Lung Cancer detection from CT scan data using Convolution Neural Network

Minor Project Report
Submitted By

Shreshth Saxena(38)

Surajit Das (41)

In Partial fulfillment of the requirements

For the award of the degree of

M.Sc. Computer Science

Under Supervision of

Prof. Dr. Naveen Kumar

DEPARTMENT OF COMPUTER SCIENCE

UNIVERSITY OF DELHI
NEW DELHI- 110 007

Abstract

The recent surge of Deep Learning has led to breakthrough advancements in almost every field of its application. A particular deep learning architecture, arguably the most popular one is the Convolution Neural Networks. The interest in convnets has seen an exponential increase due to their effectiveness and scalability. CNNs have become the go-to solution for image data problems and has provided results that are at par with if not better than human standards. The simplicity of the CNN architecture is another big factor of its success. The image processing and classification capabilities of CNN have found great usage in medical field, making it possible to detect and classify diseases as severe as Cancer effectively for the sake of better care.

In this project, we've initiated an elaborate study of Convolution Neural Networks, built multiple architectures from scratch and furthered our understanding with the preparation of an elementary dog-cat CNN classifier model followed by a more extensive CNN model for detection of lung cancer in a patient. The project is built on Google's interactive and versatile cloud platform for AI development Google Colaboratory, using the open-source neural network library 'Keras' for model development and libraries such as matplotlib and tensorboard (tensorflow) for result plotting and analysis. Data for training and testing our model was extracted from the '*LUNA2016 medical image database*'. The model was tuned using Grid-Search and achieved over 97% test accuracy in its final iterations. To culminate, we have enlisted some future-work prospects like De-convolution/Translated-Convolution, implement one or more named CNN networks like Inception or Alexnet, test the model on larger images etc.

1. **Introduction**

The use of Convolutional Neural Networks can be traced back to the nineties for character recognition purposes(Le Cun et al., 1997) but it wasn't until the 2012 AlexNet that it grew to the widespread acclaim that we know of today. In less than a decade, researchers have progressed from single-digit layers in a CNN model to triple-digits, integrating various other data science techniques to create umpteen possible configurations.

The architecture and working of a Convolution Neural Network can be understood better by a simple binary image-classification model such as a dog-cat CNN that classifies an image as one of the two preset classes, Dog or Cat.

The architecture of CNN models is predominantly similar, beginning with a few convolution layers that apply various *convolution filters* or *kernels* or *masks* to the input image. An image is represented as a matrix of gray-scale or color intensity values at the pixel represented by the matrix cell indices. Each filter/kernel can be thought of as a feature extractor that extracts positions of that particular feature represented by the kernel, on the input image. The convolution operation hence produces a *feature map*.

The convolution layer are each followed by a pooling layer generally that sub-samples an image to provide lower dimensional matrices for better computations.

A series of convolution + pooling layers are followed by a number of densely or fully connected layers after flattening the output. The fully connected layers operate as a typical neural network and finally classifies to binary (sigmoid/relu) or multiple classes (softmax).

The medical field is a likely ground for machine learning practice and application, as medical regulations allow increased sharing of anonymized data for the sake of better care. The field is pretty young and flourishing at the forefront of technology. This problem is interesting and promising in that it has impactful implications for the future of healthcare, deep learning applications affecting personal decisions, and computer vision in general.

Cancer is a disease that needs no documentation of its perils. It could be present in almost any part of the body like lungs, breast, prostate, skin etc. Lung cancer is the leading cause of cancer-related deaths worldwide. The National Lung Screening Trial (NLST), a randomized control trial in the U.S. including more than 50,000 high-risk subjects, showed that lung cancer screening using annual low-dose computed tomography (CT) reduces lung cancer mortality by 20% in comparison to annual screening with chest radiography.

Due to the absence of any true remedy or cure for the disease, detection in the early stage is crucial in preventing its spread. In this project, we are interested to train a convolution neural network and then use the trained model to solve a binary image classification problem to classify as positive or negative results.

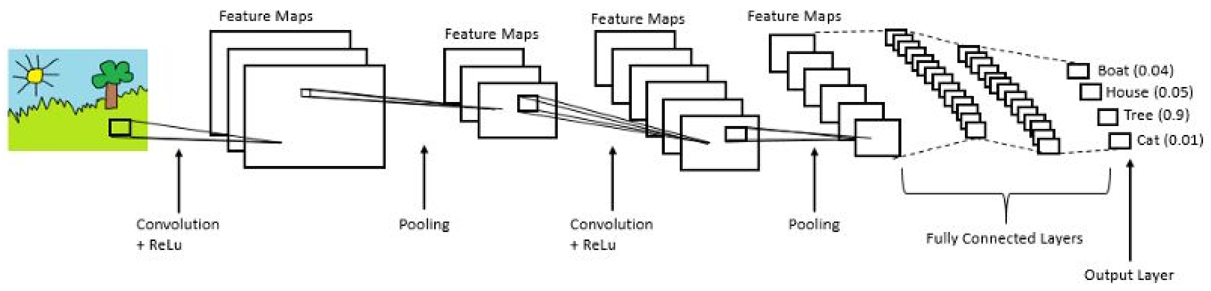
2. Background

Before getting started with model construction and tuning we gleaned all the necessary knowledge from sources like

- Deeplearning.ai by Andrew Ng Course 1-2
- Deeplearning.ai by Andrew Ng Course 4
- Keras documentation
- Towards-data-science blogs

The deeplearning.ai courses provided an elaborate explanation of Neural Networks and CNN with the development of elementary layers, activations and back-propagation mechanisms without any predefined framework. This helped in getting a robust understanding of the maths involved and the use of each parameter or argument that is used later on. The course then talked about improving neural networks by use of hyperparameter tuning, regularization, and optimization. It explained about the training-validation-test data split, bias and variance, normalization, gradient-checking, types of regularization, weight initialization, overfitting/underfitting and other such significant aspects of model creation and optimization.

Course-4 of the specialization got us introduced with the use of Convolution Neural Networks for computer vision tasks. It got us familiar with the CNN building blocks and vocabulary, talking more about the mathematical operations involved in convolution. We created our first CNN model as a programming assignment and moved on to create another one from scratch, this time a cat-dog image classifier.



The elaborate Keras documentation next helped us to build our first Convolution Neural Network to classify images with a ‘Dog’ or ‘Cat’ label. The model was built using the *sequential* API in Keras and consists of three *convolution-2D* layers followed by a *max-pooling-2D* layer each. The final out is then flattened and fed to a densely connected layer feeding it to the final output layer with one node operating the sigmoid function and providing output:
0 for cat
1 for dog

The model inputs images of dimensions 150 x 150, using 2000 images for training and 800 images for validation. The number of images is further increased by making use of the Image Processing class in Keras called ImageDataGenerator which generates batches of tensor image data with real-time data augmentations such as zooming, flipping, scaling etc. The model was compared on *categorical crossentropy* and *binary crossentropy* loss functions and *RMSprop* optimizer and *adagrad* optimizers.

After getting a good grasp at model creation and tuning, we needed to visualize and analyze the model results and its architecture. The Python libraries such as *seaborn* and *matplotlib* were a great help in achieving the purpose. The tensorflow visualization toolkit, *TensorBoard* opened new horizons however. It made it easier to understand, debug and optimize the Tensorflow code. It also made it easier to present our model architecture through block diagrams and flow charts and analyze the accuracy and loss through graphs with a large number of other unexplored features which we never seem to end. All this was possible with a few lines of code to enable tensorboard on our already existing model definition and see it all on a locally hosted browser window.

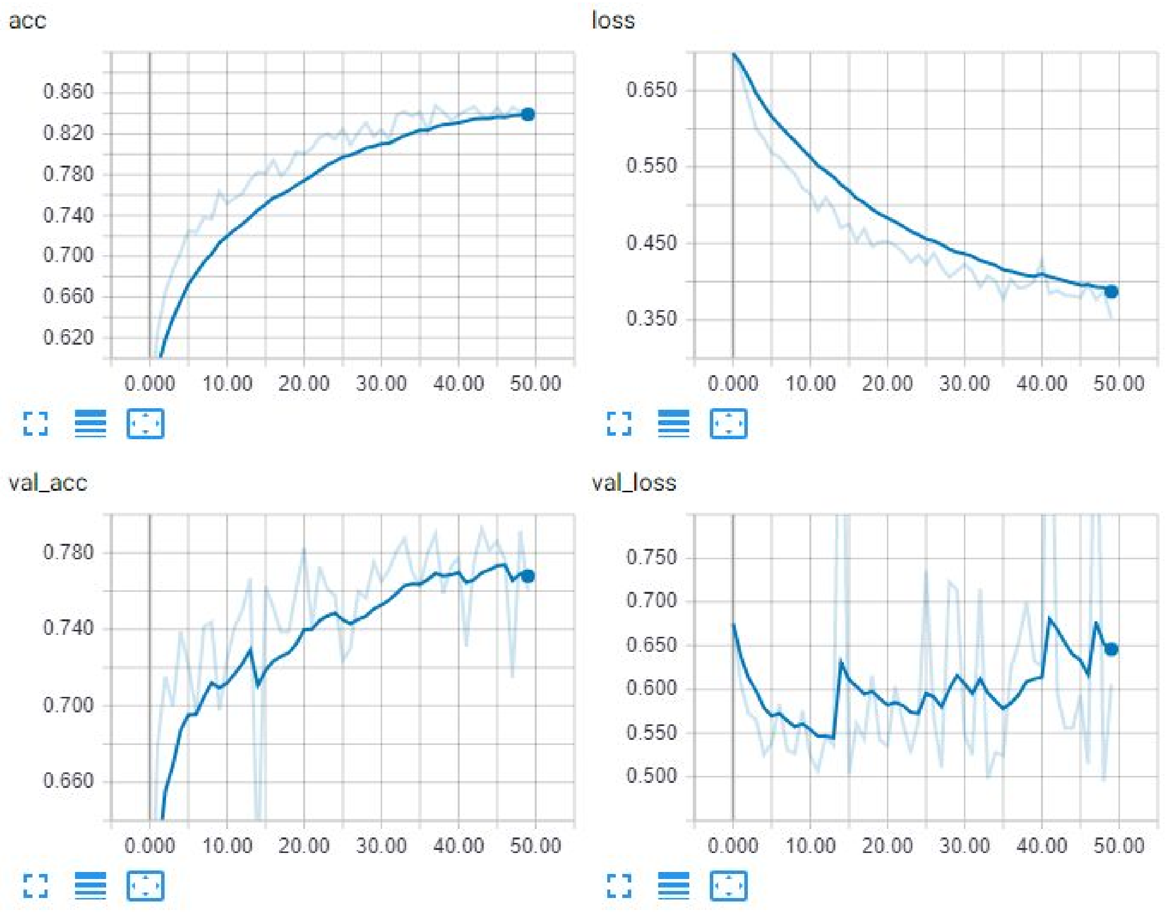
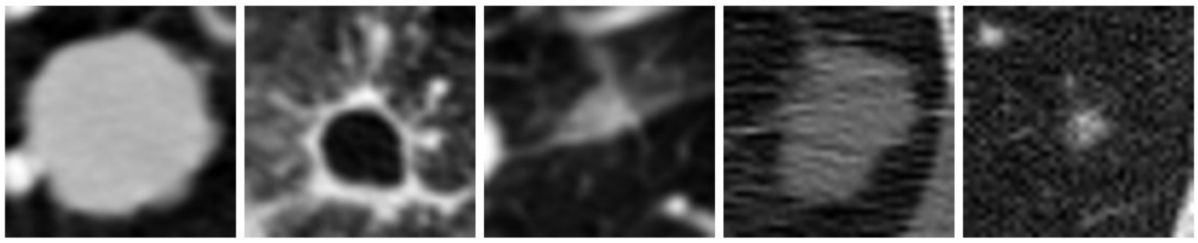
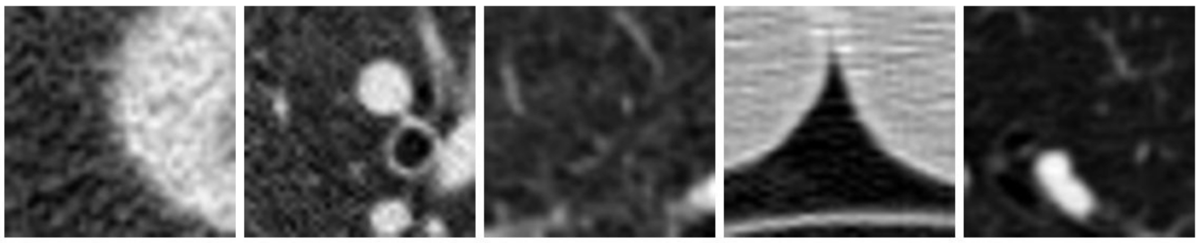


Figure : Tensorboad graphs for training and validation acc/loss of the Cat-Dog CNN model

Our final task was to apply our learnings to create a Cancer prediction CNN model. We indulged ourselves into extensive Research Paper readings and learned as much as we could about Cancer and the application of Deep Learning to the Medical domain. We decided to move forward with the detection of Lung Cancer nodule model as the model was matched our caliber and the data was freely available from the *LUNA2016 Medical Image Database.*


Examples of cancerous images


Examples of non-cancerous images

3. Deep Learning

3.1 Artificial Neural Network

An ANN mimics the working of a human neural system by operating on hidden layers consisting of neurons that are connected to each other and activate on stimuli from the neighbouring neurons. The various methods involved and terminology related to ANNs have been briefed below.

Preprocessing

Deep neural network (Convolution neural network in this case) is used. The Deep neural network uses multiple hidden layers between input and output layers. Every hidden layer can have different no. of units. In fact, no. of hidden layers and units in each hidden layer are also hyperparameters for the deep learning algorithm.Here 'L' stands for the no. of hidden layers in a neural Network. In deep learning networks, each layer of units trains on a distinct set of features based on the previous layer's output. The further we advance into the neural net, the more complex the features nodes can recognize, since they aggregate and recombine features from the previous layers. Due to this property deep nets can handle very large high dimensional data with large no. of parameters.

Usable Function

Sigmoid function

A Sigmoid function is a mathematical function which has a "S" shaped curve. The sigmoid function is represented by the equation

$\sigma(t)=1/(1+e^{(-t)})$

The sigmoid function have a domain of real numbers and returns the value -1, 1 or 0, 1 depending upon the convention used. The values of
$\sigma(t)$ depends

if $t \rightarrow \infty$ then $\sigma(t)=1$
if $t \rightarrow -\infty$ then $\sigma(t)=0$

Hyperbolic tangent function (tanh)

The hyperbolic tangent function is similar to cosine and sine function. It is represented by the equation
tanx h= 〖(e〗 ^x-e^(-x)) / (e^x+e^(-x))

The functions has a domain of real numbers and returns a values [0,1]
if h→ ∞   then tanx(h)=1
if h→ -∞   then tanx(h)=0

The slope of the function is given by

if tanx(h)=g(h)

g^' (h)=1-tanx(h)^2

ReLU and leaky ReLU activation function

The ReLU activation function is defined by the equation
f(z)=(0,z)
where z is the input to the neuron.

The leaky ReLU activation function is defined by the equation
f(z)=(0.01z,z)

Gradient descent
Gradient descent is a first-order iterative optimization algorithm. To find a local minimum of a function using gradient descent, one takes steps proportional to the negative of the gradient (or of the approximate gradient) of the function at the current point.

Loss (error) function
The loss or error function is used to calculate the accuracy of the model. It is given by equation
L(ŷ,y)= -(y□log log (ŷ) +(1-y) □log log (1-ŷ))
Here y is the true label and ŷ is the predicted label.
So,
if y=1   L(ŷ,y)= -□log log (ŷ)
this means we want log ŷ to be as big as possible. (ŷ is close to 1).
if y=0   L(ŷ,y)= -□log log (ŷ)
this means we want log (1-ŷ) to be large and ŷ should be small. (ŷ is close to 0).

Cost function
Cost function is the average of all the values of loss function which means we need smallest possible value of cost function.
It is defined by
J(w,b)=1/m∑L(ŷ^i,y^i)
J(w,b)=-1/m∑(y^i □log log (ŷ^i) +(1-y^i) □log log (1-ŷ^i))
We need to define values of w, b such that it minimizes the cost function.

3.2 Convolution Neural Network

Convolution Neural Network is a class of Deep Neural Network. It is used on image data and used to analyze the different features of the images. The concept of CNN is derived from biological process. Like neurons are connected with each other, nodes of CNN are connected with each other and transfer values or signals.
CNN is highly used in image classification. But the process may need some preprocessing depending on the nature of the dataset.
Tuning is the most important part in CNN, i.e accuracy on getting correct classification.
Two very important terms regarding Neural Network are parameter and hyperparameter. There are difference between them. Parameters are those which the model learns from training data like weights and biases. Prediction process needs the help of parameters. Parameters are the confidence of neural network. These are the keys of machine learning algorithms. On the other hyperparameters are provided to the model, for example number of hidden layers and nodes, activation functions, number of filters kernel size, stride, pooling, learning rate etc. hyperparameters often help to estimate parameters. It’s on the hand of the developer to set the hyperparameters carefully. Mainly hyperparameters are tuned to increase the efficiency of the model.

3.3 Deep Learning Libraries (TensorFlow and Keras)

Tensorflow
It is an open source software library supporting high performance numerical operations on variety of platforms like CPU,GPU,TPU. AI organization of Google developed this. It provides various support in many scientific domain like machine learning, deep learning etc.

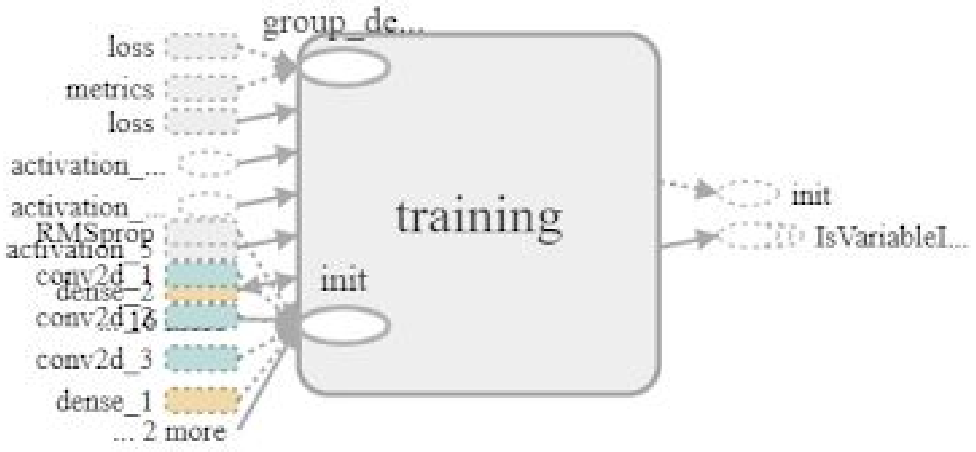
Keras
Keras is a high level API on Neural Network. Which is developed in python language and can run on Tensorflow, Theano and CNTK.

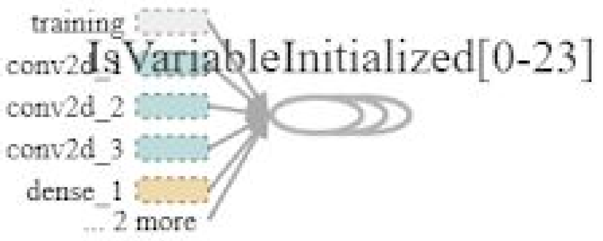
- It is very user friendly
- It is well documented.
- It is scalable.
- It runs on CPU and GPU.
- It allows very fast and easy prototyping.

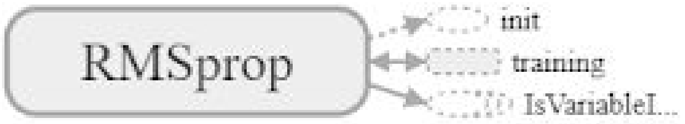
3.4 TensorBoard

The computations you'll use TensorFlow for - like training a massive deep neural network - can be complex and confusing. To make it easier to understand, debug, and optimize TensorFlow programs, we've included a suite of visualization tools called TensorBoard. You can use TensorBoard to visualize your TensorFlow graph, plot quantitative metrics about the execution of your graph, and show additional data like images that pass through it. When TensorBoard is fully configured, it looks like this:

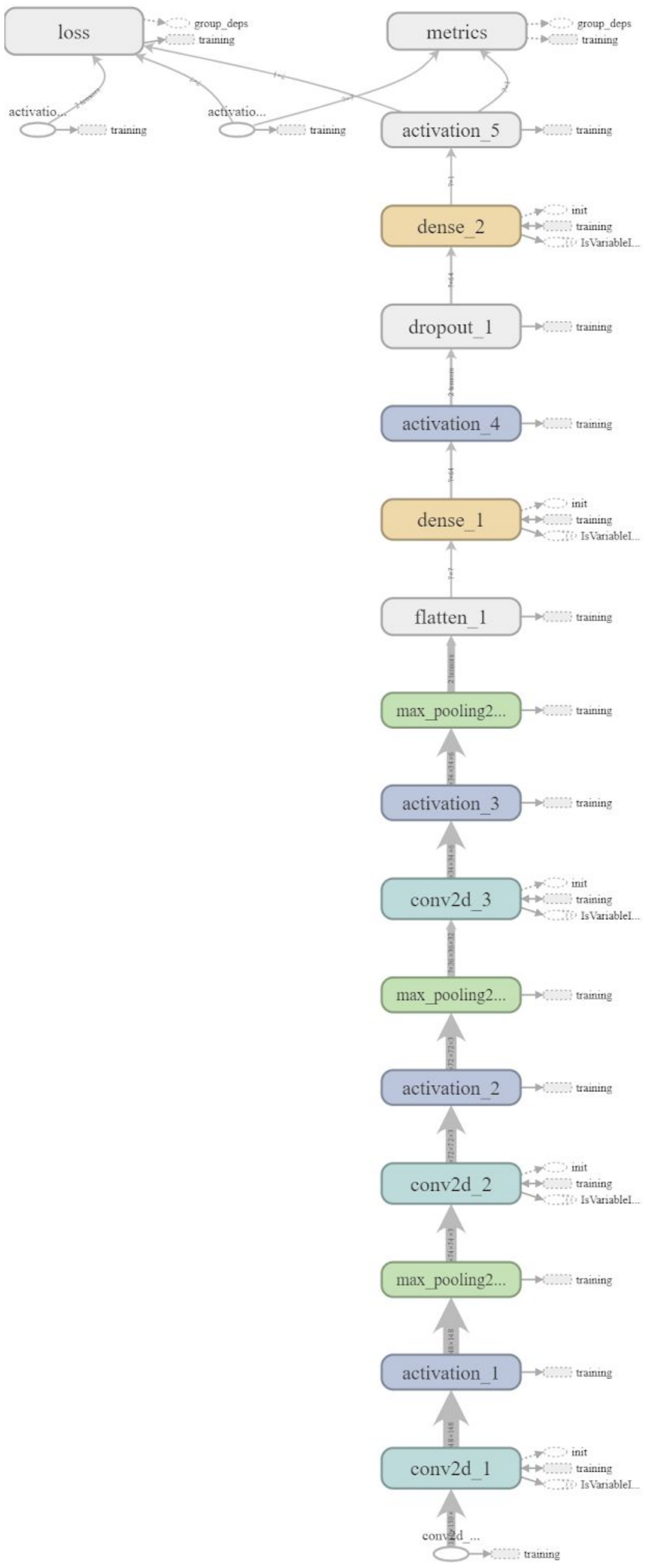
The computations of Tensorflow can be sometimes very complex and very confusing. But when it comes to in the form of graph i.e when a very complex thing is visualized in certain matter it becomes easy to interpret. Tensorboard offers nothing but visualizing the computations.







Figures above and below : Cat-Dog model visualization through TensorBoard graphs


loss
group_deps
training
metrics
group_deps
training
activatio...
training
activatio...
training
activation_5
training
dense_2
init
training
IsVariableI...
dropout_1
training
activation_4
training
dense_1
init
training
IsVariableI...
flatten_1
training
max_pooling2...
training
activation_3
training
conv2d_3
init
training
IsVariableI...
max_pooling2...
training
activation_2
training
conv2d_2
init
training
IsVariableI...
max_pooling2...
training
activation_1
training
conv2d_1
init
training
IsVariableI...
conv2d_...
training

4. Lung Cancer debrief

In simple words cancer is abnormal growth of cells, and ultimately to the stoppage of the essential cellular functions of the organism. These cells are generally called ‘tumor cells’ and they often clump together into lumps to form ‘tumors’. They also carry the potential to invade to other parts of the body of the organism and have detrimental effects there.

Lung cancer can be divided into four stages depending on severity as following

- Stage 1: Cancer is found in the lung only.
- Stage 2: Cancer is grown to nearby lymph nodes.
- Stage 3: Cancer is in the lung and lymph nodes are grown in the middle of the chest.
- Stage 3A: Cancer is found in lymph nodes only on the same side of the chest where it first started..
- Stage 3B: Cancer has spread to lymph nodes on the opposite side of the chest or to lymph nodes above the collarbone.
- Stage 4: Cancer has spread to both lungs, into the area around the lungs, or to distant organs.

Early symptoms may include

- Bad painful cough
- Cough with phlegm or blood
- Heavy chest pain while deep breathing, laughing, coughing or any other muscular activities near chest
- shortness of breath
- weakness and fatigue
- loss of appetite and weight loss

4.1 Causes

About ninety percent of lung cancer cases involve smoking. Smoking causes destruction of lung tissues, lung can repair them but heavy smoking makes lung stopping it’s natural behaviour.
A radioactive gas Radon, is the second leading cause, according to the American Lung Association.

Breathing in other hazardous substances can also cause lung cancer if it happens over a long period of time. A type of lung cancer called mesothelioma is almost always caused by exposure to asbestos.
Other substances that can cause lung cancer are:

- nickel
- petroleum products
- uranium
- arsenic
- Cadmium
- Chromium

Inherited genetic mutations may be the reason to develop lung cancer, especially if you smoke or are exposed to other carcinogens.
But above all there may be no specific reason for lung cancer.

4.2 RIsk factors

Above all the biggest risk factor is smoking. Inhaling toxic substances increases risk of getting lung cancer. Secondhand smoke is also a major risk factor. Other rish facors may include family health history, previous therapy or health history etc.

4.3 Diagnosis

- **Imaging tests**: An abnormal lump can be seen on X-ray. MRI, CT, and PET scans. These scans produce more detail and find smaller lesions.
- **Sputum cytology**: Microscopic examination of phlegm of cough can determine if cancer cells are present.

4.4 Treatment

- Self-care
- Quitting smoking
- Medications
- Chemotherapy and Targeted therapy
- Surgery
- Pulmonary lobectomy and Video-Assisted thoracoscopic surgery
- Medical procedure
- Thoracotomy and Radiation therapy
- Supportive care
- Palliative care
- Specialists

5. Methodology

5.1 Problem Statement

The Goal of the project is to train a Convolution Neural Network for binary image classification i.e detecting whether a person has lung cancer or not , which includes following tasks:

● Fetch and Preprocess the whole dataset.
● Train a Neural network on the training data.
● Optimize the network to improve accuracy.
● Compare the performances of Algorithms used.

Inputs: The inputs to the network are 40*40 pixel image snippets.
Outputs: The output of the network is the class label for the input image.

5.2 Data source

Publicly available LIDC/IDRI database is used. This data uses the Creative Commons Attribution 3.0 Unported License. Scans with a slice thickness greater than 2.5 mm were excluded. In total, 888 CT scans are included.Each radiologist marked lesions they identified as non-nodule, nodule < 3 mm, and nodules >= 3 mm.

Data Description :
Total 2948 images are used.
The data includes three datasets:

● Training Data: Contains total 2064 grayscale images
● Validation data: Contains 442 grayscale images
● Testing data: Contains 442 grayscale images

Image size 40*40 pixels

5.3 Model

The model is implemented using the *Sequential* API in Keras. It consists of three Convolution-2D layers with 16, 32 and 64 kernels of size (3,3), (5,5) and (7,7) respectively each followed by a Maxpooling-2D layer of size (2,2) pooling with a stride of 2. Maxpooling layers reduce the dimensionality of data thereby reducing the number of parameters, leading to a reduction in training time and tackling overfitting. Pooling layers downsample each feature map independently. They reduce the height and width, keeping the depth constant. In the end we have fully connected layers that flatten the last convolution layer's output and connect every node of the present layer with the other node of the next layer. Neurons in a fully connected layer have full connections to all activations in the previous layer, as they have in regular Neural Networks. We need the Flattening layers since the output of both convolution and pooling layers are 3D volumes, but a fully connected layer expects a 1D vector of numbers. The Flattening operation simply involves arranging the 3D volume of numbers into a 1D vector. The flatten output becomes an input to the fully connected layers. We then implement grid search to find the best values for hyperparameters optimizer, epochs and batch size.

5.3.1 Model description

Convolution Layer 1

Kernel size	(3,3)
Number of filters	16
Strides	(1,1)
Padding	Same
Activation	Relu

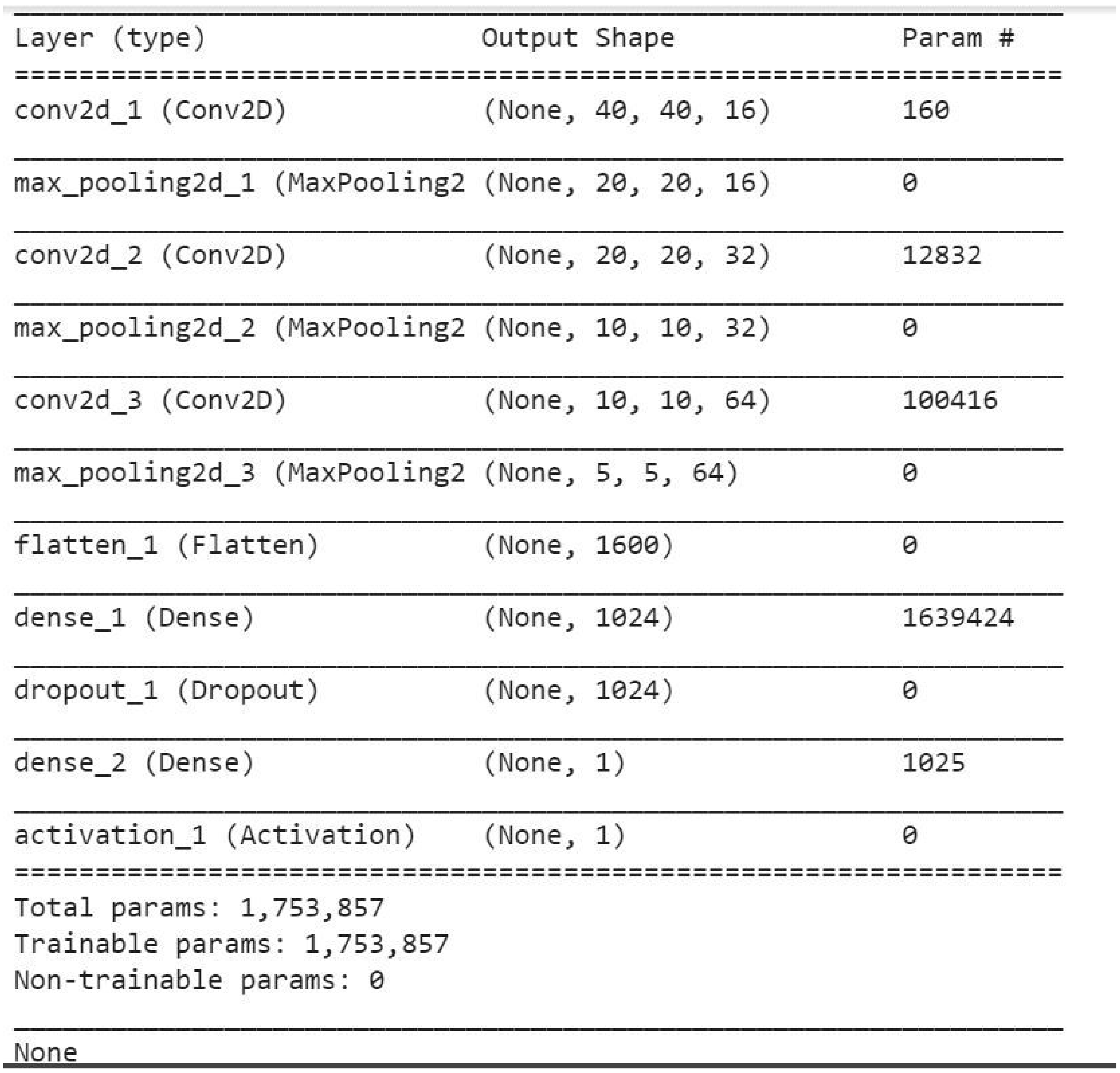
Convolution Layer 2

Kernel size	(5,5)
Number of filters	32
Strides	(1,1)
Padding	Same
Activation	Relu

Convolution Layer 3

Kernel size	(7,7)
Number of filters	64
Strides	(1,1)
Padding	Same
Activation	Relu

5.3.2 Model Summary

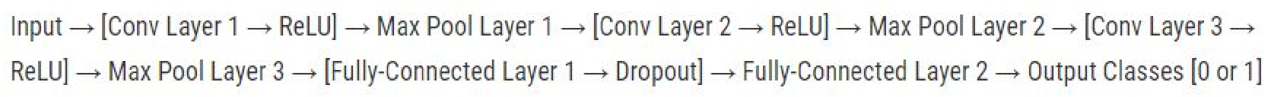


```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 40, 40, 16)        160
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 20, 20, 16)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 20, 20, 32)        12832
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 10, 10, 32)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 10, 10, 64)        100416
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 5, 5, 64)          0
_________________________________________________________________
flatten_1 (Flatten)          (None, 1600)              0
_________________________________________________________________
dense_1 (Dense)              (None, 1024)              1639424
_________________________________________________________________
dropout_1 (Dropout)          (None, 1024)              0
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 1025
_________________________________________________________________
activation_1 (Activation)    (None, 1)                 0
=================================================================
Total params: 1,753,857
Trainable params: 1,753,857
Non-trainable params: 0
_________________________________________________________________
None
```

5.3.3 Model Configuration

```
{'layers': [{'class_name': 'Conv2D',
   'config': {'activation': 'relu',
    'activity_regularizer': None,
    'batch_input_shape': (None, 40, 40, 1),
    'bias_constraint': None,
    'bias_initializer': {'class_name': 'Zeros', 'config': {}},
    'bias_regularizer': None,
    'data_format': 'channels_last',
    'dilation_rate': (1, 1),
    'dtype': 'float32',
    'filters': 16,
    'kernel_constraint': None,
    'kernel_initializer': {'class_name': 'VarianceScaling',
     'config': {'distribution': 'uniform',
      'mode': 'fan_avg',
      'scale': 1.0,
      'seed': None}},
    'kernel_regularizer': None,
    'kernel_size': (3, 3),
    'name': 'conv2d_11',
    'padding': 'same',
    'strides': (1, 1),
    'trainable': True,
    'use_bias': True}},
  {'class_name': 'MaxPooling2D',
   'config': {'data_format': 'channels_last',
    'name': 'max_pooling2d_10',
    'padding': 'same',
    'pool_size': (2, 2),
    'strides': (2, 2),
    'trainable': True}},
  {'class_name': 'Conv2D',
   'config': {'activation': 'relu',
    'activity_regularizer': None,
    'bias_constraint': None,
    'bias_initializer': {'class_name': 'Zeros', 'config': {}},
    'bias_regularizer': None,
    'data_format': 'channels_last',
    'dilation_rate': (1, 1),
    'filters': 32,
    'kernel_constraint': None,
    'kernel_initializer': {'class_name': 'VarianceScaling',
     'config': {'distribution': 'uniform',
      'mode': 'fan_avg',
      'scale': 1.0,
      'seed': None}},
    'kernel_regularizer': None,
    'kernel_size': (5, 5),
    'name': 'conv2d_12',
    'padding': 'same',
    'strides': (1, 1),
    'trainable': True,
    'use_bias': True}},
  {'class_name': 'MaxPooling2D',
   'config': {'data_format': 'channels_last',
    'name': 'max_pooling2d_11',
    'padding': 'same',
    'pool_size': (2, 2),
    'strides': (2, 2),
    'trainable': True}},
  {'class_name': 'Conv2D',
   'config': {'activation': 'relu',
    'activity_regularizer': None,
    'bias_constraint': None,
    'bias_initializer': {'class_name': 'Zeros', 'config': {}},
    'bias_regularizer': None,
    'data_format': 'channels_last',
    'dilation_rate': (1, 1),
    'filters': 64,
    'kernel_constraint': None,
    'kernel_initializer': {'class_name': 'VarianceScaling',
     'config': {'distribution': 'uniform',
      'mode': 'fan_avg',
      'scale': 1.0,
      'seed': None}},
    'kernel_regularizer': None,
    'kernel_size': (7, 7),
    'name': 'conv2d_13',
    'padding': 'same',
    'strides': (1, 1),
    'trainable': True,
    'use_bias': True}},
  {'class_name': 'MaxPooling2D',
   'config': {'data_format': 'channels_last',
    'name': 'max_pooling2d_12',
    'padding': 'same',
    'pool_size': (2, 2),
    'strides': (2, 2),
    'trainable': True}},
  {'class_name': 'Flatten',
   'config': {'data_format': 'channels_last',
    'name': 'flatten_4',
    'trainable': True}},
  {'class_name': 'Dense',
   'config': {'activation': 'relu',
    'activity_regularizer': None,
    'bias_constraint': None,
    'bias_initializer': {'class_name': 'Zeros', 'config': {}},
    'bias_regularizer': None,
    'kernel_constraint': None,
    'kernel_initializer': {'class_name': 'VarianceScaling',
     'config': {'distribution': 'uniform',
      'mode': 'fan_avg',
      'scale': 1.0,
      'seed': None}},
    'kernel_regularizer': None,
    'name': 'dense_7',
    'trainable': True,
    'units': 1024,
    'use_bias': True}},
  {'class_name': 'Dropout',
   'config': {'name': 'dropout_4',
    'noise_shape': None,
    'rate': 0.2,
    'seed': None,
    'trainable': True}},
  {'class_name': 'Dense',
   'config': {'activation': 'linear',
    'activity_regularizer': None,
    'bias_constraint': None,
    'bias_initializer': {'class_name': 'Zeros', 'config': {}},
    'bias_regularizer': None,
    'kernel_constraint': None,
    'kernel_initializer': {'class_name': 'VarianceScaling',
     'config': {'distribution': 'uniform',
      'mode': 'fan_avg',
      'scale': 1.0,
      'seed': None}},
    'kernel_regularizer': None,
    'name': 'dense_8',
    'trainable': True,
    'units': 1,
    'use_bias': True}},
  {'class_name': 'Activation',
   'config': {'activation': 'sigmoid',
    'name': 'activation_4',
    'trainable': True}}],
 'name': 'sequential_5'}
```

5.3.4 Visualization of the model



Input → [Conv Layer 1 → ReLU] → Max Pool Layer 1 → [Conv Layer 2 → ReLU] → Max Pool Layer 2 → [Conv Layer 3 → ReLU] → Max Pool Layer 3 → [Fully-Connected Layer 1 → Dropout] → Fully-Connected Layer 2 → Output Classes [0 or 1]

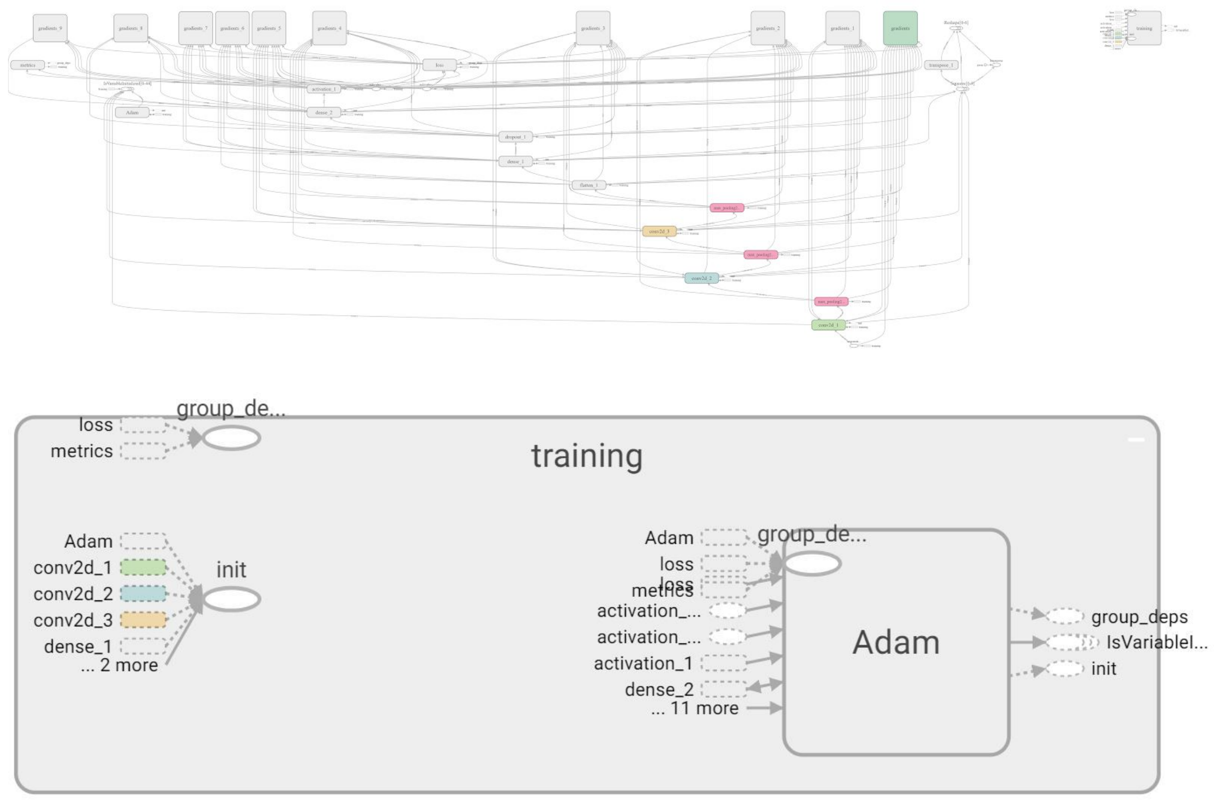


Figure : tensorboard graph representation of model

5.3.5 Hyperparameter Tuning

The model was trained on different combinations of hyperparameters and the performance in each case was recorded as below:

1.
epochs = [10,25]
batches = [50,100,104]
optimizers = ['SGD', 'adam']
Cross validation = 10
Best parameter combination
`{'batch_size': 104, 'epochs': 25, 'optimizer': 'adam'}`
Accuracy on test data: 97.05%

2.
epochs = [25,35]
batches = [50,104,150]
optimizers = ['adam']
Cross validation = 10
Best parameter combination
`{'batch_size': 150, 'epochs': 25, 'optimizer': 'adam'}`
Accuracy on test data: 97.29%

3.
epochs = [20,25,40]
batches = [200,150]
optimizers = ['adam']
Cross validation = 10
Best parameter combination
```
{'batch_size': 200, 'epochs': 40, 'optimizer': 'adam'}
```

Accuracy on test data: 96.38%

4.
epochs = [20,25,40]
batches = [200,150]
optimizers = ['adam']
Cross validation = 3
Best parameter combination
```
{'batch_size': 200, 'epochs': 40, 'optimizer': 'adam'}
```
Accuracy on test data: 97.51%

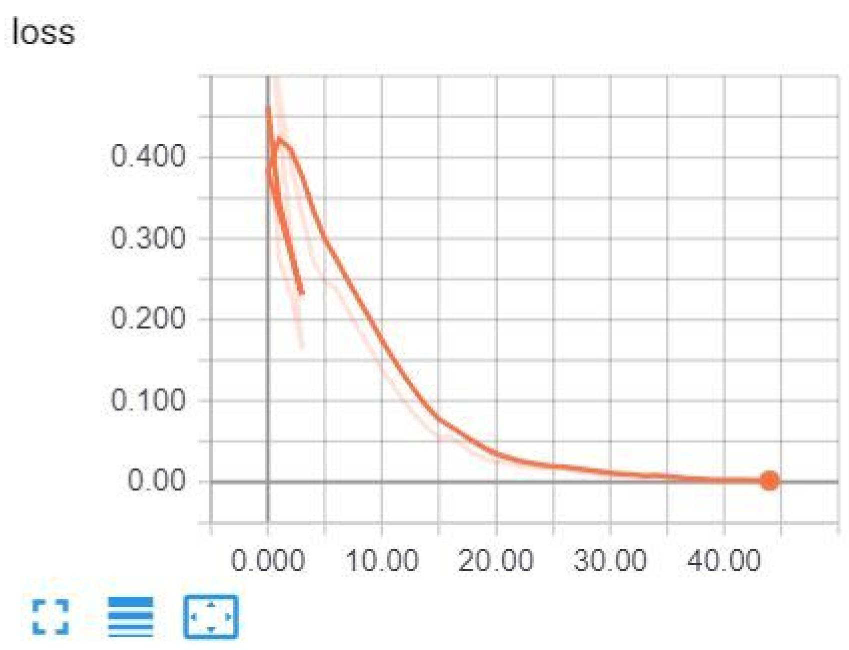
5.
epochs = [40,45]
batches = [200,250]
optimizers = ['adam']
Cross validation = 3
Best parameter combination
```
{'batch_size': 250, 'epochs': 40, 'optimizer': 'adam'}
```
Accuracy on test data: 96.83%

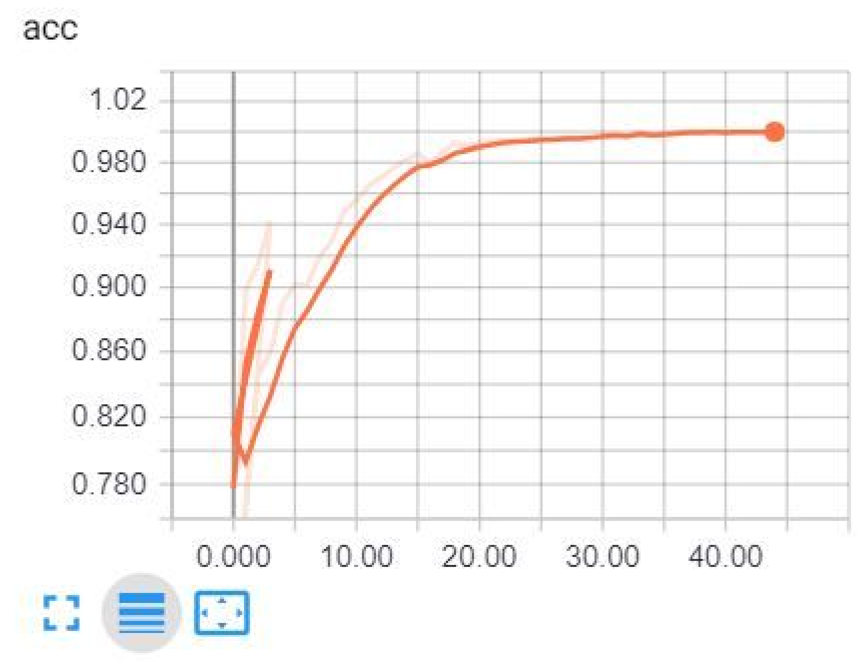
6.
epochs = [40,45]
batches = [150,250,300]
optimizers = ['adam']
Cross validation = 3
Best parameter combination
```
{'batch_size': 150, 'epochs': 45, 'optimizer': 'adam'}
```
Accuracy on test data: 97.29%

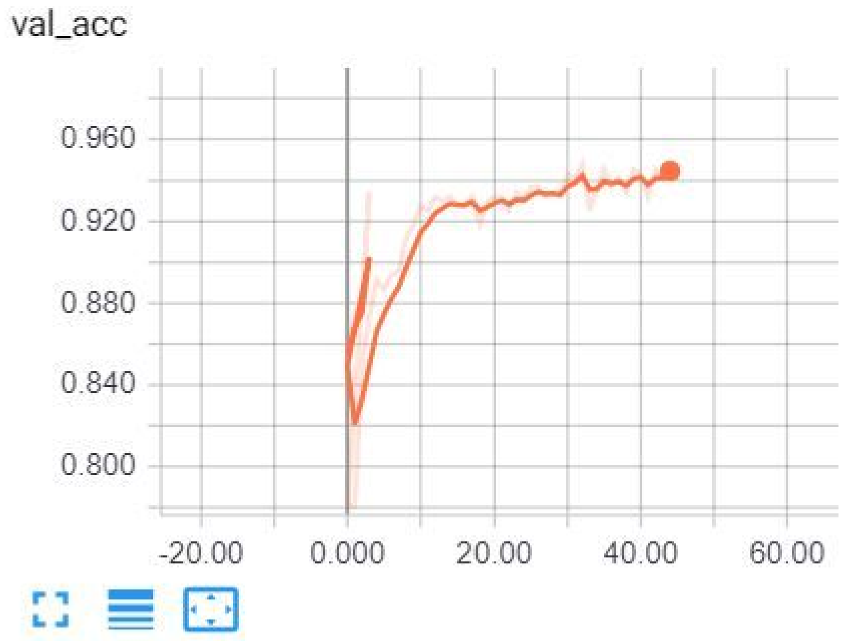
7.
epochs = [40,45]
batches = [150,250,300]
optimizers = ['adam']
Cross validation = 3
Best parameter combination
```
{'batch_size': 300, 'epochs': 45, 'optimizer': 'adam'}
```
Accuracy on test data: 97.51%

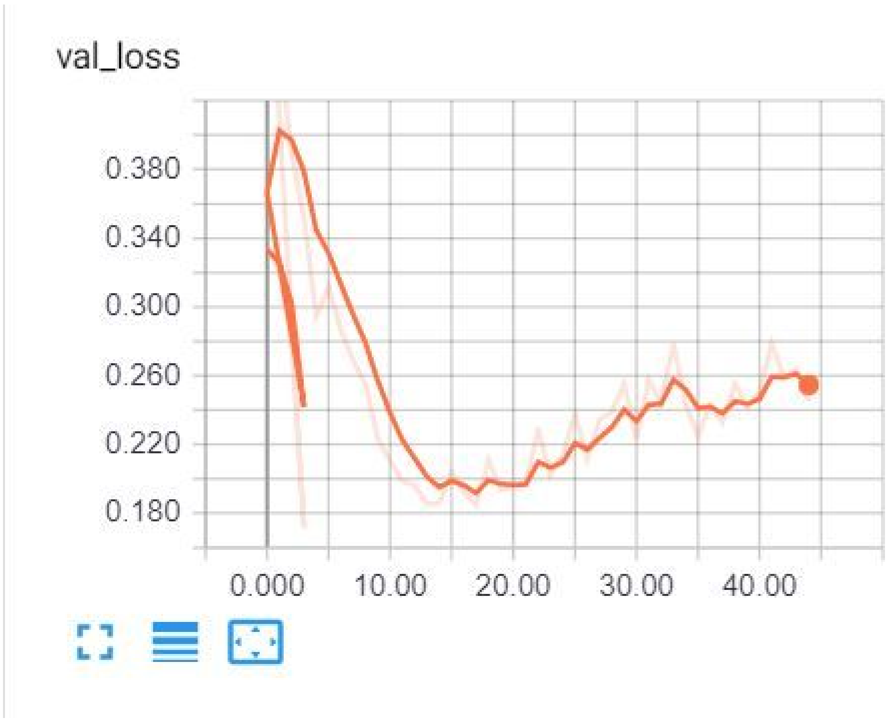
5.3.6 Results and Discussion

The best combination of parameters calculated from grid search i.e parameters of 7th experiment was used to train the model. The model achieved an accuracy of 97.51%. The final loss and accuracy graphs for training and validation have been plotted using tensorboard as below:




acc
1.02
0.980
0.940
0.900
0.860
0.820
0.780
0.000
10.00
20.00
30.00
40.00


val_acc
0.960
0.920
0.880
0.840
0.800
-20.00
0.000
20.00
40.00
60.00



5.3.7 Confusion Matrix

After finding the best combination of hyperparameters for our model, we ran a further analysis to find misclassified images of the final test results and calculated confusion matrix to determine why it was not close to 100%. Our model has classified more examples as negative when they should be positive than vice versa which might be because of the nature of some of the positive examples. It is likely that it would be just as difficult for a human to classify those images as a doctor.Also, there is always a possibility of the data being wrongly classified.

```
True Positive: 208
False Positive: 4
True Negative: 222
False Negative: 8
```

Confusion matrix

	Predicted Positive Class	Predicted Negative Class
Actual Positive Class	208	8
Actual Negative Class	4	222

6.Conclusion and Future Scope

In this project, we explored the very powerful Convolution Networks and applied it to predict the presence of lung cancer in a patient using an image snippet of a scan. Experimentation showed that CNN was highly efficient in performing the task and the accuracy was further improved by optimization of hyperparameters. The images used specify a predetermined section of the lung and the model is also rather simple but still we were able to get ground-breaking results.

We plan to explore Deconvolution, Transpose-Convolution for Upscaling and other possible extensions of CNN. For the Cancer model, we would like to implement one or more of the named CNN networks like Inception or Alexnet using transfer learning and compare the workings and result with the previous models. The current model works on images of 40 x 40 dimensions, increasing which might be plausible to perform testing on larger scans, possibly of the entire lung instead of a predetermined section.

7. References

1. https://apollack11.github.io/machine-learning.html
2. https://keras.io/
3. https://www.tensorflow.org/
4. https://www.healthline.com/health/lung-cancer#stages
5.https://towardsdatascience.com/building-a-convolutional-neural-network-cnn-in-keras-329f
bbadc5f5
6. https://machinelearningmastery.com/tutorial-first-neural-network-python-keras/