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Enhancing and Detecting the Lung Cancer using Deep Learning

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Abstract— In the medical sector cancer detection became the most challenging task. Here a lot of research is carried out by the scientific fraternity. Most medical issues are getting better answers because to modern technology like artificial intelligence and models based on neural networks. In this the first half part of the paper discuss about the CNN model by using regularization and augmentation techniques for getting the better accuracy result. The second part delas with developing and demonstrating an application for detecting the lung cancer using the deep learning (DL). Here the application is built using flask which works based on the Python programming language. This acts as an application programming interface (API) between the cloud server and the proposed application mod el. Heroku cloud platform was used as a service base to launch the software and to use the application with highest reliability. The internal functionality of the anticipated model is created on convolutional neural network (CNN) architecture with ten layers to obtain high accuracy. The model demonstrated a considerable training and validation accuracy of 94% and 92% respectively.

Keywords— CNN, Deep learning, Regularization, Augmentation, Lung Cancer, CT Images, LIDC-IDRL.

I. INTRODUCTION

A. Overview

Due to the exponential rise of data brought on by cellphones, social media, etc., deep learning is currently quite popular. But in the case of deep learning, performance likewise rises as the volume of data does. In contrast to other learning methods like machine learning (ML), as the amount of data rises, the performance either remains constant or degrades. A neural network is integrated with feature extraction and model training in deep learning. Artificial intelligence (AI) includes deep learning, which reacts and functions similarly to the human brain for pre-processing and analysis for decision-making.

A Convolutional Neural Network (CNN) is a learning method used in deep learning that may accept input as pictures for training and evaluating the model. For several decades, CNN achieved ground-breaking breakthroughs in a variety of image-related sectors [1]. Jian *et al.* address that there are various ways available for pre-processing the lung image before CNN model is applied to the images [2]. Deep learning is allegedly used to identify and categorize lung cancer, according to Tekade and Rajeswari. This study evaluates and extracts lung cancer pictures using a 2D multipath network [3]. Through the use of residual learning,

Bhatia *et al.* employ a deep learning strategy to identify lung cancer from Computerized Tomography (CT) data. The lung areas are identified here using the UNet and Resnet models, and a feature extraction approach is used to extract them [4]. CNN is too known as shift invariant which is mainly used for analyzing the visual images [5]. The major applications of

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convolutional neural networks include image classification, natural language processing, image and video recognition, medical image analysis, financial time series, image segmentation, brain-computer interfaces, and image classification [6].

B. CNN Architecture

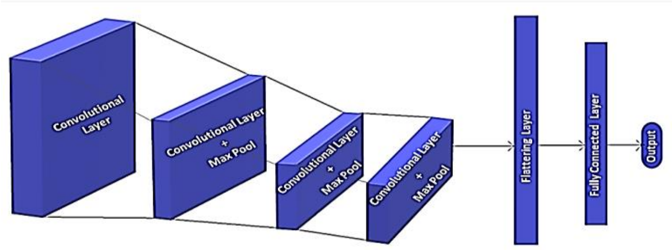

Fig. 1 CNN Architecture

In Fig. 1, the Convolutional neural network architecture is utilized to evaluate and represent pictures at various levels, and it extracts the feature from the image. CNN is a multi-layered network with hidden layers that are placed on top and structured sequentially. This is the initial layer that is utilized to extract the image's characteristics. All mathematical actions between input photos to a specific size are conducted in this layer. The convolutional layer recognizes visual properties such as edges and corners [7].

After convolutional, the Max Polling 3D layer performs the process. To cut costs, the polling layers minimize the size of the feature map. This layer is used to crop a picture. This layer is typically used as a bridge/mediator between the convolutional and fully connected layers. An artificial neural network's activity is represented by a Fully Connected Layer (FC). This layer, which comprises of weights and biases, connects two separate layers of neurons. The input picture is flattened at this layer and supplied to the FC layer. The picture will be processed for feature extraction by joining numerous convolutional layers and flattening the layers. An output layer is utilized as Dense Layer and it offers the learning properties that are created by combining the properties of the previous layer. [8].

II. LITERATURE SURVEY

Lung cancer is among the recorded malignancies in the ecosphere. It is a severe condition in which cells in the body produced at incontrollable rate, causing around 246,861 new cases (121,200 in males and 136,760 in women) and 142,890 fatalities (70,520 in men and 71,470 in women) [9]. Tumors are categorized into two sorts: non-cancerous (benign) and cancerous (cancerous) (malignant). As a result, to acquire accurate and immediate results, apply modern practices such as image processing, machine learning, and deep learning. CT reports are fewer deafening than MRI and X-Ray findings [10]. Cancer treatment is only effective when malignant cells and normal cells are accurately separated. The classification of tumour cells and training of a neural network serve as the foundation for machine learning-based cancer diagnostics. [11]. This study shows a way to categories lung cancers as malignant or benign the usage of a Convolutional Neural Network (CNN). CT scans are received from research of 7000 patients, if they may be in Dicom format. There are 10,000 photos withinside the database. proposed a layout that converts Dicom Format photos of the lungs to Jpeg or Png after which scans them for abnormalities the usage of photo processing. After the scanning is complete, the gadget calculates certain capabilities of the abnormality and feeds them right into a Model that has been taught to hit upon whether or not the ambiguity is malignant [12].

A wide range of researchers working on lung cancer detection identified to utilize several ways to detect the most tumours in the literature. However, no progress may be made inside the hit ratio of early identification of most tumours. With the advancement of technology, specific specialised tactics have been developed to anticipate and detect lung cancer in its early stages. To overcome this difficulty, three-dimensional images are displayed to detect tumours. The proposed paintings are done in 2D using CNN methods. In special studies, several specific architectures are suggested and compared. It mostly covered Convolutional Neural Networks (CNN) and versions of CNN. Convolutional Neural Networks can be trained on two-dimensional CNNs (referred to as 2D CNN/ConvNet). These architectures are modified for several applications and datasets. Fernandes *et al.*, gives the different approach of pre-processing the lung CT scan images previously providing them to CNN architecture [13]. The outcomes are improved as there may be so several non-imaging regions which can decrease the accuracy of feature extraction. In 2-D images objects of lung nodule finding may have a high positive rate.

III. EXITING METHODS

3.1 Flow Process of Data Model

Machine learning (ML) techniques known as "Deep Learning" use layers to extract features from input. It makes use of a decision-making model that analyses data and develops patterns in human lungs. The data flow mechanism for the suggested model in Fig. 2 is described in the following steps.

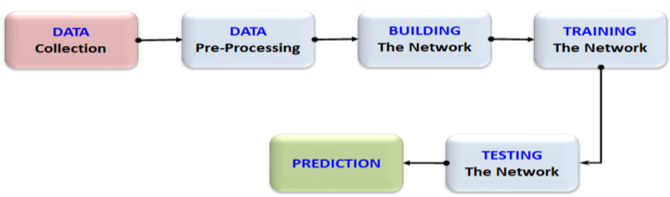

Fig. 2 Flow process of Data Model

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A. Data pre-processing

CNN is a multilayer network with hidden layers. In this work, these layers are used to extract features from CT lung images as an input to the deep learning algorithm, which is a data cleaning step for pre-processing to build the model and transforms to train a CNN using Keras that leads to classification. Outlier detection and the elimination of noisy data from the images are examples of the data pre-processing [14].

B. Building the Network

The best technique to form a model with Keras is serially. We make advantage of the 'add()' competence for adding layers to designed model. The first two layers are Conv2D layers. These layers of convolution will effort with the images from our 2-dimensional matrices as input.

C. Training the Network

Using the actual photos as input layer parameters to train a network model. An input-to-output mapping for a neural network is created using a training dataset, which is also used to update the model weights. This leads to strong outcomes from the training dataset. An effective, iterative, and recursive technique for training the functions is the back propagation network, which does this.

D. Testing the Network

Functioning of the designed neural network is carried out by applying the new lung images at the input of the model. This neural network model is divided into three sections: train, validate, and evaluate.

E. Prediction

While predicting the probability of a specific outcome, the performance of an algorithm after it has been trained on a historical dataset and applied to new data.

IV. PROPOSED METHOD

Convolutional layers, Pooling Layers, and Fully Connected (FC) layers are the three forms of layers altogether form the CNN. A CNN structure may be made while those layers are stacked. The dropout layer and the activation feature are extra key parameters in addition to those 3 layers. This is the preliminary coating that extracts the exceptional functions as of the input images. The convolution mathematical operation is achieved among the input photo and a clear out of a selected length M×M on this layer. The dot product among the clear out and the segments of the input photo in regard to the gauge of the clear out is taken via way of means of sliding the clear out throughout the input photo (M×M). The Feature map is the result; besides it contains statistics approximately the photo consisting of its crooks and edges. This characteristic map is formerly provided to similarly layers, which examine a number of different functions from the input photo and the planning is shown in Fig 3.

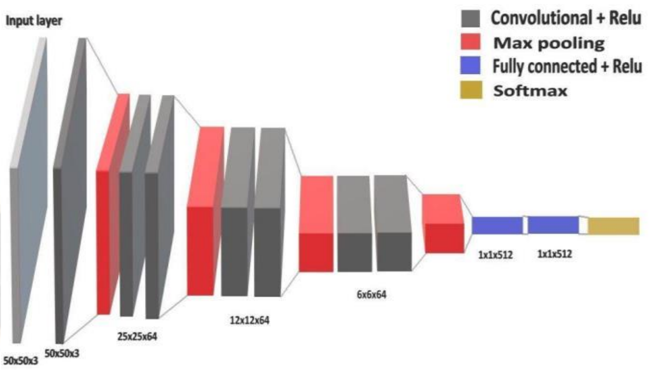

Fig. 3 Architecture of CNN

The first block uses a convolutional 2D layer with a filter size of 32, a kernel size of 3×3, and an activation function of Relu before down sampling the image with a max-pooling 2D layer.

The second block combines two convolutional 2D layers with a filter size of 64, a kernel size of 3×3, and an activation function of ReLu before down sampling the image with a max-pooling 2D layer for both layers.

The third block, like the second, has the same parameters as the second.

The fourth block combines two convolution 2D layers with a filter size of 128 and a kernel size of 3×3 while retaining the activation function as ReLu. The image is then down sampled with a max-pooling 2D layer for both layers. Finally, our model is fully coupled with dense layers when the image dimension is lowered.

A. Fully Connected Layer

A fully connected (FC) layer, made up of weights, offsets, and neurons, is used to link neurons between the two layers. Usually, the output layer comes before the final few layers of a CNN architecture. In this stage, the input pictures from the earlier layers are smoothed and given to the FC layer. The flattened vector is then sent through some further FC layers, which are often used for performing mathematical calculations. The classifying procedure kicks off at this point.

B. Dropout

The training dataset is vulnerable to overfitting when all of the characteristics are linked to the FC layer. When a model performs so well on training data that it has a negative effect on its performance when applied to new data, this is known as overfitting. A dropout layer is used to solve this problem,

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which leads to a smaller model by removing a small number of neurons from the neural network during training. 30% of the nodes in the neural network randomly drop out after passing a dropout of 0.3.

C. Activation Functions

The activation function is one of a CNN model's most crucial parameters, to sum up. The continuous and complex link between network variables is learned and approximated using them. In other words, it decides which model information should be broadcast over the network and which should not. The network becomes non-linear as a result. Some of the most popular activation functions include ReLu, SoftMax, Tanh, and Sigmoid. Each of these features has a certain purpose. For binary classification of the CNN model, Sigmoid and SoftMax functions are chosen; SoftMax is typically utilized for binary classification.

D. Compile

The model was built using an ad optimizer and "sparse categorical entropy" loss. A sparse unconditional cross-entropy loss function and a sparse unconditional accuracy measure are used to construct the spherical model. Input through the model and comparison of predictions with ground truth inputs for neural network training. This loss function works on integer objects and performs the same type of loss. scce (sparse categorical cross entropy) returns the category index of the most likely corresponding class.

V. RESULTS

5.1 Existing Method Results

In this proposed paper, the lung cancerous and non-cancerous images dataset is collected from Kaggle and Cancer Imaging Archive. This dataset consists of 3000 CT scans with observations relating coordinates and ground truth labels. It has two classes which contain 1500 Cancerous and 1500 Non-Cancerous images. The Initial step is to create an image database for training the model. Dataset is split into training (80%) and testing (20%). The dataflow is shown in Fig. 4.

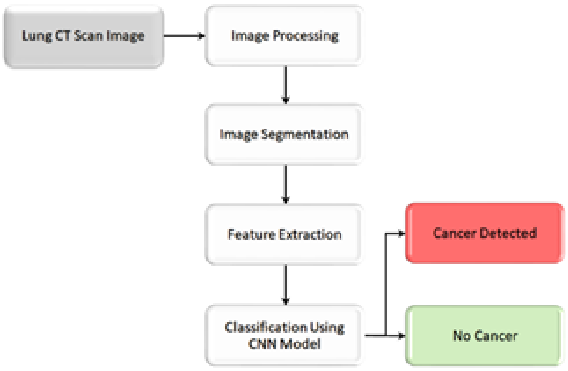

Fig. 4 Architecture Dataflow

1. Image Segmentation

Segmentation is the process of making an image representation more understandable and straightforward to examine. It can be viewed as a classification issue per pixel because it involves assigning a specific class to each pixel in a picture. Typically, image segmentation is used to identify objects and boundaries (such as lines, curves, etc.). [15].

2. Pre-processing and Feature Scaling

The generated dataset is structured in such a way that the model can be trained to crop photos everywhere the coordinates specified in the annotations. The annotations are in Cartesian coordinates and have been translated to voxel coordinates. The intensity of the image was defined in the Hounsfield scale and rescaled for image processing. To train a model, the script would generate 50x50 grayscale images for training, testing, and validation. A random function is used to generate and shuffle these. Because it reduces picture duplication, the choice and replaced methods are false. The image size is then 50x50, however non cancer and cancer are in separate folders. Concatenate non cancer and cancer photos to feed the model. The model is then trained, and the image is loaded into the model and converted to a 50X50 array. Labels are used to define the cancer and non-cancer images in order to comprehend the model. The image is now 50x50 with three channels (RGB) of colours, and the transformed image values are in an array in float 32 format. This is the best fit for the problem statement. So RGB values are 0-255, and its red hues are modified when it comes close to the value 255 to make it easier to understand, and they are scaled to 0-1. Images are now scaled; after scaling, convert the array to an image. Sklearn now uses label encoder because it is a well-organized tool for encoding the levels of definite features into numeric values. Label Encoder encodes labels with a worth between 0 and 1, where 0 represents the number of cancer labels and 1 represents non-cancer labels. If a label is repeated, it is assigned the similar rate as before. It generates a Label Encoder () instance and stores it in the label encoder variable. Then use fit and transform to assign numerical values to categorical values, which is then saved. The dataset is divided into two parts: training (80%) and testing (20%).

Simple CNN Model

Using three hidden layers, construct a straightforward CNN model. which include down sampling the output convolution feature maps, three convolutional layers, and max polling in conjunction with feature extraction from pictures. The third convolution layer's output, which consists of 128 17 x 17 feature maps, is flattened out using the flatten layer. To determine if the image should be a cancer (1) or not, this is passed to the thick layers to get the final forecast (0). All of

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this is done as part of the model-training process, which uses the fit (...) function and the following snippet to train the model. The batch size shows how many total photos are sent to the model for processing each iteration.

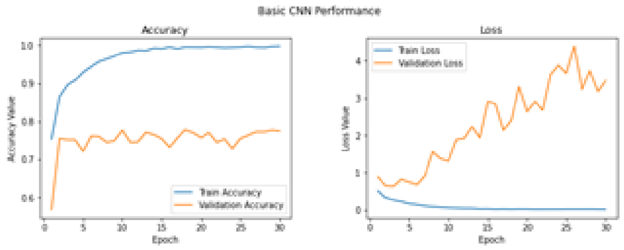

Fig. 5 Basic CNN Model

When the entire dataset has traversed the network once, an epoch has occurred, and the iterations have been finished based on the data batches. The basic CNN used in this study has a batch size of 30, and the training data comprises 3000 samples, thus there will be 100 iterations every epoch. 30 epochs were used to train the model, and it was subsequently tested on a validation set of 1000 photos. The accuracy and loss of both training and validation is analyzed in Fig. 5.

TABLE I
TRAINING AND VALIDATION OF CNN MODE

Training		Validation	
Accuracy	Loss	Accuracy	Loss
0.93	0.4	0.72	4.0

Based on the training and validation accuracy scores, it was determined from the graph that the model is rather over fitting. Use the following snippet to plot the model's accuracy and errors to gain a better understanding. After two or three epochs, the model restarts fitting to the training set of data. Our validation set's average accuracy is roughly 72%.

CNN model with Regularization

One more convolution layer is introduced when using the CNN model. The regularization is then enabled by a further dense hidden layer, followed by the addition of a 0.3 dropout. In essence, deep neural nets' dropout feature is a potent regularization technique. Input layers and concealed layers can each receive a distinct application of it. The outputs of units in our dense layers are randomly concealed by dropout and model is shown in Fig. 6.

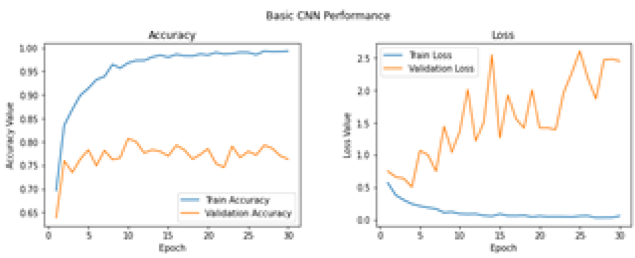

Fig. 6 CNN model with regularization

TABLE II
TRAINING AND VALIDATION OF CNN MODEL WITH REGULARIZATION

Training		Validation	
Accuracy	Loss	Accuracy	Loss
0.95	0.9	0.78	2.5

But when compared to the previous result, the model still ends up being overfit. However, there is a marginally higher validation accuracy of about 78%. Model overfitting occurs because there is a lack of training data, and the model repeatedly sees the same occurrence over the course of each epoch. Utilizing an image enhancement method would be one way to stop this. Photographs that are tiny variants of the current images will be added to the training data.

CNN model with Augmentation

Using a suitable image augmentation approach, let's enhance CNN with a regularization model by adding extra data. The prior model, however, consistently used the similar small example of data points for training. because it had trouble generalizing well and eventually developed overfitting afterward a few epochs. The concept behind image augmentation is that it adheres to a predetermined procedure of importing preexisting images from our training dataset and adding approximately image alteration operation to them. To create new, modified copies of old photos, techniques including rotation, shearing translation, zooming, and others are used is shown in Fig. 7.

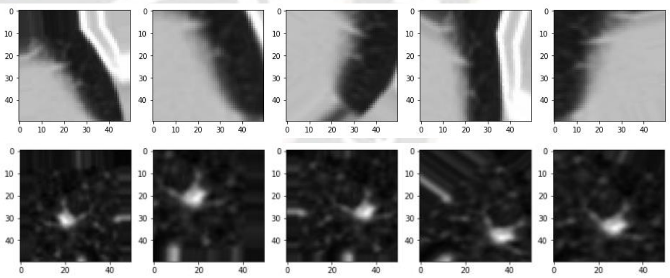

Fig. 7 CNN model with Augmentation

The model uses Python generators to feed in these new photos to our model during training because it doesn't always receive the same images due to this random alteration. Image Data Generator, a fantastic tool provided by the Keras framework, can assist us in carrying out all the aforementioned tasks. Two of the data generators for the training and validation datasets should be initialized. An unfavorable 80-20 class distribution was produced by augmentation. However, it also prohibited overly enhancing the minority class because this would lead to a minority class with minimal diversity. So, I finally came up with over fitting which is a technique used to solve an imbalanced dataset. Augmented the minority class was done using the process is shown in Fig. 8.

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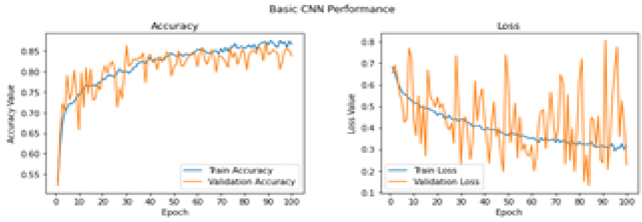


Fig. 8 CNN model with Augmentation result

TABLE III
TRAINING AND VALIDATION OF CNN MODEL WITH AUGMENTATION

Training		Validation	
Accuracy	Loss	Accuracy	Loss
0.98	0.01	0.82	0.8

Proposed CNN Model Results

Following the application of the dataset and the application of several approaches, the results show 94.6% training accuracy and 92% validation accuracy, with an average validation loss of 0.4. The model obtains a loss of 0.6 and an accuracy of 82% when evaluated on unseen test data is shown in the Fig. 9 and Fig. 10.

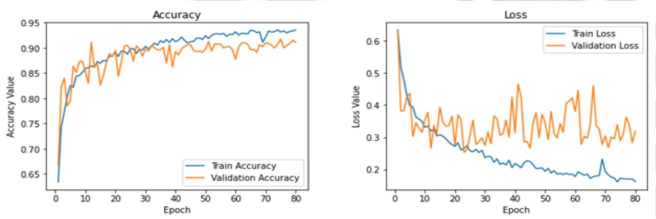
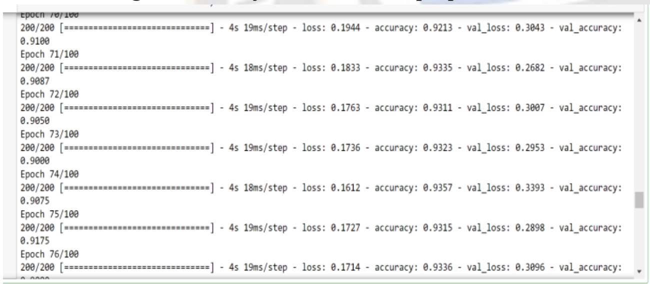


Fig. 9 Accuracy and loss of the proposed model



```
200/200 [==============================] - 4s 19ms/step - loss: 0.1944 - accuracy: 0.9213 - val_loss: 0.3043 - val_accuracy:
0.9100
Epoch 71/100
200/200 [==============================] - 4s 18ms/step - loss: 0.1833 - accuracy: 0.9335 - val_loss: 0.2682 - val_accuracy:
0.9087
Epoch 72/100
200/200 [==============================] - 4s 19ms/step - loss: 0.1763 - accuracy: 0.9311 - val_loss: 0.3007 - val_accuracy:
0.9050
Epoch 73/100
200/200 [==============================] - 4s 19ms/step - loss: 0.1736 - accuracy: 0.9323 - val_loss: 0.2953 - val_accuracy:
0.9000
Epoch 74/100
200/200 [==============================] - 4s 18ms/step - loss: 0.1612 - accuracy: 0.9357 - val_loss: 0.3393 - val_accuracy:
0.9075
Epoch 75/100
200/200 [==============================] - 4s 19ms/step - loss: 0.1727 - accuracy: 0.9315 - val_loss: 0.2898 - val_accuracy:
0.9175
Epoch 76/100
200/200 [==============================] - 4s 19ms/step - loss: 0.1714 - accuracy: 0.9336 - val_loss: 0.3096 - val_accuracy:
```

Fig. 10 History of the model

TABLE IV
TRAINING AND VALIDATION OF CNN MODEL

Lung Cancer Classification	Accuracy %	Sensitivity %	Specificity %
Proposed Architecture	77%	52%	84%

VI. IMPLEMENATION

We have developed a user-friendly web application utilizing the Flask API that has been deployed on cloud Heroku to improve access to medical treatment.

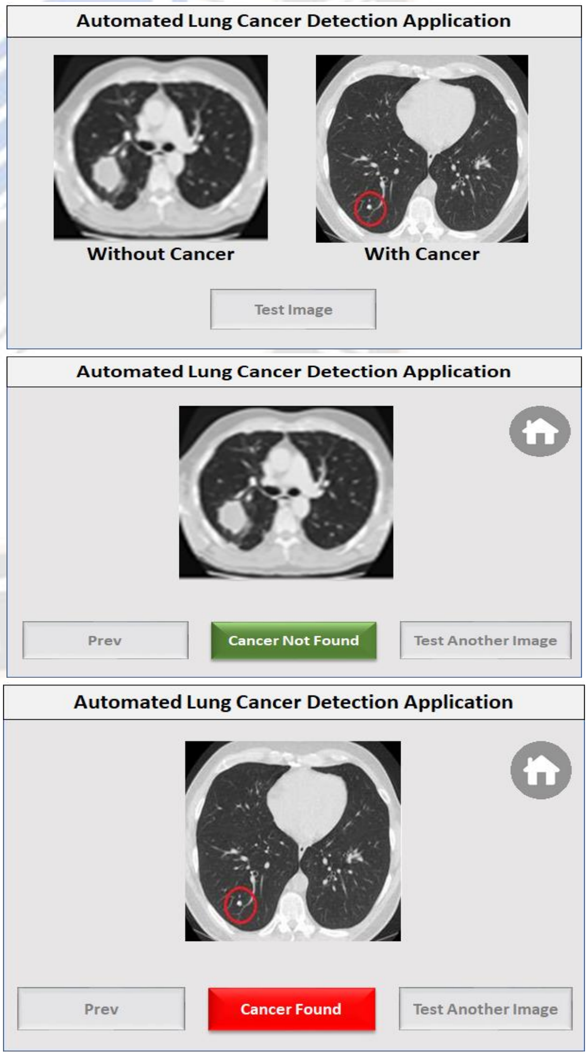
A. Building a User Friendly App and Deployement

A user-friendly software is created so that everyone may use it and gain from it. With CNN's assistance, an all-purpose user-friendly app was developed utilizing the flask microweb framework, a python-based tool that serves as an API between cloud servers and apps. The proposed software was launched using the Heroku cloud platform as a platform service. One of the first cloud computing platforms, with a clear grasp of how to use the app and a high degree of dependability, is Heroku.

TABLE V
TEST RESULTS OF ACCURACY, PRECISION, RECALL AND F1.

	Precision	**Recall**	**F1 score**	**Support**
0	0.83	0.83	0.83	1340
1	0.19	0.20	0.20	282
Accuracy			0.72	1622
Macro avg	0.51	0.51	0.51	1622
Weighted Avg	0.72	0.72	0.72	1622

Sample Screens of the Proposed Model



VII. COMPARING EXISTING AND PROPOSED MODEL

Systems	Different Models Used	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
Existing Model	Basic CNN Model	0.93	0.4	0.72	4.0
	CNN model with Regularization	0.95	0.9	0.78	2.5
	CNN Model with Augmentation	0.98	0.01	0.82	0.8
Proposed Model	Own CNN model with ten layers	94.6	0.4	0.82	0.6

VIII. CONCLUSION AND FUTURE SCOPE

The imaging datasets for lung cancer and non-cancer are examined in this article. However, there is an overfit in the validation and training accuracy while training the simple CNN model. The basic model has a lower level of precision. To speechless this issue, regularization is useful to improve the model, resulting in a 5% increase in validation and training accuracy. However, there is a minor over fit in the model, therefore an augmentation approach is applied to boost the accuracy, which achieves a nearly 10% increase in accuracy and reduces the over fitting problem. As a result, the authors of this study created a DL-based application to detect lung cancer photos with an improved training accuracy of 94.6% and validation accuracy of 92%, as well as an average validation loss of 0.4. This tool is more adaptable and user-friendly for detecting lung cancer from CT scans.

LIST OF ABBREVIATIONS

API Application Programming Interface
CNN Convolutional Neural Networks
CSMIR Content Supported Medical Image
CT Retrieval
DFD Computed Tomography
DL Data Flow Diagram
FC Deep Learning
IDRI Fully Connected
LIDC Image Database Resource Initiative
LUNA Lung Image Database Consortium
TCIA Lung Nodule Analysis
The Cancer Imaging Archive

CONFLICT OF INTEREST

The authors have no conflict of interest to carry out this research work as there is no financial institution or organization is involved directly or indirectly to invest any kind of funds till date. Therefore, this work is entirely free from any kind of conflicts

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