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An Observation and Analysis the role of Convolutional Neural Network towards Lung Cancer Prediction

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Abstract

Lung cancer is one of the most serious and prevalent diseases, causing many deaths each year. Though CT scan images are mostly used in the diagnosis of cancer, the assessment of scans is an error-prone and time-consuming task. Machine learning and AI-based models can identify and classify types of lung cancer quite accurately, which helps in the early-stage detection of lung cancer that can increase the survival rate. In this paper, Convolutional Neural Network is used to classify Adenocarcinoma, squamous cell carcinoma and normal case CT scan images from the Chest CT Scan Images Dataset using different combinations of hidden layers and parameters in CNN models. The proposed model was trained on 1000 CT Scan Images of cancerous and non-cancerous cells to find the best combination of parameters in CNN to predict lung cancer accurately. The proposed system recorded the highest accuracy of 92.79%. In addition to that, the paper addresses 192 observations made using the CNN model.

Keywords: Convolutional Neural Network (CNN), CT scan images, Lung Cancer, Machine Learning, Prediction System.

Introduction

Lung cancer is acknowledged as the most common reason behind death due to cancer accounting for about 20% of cancer deaths. Most of the cases of lung cancer are because of prolonged smoking [1] whereas lung cancer in people who do not smoke can be caused by passive smoking, air pollution, exposure to diesel exhaust or certain chemicals [2].

Finding the best combination of parameters in a Convolutional Neural Network to predict lung cancer has been the major objective of this work. 192 combinations of different parameters in CNN are tested on a dataset of CT scan images of cancerous and benign lung cells to find out the best combination to predict lung cancer with the help of a Convolutional Neural Network.

Imaging tests like Chest X-Ray, Computed Tomography (CT) Scan, Magnetic Resonance Imaging (MRI) Scan, and Positron Emission Tomography (PET) Scans are done to identify cancerous cells in the lung. The result of these tests when suggests that a person might have lung cancer, Sputum Cytology, Thoracentesis, Needle Biopsy, Fine Needle Aspiration (FNA) Biopsy, Core Biopsy, Transthoracic Needle Biopsy, Bronchoscopy are done to be sure of the diagnosis [3]. While performing these tests, the assessments of the slides by experienced pathologists are crucial in the diagnosis of lung cancer. While it is extremely time consuming, there also lies a chance of misjudgment of cancerous cells or their type which can lead to an incorrect treatment and cost lives.

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Machine Learning is a branch of Artificial Intelligence that gives machines the ability to learn without being specifically programmed. The machines are exposed to data by which they learn about a certain task through experiences. In the previous research work done on Lung cancer detection using image data specifically CT scan images, most of the researchers have applied Support Vector Machine (SVM), Naïve Bayes and Convolution Neural Networks for lung cancer detection. This research paper has considered using Convolutional Neural Network (CNN) in different combinations of parameters and hidden layers to classify adenocarcinoma, squamous cell carcinoma and normal cases. There were no papers found which used CNN models in different combinations of parameters and compared their results such as accuracy, precision, sensitivity, specificity, and AUC score.

Among the classification models used in image detection and classification, Convolutional Neural Network works the best. One of the reasons for this is that with the increment of each hidden layer, the model's ability to understand images increases. Beyond this CNN does not need any human supervision to detect important features of an image and classify them into specific classes which is one of its biggest advantages. Also being computationally efficient plays a major role in choosing CNN for the proposed work.

A total number of 192 observations can be derived from the combinations of parameters in CNN whose accuracy, precision, sensitivity, specificity and AUC score have been captured and observed to find the best combination to use for prediction of lung cancer which is discussed in detail in the result analysis section. The detailed discussion of the 192 observations using different parameters in different combinations on the CNN model of different layers is considered as the novelty of the work that can be used to determine which CNN model to use in terms of different metrics. The proposed work contributes to the field of Artificial Intelligence, especially in the field of Lung cancer prediction using Machine Learning with its findings on which CNN model works best for this. The observations made in this paper can be further used to predict lung cancer more effectively with the use of CNN models and to open a broader spectrum of research on the parameters that work and that does not work in benefit for CNN.

In section 2, previous related research papers are reviewed. The proposed methodology is illustrated briefly in Section 3 and the obtained outputs are discussed with tables and graphs in Section 4. The conclusion of the paper is stated in Section 5 and cited sources are referred to in the References section.

Literature Review

In the past few years, great progress has been made in creating classifiers for image detection and recognition using various machine learning algorithms. Some of the related research works done in the past are discussed below:

Cruz JA, Wishart DS[4] have compared and evaluated the performances of different machine learning algorithms like Decision Tree, Naive Bayes, k-Nearest Neighbour, Neural Network, Support Vector Machine (SVM), Genetic Algorithm, Linear Discriminant Analysis (LDA), Evolving Fuzzy Neural Network and identified trends related to the types of training data used, kinds of predictions made, types of algorithms used in predicting cancer. While ANN was mostly used in the prediction of Cancer, it is clear that a rising number of alternative machine learning techniques are being deployed, and they are being applied to many different types of cancers to predict at least three distinct kinds of outcomes.

Shaikh FJ, Rao DS [5] have also compared the results of various machine learning algorithms like Decision Tree (93.6%), Naive Bayes (67%), EFuNN and the Bayesian classification were mixed in a hierarchic modular structure. (87.5%), Artificial Neural Network (91.2%), Evolving Neural Network (78.5%), Support Vector Machine (SVM) (69%), Logistic Regression (89.2%) where Decision Trees and ANN give a closely accurate outcome.

Similarly in other review papers of machine learning algorithms [6] which are used to detect and classify images Multilayer perceptron (MLP), Recurrent neural network (RNN), Convolutional neural network (CNN), Graph convolutional neural networks (GCNNs) , Generative adversarial networks (GANs),Layer-wise Relevance

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Propagation (LRP) , SVM , k-nearest neighbors, CUP-AI-Dx algorithm, Random forest, logistic regression, gradient boosting machine was used repeatedly whereas the most used algorithm was Convolutional Neural Network which also gave better accuracy [7] .

Dabeer S, Khan MM, Islam S proposed a 3-layer CNN model trained on BreakHis database's histopathological stained images for Breast Cancer prediction which achieved an accuracy of 93% [8].

Zuluaga-Gomez J et al also trained a CNN model for Breast Cancer prediction on 57 patients database of thermal images which recorded an accuracy of 92% which outperformed several CNN architectures like SeResNet50, Inception and ResNet50 [9].

Fu'adah YN, Pratiwi NC, Pramudito MA, Ibrahim N proposed a Skin Cancer Classification System which used CNN model with three hidden layers and several optimizers such as SGD, RMSprop, Adam and Nadam with a learning rate of 0.001 Adam optimizer achieves the best accuracy value of 99% in identifying the skin cells from the ISIC dataset into 4 classes [10].

Tasnim Z, Chakraborty S, Shamrat FMJM, Chowdhury AN, Nuha HA, Karim A, et al proposed a CNN with max pooling and average pooling layers and MobileNetV2 models for Colon Cancer Diagnosis where MobileNetV2 outperforms the other two with an accuracy of 99.67% [11].

R. Kavitha,Kiruba Jothi,Saravanan,Mahendra Pratap Swain,José Luis Arias Gonzáles,Rakhi Joshi Bhardwaj, et al proposed a system to predict cervical cancer using the CNN, MLP, and ANN algorithms. The system utilizes fuzzy c-means method for image segmentation and ACO algorithm as the feature selection method. Trained and tested on the Herlev dataset, the ACO-CNN classifier records the highest accuracy [12].

Zaki SM, Jaber MM, Kashmoola MA proposed a Covid 19 Infection diagnosis system that used Chest X-Ray images where SVM and Neural Network both gives an approximate AUC score of 0.999 which satisfyingly diagnoses Covid-19 [13].

Kareem AK, AL-Ani MM, Nafea AA proposed an autism spectrum disorder detection system using 1-D CNN on three different datasets where CNN shows better accuracy than any other Machine Learning model. The best recorded accuracies are 99.45%, 98.66%, and 90% for Adults, Children, and Adolescents respectively [14].

Kalaivani N, Manimaran N, Sophia DrS, D Devi D proposed a CNN model where 85% of data was used for training and 15% was used for testing which achieved 90.85% accuracy [15]. A densely connected convolution neural network (DenseNet) and ADABOOST (Adaptive Boosting) were deployed, and the accuracy of the pictures is calculated based on the sample weights of the images.

Whereas Chauhan R, Ghanshala KK, Joshi RC used CNN model on two different datasets MNIST, CIFAR-10 and got accuracies 99.6% and 80.17% respectively [16]. Data augmentation layer, dropout layer and RMSprop optimizer were used in this work.

There are many research papers discussing CNN used on histopathological images which achieved better accuracies than SVM or other algorithms. Yashaswini S and Prasad KV compared the performances of CNN and SVM on LIDC-IDRI dataset where CNN outperformed SVM with 90% accuracy [17].

Hatuwal BK, Thapa HC [18] used the CNN model on LC25000 Lung and colon histopathological image dataset to classify images into three different categories benign, Adenocarcinoma, and squamous cell carcinoma. The model recorded an accuracy of 96.11% in training and 97.20% in validation.

Except these, there were numerous papers which used CNN in a particular structure, mostly 3-layer CNN model on CT scan images but the use of regularized or augmentation layer is not noticed commonly [19-22].

Pandian R, Vedanarayanan V, Ravi Kumar DNS, Rajakumar R proposed Googlenet model for cancer detection in their research paper which achieved 98% accuracy [23].

Ponnada VT, Srinivasu SVN proposed a new CNN model named EFFI-CNN, which was developed based on the experiments performed in ICDSSPLD-CNN and EASPLD-CNN [24].

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Proposed Methodology

In this proposed work, Convolutional Neural Network was used on a Chest CT scan image dataset using combinations of different parameters like dropout layer, data augmentation layer, regularizes, optimizers, epochs and the number of hidden layers.

The proposed methodology has 3 stages, Dataset Collection, Data Pre-processing and CNN Model Building.

The following Fig. 1 shows a block diagram of the proposed methodology.

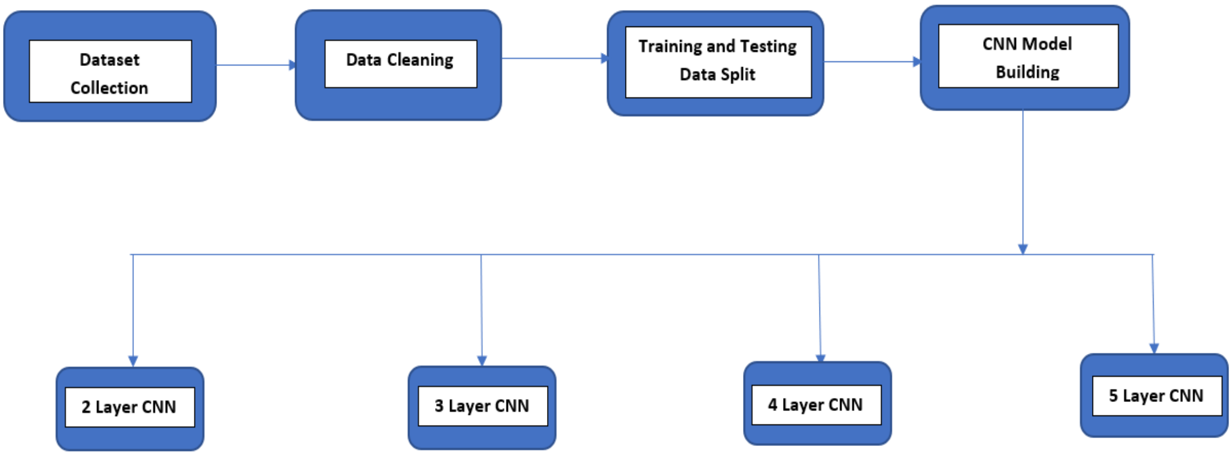

Figure 1. Block Diagram of Proposed Methodology.

Dataset Collection

The Chest CT Scan Images Dataset was found in Kaggle [25]. Three classes of images, Adenocarcinoma, Squamous Cell Carcinoma and normal case Computed Tomography (CT) Scans are considered for work. There were a total number of 1000 images in the dataset. All the images are in .png and .jpg format in the dataset to fit the model. Fig.2 shows the graphical bar representation of the classes in the dataset.

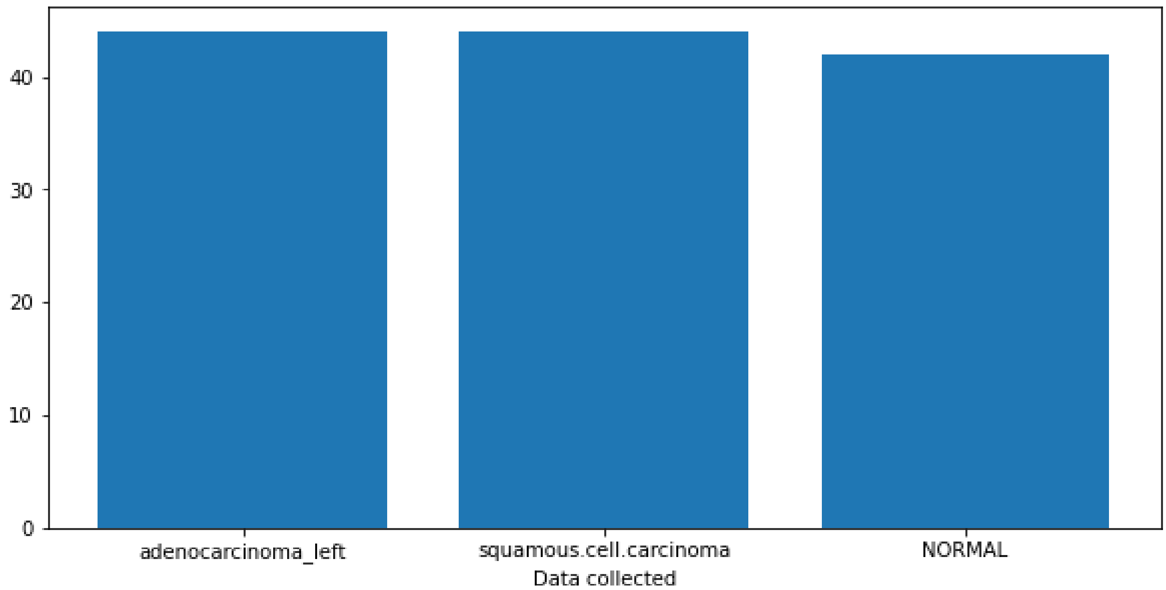

Figure 2. Graphical Bar-Graph Representation of Dataset.

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Data Pre-processing

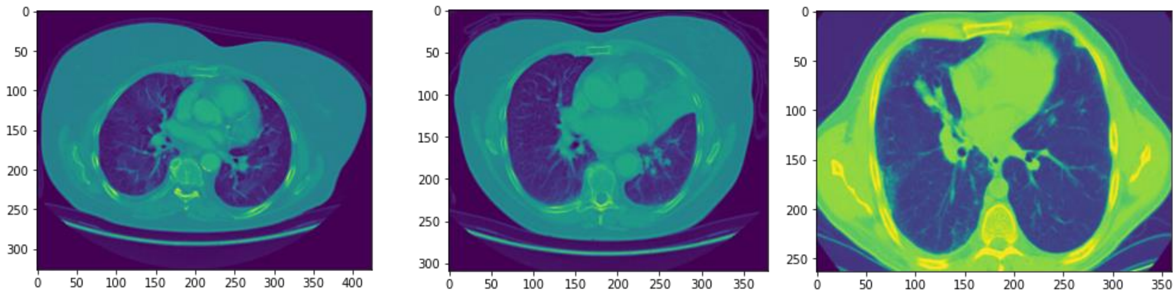
To eliminate the limitations of processing power, all the images of the dataset were resized into 256*256-pixel sized images. As all the images were resized into lower dimension images, processing of the images is faster. To resize the images, the resize function from OpenCV library was used with the parameters as the images and image size 256,256.

Next the image data array was reshaped using (-1,1) as the images are the only feature used for the model predictions.

The possible values for each pixel are 0 to 256 where a color code is represented by each digit. The computation of large numeric values may become more difficult when utilizing the picture as-is and running it through a Deep Neural Network.

The data can be normalized to fall between 0 and 1 to lessen this. Since pixel values vary from 0 to 256, the range is 255 except for 0. All of the pixel values were divided by 255 to change the range to be from 0 to 1.

Some random images from the dataset are shown in Fig.3



3.(a) 3.(b) 3.(c)

Figure 3. Random images from dataset (a) Squamous Cell Carcinoma (b) Adenocarcinoma (c)Normal.

The dataset was spilt for training and testing data in 3:1 ratio.

CNN Model Building

Convolutional Neural Network was first introduced by Yann LeCun in 1980 [26] and was built on the work of Kunihiko Fukushima's Neocognitron . CNN is an area in deep learning that specializes in pattern recognition. It incorporates multiple layers like Convolutional Layers, Pooling Layers which are used to detect different features of an image. A filter is applied to an image to make the output better after each layer. After each layer, the filters increase complexity to identify unique features of the images.

In each convolutional layer, each image goes through a set of filters and finds out unique features of the image and that's how CNN acknowledges the images. After each layer, CNN applies a Rectified Linear Unit (ReLU) function on the feature map, to introduce non-linearity in CNN models. In pooling layer, MaxPooling selects the pixel with the maximum value and sends into the output.

The proposed method uses Convolutional Neural Network on the dataset and tries out different numbers of layers, dropout layers, regularizes, optimizers, epochs and data augmentation to observe the results and find out the best way to use CNN on this dataset.

In the proposed work, CNN models are divided into 4 categories based on the number of hidden layers inside them such as 2 Layer, 3 Layer, 4 Layer and 5 Layer.

In these models, there are 2D Convolutional Layers followed by Rectified Linear Unit (ReLU) layer which applies an element wise activation function on the images and MaxPooling Layer of size (2,2). One flatten layer, two dense layers, one with the value of 16 and another with value of three with softmax activation function are used to get the final output. Sparse Categorical Cross-entropy is used as the loss function of this model.

Adaptive Moment Estimation (Adam) and RMSprop are used as optimizers in different observations. To avoid overfitting the CNN Model, L1 and L2 regularizes are used. Dropout Layer of value 0.25 has been introduced before the flattening layer in some observations. The number of Epochs is 10 and 50 to observe the variance in the results.

The data augmentation layer has horizontal flip transformation as well as random rotation and random zoom both with value 0.1.

The batch size is 8 for the compilation of all the models and accuracy, precision, sensitivity, specificity and AUC score have been observed for the final analysis. Confusion matrices are also plotted to observe the performance of the different CNN Models.

All the models are observed using different parameters and a total number of 192 observations were made from them.

The proposed work contributes to the field of lung cancer prediction using machine learning as it shows the best combination of parameters in CNN model that can accurately classify cancerous and benign cells. It also contributes with a detailed discussion of 192 observations made from different layered CNNs which can be used in further research of the field. The result analysis of the proposed work shows the best and the worst possible combinations of parameters in CNN models that can be used to determine which combination should be used to build an efficient model that can accurately predict lung cancer.

CNN 2 Layer Model

CNN 2 Layer models incorporate 2 Convolutional Layer followed by ReLU and MaxPooling Layer. 48 observations were drawn using different parameters on the models. All the combinations in the observations in CNN 2 Layer Model are shown in Fig. 4

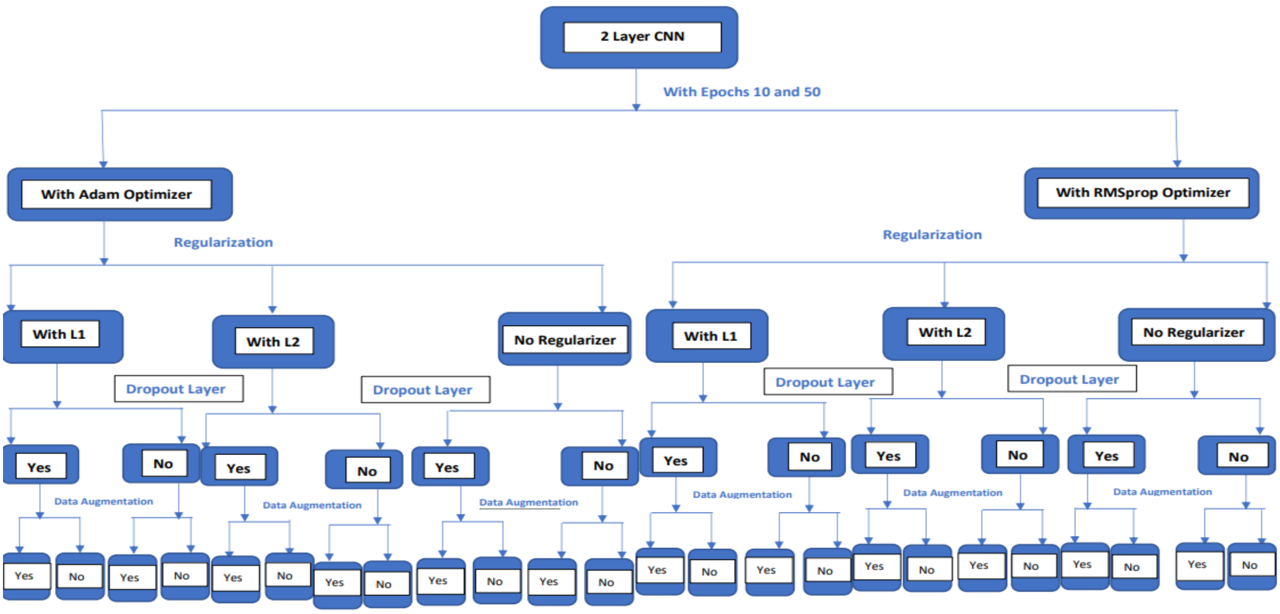


Figure 4. Observations on CNN 2 Layer Model.

CNN 3 Layer Model

CNN 3 Layer Model consists of 3 Convolutional Layers with ReLU Layer and MaxPooling Layer. Optimizers, Dropout Layer, Data Augmentation Layer, Number of Epochs, Regularizes were used in different combinations to get a total number of 48 observations. All the combinations in the observations in CNN 3 Layer Model are shown in Fig. 5

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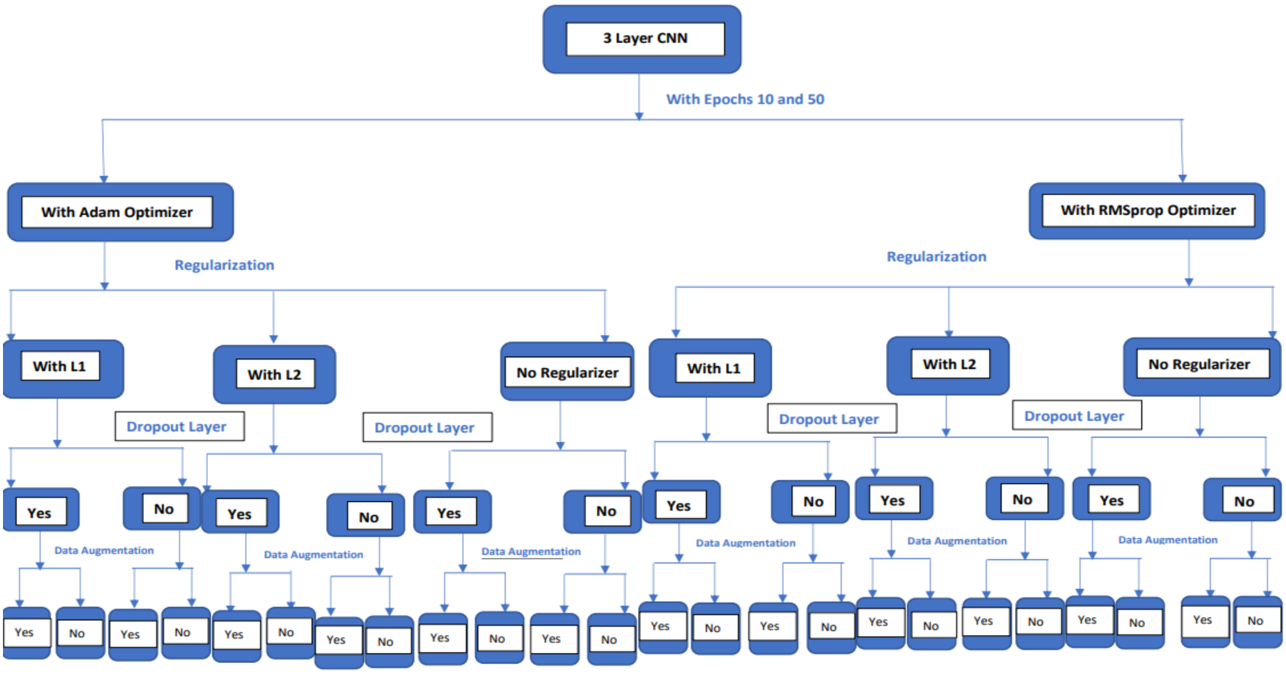

Figure 5. Observations on CNN 3 Layer Model.

CNN 4 Layer Model

It consists of 4 Convolutional Layers with ReLU as the activation layer & MaxPooling Layer with different parameters used on the model. All the combinations in the observations in CNN 4 Layer Model are shown in Fig. 6

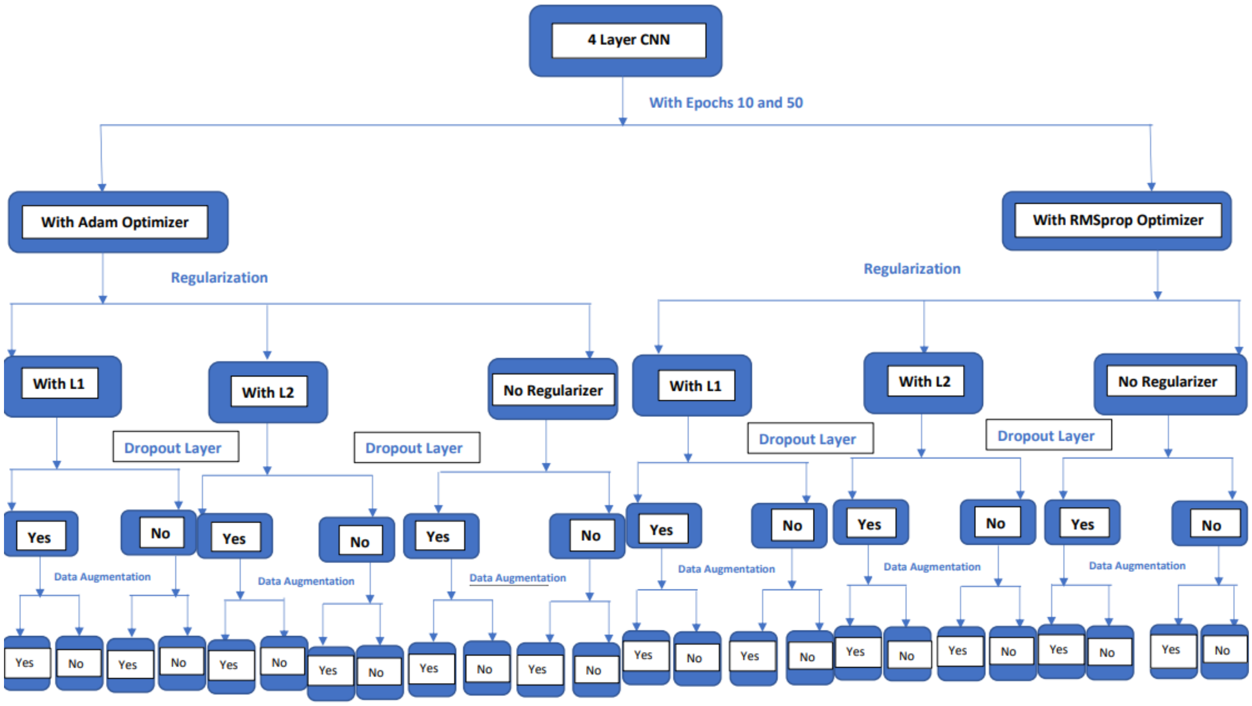

Figure 6. Observations on CNN 4 Layer Model.

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CNN 5 Layer Model

The CNN 5 Layer Model consists of 5 Convolutional Layers, followed by ReLU as the activation function layer and MaxPooling as the pooling layer. All the combinations in the observations in CNN 5 Layer Model are shown in Fig.7

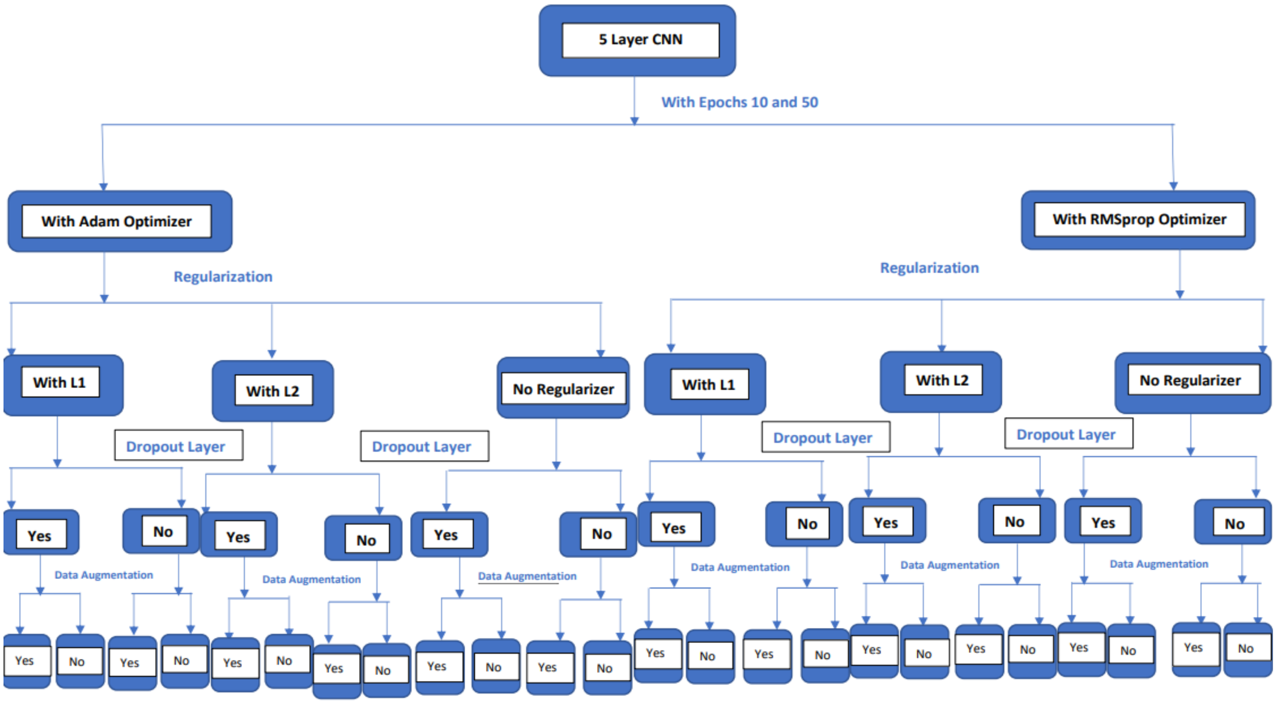

Figure 7. Observations on CNN 5 Layer Model.

Results and Discussion

The dataset that has been used in this paper consists of CT scan images of people who are diagnosed with Adenocarcinoma, Squamous Cell Carcinoma and also scans of normal people. The images were trained for 10 and 50 epochs to see the variation in results. Various performance metrics were considered at the time of analysis. The results for each model are shown using different parameters like Accuracy, Precision, Specificity, Sensitivity and AUC Score.

Accuracy is the ratio of the accurate predictions to the total predictions in a model.

Accuracy=Number of accurate predictions /Total number of predictions

The ratio of accurately categorized positive samples to the total number of samples classified as positive is called as the precision of the model.

Precision=True Positive / (True Positive+False Positive)

Sensitivity also known as the True Positive Rate or Recall of a model is the ratio of correctly classified positive samples to the number of total positive samples in data.

Sensitivity=True Positive / (True Positive+False Negative)

Specificity also known as the True Negative Rate is the ratio of the correctly categorized negative samples to the number of total negative samples in data.

Specificity=True Negative / (True Negative+False Positive)

The true positive or the true negative rate of a prediction made using a model can be shown by a Receiver Operating Characteristic curve or ROC curve. The specificity and sensitivity of the model are assessed using the ROC curve's Area under Curve score or AUC score. The model more closely fits the data the closer the AUC score value is to 1.

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CNN 2 Layer Model Observation

There were 48 observations made from CNN 2 Layer models. The following Table 1 shows the all the observations and their results.

Table 1. Observations and their results on CNN 2 Layer Model

Observation	CNN 2 Layer Model Specification	Epochs	Accuracy	Precision	Sensitivity	Specificity	AUC Score
1	No Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	10	85.14	86.49	87.49	12.51	0.9697709676
2	No Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	10	77.03	78.98	79.97	20.03	0.929253006
3	No Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	50	84.23	86.39	86.04	13.96	0.962295993
4	No Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	50	82.43	85.55	83.87	16.13	0.9581412609
5	No Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	10	84.23	86.3	85.49	14.51	0.9561785789
6	No Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	10	75.68	77.6	79.86	20.14	0.9275262188
7	No Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	50	84.23	86.34	86.95	13.05	0.9501921657
8	No Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	50	74.32	76.49	77.06	22.94	0.9148527009
9	L1 Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	10	85.59	86.69	87.42	12.58	0.9602568549
10	L1 Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	10	72.97	78.83	74.05	25.95	0.9020402569
11	L1 Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	50	86.04	87.33	88.01	11.99	0.9638008712
12	L1 Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	50	65.32	67.89	68.86	31.14	0.8665059225
13	L1 Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	10	86.93	89	87.49	12.51	0.967412952
14	L1 Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	10	75.23	78	77.33	22.67	0.9087376179
15	L1 Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	50	83.33	85.22	84.91	15.09	0.9587463823

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16	L1 Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	50	68.46	72.39	70.61	29.39	0.8715529523
17	L2 Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	10	85.13	86.96	87.63	12.37	0.9627220954
18	L2 Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	10	76.13	79.7	78.03	21.97	0.923446078
19	L2 Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	50	83.33	85.53	84.61	15.39	0.960345432
20	L2 Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	50	78.38	81.83	80.12	19.88	0.9466737901
21	L2 Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	10	84.23	86.44	86.75	13.25	0.9583855472
22	L2 Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	10	74.32	82.63	75.49	24.51	0.9226647348
23	L2 Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	50	86.04	87.4	87.4	12.6	0.9651332573
24	L2 Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	50	80.18	82.52	82.76	17.24	0.9458728667
25	L1 Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	10	87.39	88.22	89.59	10.41	0.9676889396
26	L1 Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	10	73.42	76.59	75.19	24.81	0.9076998672
27	L1 Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	50	84.23	86.72	87.31	12.69	0.9643062269
28	L1 Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	50	61.26	64.35	66.51	33.49	0.8573638337
29	L1 Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	10	86.03	87.83	87.51	12.49	0.9635015739
30	L1 Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	10	71.17	73.5	73.99	26.01	0.9075208483
31	L1 Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	50	85.14	86.56	87.23	12.77	0.9615053258
32	L1 Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	50	68.02	70.89	70.63	29.37	0.8721692624
33	L2 Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	10	84.68	86.31	86.74	13.26	0.9624992541

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34	L2 Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	10	75.23	77.82	77.45	22.55	0.9180848326
35	L2 Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	50	84.23	86.23	85.68	14.22	0.9571324144
36	L2 Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	50	68.92	71.38	72.01	27.99	0.8724014277
37	L2 Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	10	85.58	87.09	87.17	12.83	0.9597729443
38	L2 Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	10	73.42	79.24	75.01	24.99	0.9180773735
39	L2 Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	50	82.88	84.67	84.53	15.47	0.9567286893
40	L2 Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	50	70.72	74.13	72.81	27.19	0.8804321071
41	No Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	10	83.78	87.33	87.12	12.88	0.9618055556
42	No Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	10	74.32	79.31	75.47	24.53	0.9243682122
43	No Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	50	83.33	85.58	84.81	15.19	0.9569347476
44	No Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	50	74.77	78.3	76.71	23.29	0.9406990318
45	No Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	10	84.68	86.77	86.48	13.52	0.9558168114
46	No Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	10	69.37	79.91	70.05	29.95	0.9072663056
47	No Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	50	82.88	85.19	84.37	15.63	0.9475674864
48	No Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	50	76.13	77.75	79.11	20.89	0.9200111514

From the above table it is clearly visible that Observation 25 gets the highest accuracy among 2 Layer Models with an accuracy of 87.39%. This CNN model had L1 regularizer, Dropout Layer, no data augmentation layer, ADAM optimizer and it was trained for 10 epochs and that gives the best accuracy. Below Figs. 8 and 9 shows the model accuracy and the model loss plot against epochs for training and validation images.

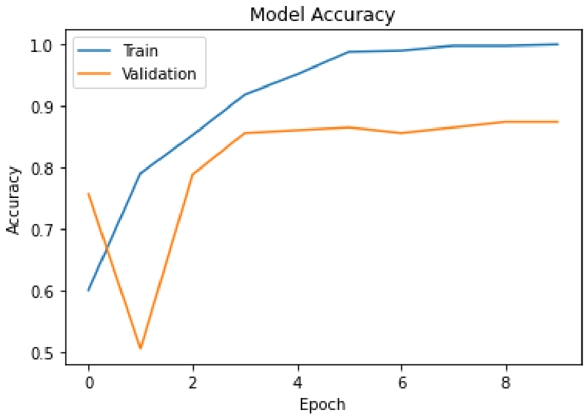

Figure 8. Observation 25 Plot of Model Accuracy vs Epochs for training and validation data.

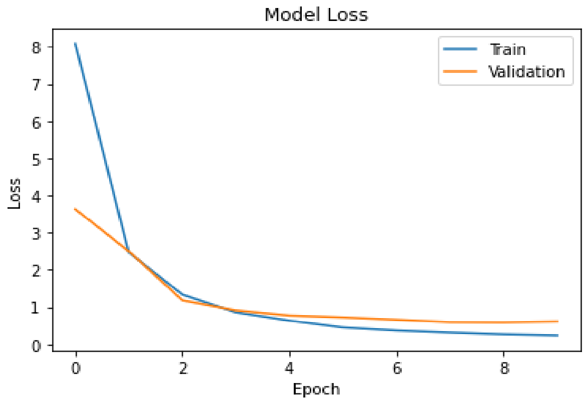

Figure 9. Observation 25 Plot of Model Loss vs Epochs for training and validation data.

The predicted and the true label of the validation images in the categories labelled are shown in the confusion matrix of the model in Fig.10

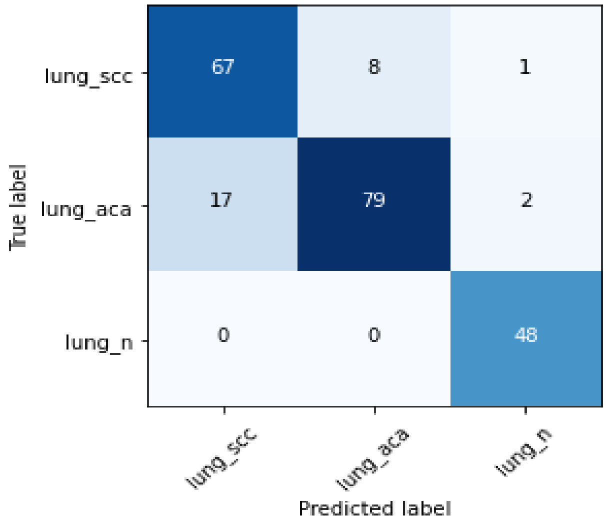

Figure 10. Confusion Matrix of different categories of images in Validation data for Observation 25.

CNN 3 Layer Model Observation

There were a total number of 48 observations made from CNN 3 Layer models. All the observations and their results are shown in the following Table 2.

Table 2. Observations and their results on CNN 3 Layer Model.

Observation	CNN 3 Layer Model Specification	Epochs	Accuracy	Precision	Sensitivity	Specificity	AUC Score
49	No Regularizer+ADAM Optimizer+ No Dropout+ No Augmentation	10	85.58	87.02	87.02	12.98	0.9531399182
50	No Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	10	71.62	75.57	72.72	27.28	0.9104532164
51	No Regularizer+ADAM Optimizer+ No Dropout+ No Augmentation	50	84.68	86.39	86.13	13.87	0.9631099699
52	No Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	50	63.96	67.42	65.86	34.14	0.8459784133
53	No Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	10	85.59	87.35	87.02	12.93	0.953363692
54	No Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	10	72.97	78.68	74.67	25.33	0.9207006542
55	No Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	50	83.33	85.72	84.66	15.34	0.9495973005

56	No Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	50	69.37	73.59	71.12	28.88	0.8823947891
57	L1 Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	10	87.39	88.22	89.23	10.77	0.9648777823
58	L1 Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	10	68.02	72.2	67.57	32.43	0.8827761368
59	L1 Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	50	87.84	89.12	89.63	10.37	0.9644861782
60	L1 Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	50	63.51	66.47	67.61	32.39	0.8453248076
61	L1 Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	10	88.74	89.71	90.46	9.54	0.9680283298
62	L1 Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	10	69.37	75.3	71.07	28.93	0.8963927676
63	L1 Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	50	84.23	86.01	86.4	13.6	0.960089957
64	L1 Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	50	64.41	66.58	68.09	31.91	0.8560454335
65	L2 Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	10	89.19	90.42	90.56	9.44	0.972228749
66	L2 Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	10	69.37	72.29	73.2	26.8	0.8880264277
67	L2 Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	50	86.94	87.72	88.5	11.5	0.964488043
68	L2 Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	50	69.82	72.46	73.47	26.53	0.871117526
69	L2 Regularizer+ RMSprop Optimizer+No Dropout+ No Augmentation	10	89.64	90.8	90.64	9.36	0.966391052
70	L2 Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	10	74.77	78.66	76.71	23.29	0.9226945712
71	L2 Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	50	88.74	89.96	89.97	10.03	0.9655062135
72	L2 Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	50	65.77	69.14	68.37	31.63	0.8755314626
73	L1 Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	10	89.63	90.62	90.9	9.1	0.9723620808

74	L1 Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	10	64.41	75.2	60.77	39.23	0.8433947592
75	L1 Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	50	89.64	90.83	91.23	8.77	0.9674362618
76	L1 Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	50	79.73	80.91	82.82	17.18	0.94275775
77	L1 Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	10	88.29	90.17	89.39	10.61	0.9735741884
78	L1 Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	10	70.72	74.98	76.31	23.69	0.9015134563
79	L1 Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	50	89.64	90.84	90.39	9.61	0.9676674946
80	L1 Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	50	81.98	85.14	83.34	16.66	0.948373538
81	L2 Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	10	86.49	88	88.07	11.93	0.9719676796
82	L2 Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	10	72.52	80.5	73.83	26.17	0.908778643
83	L2 Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	50	85.14	87.09	86.3	13.7	0.958067602
84	L2 Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	50	84.68	86.09	86.67	13.33	0.9616260704
85	L2 Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation]	10	86.49	88.03	87.97	12.03	0.9664693728
86	L2 Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	10	74.32	80.21	75.79	24.21	0.9196633697
87	L2 Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	50	86.49	89.57	86.82	13.18	0.9661449009
88	L2 Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	50	72.97	76.27	75.63	24.37	0.8950244846
89	No Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	10	86.94	88.74	88.83	11.17	0.9604349415
90	No Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	10	75.23	78.32	76.94	23.06	0.9237202008
91	No Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	50	85.59	87.03	86.97	13.03	0.9654111096
92	No Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	50	66.67	70.81	68.57	31.43	0.867872807
93	No Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	10	88.29	89.98	88.81	11.19	0.9620750164
94	No Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	10	81.53	83.8	83.1	16.9	0.9490318057
95	No Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	50	82.88	85.62	84.87	15.13	0.9566410446
96	No Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	50	76.58	76.99	79.46	20.54	0.9443512054

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From the above table it is clearly visible that Observation 69,75,79 gets the highest accuracy among 3 Layer Models with accuracy of 89.64%. Though looking at the other metrics like precision, AUC score, observation 79 with RMSprop optimizer and with L1 regularizer, dropout layer, no data augmentation layer, RMSprop optimizer with epochs 50 works the best with this dataset in CNN 3 Layer model. The model accuracy and the model loss plot against epochs for training and validation images are shown below in Figs. 11 and 12.

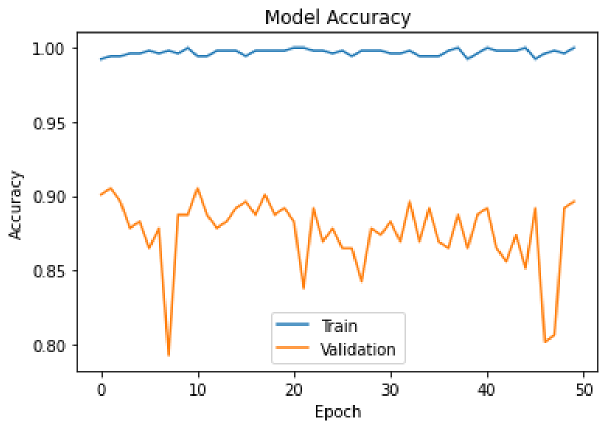

Figure 11. Observation 79 Plot of Model Accuracy vs Epochs for training and validation data.

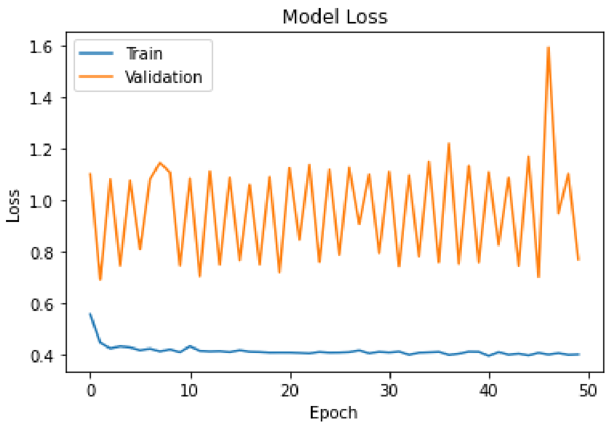

Figure 12. Observation 79 Plot of Model Loss vs Epochs for training and validation data.

The predicted and the true label of the validation images in the categories labelled are shown in the confusion matrix of the model in Fig.13

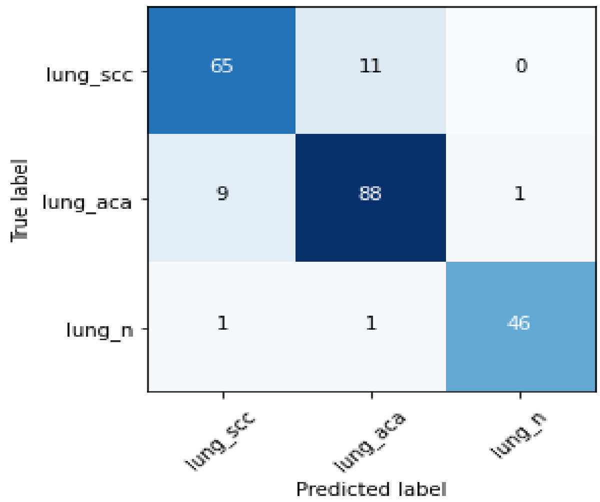

Figure 13. Confusion Matrix of different categories of images in Validation data for Observation 79.

CNN 4 Layer Model Observation

There were 48 observations made from CNN 4 Layer models. The following Table 3 shows the all the observations and their results.

Table 3. Observations and their results on CNN 4 Layer Model

Observation	CNN 4 Layer Model Specification	Epochs	Accuracy	Precision	Sensitivity	Specificity	AUC Score
97	No Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	10	89.19	89.52	90.56	9.44	0.9802025525
98	No Regularizer+ADAM Optimizer+No Dropout+ Data	10	69.82	76.82	71.5	28.5	0.9049269379

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	Augmentation Layer						
99	No Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	50	89.64	90.68	91.2	8.8	0.9818025346
100	No Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	50	89.19	91.22	89.97	10.03	0.9687057115
101	No Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	10	90.09	91.26	90.7	9.3	0.9625430764
102	No Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	10	78.83	79.74	81.66	18.34	0.9382869376
103	No Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	50	91.89	92.7	93	7	0.9766352265
104	No Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	50	90.54	92.92	90.99	9.01	0.9822015977
105	L1 Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	10	73.87	81.46	73.2	26.8	0.9314609067
106	L1 Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	10	67.57	74.27	68.44	31.56	0.8627670366
107	L1 Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	50	86.94	88.16	88.3	11.7	0.9687844984
108	L1 Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	50	69.37	72.79	71.14	28.86	0.8609619286
109	L1 Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	10	76.58	79.85	80.93	19.07	0.9357396467
110	L1 Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	10	72.97	76.01	74.04	25.95	0.8764666503
111	L1 Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	50	86.94	88.24	87.8	12.2	0.961882944
112	L1 Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	50	72.07	73.81	74.39	25.61	0.9128261502
113	L2 Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	10	86.49	88.46	87	13	0.963688052
114	L2 Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	10	68.47	74.95	69	31	0.8972067445
115	L2 Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	50	91.89	92.31	93.09	6.91	0.9766995614

116	L2 Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	50	63.06	67.01	66.04	33.96	0.85713 07361
117	L2 Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	10	90.09	90.78	91.28	8.72	0.97582 68439
118	L2 Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	10	73.42	78.95	74.66	25.34	0.90573 06585
119	L2 Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	50	90.09	91.06	91.63	8.37	0.97577 55624
120	L2 Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	50	62.61	67.82	65.36	34.64	0.85033 64065
121	L1 Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	10	71.17	74	73.4	26.6	0.90543 78879
122	L1 Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	10	64.86	66.94	68.77	31.23	0.86550 36028
123	L1 Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	50	85.14	87.06	86.72	13.28	0.95632 03022
124	L1 Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	50	65.77	72.72	64.7	35.3	0.84544 13564
125	L1 Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	10	78.38	80.91	80.07	19.93	0.92969 96211
126	L1 Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	10	67.12	76.19	67.8	32.2	0.88733 08644
127	L1 Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	50	87.39	89.09	88.13	11.87	0.96265 96253
128	L1 Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	50	64.41	70.87	68.17	31.83	0.85426 45677
129	L2 Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	10	88.74	89.99	90.36	9.64	0.97146 04592
130	L2 Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	10	72.97	74.77	76.44	23.56	0.90253 25591
131	L2 Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	50	89.64	90.34	91.2	8.8	0.97242 4551
132	L2 Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	50	63.96	69.49	67.1	32.9	0.85922 76823
133	L2 Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	10	89.19	90.1	89.89	10.11	0.97041 33847

134	L2 Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	10	72.52	78.8	73.93	26.07	0.9137706618
135	L2 Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	50	88.74	89.28	90.16	9.84	0.9776953545
136	L2 Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	50	88.29	89.6	89.57	10.43	0.9742585631
137	No Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	10	86.94	87.53	88.14	11.86	0.972713592
138	No Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	10	75.23	81.25	76.67	23.33	0.9329070444
139	No Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	50	92.79	93.55	92.9	7.1	0.9769848729
140	No Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	50	87.84	90.22	88.66	11.34	0.9760963047
141	No Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	10	91.44	92.28	92.23	7.77	0.9805978861
142	No Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	10	83.33	84.26	85.74	14.26	0.9510196623
143	No Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	50	90.54	91.89	90.46	9.54	0.9671341673
144	No Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	50	90.54	90.95	91.47	8.52	0.9839414384

From the above table it is clearly visible that Observation 139 gets the highest accuracy among 4 Layer Models with accuracy of 92.79% which has a Dropout layer but doesn't consist of any data augmentation layer or regularizer. The model is trained with ADAM optimizer for epochs 50. This model works best with the used dataset in the proposed work. The model accuracy and the model loss plot against epochs for training and validation images are shown below in Figs. 14 and 15.

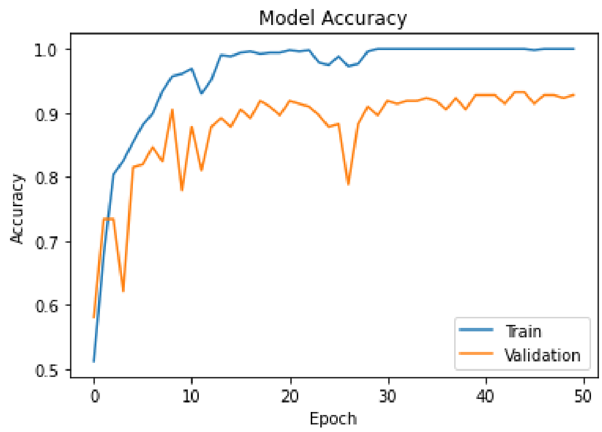

Figure 14. Observation 139 Plot of Model Accuracy vs Epochs for training and validation data.

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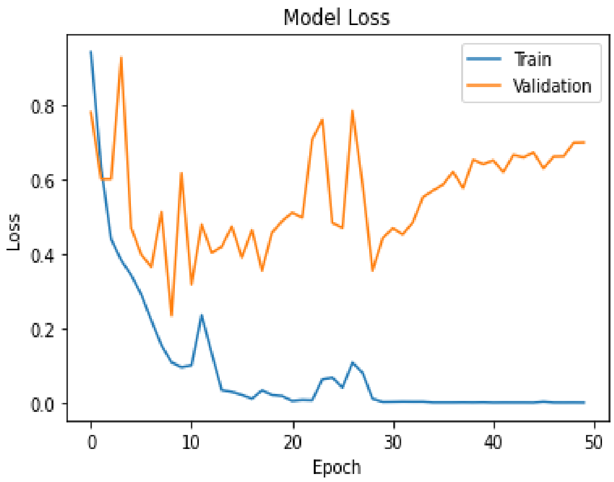

Figure 15. Observation 139 Plot of Model Loss vs Epochs for training and validation data.

The predicted and the true label of the validation images in the categories labelled are shown in the confusion matrix of the model in Fig.16

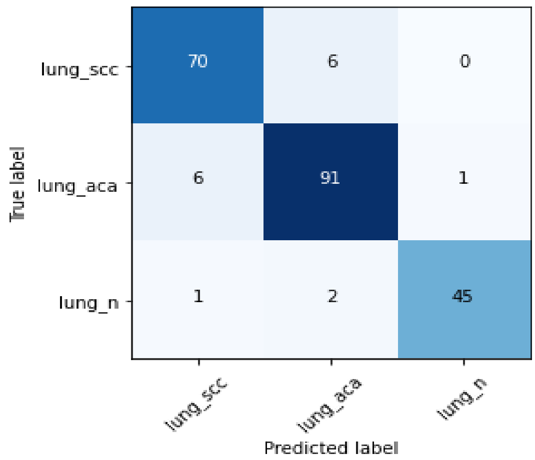

Figure 16. Confusion Matrix of different categories of images in Validation data for Observation 139.

CNN 5 Layer Model Observation

There was total 48 observations made from CNN 5 Layer models. All the observations and their results are shown in the following Table 4.

Table 4. Observations and their results on CNN 5 Layer Model

Observation	CNN 4 Layer Model Specification	Epochs	Accuracy	Precision	Sensitivity	Specificity	AUC Score
145	No Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	10	92.34	93.01	93.28	6.72	0.9865838331
146	No Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	10	80.63	82.83	82.22	17.78	0.9420687135
147	No Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	50	90.54	91.81	91.32	8.68	0.9762454872
148	No Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	50	71.62	74.16	73.64	26.36	0.8529881251
149	No Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	10	90.99	92.02	91.76	8.24	0.9868225251
150	No Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	10	78.83	80.97	80.67	19.33	0.9441246345
151	No Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	50	90.54	91.16	91.51	8.49	0.9747834989
152	No Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	50	92.34	93.02	93.03	6.97	0.986714834
153	L1 Regularizer+ADAM Optimizer+No Dropout+ No	10	44.14	14.71	33.33	66.67	0.5

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	Augmentation						
154	L1 Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	10	44.14	14.71	33.33	66.67	0.5
155	L1 Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	50	44.14	14.71	33.33	66.67	0.5
156	L1 Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	50	44.14	14.71	33.33	66.67	0.5
157	L1 Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	10	44.14	14.71	33.33	66.67	0.5
158	L1 Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	10	44.14	14.71	33.33	66.67	0.5
159	L1 Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	50	44.14	14.71	33.33	66.67	0.5
160	L1 Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	50	44.14	14.71	33.33	66.67	0.5
161	L2 Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	10	80.63	84.67	82.02	17.98	0.9400407641
162	L2 Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	10	44.14	14.71	33.33	66.67	0.608372214
163	L2 Regularizer+ADAM Optimizer+No Dropout+ No Augmentation	50	85.59	87.31	86.94	13.06	0.956343612
164	L2 Regularizer+ADAM Optimizer+No Dropout+ Data Augmentation Layer	50	67.12	70.71	69.22	30.78	0.8571279389
165	L2 Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	10	86.04	88.51	86.78	13.22	0.9539949203
166	L2 Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	10	44.14	14.71	33.33	66.67	0.5
167	L2 Regularizer+ RMSprop Optimizer+ No Dropout+ No Augmentation	50	84.23	85.79	86.01	13.99	0.9590717866
168	L2 Regularizer+ RMSprop Optimizer+ No Dropout+ Data Augmentation Layer	50	81.08	85.46	81.76	18.24	0.9399671053
169	L1 Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	10	44.14	14.71	33.33	66.67	0.5
170	L1 Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	10	44.14	14.71	33.33	66.67	0.5

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171	L1 Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	50	44.14	14.71	33.33	66.67	0.5
172	L1 Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	50	44.14	14.71	33.33	66.67	0.5
173	L1 Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	10	44.14	14.71	33.33	66.67	0.5
174	L1 Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	10	44.14	14.71	33.33	66.67	0.5
175	L1 Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	50	44.14	14.71	33.33	66.67	0.5
176	L1 Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	50	44.14	14.71	33.33	66.67	0.5
177	L2 Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	10	77.93	82.51	79.4	20.6	0.933276271
178	L2 Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	10	68.47	71.77	70.98	29.02	0.8841523451
179	L2 Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	50	86.04	87.34	87.42	12.58	0.9647575039
180	L2 Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	50	68.92	72.91	70.57	29.43	0.875310486
181	L2 Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation]	10	81.98	86.14	82.73	17.27	0.950085407
182	L2 Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	10	74.77	76.13	78.3	21.7	0.9093679138
183	L2 Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	50	86.94	88.03	88.4	11.6	0.9601179288
184	L2 Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	50	68.02	69.63	69.54	30.46	0.8540538474
185	No Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	10	86.48	87.87	88.12	11.88	0.9680786788
186	No Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	10	66.22	76.68	66.17	33.83	0.9114928318
187	No Regularizer+ADAM Optimizer+ Dropout+ No Augmentation	50	90.54	91.83	90.97	9.03	0.9775508339
188	No Regularizer+ADAM Optimizer+ Dropout+ Data Augmentation Layer	50	68.92	73.28	71.01	28.99	0.9054677244
189	No Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	10	83.78	84.99	85.99	14.01	0.9753177587

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190	No Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	10	84.68	86.57	86.08	13.92	0.95531 42529
191	No Regularizer+ RMSprop Optimizer+ Dropout+ No Augmentation	50	92.34	94.18	92.83	7.17	0.97710 88808
192	No Regularizer+ RMSprop Optimizer+ Dropout+ Data Augmentation Layer	50	69.37	72.01	71.94	28.06	0.89203 75716

From the above table it is clearly visible that Observation 145,152,191 gets the highest accuracy among 3 Layer Models with an accuracy of 92.34%. Though looking at the other metrics like precision, observation 191 with RMSprop optimizer and with no regularizer, dropout layer, no data augmentation layer, RMSprop optimizer with epochs 50 works the best with this dataset in CNN 5 Layer model. Below Figs.17 and 18 shows the model accuracy and the model loss plot against epochs for training and validation images.

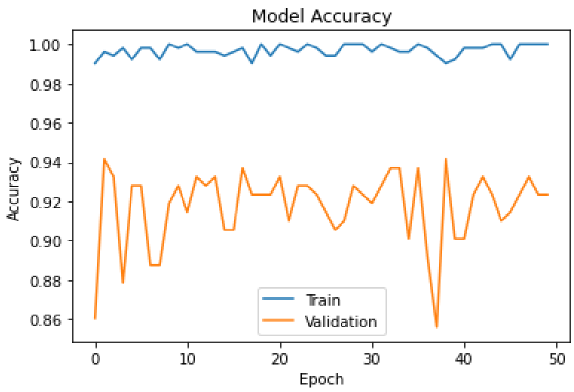

Figure 17. Observation 191 Plot of Model Accuracy vs Epochs for training and validation data.

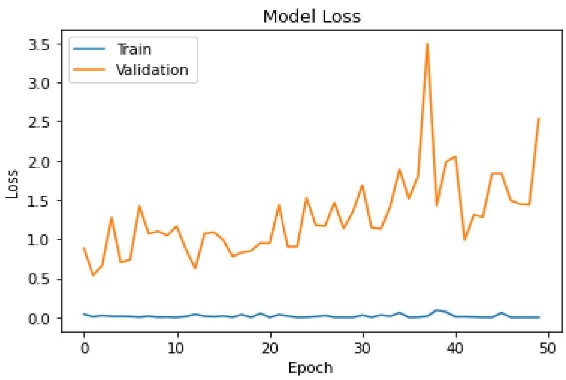

Figure 18. Observation 191 Plot of Model Loss vs Epochs for training and validation data.

The predicted and the true label of the validation images in the categories labelled are shown in the confusion matrix of the model in Fig. 19

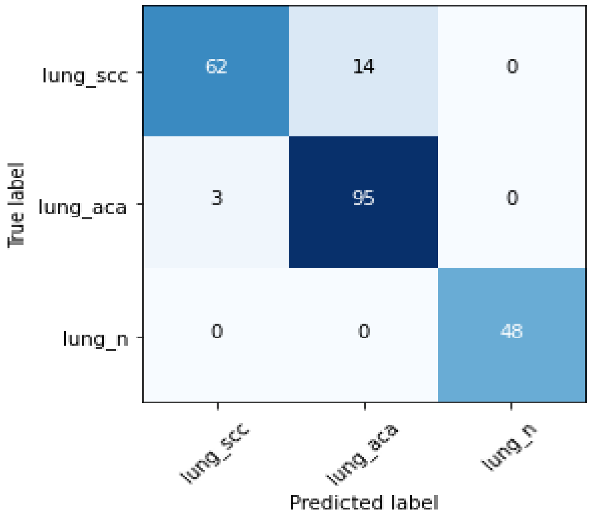

Figure 19. Confusion Matrix of different categories of images in Validation data for Observation 191.

Also, in CNN 5 Layer Models using L1 regularizer in convolutional layers radically drops the accuracy to 44.14%, with or without Dropout and Data Augmentation Layer.

The following table 5 shows the comparison of results between the related works in the Literature Review section and the best result achieved from the proposed methodology.

Table 5. Observations and their results on CNN 5 Layer Model

Reference Number	Model used	Dataset used	Accuracy
8	CNN 3 Layer	A dataset of 201 Lung Images	90.85
9	CNN 4 Layer	CIFAR-10	80.17
10	CNN 4 Layer	LIDC-IDRI dataset	90
15	CNN 3 Layer	LUNA16	80
16	VGG-16 CNN	CT Images are collected from Sathybama Hospital, Chennai,India	83
17	EFFI-CNN	CT scan images from LIDC-IDRI and Mendeley data sets	87.02
Proposed Methodology	CNN 4 Layer Model with a Dropout layer without any data augmentation layer or regularizer and trained with ADAM optimizer for epochs 50.	Chest CT Scan Images Dataset from Kaggle	92.79

As the above table shows, the proposed methodology outperforms the previous related works with an accuracy of 92.79% and quite efficient in classifying cancerous and non-cancerous cells accurately.
From all the observations, it is quite clear that Squamous Cell carcinoma case is difficult to identify whereas normal cases were identified right in most of the cases for the used dataset. Also, the observations made it clear that adding a dropout layer increases the accuracy of the CNN model whereas regularizers didn't make any difference to the results. By comparing all the results, it has been found that CNN 4 Layer model with a dropout layer of (0.25) and Adam optimizer, trained for 50 Epochs works best for Chest CT Scan dataset.

Conclusion

Convolutional Neural Network was used for Lung Cancer Detection in the proposed work. Images are classified into three categories normal, adenocarcinoma, and squamous cell carcinoma. CNN model was observed with different parameters and the best accuracy of 92.79% was achieved in 4-layer CNN model with dropout layer, without regularizer or data augmentation layer, Adam optimizer and Epochs 50. The precision, sensitivity, specificity, AUC score was calculated for each model and confusion matrices and model accuracy and loss graphs were plotted for the best models in each category of CNN models based on hidden layers. In the future, the accuracy of the system can be further improved by increasing the number of hidden layers and observing different combinations of parameters in the CNN model. Normal, adenocarcinoma and squamous cell carcinoma cases were classified quite efficiently by the proposed work.

Authors' Declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are mine/ours. Furthermore, any Figures and images, that are not ours, have been included with the necessary permission for re-publication, which is attached to the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee in JIS College of Engineering.

Authors' Contribution Statement

S.M, A.B.M and T.S designed the study. S.M performed the experiments and analyzed the results. S.M wrote the paper with input from A.B.M and T.S.

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ملاحظة وتحليل دور الشبكة العصبية التلافيفية في التنبؤ بسرطان الرئة

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الخلاصة

يعد سرطان الرئة من أخطر الأمراض وأكثرها انتشارًا ، حيث يتسبب في العديد من الوفيات كل عام. على الرغم من أن صور التصوير المقطعي المحوسب تستخدم في الغالب في تشخيص السرطان ، إلا أن تقييم عمليات الفحص يعد مهمة معرضة للخطأ وتستغرق وقتًا طويلاً. يمكن للنموذج القائم على التعلم الآلي والذكاء الاصطناعي تحديد أنواع سرطان الرئة وتصنيفها بدقة تامة ، مما يساعد في الكشف المبكر عن سرطان الرئة الذي يمكن أن يزيد من معدل البقاء على قيد الحياة. في هذا البحث ، تُستخدم الشبكة العصبية التلافيفية لتصنيف السرطانة الغدية وسرطان الخلايا الحرشفية وصور المسح المقطعي المحوسب للحالة العادية من مجموعة بيانات صور مسح الصدر بالأشعة المقطعية باستخدام مجموعات مختلفة من الطبقة المخفية والمعلمات في نماذج CNN. تم تدريب النموذج المقترح على 1000 صورة مسح مقطعي للخلايا السرطانية وغير السرطانية للعثور على أفضل مزيج من المعلمات في CNN للتنبؤ بسرطان الرئة بدقة. سجل النظام المقترح أعلى دقة بلغت 92.79٪. بالإضافة إلى ذلك ، تتناول الورقة 192 ملاحظة تمت باستخدام نموذج CNN.

الكلمات المفتاحية: الشبكة العصبية التلافيفية (CNN)، صور الأشعة المقطعية ، سرطان الرئة ، التعلم الآلي ، نظام التنبؤ.