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Detection of Lung Cancer diseases Based on CT SCAN Images using Deep Learning

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Abstract: Increased health risks originate from changes in the natural surroundings, climate, and way of life. India is the leading nation in respiratory illness mortality. They were always the second-leading mortality cause globally in 2017 behind heart disease, claiming the lives of 1 million (958,000) Indians. Severe effects of lung cancer, especially death, can be avoided by timely detection and treatment. The better diagnostic technique at the present is a chest X-ray, which is necessary for clinical therapy. By using Deep Learning to detect lung diseases from chest X-rays, a person with lung disease may be able to save their own life. Lung tumor is yet another name for lung cancer. It is a malignant tumor illness that causes uncontrolled cellular proliferation in the lung tissue. The much more common sources of lung cancer by just using tobacco products and smoking. One of the most common causes of death in the entire world is lung cancer. The ResNet-50 (Residual Network) pre-trained Deep Learning model used for image classification of the Convolutional Neural Network is a very successful method. Neural network (also known as Convolution or CNN). ResNet-50, which now has 50 layers, has been trained using just a million images from the ImageNet database in 1000 various categories. The ability to forecast outcomes quickly and accurately tends to make this possible. This paper presents a practical strategy for just using deep learning to recognize lung problems. Its primary objective is to develop a method that will assist radiologists to identify lung problems. This will be especially beneficial in remote locations in which radiologists are in short supply. To evaluate the efficacy and correctness of various models for trying to identify lung cancer from chest x-ray image data, the RESNET 50 model is used.

Keywords: climate, respiratory, illness, mortality, detection, clinical therapy, lung tumor, malignant tumor, proliferation, tobacco products, radiologists.

I. INTRODUCTION

According to information provided by the World Health Organization, Siberia and Hungary have been the regions with the highest age-standardized lung cancer rates two segments with the greatest age-standardized incidences of lung cancer in 2018. A person with lung disease may be able to save their own life by utilizing Deep Learning to detect the diseases from chest X-rays. This is achievable because it is possible to forecast the outcomes quickly and precisely. This paper shows a practical method for employing deep learning to diagnose lung disorders. Fund for World Cancer Research (WCRF). With an estimated 1.8 million cases globally in 2012, lung cancer was the second most common cause of cancer-related mortality in both men and women, after breast Cancer. Therefore, generally speaking, the results are better in developing countries. Based on the cell in which the disease first formed, there are two distinct forms of lung cancer. While secondary lung cancer is considered to start outside the lungs, primary lung cancer is known to start inside the lungs. The two new classifications for primary lung cancer are Small Cell Lung Cancer (SCLC) and Non-Small Cell Lung Cancer (NSCLC). The best diagnostic tool now available is a chest X-ray, which is essential to clinical therapy. A person with lung disease may be able to save their own life by using Deep Learning to forecast the diseases from chest X-rays. By utilizing deep learning to predict diseases from chest X-rays, it might be able to save the life of a person with lung disease. This is possible because of the ability to forecast outcomes quickly and accurately. This study offers a useful approach for the expert detection of lung conditions using deep learning. It focuses on creating a tool to assist radiologists in making lung disease diagnoses. This will be especially helpful in rural areas where radiologists are hard to come by. We apply RESNET 50 to identify the model with the best accuracy and performance for predicting lung cancer from chest x-ray images.

In Iraq and the eastern Mediterranean, cancer ranks third in terms of mortality, and its incidence of occurrence is gradually increasing. The largest and most obvious rise is in smoking. Other contributing factors include pollution, a poor diet, ongoing contact with carcinogens in the environment and food supply, as well as a decline in physical activity. Approximately (4525) men and (3959) women died in Iraq from cancer-related causes in 2014, totaling 8211 deaths. Lung cancer was the most common type of cancer-related death, accounting for (1339) of the predicted total death toll (918). They were for men, whereas (421), which made up all of the lung cancer cases, in the overall approximated estimates, were for women. There were 16.31% deaths from all other cancers. The complete number appeared in 2016.

II. RELATED WORK

The early detection of lung cancer has always been one of the top priorities in the health world. Currently, various writers are working to enhance the functionality of the numerous algorithms used to predict lung cancer. Many authors have investigated a wide range of machine-learning methods. Even when lung cancer has been fully detected, the appropriate stages still need to be determined. The following is a list of relevant papers by different authors that cover lung cancer detection and the many techniques and methods that they implement. To identify lung cancer, T. Panduranga Vital, and M. Murali Krishna, (2018) employed the Decision Tree, ADT, Naive Bayes, Bayes Net, K Star, and Random Forest algorithms. The research demonstrated positive results for cancer prediction with an accuracy of over 96%, however, the problem was that the accuracy metric could lead to misleading associations. Convolutional Neural Networks [CNN] and Deep Learning were used by Timor Kadir, Fergus Gleeson, (2018), and others to find lung cancer. A CADs tool might be categorized as one of the numerous lung cancer risk models that have been created and validated. The major problem with this paper was the sheer volume of required data sets. Risk score regression, risk score thresholding, texture feature extraction, and nodule segmentation were the metrics employed.

Deep learning technology was employed by Puspanjali Mohapatra, Baldev Panda, and Samiksha Swain (2019) to identify lung cancer. The model created by the authors is capable of achieving an accuracy of 81 percent for 120000 image samples. This paper's limitation to using only high-resolution photographs is a drawback. The measures used in this study were recall, precision, FI score, and accuracy.

III. METHODOLOGY

A. *Existing System*

The current system has no idea like CNN model-based lung cancer prediction. All predictions are made manually or with the help of simple machine-learning models. Machine learning (ML) can categorize the presence or absence of lung cancer, but those models are unable to accurately and precisely categorize the information.

Dis Advantages of the Existing system:

1) Every present scheme can only classify a small number of classes.
2) No system in place can categorize chest x-ray images and then attempt to identify cancer symptoms.
3) All of the ML techniques now in use attempt to categorize patient information from the raw dataset.
4) There is no reliable model to categorize real-time chest x-rays for accurate detection and prediction.

B. *Proposed System*

In the proposed effort, we want to create a program that can be used for actual chest x-ray pictures to predict the presence of lung cancer. We attempt to gather sample chest X-ray images from the KAGGLE website that show cancer symptoms to train the system. As soon as the system has been trained, we may check the performance of each model by presenting dynamic images. It may be possible to save the life of someone who has lung disease by using deep learning to forecast the diseases from chest X-rays. This is achievable because results may be predicted promptly and with high precision. The expert identification of lung ailments using Deep Learning is presented in this research as a practical method. It is concentrated on developing a method to support radiologists to detect respiratory symptoms. This will be especially useful in remote locations where radiologists are scarce. To predict lung cancer from chest x-ray pictures, we utilize the RES NET-50 model to determine which model has the highest accuracy and performance.

Advantages of the Proposed System:

1) The suggested approach classifies checking x-ray pictures very well.
2) The suggested system provides clinicians with reliable recommendations.
3) The suggested approach can classify chest x-rays and determine image correctness.

C. *Feasibility Study*

This stage helps determine the project's viability and presents a business proposal containing a very simple project plan and cost estimates. The feasibility of the proposed method must be assessed during system analysis. This will guarantee that the suggested adjustment won't place far too much pressure on the company. Knowing the primary system requirements in more detail is necessary for the feasibility study. The three components stated below determine the feasibility analysis.

1) *Economic Feasibility:* The purpose of this analysis is to determine what kind of financial impact the system will have on the business. The corporation has a limited budget to devote to the study and development of the system. There must be proof to back up the costs. As a result, the developed system was finished within budget attributable to the public domain nature of the majority of the technology. Only specialized items are required to be purchased.
2) *Technical Feasibility:* This study's objective is to evaluate the system's viability during the design and implementation phases. Any integration must not significantly tax the available technological infrastructure. As a result, the number of technological resources will be extremely limited. The client will therefore be subject to high expectations. Because the system's implementation just requires minimal or no adjustments, it must have moderate demand.
3) *Social Feasibility:* The purpose of the study is to evaluate the user's level of system acceptability. This covers what they would need for the user to correctly operate the system. The system should also not make the user feel threatened; rather, they should perceive it as a need. The only factors that affect how receptive people are to a system are the methods used to inform and familiarize the user with it. His confidence must be boosted as he is the system's primary user and constructive criticism is appreciated.

IV. RES NET-50 MODEL

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times23$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

FIG 1. RES NET-50 Architecture

Three months in the fall of 2019 were devoted to compiling the lung cancer dataset for the Iraq-Oncology Teaching Hospital/National Institutes for Cancer Diseases (IQ-OTH/NCCD). There are CT scans of healthy individuals as well as lung cancer patients who are at various stages of the disease. In the two canters, radiologists and oncologists commented on IQ-OTH/NCCD slides. 1190 images in all, taken from slices of 110 cases' CT scans, help compensate the dataset. Three components, benign, and malignant—are used to categorize these circumstances. These are classified into 40 malignant patients, 15 benign cases, and 55 normal patients. Each CT scan included several slices and was first collected in DICOM format. There are 80 to 200 of these slices in total, and each one shows a different aspect and angle of the human chest. There are differences amongst the 110 cases in terms of gender, age, level of education, locale, and way of life. The majority of them originate from locations in Iraq's middle, specifically from the provinces of Baghdad, Wasit, Diyala, Salahuddin, and Babylon. On Kaggle, customers can access the dataset online.

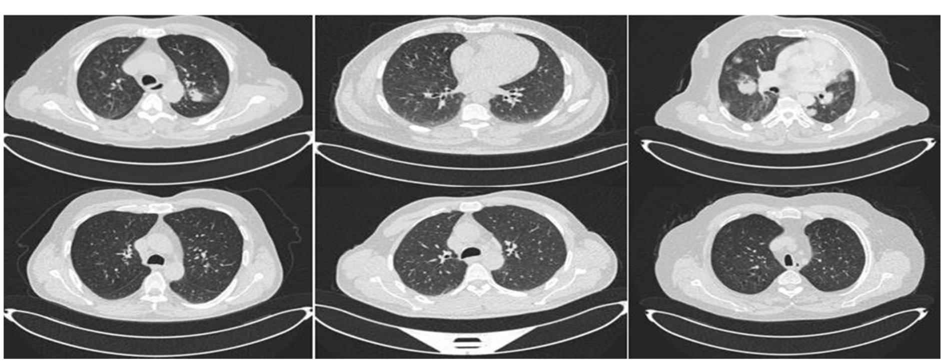


Fig.2.Example CT scan images from the IQ-OTH/NCCD dataset

ResNet-50 is the designation of a convolutional neural network with 50 layers. A pre-trained version of the network that has been trained on more than a million images is available in the ImageNet database [1]. The trained network is capable of categorizing images into 1,000 different object categories, such as diseases, a broad assortment of animals, the keyboard, mouse, and pencil, among many others. In the proposed application, we used the RESNET 50 CNN model and discovered that lung pictures might be categorized with just an accuracy of more than 80%.

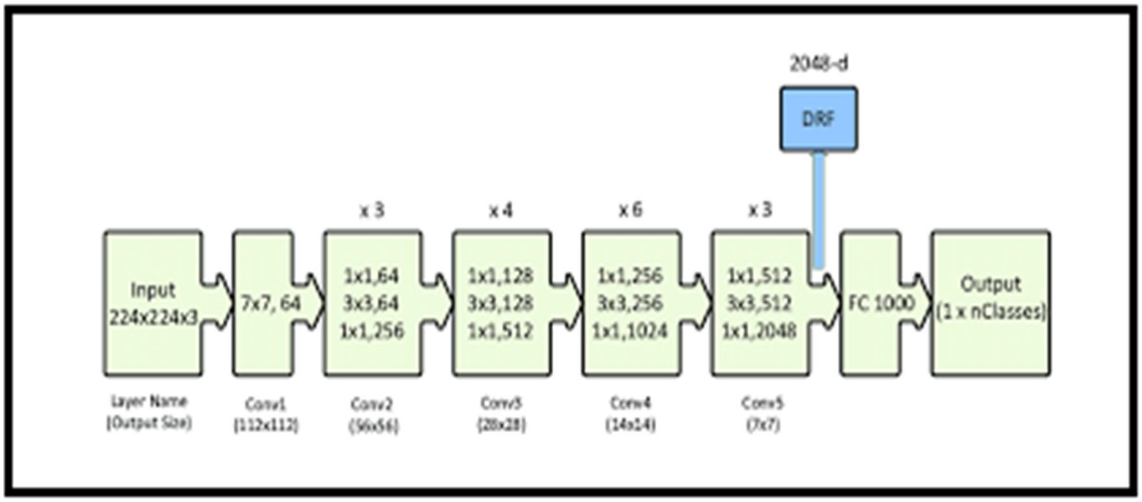


Fig.3.RESNET -50 Model

When employed more than once, the CONV layer reads input feature maps or images from the preceding layer or via data input ports. It then transforms these inputs using numerous groups of kernels to produce a collection of output feature maps. In general, a POOL layer that subsamples the features from the previous CONV layer follows any CONV layer. The classifier layer's final step is to generate the potential of each class inferred by the initial input data. An important component of CNN's structure is its convolution layer, which is in charge of extracting features that commonly combine linear "convolution operation" and nonlinear "activation function" processes. Convolution operations are a special class of linear operations that are used in CNN to extract features. They work by applying a kernel, which is a small-size array, over a tensor, which is also an array. The stands for the input. The image below, which has been converted into an array of numbers, illustrates how a computer perceives an image.

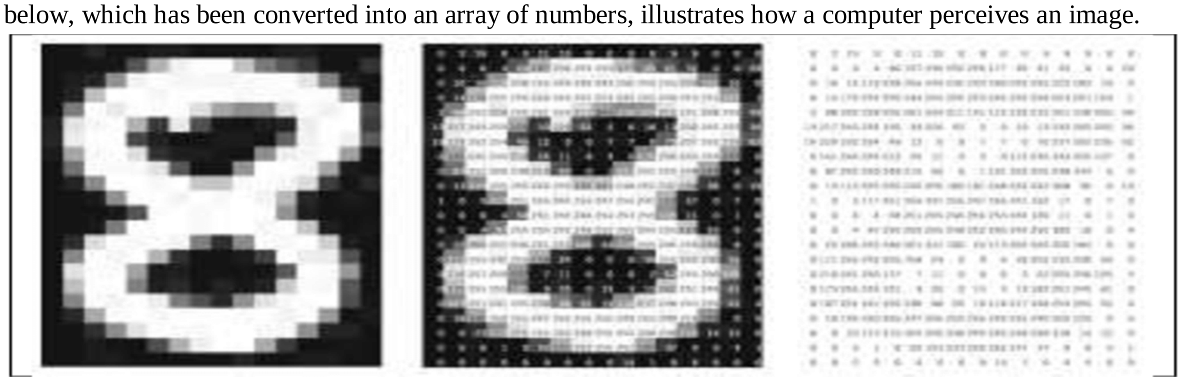


Fig.3 A computer sees an image as an array of numbers (34)

After conducting an element-wise product calculation at all points between every kernel element and the tensor array, the resulting array reflects the output value and is referred to as a feature map. When compared to the input tensor, the output feature map is narrower and taller, necessitating the above-mentioned action known as padding, which involves adding zeros to each tensor side to maintain the same size of the input and output. Stride is a method of shrinking the size of a feature map, in contrast to the padding procedure, and it denotes the interval between every two successive kernel points. Another method that accomplishes the same result is a pooling operation. The result of the convolution operation is then transferred into an activation function, such as the sigmoid, tangent, or RELU, which is a typical and well-known nonlinear function.

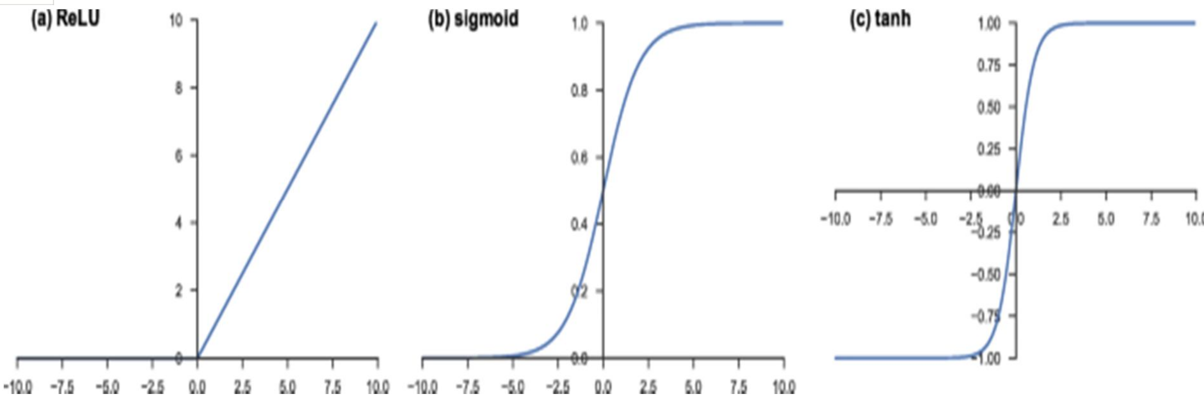
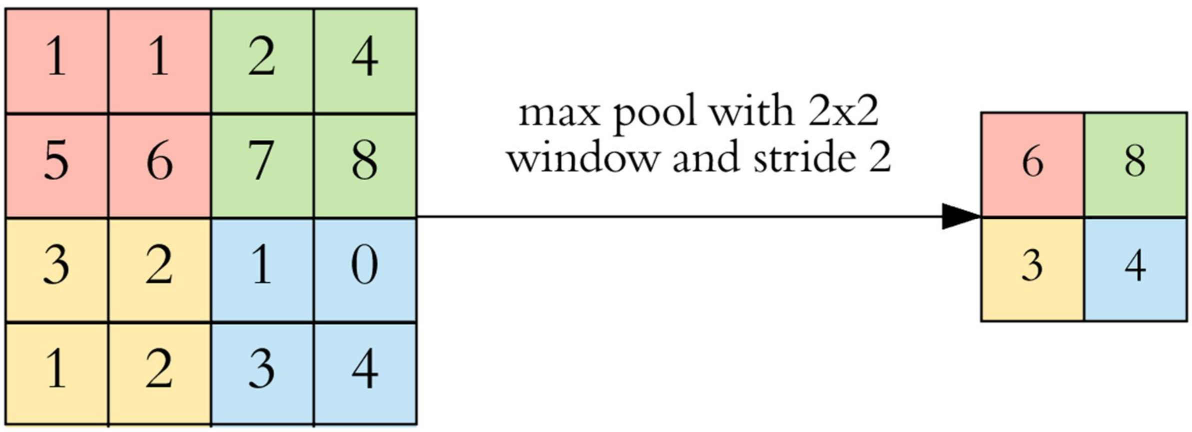


Fig 4. Activation functions commonly applied to neural network

Now next example shows the information given above and how a max-pooling function is carried out in the figure below:



The procedure of smoothing, which converts the final output map into a one-dimensional array, links the array to a deep network, which is a fully connected layer. In the final layer, a special activation function was utilized, which is different from the other layers in the CNN the most popular kind is the convolution layer's function.

A. *LOAD The Dataset*

```
from google.colab import files
files.upload()

    Choose Files kaggle.json
    • kaggle.json(application/json) - 63 bytes, last modified: 7/26/2022 - 100% done
    Saving kaggle.json to kaggle.json
    {'kaggle.json': b'{"username":"b131832","key":"1ea3732629421f41f8d7e3ea75d7152e"}'}

!mkdir -p ~/.kaggle
!cp kaggle.json ~/.kaggle
!chmod 600 ~/.kaggle/kaggle.json

!kaggle datasets download -d andrewmvd/lung-and-colon-cancer-histopathological-images

    Downloading lung-and-colon-cancer-histopathological-images.zip to /content
    100% 1.75G/1.76G [00:11<00:00, 198MB/s]
    100% 1.76G/1.76G [00:11<00:00, 160MB/s]
```

Here, it is obvious that the dataset has been loaded successfully, and we can also make out the Kaggle. Once the JSON file is built using the current user's email address, we may access the input files from that personalized account rather than physically uploading that file.

B. UNZIP the Data Set for Extracting the Images

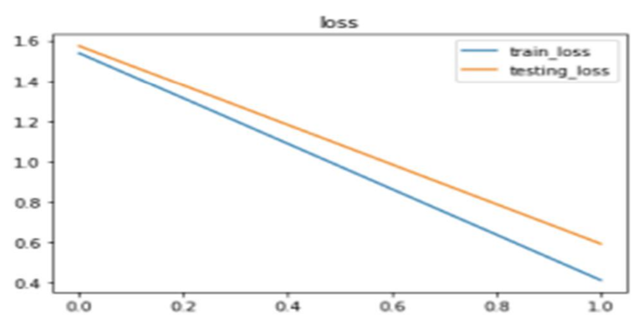
The dataset must be unzipped before we can train the lung images for the application.

```
!unzip /content/lung-and-colon-cancer-histopathological-images.zip

      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc910.jpeg
      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc911.jpeg
      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc912.jpeg
      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc913.jpeg
      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc914.jpeg
      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc915.jpeg
      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc916.jpeg
      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc917.jpeg
      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc918.jpeg
      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc919.jpeg
      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc92.jpeg
      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc920.jpeg
      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc921.jpeg
      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc922.jpeg
      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc923.jpeg
      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc924.jpeg
      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc925.jpeg
      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc926.jpeg
      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc927.jpeg
      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc928.jpeg
      inflating: lung_colon_image_set/lung_image_sets/lung_scc/lungscc929.jpeg
```

C. Plot The Training Loss

```
# plotting the loss
plt.plot(history.history['loss'],label = 'train_loss')
plt.plot(history.history['val_loss'], label = 'testing_loss')
plt.title('loss')
plt.legend()
plt.show()
```



D. Check The Confusion Matrix

```
# CHECKING THE CONFUSION MATRIX

from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import f1_score
Y_pred = model.predict(validate_set)
y_pred = np.argmax(Y_pred ,axis =1)
print('Confusion Matrix')
confusion_matrix = confusion_matrix(validate_set.classes, y_pred)
print(confusion_matrix)
print('Classification Report')
target_names = ['aca','n', 'scc']
print(classification_report(validate_set.classes, y_pred, target_names=target_names))

     Confusion Matrix
     [[998   1   1]
      [  5 995   0]
      [233   0 767]]
```

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E. Classification Report And Model Accuracy

Model For a person with the disease, using deep learning to anticipate lung ailments from chest X-rays may save their life. The findings may be quickly predicted with a high level of accuracy, making this practicable. The expert lung disease diagnosis method described in this paper makes use of deep learning.

From the above window, we can identify the model accuracy as well as the classification report for the given input data.

```
     Classification Report
                  precision    recall  f1-score   support

             aca       0.81      1.00      0.89      1000
               n       1.00      0.99      1.00      1000
             scc       1.00      0.77      0.87      1000

        accuracy                           0.92      3000
       macro avg       0.94      0.92      0.92      3000
    weighted avg       0.94      0.92      0.92      3000



result = model.evaluate(validate_set,batch_size=128)
print("test_loss, test accuracy",result)

     24/24 [==============================] - 525s 22s/step - loss: 0.5944 - accuracy: 0.920(
     test_loss, test accuracy [0.5943650603294373, 0.9200000166893005]
```

From the above window, we can identify the model accuracy as well as the classification report for the given input data.

V. CONCLUSION AND FUTURE DIRECTIONS

The important aim of this current application is lung cancer disease prediction utilizing the CNN Model. For a person with the disease, using deep learning to anticipate lung ailments from chest X-rays may save their life. The findings may be quickly predicted with a high level of accuracy, making this practicable. The expert lung disease diagnosis method described in this paper makes use of deep learning. It focuses on creating a method to help radiologists detect lung illnesses. This will be especially helpful in remote locations where radiologists are scarce. We apply the RESNET 50 Model to predict lung cancer from chest x-ray images, and we can see that the suggested model achieves an accuracy of nearly 92 percent by conducting numerous trials on the Kaggle dataset. To improve the model's accuracy and lower the loss percentage, we plan to apply the same work to some more powerful CNN models in the future.

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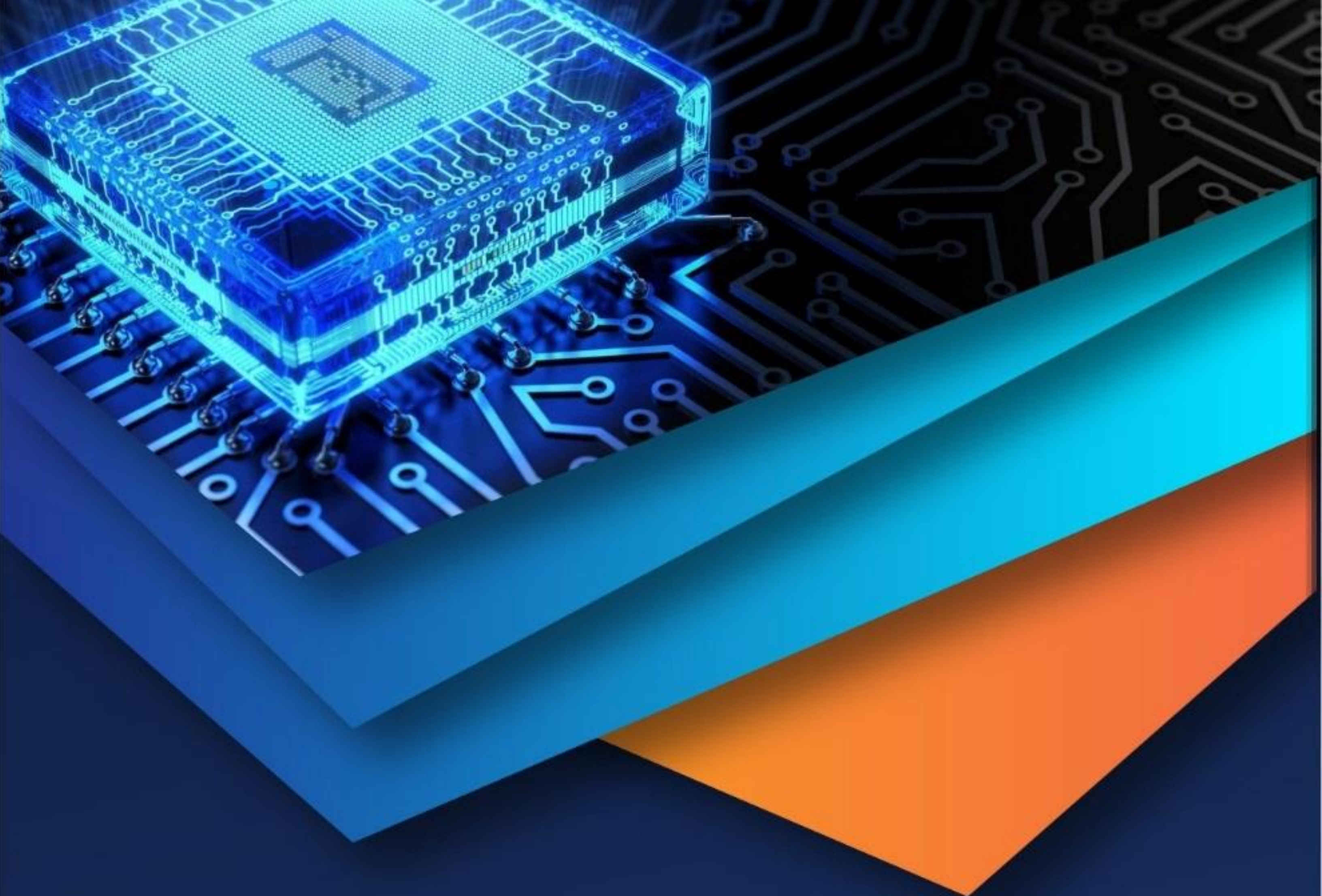

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