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# Image classifier differentiating tumour from healthy MRI scans using Convolutional Neural Networks

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# IMAGE CLASSIFIER DIFFERENTIATING TUMOUR FROM HEALTHY MRI SCANS USING CONVOLUTIONAL NEURAL NETWORKS

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## ABSTRACT

This study was created using a simple algorithm that may be implemented on MRI scan machines to aid medical professionals in making a more accurate decision by having a second opinion. The system is inspired on a smartphone-based skin disease classifier which was implemented with multiple techniques of data augmentation. It is also trained on multiple pre-trained and untrained algorithms for machine learning application. The raw data of MRI has a dimension of 50 x 50 and in colored form. When worked on raw data it did not yield great results having only an 80% accuracy and a 50% validation accuracy after. We implemented data augmentation techniques to increase the accuracy and to implement a reasonable comparison among the different CNN models. The data was resized and recolored to a monochrome to have the same dimensions and tone to have a better prediction on the data. These images were then trained on a well-known pre-trained Convolutional Neural Network (CNN) and a small model comprising of 3 layers for control independent variable. At first, we only got 90% as the best validation accuracy that belongs to the untrained 3-layer algorithm. However, decreasing learning rate to 0.0001 increased our best validation accuracy from 90% to 95% that validation accuracy belonging to VGG 16 and 19.

**Keywords:** MRI scan, data augmentation, convolutional neural network (CNN), VGG 16, VGG 19.

## INTRODUCTION

This study is inspired by the study on skin disease using Mobilenet which used different sampling method like undersampling, oversampling and imbalanced datasets. For the preprocessing includes the default and data augmentation of input data. It also showed in their study that oversampling of data and data augmentation provides a high accuracy of 94.4% [1].

According to Farrugia, a brain tumour is a brain problem wherein uncommon cells developed in your brain [2]. There are a lot of types of brain tumours. The first is the benign or the non-cancerous type of brain tumour and the second one is the malignant or the cancerous type of brain tumour. A brain tumour is divided into two: the primary and the secondary tumours. A primary tumour starts the spreading inside the brain while the secondary tumour starts from the outside.

As part of the developmental stage of children, children are more prone to such events but tumours of the central nervous system (CNS) can be destroyed when treated early. Since they frequently influence children, it is troublesome to treat, and as often as possible cause mental disability or passing. Modern bits of knowledge into the causes and potential treatment of CNS tumours have come from finding associations with qualities that control cell development, separation, and passing amid typical improvement. According to Wechsler and Scott, primary brain tumours begin when there is a variation happen in their DNA or deoxyribonucleic acid [3]. These changes allow the cells to spread and multiply in the brain. The outcome of having an uncommon cell in the brain will

form a tumour. The primary brain tumour is unusual to adults but rather the secondary brain tumour since adults is prone to sickness, they have higher chances of having the secondary brain tumour than a primary brain tumour. Furthermore, secondary brain tumour usually having when an individual inherited the cancer from their relatives.

The technologies that are used to check up a patient for a brain tumour are the MRI or Magnetic Resonance Imaging and the commonly-used CT scans or the Computed Tomography. These tests are ordinarily done with infused differentiate fabric, which is a liquid that encompasses strong zones, such as brain tumours, to way better characterize the edges. According to Ronen from Brain tumour Center, Magnetic Resonance Imaging (MRI) may be a non-invasive imaging innovation used for many applications, counting neuroimaging [4]. It could be a standard neuroimaging strategy for the discovery of tumours and the encompassing anatomical structures within the brain. Based from Cancer Center in the internet, a CT scan (Computed Tomography) lets the doctors see what is inside in our body. It will display the X-ray copy of your body that indicate your internal organs, bones, etc. [5]. CT scan differ from other normal X-ray since it is more detailed.

Numerous times, due to a person encountering over side effects, a tumour within the brain can be misdiagnosed. In most cases, when a person is encountering these side effects, the doctor will arrange tests such as CT scan, MRI, and EEG. Furthermore, more conclusive tests are accessible, such as a myelogram, PET check, X-ray of the skull, spinal tap, or angiogram. In case



a doctor confuses the comes about of these tests or falls flat to arrange them through and through, restorative misbehaviour enters in. According to Stanislaw, brain tumours are most misdiagnosed since a doctor failed to arrange advanced testing based on indications [6]. Since the side effects of brain tumours frequently mirror indications of other more common maladies, doctors regularly analyse and endorse treatment for another sickness.

There are a lot of Machine Learning applications in Medicine. Machine Learning has a huge contribution in restorative industry, and it is uncovered through this in-depth illustration of how the innovation can be connected to supply a restorative determination. There are lot of usage of machine learning and one of it is medical field. Machine Learning in medical field has an advance in accuracy pharmaceutical with the help of Microsoft Project Hanover. At a show, a few companies are applying machine learning methods in medicate disclosure. Based from the article authored by Talha Dar, the applications of Machine Learning in the medical world are the surgical machines for conducting any operation on a patient, data analysis for patient's interpretation of data, drug production for further and faster development of medicine, and machine algorithm that can change therapeutic information into potential causes of maladies by looking at past designs [7].

## CONCEPTUAL LITERATURE

Firdaus *et al.*, researchers found a helpful topic to enhance the diagnosis technique in medical field. The topic says a medical image amplifying the quality of the image to foresee any critical parts in patient's X-ray or medical image. The methods they used are CNN or the Convolutional Neural Network and OOP or the Object-oriented Programming via deep learning [8].

Ashhar *et al.* compared the classification of lung cancer via deep learning and CT scan. The research indicated how Computed Tomography and deep learning detect lung cancer. The method they used for this research is Convolutional Neural Network (CNN) via deep learning [9].

Mohapatro *et al.* introduced the sensor data of the patient's bio-medical using machine learning. Their proposed system has become helpful to a certain hospital with plenty of patients since the research indicated that the device would monitor the patient's health no matter how many patients. The method they used is Raspberry Pi3 and machine learning [10].

Mashudi *et al.* implemented Internet of things (IoT) by applying the healthcare system on it. In their study, they indicated that the person's health can be monitored through the Internet in any device or most commonly, smartphones. Their proposed method monitors the person's health but in ours specifically brain tumour. The method they used is machine learning [11].

Mubeena *et al.* implemented an image segmentation for brain tumour using artificial bee colony algorithm. Our topic is similar to this since the main focus is the brain tumour using Magnetic Resonance Imaging

(MRI). The only difference is that the researcher used artificial bee colony algorithm while us, we differentiate the MRI scans with tumour and healthy MRI scan in Convolutional Neural Networks (CNN) [12].

Nilesh *et al.* for an instance ordered features that were extracted from the grey level co-occurrence matrix of the infected region and in this manner arrived at an accuracy of 96.51% [13].

Abishek *et al.* presented the solution for the stated problem by processing an Image Dataset of Brain tumour of different patient utilizing Tensorflow. The image is differentiated based on features investigated from the Dataset. They used Deep Neural Featurizer which uses Inception V3 and image classification dependent on logistic regression. They introduced to deep learning models, propose large-scale computing platform, and combined altogether to have better understanding regarding image classification and retrieval [14].

Patel *et al.* utilized the biological information outcomes which have improved by 10.27%. The fractal search calculation of algorithm is executed to diminish the time complexity of the tumour division process. The division processing time has been reduced by 41.75% on GPU while 23.68% on CPU and improves the segmentation result by 2.76%. They used 3D CNN with the biological structural information of the brain. For example, the brain has a symmetric construction which can be divided into two almost equivalent half. Data from each half can help CNN model to separate the abnormal tissues from normal tissues. By utilizing the 3D design adequate measure of search time to find the tumour inside, the brain image can be reduced [15].

Jahan *et al.*'s approach is to use an algorithm that can detect brain tumour with the help of Fmri images. It uses machine learning where they reshaped image into 128×128 pixels, then they separate the image into 64 windows of size 16×16. This algorithm acquired an accuracy of 88.333% but it is considered as invalid because the dataset contains 60 images only and that is not enough for training neural network. On the bright side, they successfully obtained an even better accuracy of 92.17% after increasing the performance of run-time, adding feature such as gray level co-occurrence matrix and lastly after 9000 to 10000 training steps [16].

D. Ramamurthy *et al.* used semi interactive prediction algorithm. In this approach, they used different imaging technique so that tumour can be detected by its size and location. On this methodology, they first input the scan images of a brain on a program, second is groupings of foreground and background seed to obtain volume of interest (VOI), next is run the Cellular Automata (CA) algorithm twice to calculate tumour strength and background strength, lastly is to run an Rough Set Theory (RST) algorithm to identify the necrotic region [17].

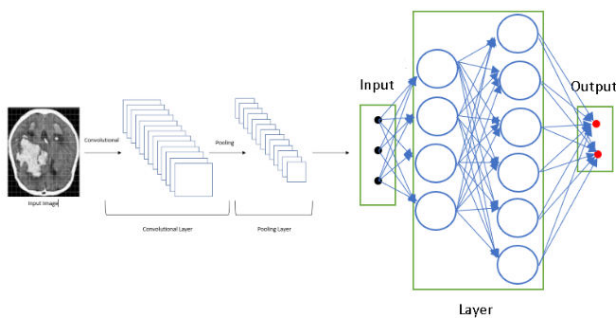
A cyst may appear similar to a tumour externally, but they have very different causes. A tumour is a solid mass of tissue, and a cyst is a sac filled with a substance. Methodology is taken to consideration for identification of the cyst in the brain through MRI/ CT Scan images. In this study by Lavanya *et al.*, image processing technique was



used to detect the presence of cyst with the help of Java programming. The approach used is black and white conversion of scan images. Next is conversion from black and white to shades of gray images after converting images. Lastly, they were represented in a matrix model by using the concept of array [18].

### CONVOLUTIONAL NEURAL NETWORK

With the rapid advancement in the field of Artificial intelligence, it is no secret that it is implemented on every field of industry may it be medicine or labor, accountancy, or manufacturer. Every field now utilizes Artificial intelligence. It is everywhere and makes life so much easier by leaving most of the work to the computers [19].

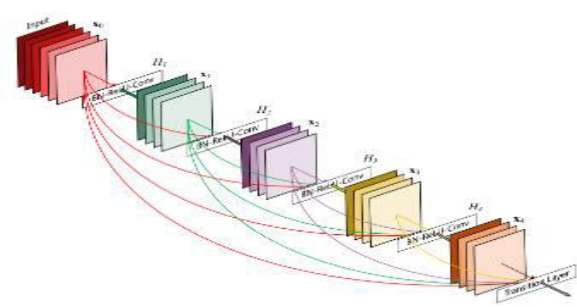


**Figure-1.** Convolutional Neural Network used in the research [19].

Breakthrough in Artificial intelligence replicates the mind. How it thinks how it understands paved way to the machine learning era not only that dull task such as put  $x$  in  $x$  and  $Y$  in  $Y$  be done by machines but also complicated stuff like predicting stocks, dogs or cats, or playing chess and even making an accurate medicinal prediction through neural networks [19]. Figure-1 shows the illustration of the Convolutional Neural Network [19]. Equation 1 shows a Simple Layer Equation used for the Cats and Dogs Prediction [18].

$$Z^{[1]} = W^{[1]}x + b^{[1]} \rightarrow a^{[1]} = \sigma(z^{[1]}) \rightarrow Z^{[2]} = W^{[2]}a^{[1]} + b^{[2]} \rightarrow a^{[2]} = \sigma(z^{[2]}) \rightarrow l(a^{[2]}, y) \quad (1)$$

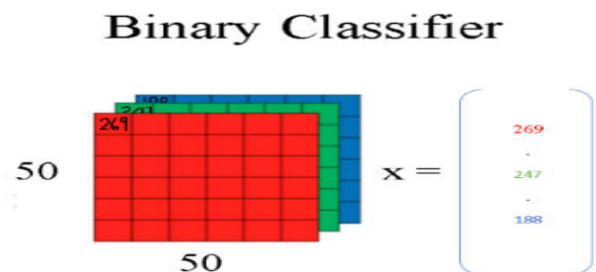
More specifically, Convolutional Neural Networks are forms of algorithm that take an input, e.g. image. For image, it understands each pixel and creates a correlation between the data given. The more complex the image, the less accurate the prediction will be. In terms of complexity, if our data has too many varying variables; for instance, it has different color pallets or varying dimensions and having shapes and edges that is either too closely related to what you are supposed to be differentiating, it could often hurt the prediction [20]. Figure-2 shows the 5-layer dense block that is more complex than our implemented 3-layer model.



**Figure-2.** 5-layer dense block for each layer preceding feature map [20].

### SYSTEM ARCHITECTURE

In a CNN architecture, there is a convolutional tool which differentiates and separates the varying variables that helps to distinguish the dataset categories. Figure-3 shows how the binary Classifier works on RGB values of the data [19]. Each pixel representing a certain weight values is then flattened and computed by Length  $\times$  Width  $\times$  RGB values which is 3 to get the parameters.



**Figure-3.** Operation of Binary Classifier on RGB values of the data [19].

$$50 \times 50 \times 3 = 7500 \\ n = n_x = 7500 \quad (2)$$

Equation 2 shows the equation for the Binary Classifier on RGB Values. The fully connected layers that serve as the algorithm. The algorithm or the connected layers is comprised of 3 types: the pooling layers, convolutional layers, and the fully connected layers. In addition to create a prediction that would separate a category from the others, the drop out and activation functions are used [19]. Equation 3 shows the Binary Classification Notation working on the Figure 3's values [19].

$$X = \begin{bmatrix} x^{(1)} & x^{(2)} & x^{(3)} & \dots & x^{(m)} \end{bmatrix} \quad n_x = 7500$$

$m_{train}$

$$(X, Y) \quad X \in \mathbb{R}^{n_x}, Y \in \{0,1\} \\ Y = [y^1, y^2, y^3, \dots, y^m] \\ Y_{shape} = (1, m) \quad (3)$$

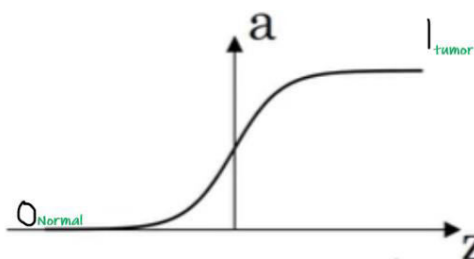


The convolutional layer is the first layer in the architecture in this layer. The features are taken and studied to be differentiated, to see the different categories, and where they vary. Following that is the pooling layer. The pooling layer lessens the connections to independently perform computations on certain parts of the image. Here, we used max pooling which takes the largest element and works on [19]. Figure-4 shows the illustration for max pooling which shows that the largest values are taken and separated. It is taken from a Cats and Dogs Classifier [19].



Figure-4. Max pooling [19].

Because in our data sets, there is only 1 varying simple differentiation which is the tumour that would act as the abnormalities in the data. In this study, we focus on knowing if the MRI scan has a tumour and where is it and to top it all up the fully connected layers which contains the weights or the decisions of the program. As seen on our first trial, the data seems to be overfitting showing great results in accuracy but not so much on validation accuracy. We applied a dropout layer that drops decisions and changes biases that could have been the result of uneven datasets. Finally, the activation layers which gives us the response that human language can comprehend a normal or tumour response. We used a sigmoid activation function which only prints out a binary having only 2 categories [19]. Equation 4 shows the sigmoid activation function formula that is used on the program to classify whether the prediction is healthy or tumour.



$$\text{sigmoid: } a = \frac{1}{1+e^{-z}} \quad (4)$$

## METHODOLOGY

### Dataset

The images needed for the development of the project are collected from the Kaggle.com [21]. Table-1 shows the datasets that was taken from Kaggle.com having 493 total pictures that is divided into 225 (tumour) and 268 (normal). The dataset is divided for testing and validation. The validation data set is excluded from the training of data set but is used to verify its accuracy in prediction. The test data set works the same, but it gives an

unbiased estimate of the models' accuracy while the training is fed unto models to give its predictions.

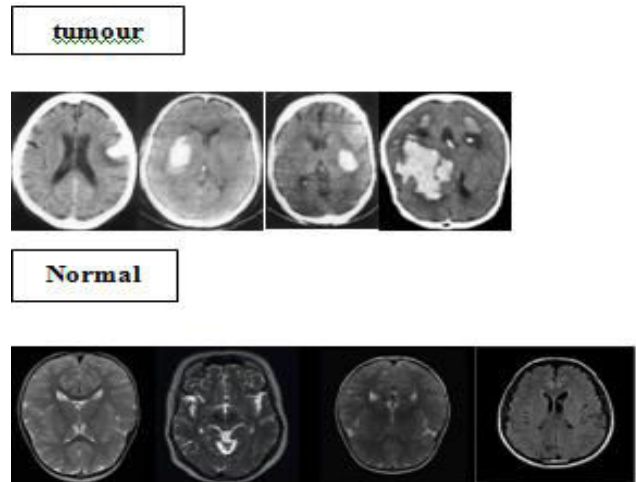


Figure-5. Sample images of the dataset [21].

Table-1. Number of data sets.

	Images	Train	test	Validation
Tumour	225	225	90	90
Normal	268	268	90	90
Total	493	493	180	180

### Experiment

The program was implemented using PyCharm IDE and Keras platform having Tensorflow as backend in the system. The system as before mentioned will print out binary values through its activation function. Those binary values are given assignments as tumour or normal. Table-2 shows the accuracy and time it took for each epoch to run in the models.

Table-2. Accuracy of each models on 20 epochs.

MODEL	ETA	ACCURACY%
3LAYER	30s	93.5
VGG16	5.53m	95
VGG19	7.57m	95
Xception	15.21m	71
Densenet121	1m	66
Densenet169	2m	82.78
Densenet201	2m	88
Resnet50	17m	50

Easy Capturing of the Fish's Eye and Gill.

## EXPERIMENTS AND RESULTS

Figures 6.1 to 6.8 shows the confusion matrices for the 3 Layer, VGG 16, VGG 19, Xception, Densenet 121, Densenet 169, Densenet 201 and Resnet50 on 20

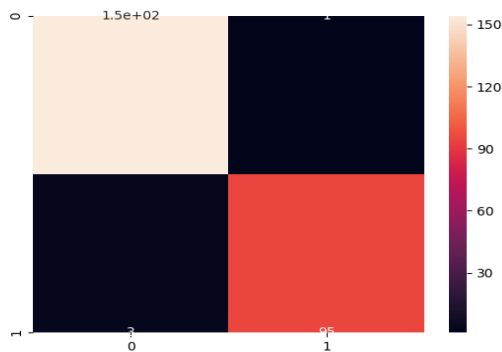




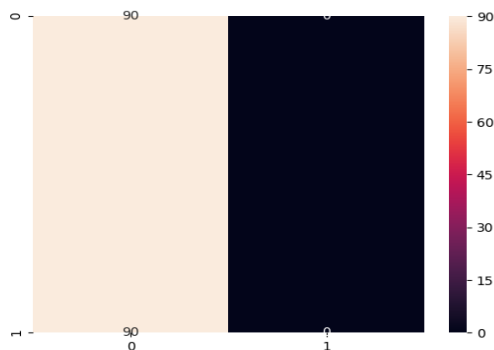
epochs at a learning rate of 0.0001. This is to visualize when and where the program is having trouble at detecting for tumour or healthy MRI. These variables may change in future studies when implementing predictions of likelihood that an MRI scan may develop Tumour

As seen from the data gathered instances like this that factors in simple data sets with the same contrast and dimensions not factoring out any variables but only detecting any anomalies within the small data. Tied up with a 95% accuracy the VGG 16 and 19 showed the best results in both accuracy and validation accuracy. It also displays that all the CNN models are having the same problem at the same points.

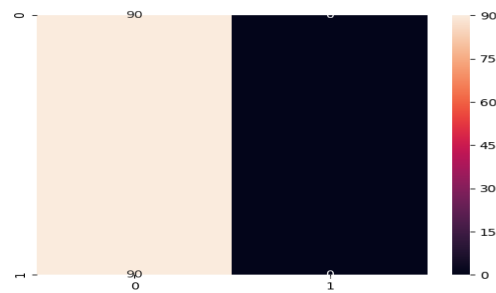
As the data is prepared an imbalance is seen in the datasets. There are more healthy MRI scan than Tumour MRI scan. Therefore, undersampling technique is implemented that allows a fair comparison within the Data. Some healthy datasets were removed to match the Tumour MRI scans.



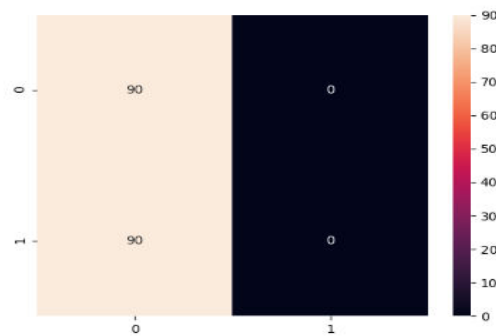
**Figure-6.1.** Confusion matrix of 3 Layer model on 20 epochs.



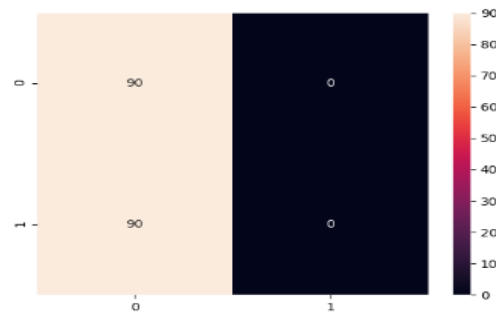
**Figure-6.2.** Confusion matrix of VGG16 on 20 epochs.



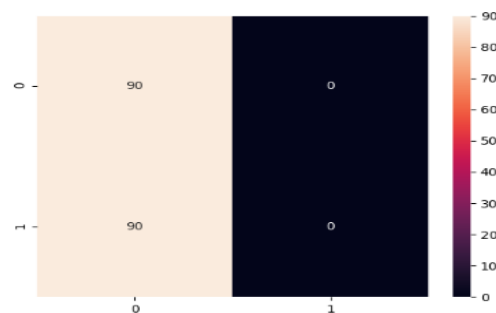
**Figure-6.3.** Confusion matrix of VGG19 on 20 epochs.



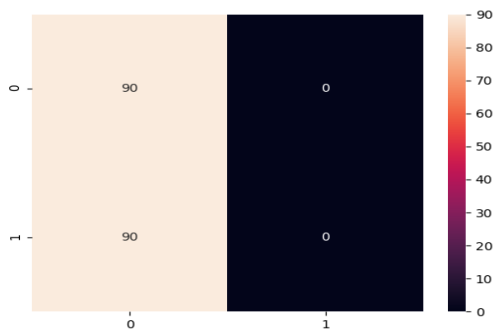
**Figure-6.4.** Confusion matrix of Xception on 20 epochs.



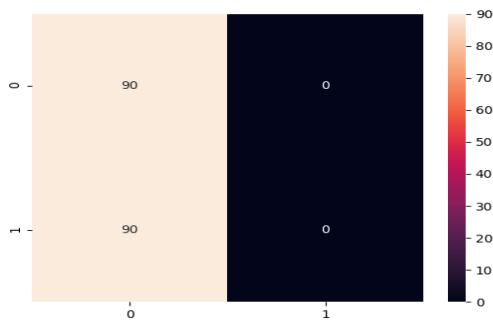
**Figure-6.5.** Confusion matrix of Densenet121 on 20 epochs.



**Figure-6.6.** Confusion matrix of Densenet169 on 20 epochs.



**Figure-6.7.** Confusion matrix of Densenet201 on 20 epochs.

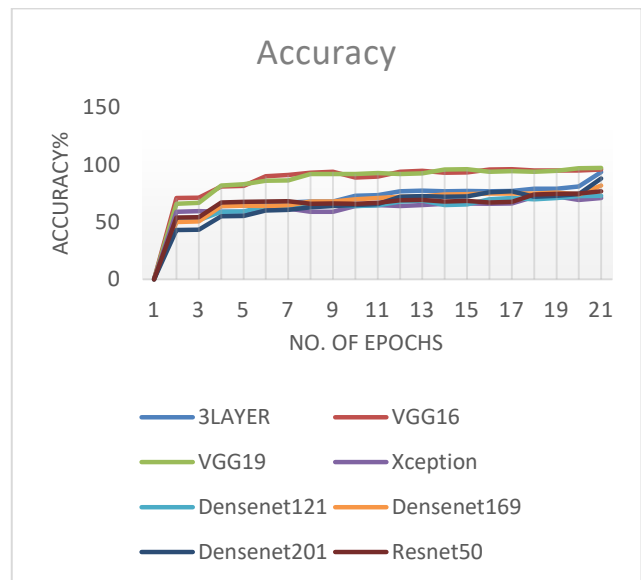


**Figure-6.8.** Confusion matrix of Resnet50 on 20 epochs.

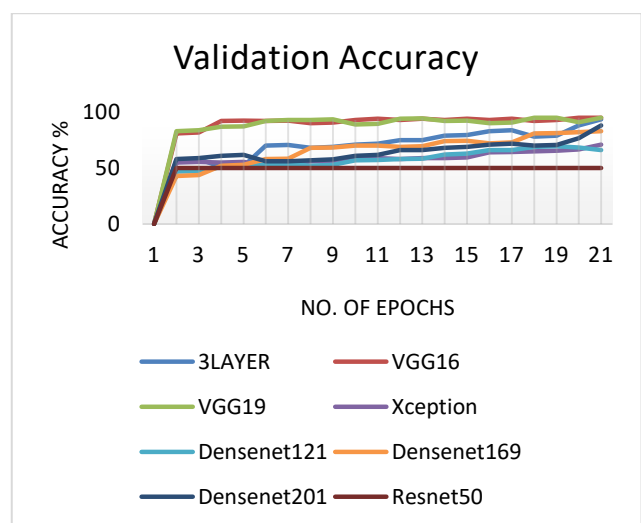
#### ACCURACY AND VALIDATION ACCURACY

Then, the differentiation of Validation Accuracy and Accuracy were plotted to see which models had overfitting. Figures 7.1 and 7.2 visualizes the Accuracy and Validation Accuracy to find whether the model is overfitting. Table-3 shows the comparison of the Validation Accuracy and the Accuracy of each model at 20 epochs. It also shows the Comparison of Validation Accuracy and the Accuracy to see which model is overfitting.

Figures 7.1 and 7.2 shows similarities and the trend does not go far off therefore having no overfitting the final output shows excellent results from a 70 % accuracy from Resnet50 upto an outstanding 95 % accuracy belonging to both VGG16 and VGG19 and a validation accuracy from 50% belonging to Resnet50 upto also a 95% validation accuracy also belong to VGG16 and 19



**Figure-7.1.** Accuracy of the models.



**Figure-7.2.** Validation Accuracy of the models.

**Table-3.** Validation Accuracy and Accuracy.

MODEL	VALIDATION ACCURACY	ACCURACY
3LAYER	93.5	93.5
VGG16	95	95.88
VGG19	95	97.16
Xception	71	71
Densenet121	66	73
Densenet169	82.78	82
Densenet201	88	88
Resnet50	50	77

Further testing shows that different learning rate helped increase the accuracy for different pretrained models as seen with the VGG models decreasing the



learning rate increased the accuracy from 55% to 95% using 0.1 learning rate up to 0.0001 learning rate.

## CONCLUSIONS

This study is used to classify an image of an MRI scan whether it shows signs of tumour just by identifying each pixel in the picture which could be very hard to detect by the naked eye alone.

As seen from the data gathered instances like this that factors in simple data sets with the same contrast and dimensions not factoring out any variables but only detecting any anomalies within the small data. Tied up with a 95% accuracy the VGG 16 and 19 showed the best results in both accuracy and validation accuracy.

Further research and more data would have to be done and used if it were to be used to predict and interpret patterns on the MRI scans to look for correlation in soon to be tumours. The proposed method needs to be improved by having more datasets and better algorithm to find patterns and predict not just detect when and where a tumour may grow from the MRI scans alone.

When worked on raw data it did not yield great results having only an 80% accuracy and a 50% validation accuracy after. We implemented data augmentation techniques. The data was resized and recolored to a monochrome to have the same dimensions and tone which will have a better prediction on the data. These images were then trained on a well-known pre-trained convolutional Neural network (CNN) and a small model comprising of 3 layers for control independent variable. At first, we only got 90% as the best validation accuracy that belongs to the untrained 3-layer algorithm. However, decreasing learning rate to 0.0001 increased our best validation accuracy from 90% to 95% that validation accuracy belonging to VGG 16 and 19.

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