International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 10 Issue: 11
DOI: https://doi.org/10.17762/ijritcc.v10i11.5777
***Article Received**: 20 August 2022 **Revised**: 01 October 2022 **Accepted**: 15 October 2022*

Comparative Analysis of CNN Regularisation and Augmentation Techniques with Ten Layer Deep Learning Model To Detect Lung Cancer

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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 model. 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 proposed model is based 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 great deal of interest is being placed in deep learning currently as a result of the exponential growth in data due to cellphones, social media, etc. With deep learning, performance also increases with data volume. The performance of other learning methods, such as machine learning (ML), remains constant or degrades as the amount of data increases. In deep learning, a neural network is integrated with feature extraction and model training. Artificial intelligence (AI) includes deep learning, which works similarly to the human brain in preprocessing and analyzing information to make decisions.

A Convolutional Neural Network (CNN) is a method of deep learning that accepts images as input for training and evaluating. Over the course of several decades, CNN achieved ground-breaking breakthroughs in a number of image-related fields [1]. According to Jian et al., lung images can be pre-processed in various ways before CNN models are applied [2]. According to Tekade and Rajeswari, deep learning can detect and categorize lung cancer. With the help of a 2D multipath network, this study evaluated and extracted lung cancer Images. In their study, Bhatia et al. employed residual learning to identify lung cancer from Computerized Tomography (CT) images. An extraction approach is used to extract lung areas using UNet and Resnet models [4]. CNNs, also known as shift invariants, are used to analyze visual images [5]. In addition to image classification, convolutional neural networks are used for natural language processing, image and video recognition, medical image analysis, financial time series analysis, image segmentation, and brain-computer interfaces.

II. LITERATURE SURVEY

Lung cancer is one of the most common malignancies in the world. It is a severe condition in which cells in the body grow out of control, causing around 235,760 new cases (119,100 in males and 116,660 in women) and 131,880 fatalities (69,410 in men and 62,470 in women) [9]. Tumors are classified into two types: non-cancerous (benign) and cancerous (cancerous) (malignant). As a result, to acquire accurate and immediate results, apply modern techniques such as image processing, machine learning, and deep learning. CT reports are less noisy than MRI and X-Ray findings [10]. Only when tumor cells are accurately segregated from normal cells, cancer treatment be effective. The basis for machine learning-based cancer diagnosis is the classification of tumor cells and the training of a neural network [11]. This studies shows a way to categorise lung cancers as malignant or benign the usage of a Convolutional

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Neural Network (CNN). CT scans are received from research of 7000 patients, if they may be in Dicom format. There are 10,000 Images with inside the database. proposed a layout that converts Dicom Format Images 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 before providing them to CNN architecture [13]. This results in better results as there are so many non-imaging regions which can reduce the accuracy of feature extraction. In 2D images objects of lung nodule detection may have a high positive rate.

A. CNN Architecture

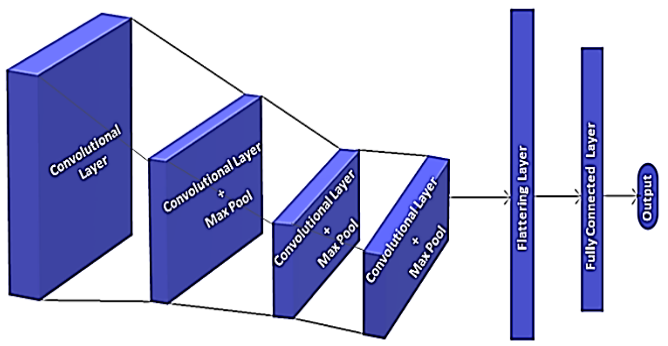

Fig. 1 CNN Architecture

In Fig. 1, the Convolutional neural network architecture is utilized to evaluate and represent images 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 images 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 minimise the size of the feature map. This layer is used to crop a image. 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 image is flattened at this layer and supplied to the FC layer. The image will be processed for feature extraction by number of convolutional layers and flattening the layers. Dense Layer is used as an output layer, and it provides the learning characteristics which are obtained from the combinations of the characteristics of the previous layer [8].

III. EXITING METHODS

3.1 Flow Process of Data Model

Deep learning (DL) techniques used as "CNN " 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.

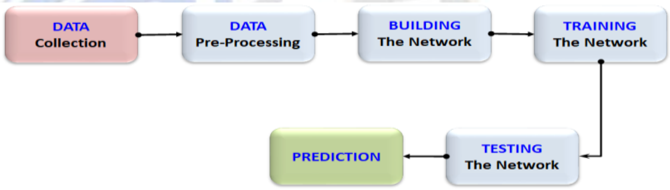

Fig. 1 Flow process of Data Model

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 build a model with Keras is sequentially. We make advantage of the 'add()' capability to add layers to our model. Our first two layers are Conv2D layers. These layers of convolution will work with the images from our 2-dimensional matrices as input.

C. Training the Network

Using the actual Images 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

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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. CNN WITH REGULARIZATION AND AUGUMENTATION TECHNIQUES

A. 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 Images. 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 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 Images are sent to the model for processing each iteration.

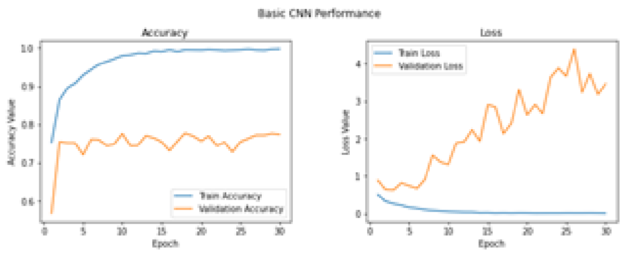

Fig. 2 Basic CNN Model

An epoch is when the complete dataset has passed through the network once, therefore the iterations are completed based on the data batches. In this paper basic CNN uses a batch_size of 30 and training data has 3000 samples, which indicates that there will be a total of 100 iterations per epoch. To train the model for a total of 30 epochs and validate it consequently on the validation set of 1000 images. 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%.

B. 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.

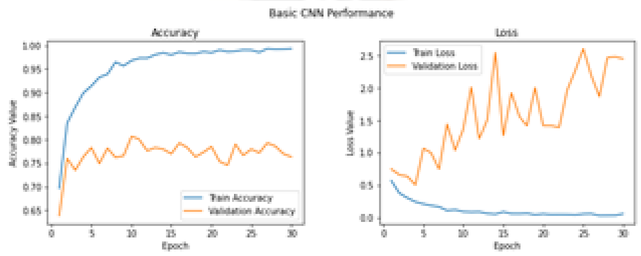

Fig. 3 CNN model with regularization

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.

C. 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 same small sample of data points for training. because it had trouble generalizing well and eventually developed overfitting after a few epochs. The concept behind image augmentation is that it adheres to a predetermined procedure of importing preexisting images from

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our training dataset and adding some image transformation operation to them. To create new, modified copies of old Images, techniques including rotation, shearing translation, zooming, and others are used is shown in Fig. 7.

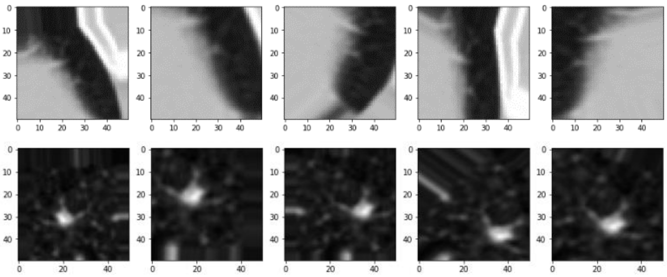

Fig. 4 CNN model with Augmentation

Due to this random transformation, the model doesn't get the same images each time and it leverages python generators to feed in these new images to model during training. The Keras framework has an excellent utility called ImageDataGenerator that can help us in doing all the preceding operations. Initialize two of the data generators for the training and validation datasets. Augmentation resulted in an 80-20 class distribution, which was not entirely ideal. But it also did not allow augmenting the minority class too much because it might result in a minority class with little variation. 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.

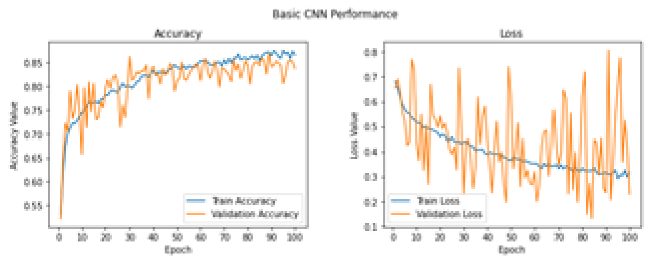

TABLE III
TRAINING AND VALIDATION OF CNN MODEL WITH AUGMENTATION

Training		Validation	
Accuracy	Loss	Accuracy	Loss
0.98	0.01	0.82	0.8

V. PROPOSED METHOD

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 annotations describing 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%).

A. Pre-processing and Feature Scaling

The generated dataset is structured in such a way that the model can be trained to crop Images around 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 Images 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 very efficient tool for encoding the levels of categorical features into numeric values. Label Encoder encodes labels with a value 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 allocated the same value 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. Segmentation is to simplify and change the representation of an image into something that is more meaningful and easier to analyze.it is a process of classifying each pixel in an image belonging to a certain class and hence can be thought of as a classification problem per pixel. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc. [15].

Convolutional has 10 hidden layers, pooling layers, and fully connected (FC) layers are the 3 forms of layers that make up the CNN. A CNN structure may be built 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 layer that extracts the exceptional functions from the input images. The convolution mathematical operation is performed among the input images and a clear out of a selected length M×M on this layer. The dot product among the clear out and the sections of the input images in regard to the scale of the clear out is taken via way of means of sliding the clear out throughout the input image (M×M). The Feature map is the

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result, and it contains statistics approximately the image consisting of its corners and edges. This characteristic map is then provided to similarly layers, which examine a number of different functions from the input image and the architecture is shown in Fig. 3.

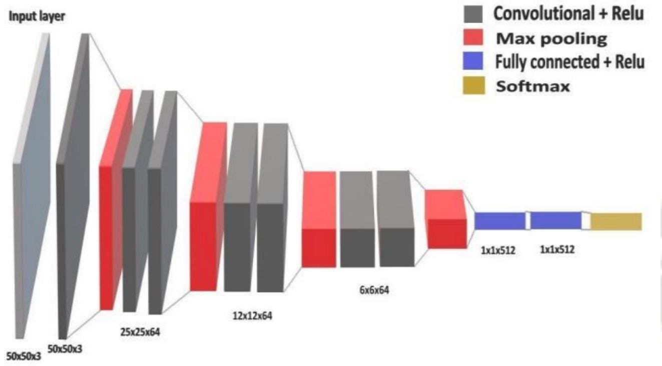


Fig. 5 Architecture of CNN

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.

B. Fully Connected Layer

The weights and offsets and neurons form a fully connected (FC) layer, which is used to connect neurons between the two layers. The last several layers of a CNN architecture are usually placed before the output layer. The input images from the previous layers are smoothed and fed to the FC layer in this step. The flattened vector is then sent through some additional FC layers where mathematical operations are usually performed. From this moment the classification process begins.

C. Dropout

When all of the features are connected to the FC layer, the training dataset is prone to overfitting. Overfitting happens when a model performs so well on training data that it has a negative impact on its performance when applied to new data. To address this issue, a dropout layer is employed, in which a few neurons are removed from the neural network during the training process, resulting in a smaller model. After passing a dropout of 0.3, 30% of the nodes in the neural network are dropped out at random.

D. Activation Functions

Finally, the activation function is one of the most important parameters of a CNN model. They are used to learn and approximate the continuous and complex relationship between network variables. In other words, it determines which model information should and should not be transmitted at the network end. This gives the network non-linearity. The ReLu, SoftMax, Tanh and Sigmoid functions are some of the most commonly used activation functions. Each of these functions has a particular purpose of use. Sigmoid and SoftMax functions are preferred for binary classification of CNN model, SoftMax is usually used for binary classification.

E. Compile

The model was built using an ad optimizer and "sparse categorical entropy" loss. A sparse categorical cross-entropy loss function and a sparse categorical 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

VI. 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.

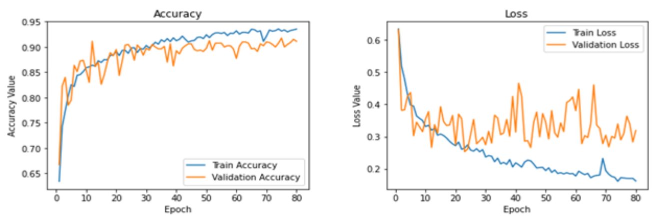
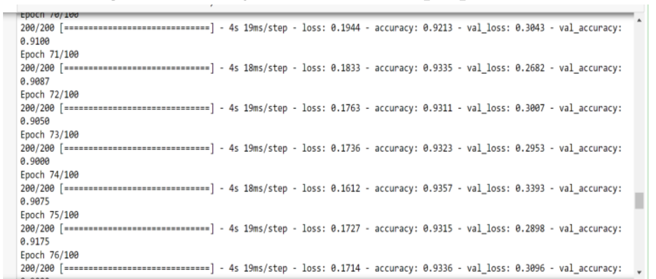


Fig. 6 Accuracy and loss of the proposed model



```
Epoch 70/100
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. 7 History of the model

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TABLE IV

TRAINING AND VALIDATION OF CNN MODEL

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

VII. IMPLEMENTATION

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*

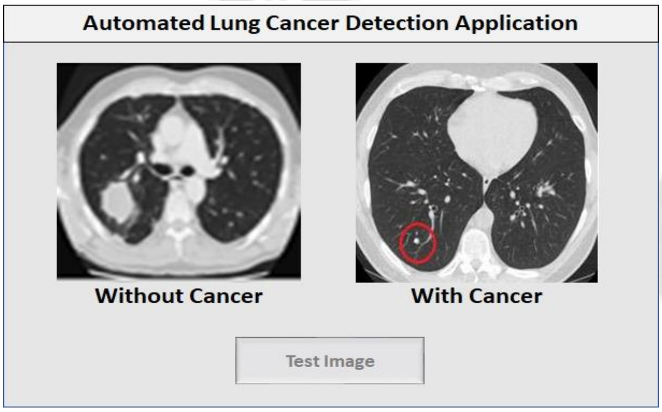
A user-friendly software is created so that everyone may use it and gain from it. With CNN's assistance, an all-purpose user-friendly app was developed utilizing the flask microweb framework, a python-based tool that serves as an API between cloud servers and apps. The proposed software was launched 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.

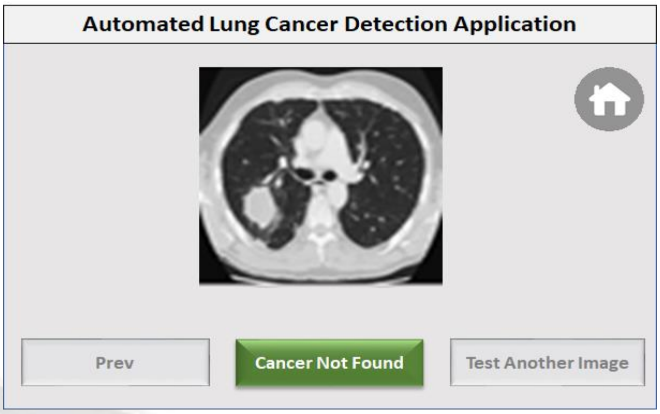
TABLE V

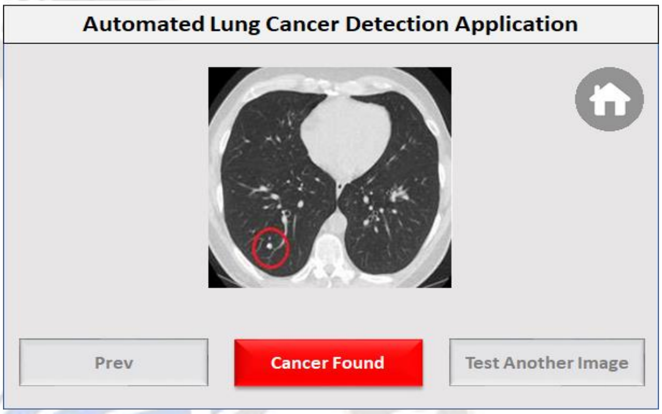
TEST RESULTS OF ACCURACY, PRECISION, RECALL AND F1.

	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







VIII. 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
	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	CNN model with ten layers	94.6	0.4	0.82	0.6

IX. 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 overcome this issue, regularization is applied 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 Images 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

ACKNOWLEDGMENT

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Citation: A. Madhavi. Comparative analysis of CNN Regularisation and Augumentation Techniques with ten Layer Deep Learning Model to Detect Lung Cancer