (SCLC) and non- small cell lung carcinoma (NSCLC) are the two most common forms of malignant

tumours (NSCLC). Lung cancer is one of the most fatal diseases, with a 19.4% mortality rate. To diagnose lung malignancies early, a variety of imaging techniques are used, including computed tomography (CT), sputum cytology, chest X-ray, and magnetic resonance imaging (MRI). Tumors are classified as non-cancerous (benign) or cancerous (cancerous) during the detection process (malignant). Lung cancer is caused mostly by cigarette smoking, although other factors such as environmental pollutants, particularly air pollution, and excessive alcohol use may also play a role. When lung cancer spreads to the brain, it can cause vision problems and weakness on one side of the body. Coughing up blood, chest pain, and shortness of breath are all symptoms of primary lung cancer. Unfortunately, most diagnoses are made at later stages of the disease, owing to a lack of early-stage symptoms, and when cancer is detected early, the chances of survival increase. The physical examination and diagnosis procedure can be greatly expanded with the use of picture modification methods. With the development of computer learning methods, a number of experts are seeking to detect cancer early on. In the identification of cancer cells among normal tissues, the neural network plays a key role, which in turn provides an important instrument for building an assistive AI-based diagnosis of cancer. Here we present the help of a Convolutional Neural Network (CNN) and transfer learning models to identify lung tumors as malignant or benign. Traditionally, machine learning and deep learning algorithms were created to function with a certain feature-space distribution. Models must be redesigned from the start when the feature-spaces a result, deep learning models require a large amount of labeled data during training. As a result, building a machine learning-based model for a target domain with minimal labeled data for supervised learning is almost difficult. Transfer learning would considerably boost learning performance and also increase accuracy. The IQ-OTHNCCD lung cancer dataset is used for our project. We propose a convolution neural network-based classification technique and designed a manual CNN model. VGG-16 and Inception V3 architectures were also used with fine-tuning to train the model with our dataset. Image-Net pre-trained networks are mainly trained from natural images. You must fine tune your network, known as transfer learning, because to the vast contrast between natural photos and medical imaging such as CT/MRI. VGG-16 and Inception V3

architectures were employed with fine-tuning to train the model with our dataset in a comparative study of these models. Natural photos are used to train Image-Net pre-trained networks. You must fine-tune your network, known as transfer learning, because of the vast contrast between natural photos and medical imaging such as CT/MRI. Lung cancer screenings that are successful can save a lot of lives, making them incredibly useful. Manually reviewing cancer screens takes a lot of time and money, and it's not always accurate because categorizing tumours necessitates specialized radiological understanding. Deep learning, in particular, can thus help improve the quality of screenings while also lowering the expenses. Cancer is one of the most deadly diseases that lead to death. According to cancer statistics, there are 14.1 million cancer cases worldwide in 2019, with lung cancer taking first place with a 13 percent prevalence rate.

While 8.2 million people died from cancer, the leading cause of death was lung cancer, which accounted for 19 percent of all deaths. The method of early cancer identification is crucial in preventing cancer cells from proliferating and spreading. Lung nodules are tiny tissue lumps that can be cancerous or non-cancerous and are referred to as malignant or benign.

Benign tissues are most commonly non-cancerous and do not have much growth whereas malignant tissues grow very fast and can affect to other body parts and are dangerous to health.

Motivation

- Medical professionals who work in lung cancer diagnoses, such as radiologists or doctors, or any other users, would be the users in this project. A web application is designed to allow users to interact with it. A CT scan must be uploaded to the program.
- The user selects which scan to forecast, and the application pre-processes the CT scan before inferring the image to the prediction model. The model's result is subsequently presented to the user.
- The system should be able to provide information that our users can understand and apply to acquire insight.

Problem Statement

A computer tomography (CT) scan was used to detect malignant cells in a patient's lung nodules. Deep Learning was used to predict lung cancer tumour levels.

Objectives

The primary goal of our investigation is to determine whether a patient's lung contains a cancer tumor. To achieve the best results, many deep learning models were created. A user-centered design element should be included in the project.

One of the deadliest diseases, cancer is one of the leading causes of mortality. According to studies, there are 14.1 million cancer cases worldwide in 2019, with lung cancer ranking first with a 13 percent prevalence rate. While cancer claimed the lives of up to 8.2 million people, lung cancer was the leading cause of death, accounting for 19 percent of all deaths. The method of early cancer identification is critical in preventing cancer cells from proliferating and spreading.

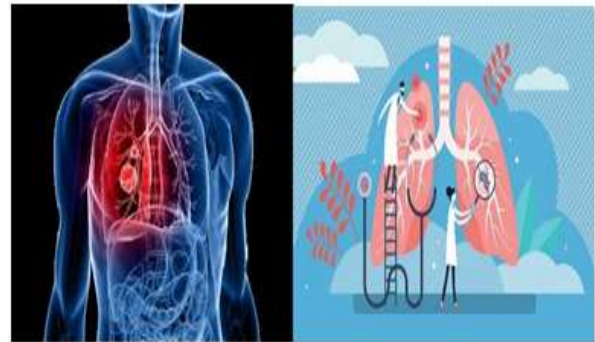


Figure 1: Lungs

II. LITERATURE SURVEY

Several lung cancer diagnosis and diagnostic systems have been presented that use diverse approaches to image recognition, computer learning, and deep learning to diagnose and identify the disease with the best outcomes. We looked at a number of lung cancer detection systems that have been proposed to the FDA. With the help of a radiologist and a clinician, the condition can be detected and classified more accurately. by combining image processing, machine learning, and other techniques

Methodologies

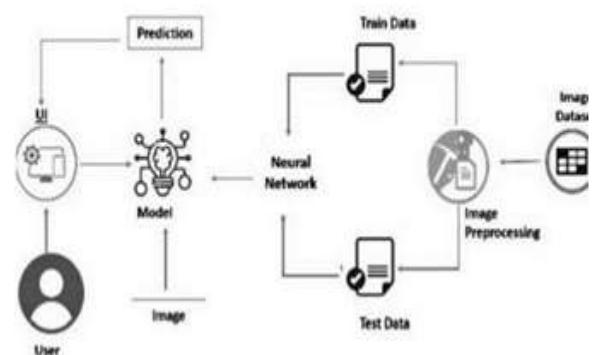


Figure 2: block diagram

Software Description: The goal of preprocessing is to improve picture data by suppressing unwanted distortions or enhancing particular visual properties that are important for

subsequent processing and analysis tasks. There are many various types of images utilized in medical imaging, but Computer Tomography (CT) scans are often chosen since they have less noise. Deep learning has been shown to be the most effective way for medical imaging, feature extraction, and object categorization. Many researchers have proposed many sorts of deep learning architectures to classify lung cancer.

The software's used: Anyone can use Google Colab to write and run arbitrary Python programs. Colab is a cloud based Jupyter notebook environment that is free to use. Many common machine learning libraries are supported by Colab and can be quickly loaded into your notebook. It gives you access to free RAM, GPU, an TPU.

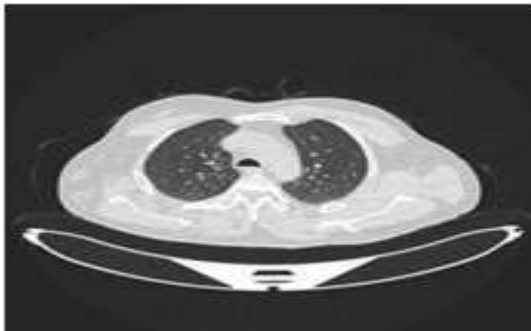


Figure 3: Normal CT scan Image

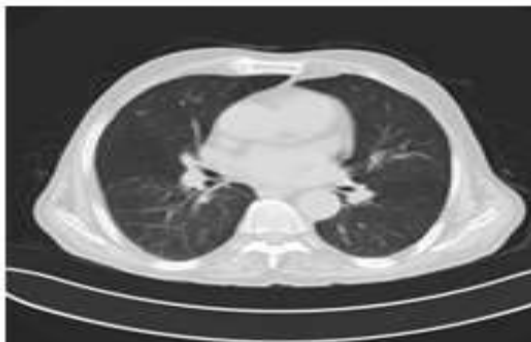


Figure 4: Malignant CT scan image



Figure 5: Benign CT scan Image

Packages Used: Tensor Flow is an open-source machine learning platform that runs from start to finish. It includes a wide range of tools, libraries, and community resources. Keras relies on it as a backend. Google's Tensor Flow is an

open- source deep learning library. It has been employed in machine learning and deep learning studies. Tensor Flow is about multidimensional arrays called tensors being computed, but what makes Tensor Flow remarkable is its ability to deploy computations on a variety of devices. Scikit-learn It was created to work with the Python numerical and scientific libraries NumPy and SciPy, and is also known as sklearn. It was used to create the confusion matrix. Scikit-learn integrates well with many other Python libraries, such as Matplotlib and Plotly for plotting. Scikit-learn is a Python module for machine learning built on top of SciPy. Python Imaging Library is a free and open-source additional library for the Python programming language that adds support for opening, manipulating, and saving many different image file formats. OpenCV: OpenCV (Open Source Computer Vision) is a well-established computer vision library which is written in C/C++ and has been abstracted to interface with C++, Python, and Java. This is a powerful tool when working with images and has a myriad of tools regarding image data manipulation, feature extraction and etc. Keras is also a Deep Learning Framework that abstracts much of the code in the other Frameworks like Tensor Flow and Theano. Keras is a deep learning API written in Python, running on top of the machine learning platform Tensor Flow. It is high-level in nature which makes it extremely simple and intuitive to use. Keras leverages various optimization techniques to make high- level neural network API easier and more performant. It supports multiple platforms and backends and has high scalability of computation. NumPy is a library in python that allows for efficient numerical computing in Python. This library is highly optimized to do mathematical tasks. In the project, NumPy is heavily used in data preprocessing and preparation. One of the main features of NumPy is its highly efficient n- dimensional array (ndarray). NumPy can also perform more efficient mathematical operations compared to the math library in Python. Matplotlib is a Python plotting library that allows programmers to create a wide variety of graphs and visualizations with ease of use. The great feature about Matplotlib is that it integrates very well and creating visualizations is simple.

Data Collection: Artificial Intelligence is strongly reliant on data; machine learning without data is difficult. It is the most important aspect that allows for the teaching of algorithms. Image data gathering is required for training and testing Convolutional Neural Networks. Two directories will be created, one for training and the other for verifying our model with photos. In patients with non-small cell lung cancer, the IQ- OTH/NCCD lung cancer dataset collection assesses the variability of tumour unidimensional, bidimensional, and volumetric parameters using computed tomographic (CT) images. It is a web-based international resource for the development, training, and assessment of computer-assisted diagnostic (CAD) approaches for the diagnosis of lung cancer. Oncologists and radiologists in



these two centers marked IQOTH/NCCD slides. The lung cancer dataset IQ-OTH/NCCD Lung cancer data from the Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases (IQ- OTH/NCCD) was collected in 2019. A total of 1190 images reflect CT scan slices from 110 instances in the collection. There are multiple slices in each scan. The number of these slices varies from 80 to 200, and each one depicts a distinct side and angle of the human chest. In our project, we divided 930 photos into two categories: cancer and non-cancer. The CT scans were obtained in DICOM format at first.

III. IMPLEMENTATION

Image Pre-processing is a method of improving image data by removing unwanted distortions or enhancing certain visual qualities that are important for subsequent processing and analysis. Images from the collection are accessible in DICOM format. The DICOM (Digital Imaging and Communications in Medicine) standard has become the industry standard for medical imaging. Images are converted to the .jpg format, along with the same labels, for successful classification. To begin, the photographs in the dataset are converted to jpeg format and saved. Cancer and Non-Cancer are two different directories in which the transformed photos are stacked. The CNN algorithm is used to extract significant characteristics from an image. All picture preprocessing is done implicitly by the CNN classifier. These photos are fed into CNN, which classifies them as malignant or non-cancerous. Normalization is a technique for modifying the range of pixel intensity values. Each image in the collection will be distinct in size. This puts the categorization accuracy in jeopardy once more, which must be avoided. The act of converting all photos to a uniform pixel size is known as data normalization. For CNN and VGG16 models, the images in the dataset are shrunk to an equal dimension of 224x224 pixels. Augmentation of images Image augmentation is the process of altering photographs to create many altered copies of the same image in order to provide the model with a larger number of training examples. For example, changing the orientation, brightness, or scaling of an input image at random so that a model can examine how an image topic appears in different conditions. It allows us to expose our classifier to a wider range of circumstances, making it more resilient. Augmentation is a technique that is commonly used to improve training, raise convolutional neural network testing accuracy, and improve deep network performance. Image augmentation generates training images artificially using a variety of processing methods or a mix of methods, such as random rotation, shifts, and other techniques. Horizontal Flip Augmentation, Horizontal Flip Augmentation, Horizontal Flip Augmentation, In the case of a vertical or horizontal flip, an image flip entails reversing the rows or columns of pixels. Rotation, rotate the image by a certain amount. We rotate in an 8-degree range here. Horizontal

Shift is a term used to describe the augmentation of a horizontal shift.

The image's pixels will shift horizontally without modifying the image's size. Some picture pixels will be trimmed off, and a new region will be created where new image pixels will be inserted to achieve the same image dimension. The Keras Image Data Generator class contains two key arguments: width shift range and height shift range, and the picture pixels will shift left-right and top-bottom based on these values. The range of Brightness, Changes the brightness of the light in an image. It will begin to darken the image if the value is less than one. If you increase the value over 1, the image will begin to brighten. The channel values are randomly shifted by a random value taken from the range given by the channel shift.. A zoom augmentation, also known as random zooming, randomly zooms in on an image and either add additional pixel values around the image or interpolates pixel values. The zoom range argument to the Image Data Generator function Object() { [native code] } can be used to control image zooming. We choose 0.15 as the zoom range for our project. Shearing is also used to change the image's orientation. The image's shape is slanted when the shear transformation is used. Shear transformation differs from rotation in that it fixes one axis while stretching the image at a specific angle known as the shear angle. We used a shear range=0.10 for our project.

Loading the dataset

A Google cloud directory holds the whole image dataset. This directory contains the photos used for training and testing. The patient's id in the directory is used to caption the photographs in each iteration. The IQ-OTHNCCD can be photographed in JPEG format. The images are piled in two different directories: Cancer and Non-Cancer. The photos are then loaded using the Image Data Generator function.

Machine learning approaches

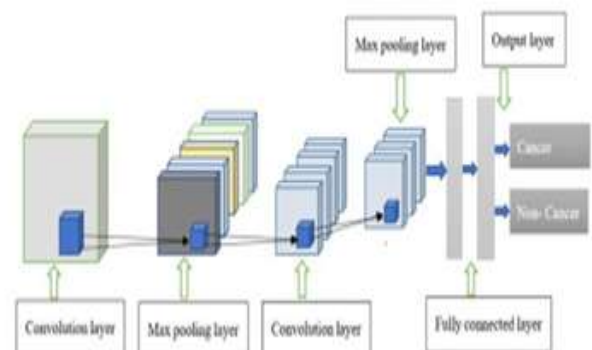


Figure 6: CNN Architecture

The CNN is built with 12 layers, five of which are convolutional, and three layers for maximal pooling. Each convolutional layer is followed by a relu activation function

due to its computing speed. A flattening layer has also been added.

Following the sigmoid activation function, a totally linked layer is added to link the current layer to the previous layer. Dropout layers are also employed to reduce the number of connections that exist between neurons.

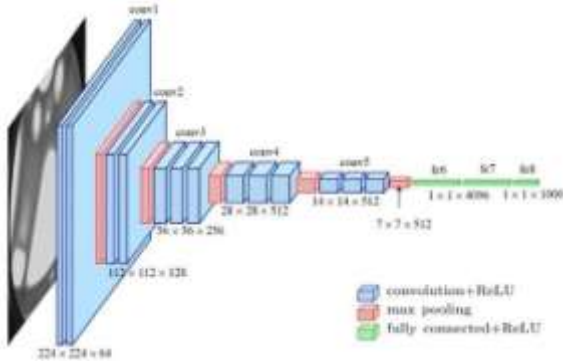


Figure 7: VGG-16 Architecture

For classification, a total of 13 convolutional layers and three dense layers are placed one after the other. The number of filters in the convolution layers increases as the architecture progresses, and the informative features are acquired by using max-pooling layers at various stages.

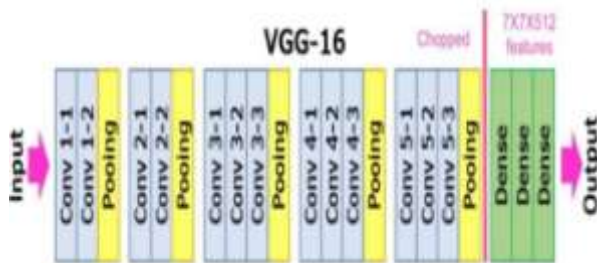


Figure 8: VGG-16 Layers

The VGG 16 model is fed images of 224x224x3 pixel dimensions. The first two layers are made up of three 3*3 convolutional layers, each with 64 filters. Following the creation of a 224x224x64 image, a pooling layer reduces the image's height and breadth to 112x112x64. The second Convolutional Network is identical to the first, except it uses Rectified Linear Units to minimize training time. A pooling layer with a max pool of 2*2 size was then added.

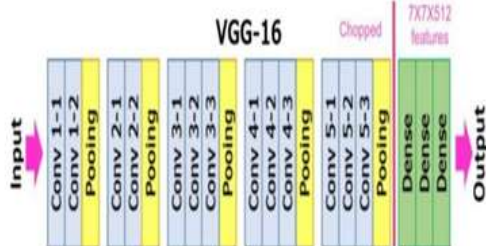


Figure 9: InceptionV3 architecture

The convolutional neural network Inception v3 can assist with object detection and image analysis. It has about 48 layers and is trained using the Image Net data set, which has 1000 classes and has a 299x299 input size. The model's symmetric and asymmetric building blocks include convolutions, average pooling, max pooling, dropouts, and completely linked layers.

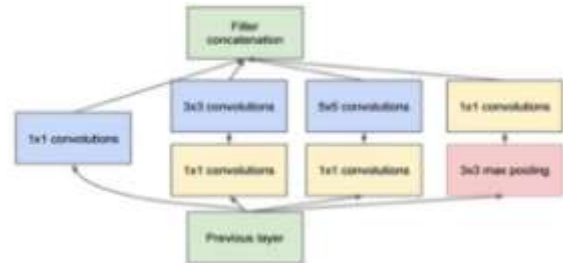


Figure 10: Inception module with dimension reduction

It performs the function of parallel filters. The model was made up of blocks that could perform convolutions using various scale filters and then combine the results into one. An Inception v3 network's architecture is built up over time using factorized convolutions, smaller convolutions, asymmetric convolutions, and so on.

Evaluation Parameters

The number of true positives, true negatives, false positives, and false negatives is displayed in the confusion matrix. These characteristics were used to assess the performance.

- True positive (TP): This is the correct classification of positive samples that are accurately anticipated as positive. For example, suppose a picture contains malignant cells and the model correctly classifies the presence of malignancy.
- True negative (TN): Negative samples for which a negative label is appropriately anticipated. For instance, if there any cancer in the image? It's non- cancer, according to the model.
- False negative (FN): positive samples that are wrongly forecasted as negative. as an example, Although the image does not include cancer, the model predicts that it will.
- False positive (FP): Negative samples with a positive label predicted inaccurately. If the image contains malignant cells, the model labels it as non-cancerous.
- Accuracy: To evaluate the classifier's performance. It's the number of correct guesses divided by the total number of predictions. $Accuracy = (TP + TN) / (TP + FP + TN + FN)$
- Sensitivity: The percentage of positive samples successfully detected, which shows the proportion of positive labels in the categorized class. $Sensitivity = TP / (TP + FN)$
- Specificity: The ratio of correctly categorized negative

cases by a model to the total number of true negatives is known as specificity. It specifies the percentage of non-cancerous images that are categorized as such. $\text{Specificity} = \text{TN} / (\text{TN} + \text{FN})$

Web-Page building for prediction

The purpose of this project is to create a proof-of-concept software that allows clinicians to input CT scans and receive predictions from a model. To do this, a web application with an integrated deep learning model was created. The web app was created with HTML, CSS, and JavaScript, with a back end written in PHP. Python uses the Flask micro framework. A CT scan must be uploaded to the program. The user selects which scan he or she wishes to perform. The application analyses the CT scan and infers the image to the predictive model. The model's output is then displayed to the user. The system should be able to provide us with information. It is proper for the user to comprehend and obtain knowledge from it. HTML (Hyper Text Markup Language) is a markup language used to create the structure of a web page. Our front end and webpage were both designed using HTML. CSS is used to style HTML elements. CSS improves the HTML webpage's colors, layout, and styling. The user uses a POST request to upload a.h5 file to the backend system. With the help of OpenCV and NumPy, the system converts the image into a data array (.npy). To supply each image to the model, we construct Numpy files and utilize the filenames to refer to the image and Numpy files.

The images are downloaded by the system. from the backend to the frontend This is accomplished by the system sending GET requests to each of the user's images. Flask is a Python- based micro web framework. It's very adaptable, simplistic, and simple to set up. Flask is also BSD licensed, allowing for greater customization. The beauty of Flask is how adaptable and simple it is to use. The term "web framework" refers to a set of libraries and modules that allow us to create web applications. Flask is a container for liquids. WSGI toolkit and jinja2 template are used. Jinja2 allows you to incorporate variables and build loops and right in the template, add if statements.

Results

- Adding Convolutional Layers and Pooling layers.
- Adding fully Connected Layers.
- Adding Output Layer.
- Configuring and compiling.

Algorithm

- Step-1: Collect the dataset.
- Step-2: Split the dataset to train and test folders.
- Step-3: Loading dataset and image –Data normalization
- * Resizing images to 224*224
- Step-4: Image Augmentation by Image Data Generator library.

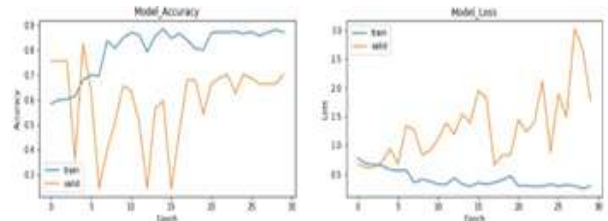


Figure 11: CNN Model Accuracy and CNN Model Loss

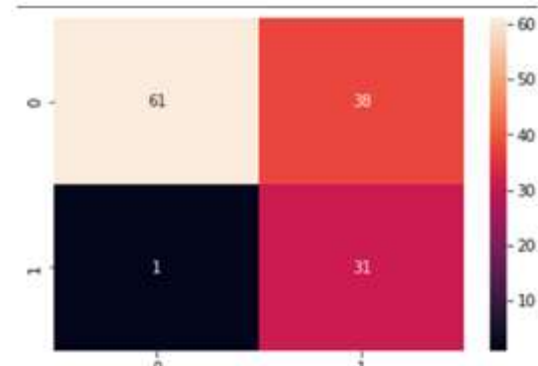


Figure 12: Confusion Matrix of CNN

A total of 131 photos are exhibited in a confusion matrix, comprising 101 images for cancer and 30 for non-cancer classes. It is used to assess the model as depicted in the figures. In the confusion matrix, the purple hue denotes a misclassification result, while the other color denotes the results of a correctly classified class. True positives (TP) are malignant pictures that have been diagnosed accurately as positive. For CNN, I'm here. True negatives (TN) are non-cancerous images that are appropriately identified as negative and have a TP of 80. TN False positives (FP) are non- cancerous pictures that are mistakenly labeled as positive by CNN. CNN's FP is 19, and false negatives (FN) are malignant images that have been wrongly labeled as non-cancerous.

- Scaling, Shearing, Zooming, flipping, and rescale.
- Rotation, width height, and channel shifting.
- Changing Brightness range.
- Step-5: Model Building
- Import all Libraries
- Initializing the model
- Step-6: In case of Implementing designed CNN Architecture

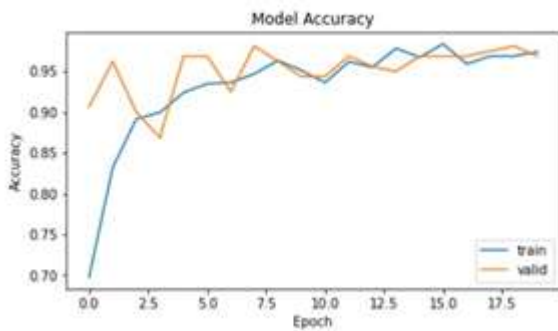


Figure 13: Model Accuracy VGG-16

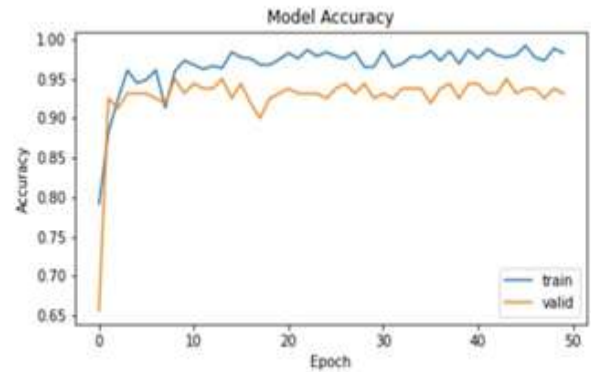


Figure 16: Model Accuracy Inception V3

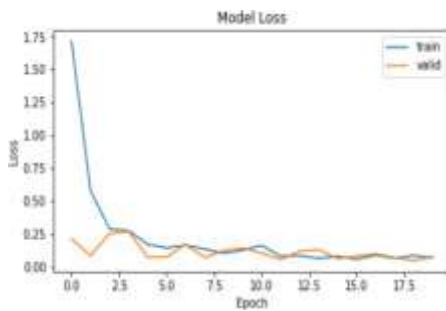


Figure 14: Model Loss VGG-16

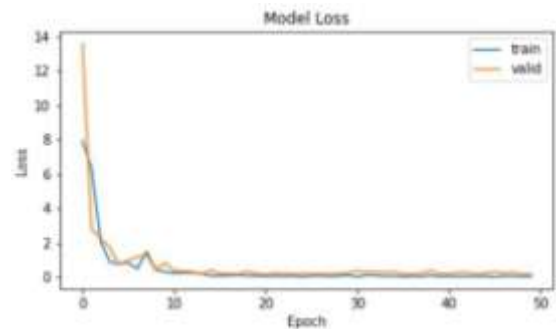


Figure 17: Model Loss Inception V3



Figure 15: Confusion Matrix of VGG-16

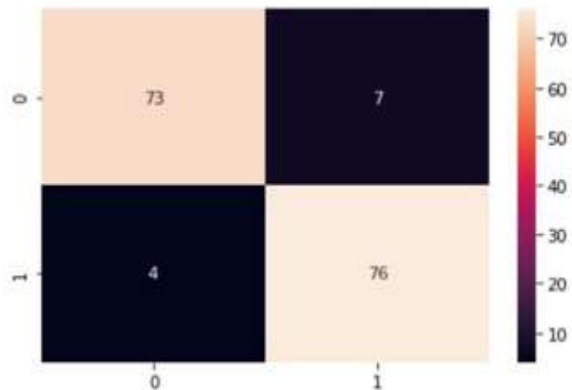


Figure 18: Confusion Matrix of InceptionV3

Overtraining epochs, this is a plot of accuracy on the training and validation datasets. The training and validation accuracy of the fine-tuned VGG16 model is observed to have a similar convergence rate in both training and validation outcomes.

This model isn't too tight. This is a plot of loss over training epochs on the training and validation datasets. The experimental results prove that transfer learning improves performance.

In a confusion matrix, there are 80 photos for each cancer and non-cancer class, for a total of 160 images. It is used to assess the model as depicted in the figures. In the confusion matrix, the black color denotes a misclassification result, while the other color denotes the results of a correctly classified class. True positives (TP) are malignant pictures that have been diagnosed accurately as positive. True negatives (TN) are non-cancerous pictures that are accurately identified as negative for VGG16 TP 75 and InceptionV3 TP 73. False positives have a TN of 80 for VGG-16 and a TP of 76 for Inception V3 (FP) The FP for VGG-16 is 5 and it represents non-cancerous pictures that



are wrongly categorized as positive. Inception V3 is 7, and false negatives (FN) are malignant images that have been categorized mistakenly as non-cancerous. VGG-16 has an FN of 0 while Inception V3 has an FN of 4. We've discovered that the VGG-16 Model excels at Identifying the difference between a CT scan with no cancer nodules and one with cancer.

IV. CONCLUSION

Deep learning techniques for lung cancer diagnosis utilizing CT scans are used in this project. Convolutional Neural Networks and Transfer Learning models such as VGG16 and Inception V3 are used in the suggested technique. We employed transfer learning to improve the validation accuracy. Transfer of knowledge The Inception V3 and VGG16 were used in the implementation. Tuning Hyper parameters and the photographs were also pre-processed. The VGG16 performed better in terms of efficiency. While predicting the output, the accuracy was 96 percent. However, Inception v3 was faster. compared to VGG16 in the training procedure. It's impossible to say which is superior. Small photos with little in-depth information can be effectively treated using VGG16, but larger images can be effectively processed with InceptionV3. As a result, it is dependent on the dataset that the model employs.

To make it more user-friendly, we designed a webpage that allows users to forecast cancer based on a CT scan they have provided. These data might be referred to radiologists and doctors for better patient treatment.

V. REFERENCES

- [1] Ruchita Tekade, Prof. Dr. K. Rajeswari, "Lung Cancer Detection and Classification using Deep Learning", 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA).
- [2] Hongyang Jiang, He Ma, Wei Qian, Mengdi Gao and Yan Li, "An Automatic Detection System of Lung Nodule Based on Multi-Group Patch-Based Deep Learning Network", IEEE Journal of Biomedical and Health Informatics 2017.
- [3] Anita Chaudhary & Sonit Sukhraj Singh, "Lung Cancer Detection on CT Images by using Image Processing", 2012 International Conference on Computing Sciences.
- [4] Bariqi Abdillah, Alhadi Bustamam, and Devvi Sarwinda, " Image processing-based detection of lung cancer on CT scan images", The Asian Mathematical Conference 2016 (AMC 2016), DOI :10.1088/1742- 6596/893/1/012063.
- [5] Mutiullah Jamil, Mehwish Bari, Adeel Ahmed, Muhammad Sabir, Sajid Naveed, "Lung Cancer Detection Using Digital Image Processing Techniques: A Review", Mehran University

Research Journal of Engineering & Technology Vol. 38, No. 2, 351-360 April 2019, p-ISSN: 0254-7821, e-ISSN: 2413- 7219, DOI: 10.22581/muet1982.1902.10.

- [6] K. Senthil Kumar, K. Venkatalakshmi, and K. Karthikeyan, "Lung Cancer Detection Using Image Segmentation by means of Various Evolutionary Algorithms", Computational and Mathematical Methods in Medicine Volume 2019, Article ID 4909846, 16 pages <https://doi.org/10.1155/2019/4909846>