International Journal of Academic Engineering Research (IJAER)
ISSN: 2643-9085
Vol. 6 Issue 3, March - 2022, Pages:29-47

Detection of Brain Tumor Using Deep Learning

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Abstract*: Artificial intelligence (AI) is an area of computer science that emphasizes the creation of intelligent machines or software that work and reacts like humans, some of the computer activities with artificial intelligence are designed to include speech, recognition, learning, planning and problem solving. Deep learning is a collection of algorithms used in machine learning, it is part of a broad family of methods used for machine learning that are based on learning representations of data. Deep learning is used as a technique to produce brain tumor detection and classification models using Magnetic Resonance Imaging (MRI) imaging for rapid and easy detection and identification of brain tumor. In this thesis, some ways and mechanisms will be reviewed to use deep learning techniques to produce a model for brain tumor detection. The goal is to find a good and effective way to detect brain tumor based on MRI to help the brain doctor in making decisions easily, accurately and rapidly. A recent report by the World Health Organization in February 2018 showed that the death rate from brain cancer or central nervous system (CNS) is the highest in the Asian continent. It is important to detect cancer early so that many of these lives can be saved. The model has been designed and implemented, including a dataset which consist of 10,000 images for brain tumor detection through the use of Deep learning algorithms based on neural networks. For testing, we have used our model, Inception, VGG16, MobileNet and ResNet models. The f-score accuracy we got for each model was as follows: Our model was 98.28, VGG16 was 99.86%, ResNet50 was 98.14%, MobileNet was 88,98%, and InceptionV3 was 99.88%.*

Keywords: Artificial intelligence**,** Deep learning, brain tumor, MRI

1.1 Introduction

Machine learning is an application of artificial intelligence (AI) that provides systems with the ability to automatically learn and improve from experience without being explicitly programmed. Machine learning focuses on developing computer programs that can access and use data in learning by itself [1].
Learning begins with observations or data, such as examples, first-hand experience, or instructions, to search for data patterns and make better decisions in the future based on the examples we provide. The primary goal is to make computers learn and act like humans do, and to improve their learning over time in an independent way, by providing them with data and information in the form of real-world observations and interactions.

There are Some Machine Learning Methods. Machine learning algorithms are often categorized as supervised or unsupervised.

- Supervised machine learning algorithms can apply what has been learned in the past to new data using tagged examples to predict future events. Starting with the analysis of a known training dataset, the learning algorithm produces a function that is inferred to make predictions about output values. The system is able to provide targets for any new inputs after adequate training. The learning algorithm can also compare its output with the intended correct output and find errors to modify the model accordingly.
- Unsupervised machine learning algorithms are used when the information used for training is not categorized or marked. Unsupervised learning examines how systems can infer functionality to describe the hidden structure of unnamed data. The system does not detect the correct output, but explores the data and can draw conclusions from the data sets to describe the hidden structures of the unnamed data.
- Semi-supervised machine learning algorithms are somewhere between supervised and unsupervised learning, where both disaggregated and unmarked data use training - typically a small amount of branded data and a large amount of unnamed data. Systems that use this method are able to significantly improve the accuracy of learning. Typically, semi-supervised learning is selected when labeled acquired data requires skilled and relevant resources in order to train / learn from it. Otherwise, getting unnamed data generally does not require additional resources.
- Reinforcement machine learning algorithms are a learning method that interacts with their environment by producing actions and detecting errors or rewards. The search for trial, error and late reward are the most important characteristics of learning reinforcement. This method allows devices and software agents to automatically determine optimal behavior in a given context in order to maximize its performance. Simple remuneration notes are required for the agent to find out the best procedure; this is known as a boost signal.

Machine learning allows analysis of huge amounts of data. Although they generally provide faster and more accurate results for identifying lucrative opportunities or serious risks, they may also require additional time and resources to properly train them. Combining machine learning with artificial intelligence and cognitive techniques can make it more effective in processing large amounts of information [2].

Deep learning is a type of machine learning (ML) and artificial intelligence (AI) that mimics the way humans acquire certain types of knowledge. Deep learning is an important component of data science, which includes statistics and predictive modeling. It is extremely useful for data scientists charged with collecting, analyzing and interpreting large amounts of data; deep learning makes this process faster and easier [3].

Brain tumor is one of the most deadly cancers. It has its high effects because it is a special item of the main nervous motor of man where each small defect can cost a lot. For this reason, it is important to find ways of early detection of anxiety about a brain tumor. This importance comes from the fact that early detection dramatically increases the possibility of treating the disease and saving patients' lives. Recently, cancer treatments have evolved considerably, especially in the early stages of infection. The chances of survival are very high for those patients who receive early treatment compared to those who do not have this opportunity in the early stages of the disease [4].

1.2 Problem Statement

Physicians often use brain X-rays to quickly and cheaply diagnose disease associated with the area. However, it is much more difficult to make clinical diagnoses with brain X-rays than with other imaging modalities such as CT or MRI. With computer-aided diagnosis, physicians can make brain X-ray diagnoses more quickly and accurately.

A brain tumor is a collection, or mass, of abnormal cells in your brain. Your skull, which encloses your brain, is very rigid. Any growth inside such a restricted space can cause problems. Brain tumors can be cancerous (malignant) or noncancerous (benign). When benign or malignant tumors grow, they can cause the pressure inside the skull to increase. This can cause brain damage, and it may threaten the person life.

Brain tumors are categorized as primary or secondary. A primary brain tumor originates in your brain. Many primary brain tumors are benign. A secondary brain tumor, also known as a metastatic brain tumor, occurs when cancer cells spread to your brain from another organ, such as your lung or breast

In this application, we hope to train a model using the dataset to help physicians in making diagnoses of brain tumor MRI.

Computerized applications can be using deep learning techniques to increase accuracy and efficiency in diagnosis.

These include Brain tumor MRI images, image processing techniques and data analysis.

1.3 Objectives of the Thesis

The objectives of this thesis are:

Main objective:

- Implementation a software model used to detect and classify brain tumor if found in brain MRI images by the following types:
  - Primary brain tumors, which start and tend to stay in the brain.
  - Metastatic brain tumors, which begin as cancer elsewhere in the body and spread to the brain.

Specific objectives:

- Rapid diagnosis and detection of brain tumor.
- Reduce the cost of diagnosis and repetitive images.
- Increase proficiency using deep learning techniques to detect brain tumor.

1.4 Brain tumor

A brain tumor is a collection, or mass, of abnormal cells in brain. or skull, which encloses your brain, is very rigid. Any growth inside such a restricted space can cause problems. Brain tumors can be cancerous (malignant) or noncancerous (benign). When benign or malignant tumors grow, they can cause the pressure inside your skull to increase. This can cause brain damage, and it can be life-threatening.

There are roughly 130 different types of brain and central nervous system tumors, all ranging from benign to malignant and from extremely rare to relatively common. But of those 130 brain tumors, it is categorized as primary or secondary.

1- Primary brain tumors there is originate in a brain. They can develop from your brain cells, the membranes that surround your brain, which are called meninges, nerve cells or glands Primary tumors can be benign or cancerous.

2- Secondary brain tumors make up the majority of brain cancers. They start in another part of the body and spread to the brain through breast cancer, kidney cancer, or skin cancer [4].
Secondary brain tumors are always malignant. Benign tumors don't spread from one part of your body to another.
There are four most common brain tumors:

1 - Meningioma these tumors are technically not brain tumors, as they form in the meninges, which are the membranes that line the skull and vertebral canal. But their growth may affect the brain by causing various disabilities such as vision and hearing impairment, memory loss, or even seizures. Incidents of meningioma increase with age, and the tumors grow slowly, so symptoms could develop gradually over time. it usually meningioma's are benign, so doctors may choose to leave asymptomatic cases alone. However, if the tumor starts adversely affecting quality of life, physicians will either surgically remove it or treat it using radiation therapy. The most common early sign of meningioma is chronic headaches.

2 - Gliomas are tumors that develop from glial cells. These cells normally: support the structure of your central nervous system, provide nutrition to your central nervous system, clean cellular waste break down dead neurons and Gliomas can develop from different types of glial cells such as:

- Astrocytic tumors such as astrocytoma's, which originate in the cerebrum.
- Oligodendroglia tumors, which are often found in the frontal temporal lobes.
- Glioblastomas, which originate in the supportive brain tissue and are the most aggressive type.
- Other primary brain tumors.

3 - Metastatic the most common brain tumor among adults, it most often stems from lung or breast cancer. Larger metastatic tumors will often be surgically resected—meaning removed—while smaller tumors may be treated with a gamma knife, which is a form of radiation therapy that focuses 200 small beams of radiation onto the tumorous area.

4 - Astrocytoma these primary tumors originate in star-shaped cells called astrocytes, which are located in the brain's cerebrum. The grade of astrocytoma tumors—meaning their level of malignancy and aggressiveness—varies; sometimes they grow slowly (Grade II) and sometimes they come on more aggressively (Grade III) [5].

1.5 Convolutional Neural Network

Convolutional neural network is powerful image processing, it is a special type of artificial neural network used in image recognition and processing that is specifically designed to process pixel data, where that the network employs a mathematical operation called convolution, it is a specialized kind of linear operation. Convolutional networks are simply neural networks that use convolution in place of general matrix multiplication in at least one of their layers [6].

A neural network is a system of hardware and/or software patterned after the operation of neurons in the human brain. Traditional neural networks are not ideal for image processing and must be fed images in reduced-resolution pieces. CNN have their "neurons" arranged more like those of the frontal lobe, the area responsible for processing visual stimuli in humans and other animals. The layers of neurons are arranged in such a way as to cover the entire visual field avoiding the piecemeal image processing problem of traditional neural networks [6].

A CNN uses a system much like a multilayer perceptron that has been designed for reduced processing requirements. The layers of a CNN consist of an input layer, an output layer and a hidden layer that includes multiple convolutional layers, pooling layers, fully connected layers and normalization layers where the most common layers are convolutional layers, grouping layers and related layers exactly as shown in the Fig. 1. Other examples may include ReLU layers, batch-leveling layers and leak layers. the removal of limitations and increase in efficiency for image processing results in a system that is far more effective, simpler to trains limited for image processing and natural language processing [6].

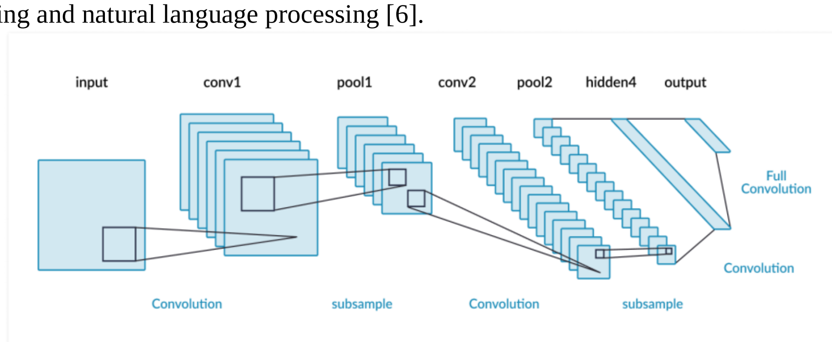

Figure 1: Architecture of Convolutional Neural Network [7]

2.2.1 Convolutional Layer

The convolutional layer or Conv layer is the core building block of a Convolutional Network, where it consists of a set of learnable filters. The height and weight of the filters are smaller than the input size. Each filter is combined with the input size to calculate the activation map of neurons. In other words, the filter is filtered through the width, the filter is filtered through the width and height of the inputs, and the point's products between the input and the filter are calculated at each spatial position. The convolutional layer output size is obtained by stacking the activation maps of all filters along the depth dimension. Because the width and height of each filter is designed to be smaller than the input, each neuron in the map is connected only to a small area of the input size, in other words, the approximate field size of each neuron is small and equal to the size of the filter. Local contact is driven by the structure of the animal's visual cortex where the receptive fields of cells are small. Local convolutional connectivity allows the network convolutional layer to learn which filters are most responsive to the local input area, thus exploiting the local spatial correlation of the inputs (for the input image, the pixels are more closely related to the nearby pixels than a distant pixel). In addition, where the activation map is obtained by twisting the filter and input, the filter parameters are shared for all local placements. Weight sharing reduces the number of parameters for expression efficiency, learning effectiveness and good generalization [8].

2.3 Network Architectures

2.3.1 VGG

VGG Transfer VGG is a neural network trained with the ImageNet dataset to classify natural images, The VGG16 architecture is proposed by Simonyan and Zisser-man, the input size of this model is fixed as 224 × 224. The images are passed through a stack of convolutional (convs) layers, where a small receptive filters of size 3 × 3. Further 1 × 1 convolution filters are also used where a linear transformation of input channels (followed by non-linearity). And in order to preserve the spatial resolution after convolution, the padding of 1 pixel for 3 × 3 conv layers is employed; the spatial pooling is executed by 5 max-pooling layers. The Max pooling is performed over a 2×2-pixel window, with stride 2, a stack of convs layers followed by three fully-connected (FC) layers have been utilized such as the first two FC layers have 4096 channels, and the third FC layer has 1000 channels (one for each class). The final layer of this architecture is the softmax layer. [19].

2.3.2 ResNet

ResNet is the deep learning network discovered in 2015, as the first neural network that could train hundreds or thousands of layers without succumbing to the "vanishing gradient" problem. ResNet is that ResNet depends on residual learning. The idea in residual learning is that the inputs of the previous layers are made more deeply available in the network. A building block, called a connection shortcut, for the remaining network [20].

2.3.3 MobileNet

MobileNet is a CNN architecture model for Image Classification and Mobile Vision. It has very less computation power to run or apply transfer learning to. This makes it a perfect fit for Mobile devices, embedded systems and computers without GPU or low computational efficiency with compromising significantly with the accuracy of the results. It is also best suited for web browsers as browsers have limitation over computation, graphic processing and storage, it which are based on a streamlined architecture that uses depth wise separable convolutions to build light weight deep neural networks.

Two simple global hyper-parameters that efficiently trade off between latency and accuracy are introduced [21].

2.3.4 InceptionV3

Inception v3 is a widely-used image recognition model that has been shown to attain greater than 78.1% accuracy on the ImageNet dataset, where it is a convolutional neural network that is trained on more than a million images from the ImageNet database [1]. The network is 48 layers deep and can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 299-by-299.

The model itself is made up of symmetric and asymmetric building blocks, including convolutions, average pooling, max pooling, concats, dropouts, and fully connected layers. Batch norm is used extensively throughout the model and applied to activation inputs. Loss is computed via Softmax [22].

2.4 Data Processing

2.4.1 Laplacian as focus measure

When we categorize cells, it is best to find the image with the best focus. There may be slight differences that distinguish a tumor cell from a normal cell and can be seen when the focus is poor in the image. One focus gauge is the use of Laplacian. The second degree derivative expressed in the plasma mass is known as high-frequency scrolling, which can be an indicator of the sharp edges of the image. The derivative of the second order expresses how the rate of change has changed. A faster change indicates a more pronounced edge. Laplacian can be expressed using a mask. The posterior measure of image focus can be a look at asymmetric contrast. Low contrast indicates some sharp edges indicating noise, and the generalized Laplacian is also used as a trigger to measure focus for better recovery of 3D objects [23].

2.4.2 Normalization

Normalization is a database design technique, often applied as part of data preparation for machine learning. The goal of normalization is to change the values of numeric columns in the dataset to a common scale to reduce redundancy, without distorting differences in the ranges of values. For machine learning, every dataset does not require normalization. It is required only when features have different ranges [24].

2.4.3 Augmentation

Augmentation is the creation of altered copies of each instance within a training dataset, used to reduce over-display by artificially enlarging the dataset. There are many methods used for conversion that can translate, such as mirroring and rotation. Dealing with the original poster in an unchanging way is the basic concept of increasing the image. Each added version of the original image will be considered a different image, with the same label, by the grid [25].

2.5 Model Evaluation

2.5.1 Performance Estimation

Once a classification model is learned, evaluating its performance is another step in classification problem. This evaluation is done based on how accurately model classifies the samples in test set. And the number of samples that are either correctly or incorrectly classified can be tabulated in a matrix called as confusion matrix as shown in table 2.1 [26].

Table 2.1: Confusion matrix for binary classification

	Predicted: YES	Predicted: NO
Actual: YES	TP	FN
Actual: NO	FP	TN

A confusion matrix is a contingency table in which rows correspond to true class and columns to predicted class. Now, explaining every element in confusion matrix.
_ TP: Number of samples which are positive and classified as positive (true positive).
_ FN: Number of samples which are positive but classified as negative (false negative).
_ FP: Number of samples which are negative but classified as positive (false positive).
_ TN: Number of samples which are negative and classified as negative (true negative).
Although, confusion matrix itself provides the general information on how good model is, various other performance measure metrics can be calculated based on it. Among other, accuracy is one of the simplest and widely used performance measure metric, and is defined as ratio of correctly classified samples to that of total number of samples in test set. Since the diagonal elements of confusion matrix are the number of correctly classified samples.

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{f-score} = 2* \frac{Recall * Precision}{Recall + Precision}$$

$$\text{Error rate} = \frac{\text{Number of incorrectly classified samples}}{\text{Total number of samples}} = \frac{FP + FN}{TP + TN + FP + FN}$$

Equivalently, error rate can be expressed also as:

Error rate = 1 - Accuracy

Even though accuracy or error rate alone can be used to assess the performance of model, this performance metric alone does not provide information on how accurate is model if dataset is highly imbalanced. Here, imbalanced dataset means majority of samples belongs to either one of the class. Suppose there is a dataset whose 90% of samples belong to positive class and remaining 10% to negative class. A classifier which classifies all the samples to positive class would achieve the accuracy of 90 % which makes classifier apparently a good classifier even if it has failed to correctly classify even a single stance of negative class? [27].

3.1 Previous Studies

A brain tumor is a group or mass of abnormal cells in your brain. Symptoms of brain tumors depend on the location and size of the tumor. The various symptoms of brain cancer include coordination issues, frequent headaches, mood swings, changes in speech, difficulty in concentration, seizures and memory loss. It is important to detect brain cancer as soon as possible. MRI can be used to detect brain cancer by MRI analysis, but this procedure differs in its consumption for a large number of cases [4].

Many research papers have been published to use artificial intelligence, expert systems and neural networks to improve the detection of brain tumor. Recently, medical centers and hospitals have begun to introduce artificial intelligence systems and applications in some disciplines to increase the accuracy of disease detection.

Many methods and models have been introduced that have contributed to increased diagnostic efficiency. Early diagnosis of gliomas plays an important role in improving treatment possibilities. There are many medical imaging techniques such as Computed Tomography (CT), Single-Photon Emission Computed Tomography (SPECT), Positron Emission Tomography (PET), Magnetic Resonance Spectroscopy (MRS) and Magnetic Resonance Imaging (MRI) that are used in combination to provide the highest detailed and valuable information about the shape, size, location and metabolism of brain tumors assisting in diagnosis. Although, MRI is considered as the standard technique used in diagnosis due to its good soft tissue contrast and widely availability. As 3D and 4D imaging are becoming routine, and with physiological and functional imaging increasing, medical imaging data is increasing in size and complexity. Therefore, it is essential to develop tools that can assist in extracting information from these large datasets [28].

The recent development of artificial intelligence combined with the accumulation of large volumes of medical images opens up new opportunities for building CAD systems in the medical applications. Artificial intelligence methods (including shallow learning and deep learning, etc.), especially deep learning, mainly replace the process of feature extraction and disease classification in the traditional CAD systems. Artificial intelligence methods have also been widely used in image segmentation of brain X-ray. Machine learning is a set of algorithmic techniques that allow computer systems to make data-driven predictions from large data. These techniques have a variety of applications that can be tailored to the medical field.

There has been a significant effort in developing classical machine learning algorithms for segmentation of normal (e.g., white matter and gray matter) and abnormal brain tissues (e.g., brain tumors) in MRI. An emerging machine learning technique referred to as deep learning (DL), can help avoid limitations of classical machine learning algorithms. Deep learning refers to multiple-layered neural networks (usually more than five) that draw a hierarchy of features from the initial input images. It is a new and popular type of machine learning technique that extracts a complex hierarchy of features from images due to its ability to self-learn rather than to extract literal features in classical machine learning algorithms. They achieve great results and generalization by training a large amount of data. DL algorithms are used in brain image analysis in different application domains like Alzheimer's disease identification, segmentation of lesion (e.g., tumors, white matter lesions, micro-bleeds) and brain tissue classification. Much of the ongoing research is limited to brain segmentation and only little work has been done for the tumor grading. Due to automatic feature extraction capability of DL based methods, recently it is getting more attention and accuracy compared to conventional classification techniques for medical imaging. It is for sure that many lives can be saved if cancer detected and suitable grade estimated through fast and cost-effective diagnosis techniques. Therefore, there is dare need to develop fast, non-invasive and cost effective diagnosis techniques. Here, DL algorithms have been proposed as a solution to expedite, automate, and improve the interpretation of several imaging examinations [28].

The proposed technique to determine an abnormal growth in the brain using Stacked Autoencoders in Deep Learning, where deep learning model is published to predict abnormal tumor input segments. The image employs a high pass filter to distinguish the effect of the heterogeneity of the MR slices and merge them with the input slices. Moreover, the intermediate filter is applied to fused slices. The quality of the resulting slices is improved by smoothing the distinct edges of the input slices.

Next, based on the severity of these slices, a growing algorithm for continuous seeds is applied, where the optimum threshold aggregates identical pixels from the input slices. Then, a two-layer proposed SSAE segment is provided. The super parameters of the model are chosen after extensive experiments. In the first layer, 200 hidden units are used and in the second layer 400 hidden units. The test is performed on the softmax layer to predict tumor-containing images and no tumors [29].

The proposed technique for detection brain tumors using high resolution that increases the accuracy of images to higher levels such as MRI images makes the important information more visible and clear and therefore, it is provided that the boundaries of the tumors in the relevant image have been found more successfully brain tumor detection based on fuzzy C-means with super-resolution and convolutional neural networks with extreme learning machine algorithms (SR-FCM-CNN) approach has been proposed. The aim of this has been segmented the tumors in high performance by using Super Resolution Fuzzy-C Means (SR-FCM) approach for tumor detection from brain MR images. then, feature extraction and pertained SqueezeNet architecture from convolutional neural network (CNN) architectures and classification process with extreme learning machine (ELM) were performed. In the experimental studies, it has been determined that brain tumors have been better segmented and removed using SR FCM method. Using the SquzeeNet architecture, features were extracted from a smaller neural network model with fewer parameters. In the proposed method, 98.33% accuracy rate has been detected in the diagnosis of segmented brain tumors using SR-FCM. This rate is greater 10% than the rate of recognition of brain tumors segmented with fuzzy C-means (FCM) without SR [30].

The proposed technique for detection brain tumors based on extreme learning, Brain magnetic resonance imaging is utilized for tumor evaluation on the basis of automated segmentation and classification methods. triangular fuzzy median filtering is applied for image enhancement that helps in accurate segmentation based on unsupervised fuzzy set method. Gabor features are extracted across each candidate's lesions, and similar texture (ST) features are calculated. These ST features are supplied to extreme learning machine (ELM), and regression ELM leaves one out for tumor classification. The technique is evaluated on BRATS 2012, 2013, 2014 and 2015 challenging datasets as well as on 2013 Leader board. The proposed approach shows better results and less computational time [31].

The proposed technique for detection brain tumors using multiple kernel-based probabilistic clustering and deep learning classifier is proposed. The proposed technique consists of three modules, namely segmentation module, feature extraction module and classification module. Initially, the MRI image is pre-processed to make it fit for segmentation and de-noising process is carried out using median filter. Then, pre-processed image is segmented using Multiple Kernel based Probabilistic Clustering. Subsequently, features are extracted for every segment based on the shape, texture and intensity. After features extraction, important features will be selected using Linear Discriminant Analysis for classification purpose. Finally, deep learning classifier is employed for classification into tumor or non-tumor. The proposed technique is evaluated using sensitivity, specificity and accuracy. The proposed technique results are also compared with existing technique which uses Feed-Forward Back Propagation Network. The results show a maximum improvement of 18% on grading performance of CNN based on sensitivity and specificity compared to NN [32].

3.2 Comment on the previous Studies

Commenting on the previous studies: It was mentioned in one of the studies that a comparison was made to determine the presence of the tumor between the deep learning structure and the basic neural networks to show an improvement in the results of the performance of convolutional neurological scores by 18%.

The researchers also mentioned that they had used a powerful system that could detect brain tumors and predict the type of that tumor by increasing the accuracy of the MRI images initially with the High Resolution approach. Thus, it leads to increased fragmentation performance. The MRI image is then segmented with a Fuzzy-C-Means approach.

In the research, SqueezeNet, one of the most recent relevant Convolutional neural network designs, is used, split tumor imagery features are extracted and classification of these features is provided by extreme learning machine. With the help of the proposed approach, both tumor segmentation and tumor classification were performed. The Super Resolution Fuzzy-C-Means - Convolutional neural network approach suggested in empirical studies turns out to lead to tumor classification at a very high success rate. In the proposed approach, tumor segmentation and classification performance is significantly reduced when brain tumor is detected without the use of SR.

Finally, we see that the proposed methods provide accurate and effective segmentation and classification results.

In addition, system performance can be improved if an extreme learning machine based workbook is applied to Convolutional neural network - based features that will be studied in the future. This work can be extended to deal with noisy images. Also, segmentation accuracy can be improved.

4.1 Introduction

Our Proposed methodology consists of collecting the dataset, identifying the tools and language to used, preprocessing the data, data augmentation, building the model architecture, compiling the model, training and validating the model.

4.2 Dataset

The data set in this study consists of a collection of 10,000 MRI brain tumor images. The numbers of images in this dataset are classified as follows: 5000 images that were diagnosed with brain tumor and 5000 images that were diagnosed to be free of brain tumor. The brain tumor images were collected from Kaggle depository website.
We divided the data set as follows:

Table 1 : Dataset division for training, validation, and testing

Brain Tumor	Training Samples	Validation Samples	Testing Samples
Yes	3500	1000	500
No	3500	1000	500
Total	7000	2000	1000

4.3 Language and tool used

We have used Python language, which is high-level languages with an easy user interface, and is a free and open source languages that allows the use of many libraries, including library keras, shutil, fnmatch, os.
The research team used several tools, the most important of which is Google Colab to write python codes, a research tool for teaching and searching for a learning machine, an easy to use and does not require any preparation for use, Google Colab is characterized by its speed in performance because it has very fast processors of type (GPU).
Google Colab is a free-to-use research project that can store and read all notebooks directly from Google Drive

4.4 Image format

Dataset was collected from a set of Brain MRI Images for Brain Tumor Detection (JPG) format, In order to fit well with the model used to give the desired results.

4.5 Preprocessing

The first thing in the data preprocessing was to resize the Brain MRI Images as the images were of various sizes, the images were resized to 200 by 200 Pixels, this image size collide with a balance between providing a high enough resolution for Brain Tumor Detection by the model and efficient training. All images were normalized to ImageNet standards.

Then the images collection has been categorized into two types, uploaded to a Google Drive account and verified to be properly and accurately uploaded using Python code in the Google Colab environment.

4.6 Data augmentation

Generating more data usually means that the model will be more robust and prevent overfitting.

Having a large dataset is crucial for the performance of the deep learning model. However, we improved the performance of the model by augmenting the images that we already have without collecting new images. Deep learning frameworks usually have built-in library for data augmentation utilities; we utilized five augmentation strategies to generate new training sets, (Rotation, width shift, height shift, horizontal flip, and vertical flip).

Rotation augmentations are done by rotating the image right or left on an axis between 1° and 359°. The safety of rotation augmentations is heavily determined by the rotation degree parameter. Shifting and flipping images are a very useful transformation to encapsulating more details about objects of interest.

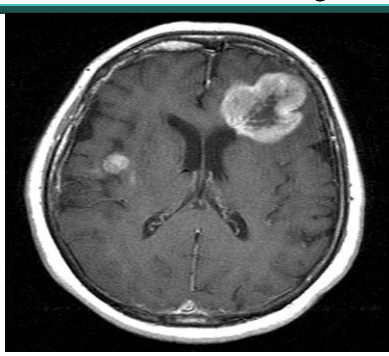

Figure 2: Original Brain MRI Image

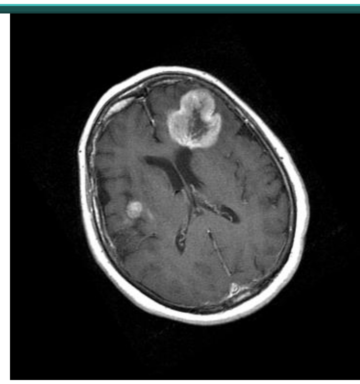

Figure 3: Brain MRI Image is rotated by 30 degrees

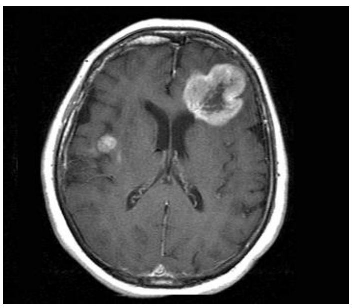

Figure 4: Brain MRI Image after width shift

Figure 5: Brain MRI Image after height shift

Figure 6: Brain MRI Image flipped horizontally

Figure 7: Brain MRI Image flipped vertically

4.7 Network Architecture

We have trained our dataset for brain tumor using a model created from scratch and four pre-trained models for deep learning: VGG16, ResNet50, MobileNet, and InceptionV3.

4.8 Training and Validating the Models

4.8.1 Model created from scratch

We created a model from scratch with 12 convolutional layers followed by a fully connected hidden layer (as shown in figure 9). Output layer uses softmax activation as it has to output the probability for each of the classes; to optimize the network Adam optimization was used.

Model is ready to train, during the training, the model will iterate over batches of the training set, each of size batch size. For each batch, gradients will be computed and updates will be made to the weights of the network automatically. One iteration over all of the training set is referred to as an epoch. Training is usually run until the loss converges to a constant.

We added checkpoint to the model to save the best validation accuracy. This is useful because the network might start overfitting after a certain number of epochs. These feature is implemented via the callback feature of Keras. Callback is a set of functions that is applied at given stages of training procedure like end of an epoch of training. Keras provides built-in function for both learning rate scheduling and model check-pointing.

We trained and validated our model and we got training accuracy of 100% and validation accuracy of 98.28% (as shown in figure 10).

```
from keras import layers
from keras import models
model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu',
      input_shape=(200, 200, 3)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(256, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(512, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Flatten())
model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dense(2, activation='softmax'))
```

Figure 8: Model architecture

Epoch 1/25
- 7s - loss: 1.3559e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0710 - val_acc: 0.9728 - val_fscore: 0.9728
Epoch 2/25
- 8s - loss: 0.0046 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0551 - val_acc: 0.9814 - val_fscore: 0.9814
Epoch 3/25
- 8s - loss: 0.0031 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0566 - val_acc: 0.9814 - val_fscore: 0.9814
Epoch 4/25
- 7s - loss: 0.0023 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0576 - val_acc: 0.9814 - val_fscore: 0.9814
Epoch 5/25
- 7s - loss: 0.0018 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0600 - val_acc: 0.9814 - val_fscore: 0.9814
Epoch 6/25
- 7s - loss: 0.0015 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0602 - val_acc: 0.9800 - val_fscore: 0.9800
Epoch 7/25
- 7s - loss: 0.0012 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0616 - val_acc: 0.9800 - val_fscore: 0.9800
Epoch 8/25

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- 8s - loss: 0.0011 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0581 - val_acc: 0.9814 - val_fscore: 0.9814
Epoch 9/25
- 8s - loss: 9.0364e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0625 - val_acc: 0.9800 - val_fscore: 0.9800
Epoch 10/25
- 7s - loss: 7.7813e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0600 - val_acc: 0.9800 - val_fscore: 0.9800
Epoch 11/25
- 7s - loss: 6.8078e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0616 - val_acc: 0.9800 - val_fscore: 0.9800
Epoch 12/25
- 7s - loss: 5.9211e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0610 - val_acc: 0.9785 - val_fscore: 0.9785
Epoch 13/25
- 8s - loss: 5.2512e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0606 - val_acc: 0.9800 - val_fscore: 0.9800
Epoch 14/25
- 7s - loss: 4.6487e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0651 - val_acc: 0.9757 - val_fscore: 0.9757
Epoch 15/25
- 8s - loss: 4.1231e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0641 - val_acc: 0.9757 - val_fscore: 0.9757
Epoch 16/25
- 7s - loss: 3.6619e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0634 - val_acc: 0.9771 - val_fscore: 0.9771
Epoch 17/25
- 8s - loss: 3.2246e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0658 - val_acc: 0.9757 - val_fscore: 0.9757
Epoch 18/25
- 8s - loss: 2.8787e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0638 - val_acc: 0.9785 - val_fscore: 0.9785
Epoch 19/25
- 7s - loss: 2.5607e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0664 - val_acc: 0.9757 - val_fscore: 0.9757
Epoch 20/25
- 7s - loss: 2.3318e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0666 - val_acc: 0.9757 - val_fscore: 0.9757
Epoch 21/25
- 8s - loss: 2.0452e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0659 - val_acc: 0.9771 - val_fscore: 0.9771
Epoch 22/25
- 7s - loss: 1.8486e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0659 - val_acc: 0.9771 - val_fscore: 0.9771
Epoch 23/25
- 7s - loss: 1.6561e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0684 - val_acc: 0.9742 - val_fscore: 0.9742
Epoch 24/25
- 7s - loss: 1.4831e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0685 - val_acc: 0.9757 - val_fscore: 0.9757
Epoch 25/25
- 7s - loss: 1.4831e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0552 - val_acc: 0.9828 - val_fscore: 0.9828

Figure 9**:** Training and validation accuracy of our model

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To visualize the training and validation of the model, we used "Matplotlib" to draw plots the accuracy and loss of the training and validation.

Figure 11 shows the learning curve of the network during training and validation. It is seen that the validation accuracy and training accuracy were increasing and it reached to 100 % training accuracy and 99.28% validation accuracy.

Figure 12 shows the loss curve of the network during training and validation. It is seen that the validation loss and training loss were decreasing with the number of iterations, that's great; it proved that the model works well.

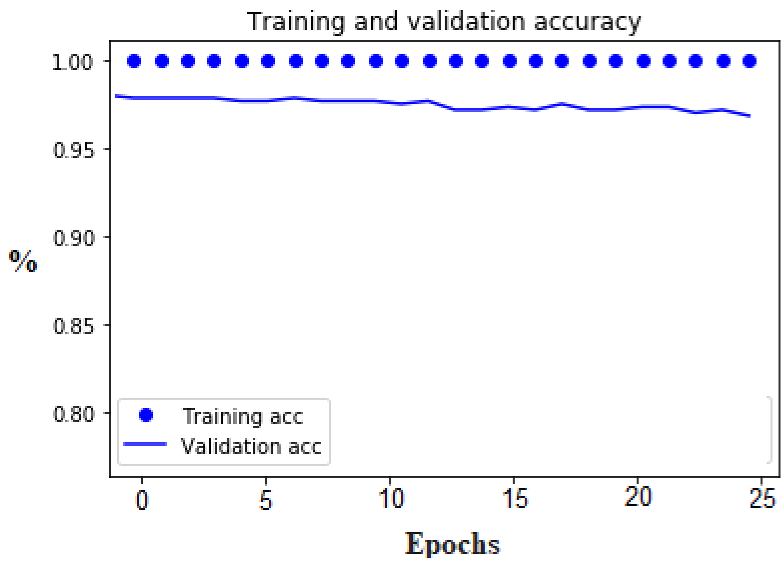

Figure 10: Training and validation accuracy curve of our model

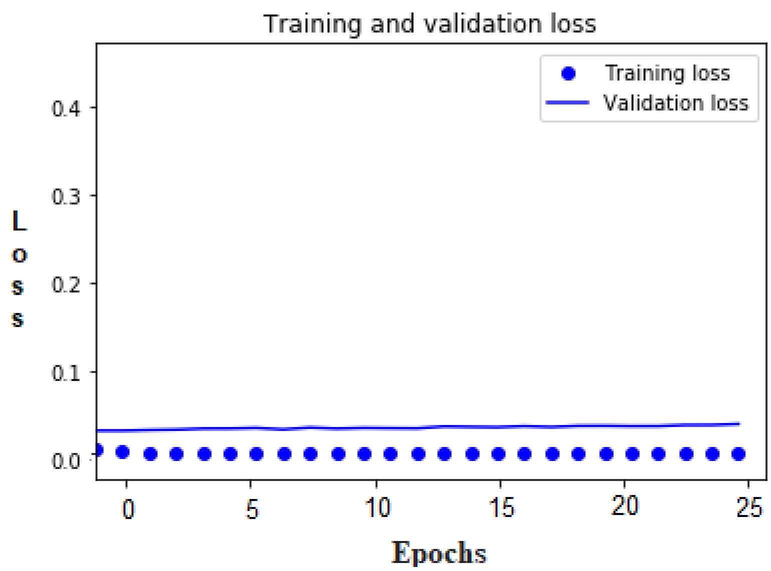

Figure 11: Training and validation loss curve of our model

4.8.2 VGG16 model

We used a pre-trained model called VGG16 network with 16 convolutional layers followed by a fully connected hidden layer, also used dropout layers in between, dropout regularizes the networks to prevent the network from overfitting, and all layers have ReLU activations except the output layer.

Note following figure 13 the value accuracy “val_acc" starts increasing. That means model built is learning and working fine. It has a training accuracy rate of approximately 99.94 %, but there is a decrease and an increase of loss and validation loss.

Figure 12 illustrates the accuracy of both training and validation of VGG16 model of the brain tumor dataset. Figure 13 shows the loss of both training and validation of VGG16 model of the brain tumor dataset.

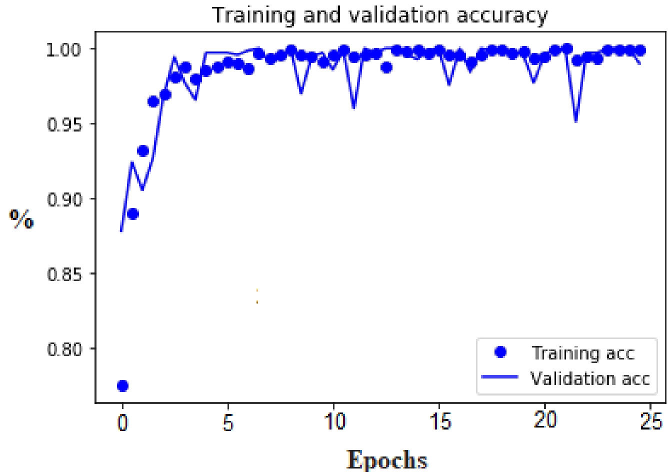

Figure 12: Training and validation accuracy curve of Vgg16

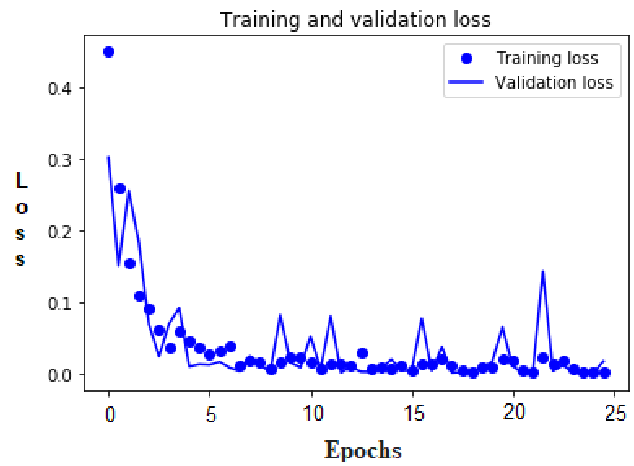

Figure 13: Training and validation loss curve of Vgg16

4.8.3 ResNet50 model

We used a pre-trained model called ResNet50 network with 50 convolutional layers followed by a fully connected hidden layer, also used dropout layers in between, dropout regularizes the networks to prevent the network from overfitting, and all layers have ReLU activations except the output layer.

We trained the brain tumor data set using the pre-trained ResNet50 model and the training accuracy reached 99.75% and validation accuracy reached 98.14%.

Figure 14 illustrates the accuracy of both training and validation of ResNet50 model of the brain tumor dataset. Figure 15 shows the loss of both training and validation of ResNet50 model of the brain tumor dataset.

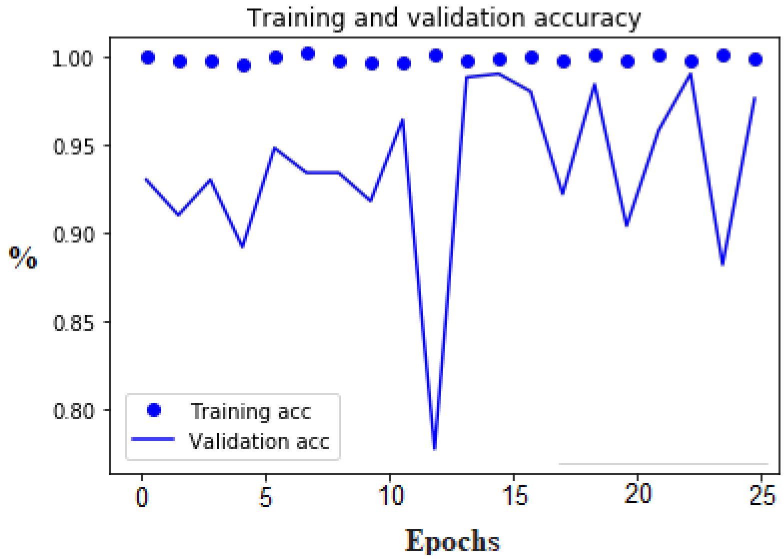

Figure 14: Training and validation accuracy curve of ResNet50

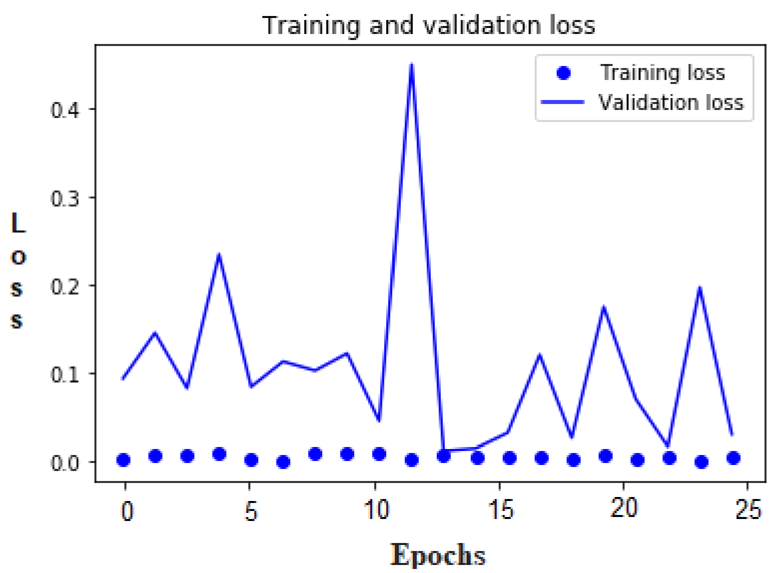

Figure 15: Training and validation loss curve of ResNet50

4.8.4 MobileNet model

We used a pre-trained model called MobileNet network with 28 convolutional layers followed by a fully connected hidden layer, also used dropout layers in between, dropout regularizes the networks to prevent the network from overfitting, and all layers have ReLU activations except the output layer.

We trained the brain tumor data set using the pre-trained MobileNet model and the training accuracy reached 99.78% and validation accuracy reached 88.98%.

Figure 16 illustrates the accuracy of both training and validation of MobileNet model of the brain tumor dataset. Figure 17 shows the loss of both training and validation of MobileNet model of the brain tumor dataset.

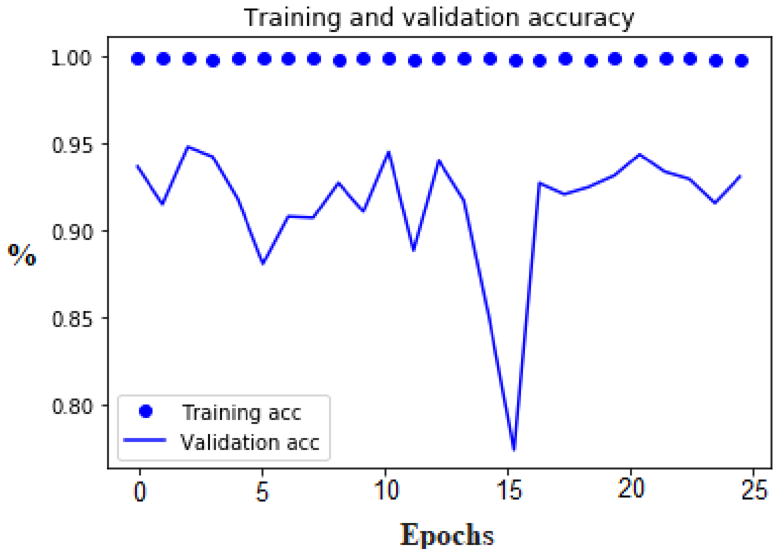

Figure 16: Training and validation accuracy curve of MobileNet

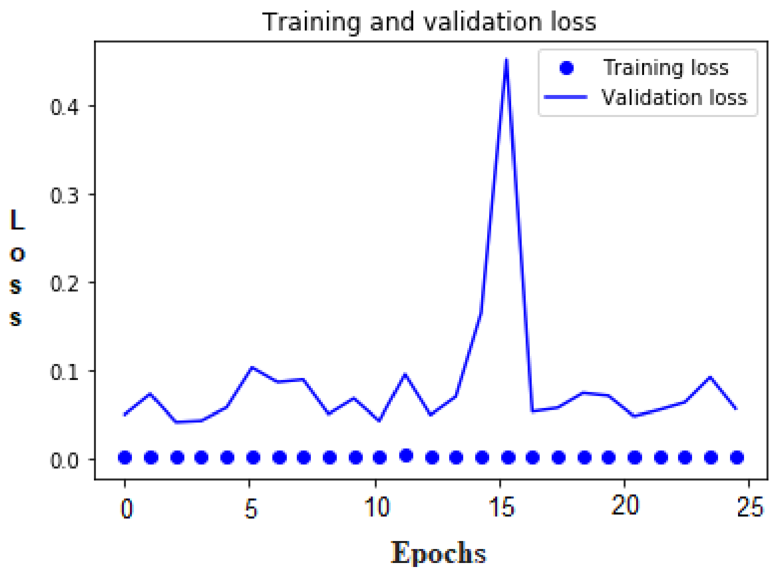

Figure 17: Training and validation loss curve of MobileNet

4.8.5 InceptionV3 model

We used a pre-trained model called InceptionV3 with 28 convolutional layers followed by a fully connected hidden layer, also used dropout layers in between, dropout regularizes the networks to prevent the network from overfitting, and all layers have ReLU activations except the output layer.

We trained the brain tumor data set using the pre-trained InceptionV3model and the training accuracy reached 99.96% and validation accuracy reached 99.88%

Figure 18 illustrates the accuracy of both training and validation of InceptionV3 model of the brain tumor dataset. Figure 19 shows the loss of both training and validation of InceptionV3 model of the brain tumor dataset.

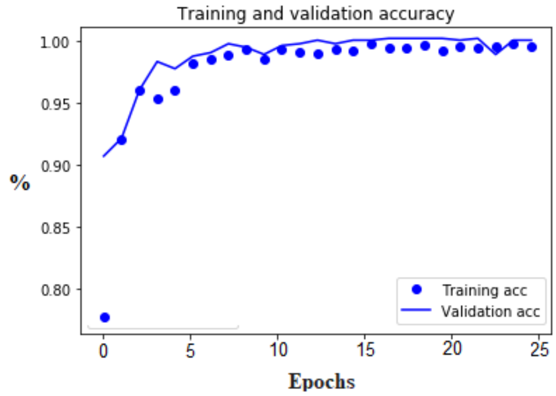

Figure 18: Training and validation accuracy curve of InceptionV3

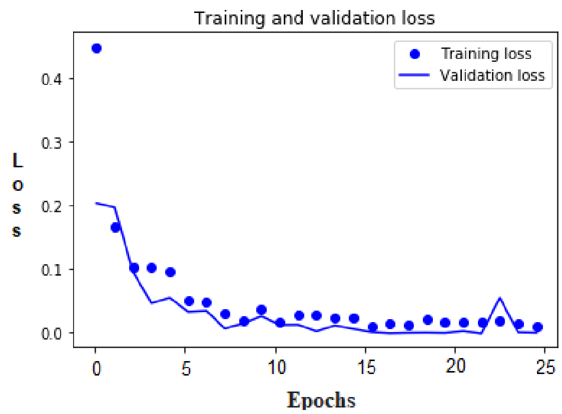

Figure 19: Training and validation loss curve of InceptionV3

5.1 Data Set for testing the model

Testing dataset organized into one folder (Brin-Tumor-test) and contains 1000 of MRI brain tumor images, (JPG) format, different from the images that used in original dataset for training; they are images of two classifications of brain-tumor and non-brain tumor distributed as in the following table:

Table 2: Distribution of Images in test dataset

Categories	Number of testing images	Image size
brain-tumor	500	200 x 200 pixels
non-brain tumor	500	200 x 200 pixels

Figure 20: Shows samples of MRI brain tumor images used for testing the 5 models.

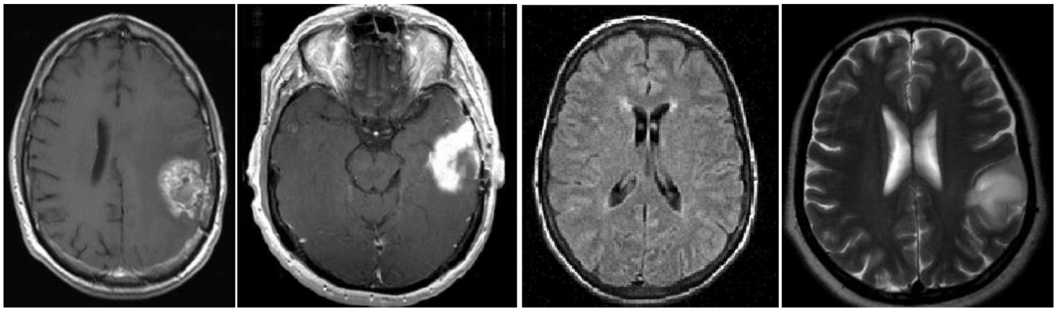

Figure 20: Samples of the MRI brain tumor images in the test dataset

5.2 Testing the model

After training and evaluated the model on the validation, the network are tested using 1000 MRI brain Tumor images, among them, 500 brain tumor, 500 without brain tumor(Normal).

Testing the models is done through loading the test images and predicting their classes using the model.predict_classes() function, probabilities of each image belonging to a specific class were calculated, by the following classification: (0:brain-tumor', 1:'normal').

Note the classification rates of network during testing, it was a surprise, the probability of results in the classification for our model, VGG16, ResNet50, MobileNet, and InceptionV3 were 98%, 99%,98%, 88%, 99% correct respectively for all test images.

5.3 Result and Discussion

We trained our custom model on the training dataset using 10,000 images for a total of 100 epochs, the results were as follows:

Table 3: Analysis of the model used in the training, validation and testing

Criterion	Our Model	VGG16	ResNet50	MobileNet	InceptionV3
Training Accuracy	100%	99.94%	99.75%	99.78%	99.96%
Validation Accuracy	98.28%	99.86%	98.14%	88.98%	99.88%
Training loss	0.0002	0.0045	0.0091	0.0052	0.0147
Validation loss	0.0552	0.0028	0.0478	0.3501	0.0020
Testing Accuracy	98%	99%	98%	88%	99%

Based on the previous table of the results, InceptionV3 and VGG16 were the best models then come our model which we created from scratch with 98.28%. ResNet50 was ranked in the 4th place. Furthermore, MobileNet came last in the fifth place.

This thesis presents a deep learning approach for the detecting whether MRI brain tumor images have brain tumor or not.

We accomplished this using our model and 4 different pre-trained models: VGG16, ResNet50, MobileNet, and InceptionV3 architectures, these model were able to correctly predict MRI brain tumor images with a balanced accuracy approximately 99% on the validation and the test set after only training for 100 epochs, due to the techniques such as adam optimization, data augmentation , dropout and others, it was possible to enhance the accuracy of model without sacrificing training efficiency, because one of the problems with machine learning, including deep learning, is overfitting. Overfitting occurs when the trained model does not generalize well to unseen cases, but fits the training data well. This becomes more apparent when the training sample size is small.

Assessment of the plot training can be used to assess the possibility of overfitting. From the curve, it is apparent that the data loss is similar for both validation and training datasets. If there were overfitting, the loss on the training data would be much greater than that of the validation data. In addition, for this reason, the cases were split three ways (training, validation, and test).

It is conceivable that the use of larger training datasets, additional image augmentation methods, and additional machine learning approaches with more ensembles could improve this result.

6.1 Conclusion

In this research, we conclude a deep, easy, fast, and effective learning method to discover whether MRI images have a brain tumor, as it is a problem doctors face and will help them make decisions easily, accurately and quickly.

A deep educational model has been built to solve this problem. This model was written in the Python language listed on the Google Collab platform, which is high-level languages with an easy and free user interface.

We have trained our dataset on brain tumor using a model created from scratch model and four pre-trained deep learning models: VGG16, ResNet50, MobileNet, and InceptionV3.

A model is developed to train dataset on brain tumor using a template created from scratch and four pre-trained models for deep learning: VGG16, ResNet50, MobileNet, and InceptionV3.

We reached a training accuracy of 100% and a validation accuracy of 99.28%. It was observed that the accuracy of the validation and accuracy of the training was on the rise and these results were better and can be used to determine the presence of a tumor in the brain

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