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EVALUATION OF OPINIONS OF TEACHERS

Unlocking the Potential of Deep Convolutional Neural Networks for Accurate Diagnosis of BrainTumors

M.Sc. THESIS

CHAUNCY YARNGO GIBSON

Supervisor

Assoc.Prof. Dr Sertan Serte

Nicosia

January,2023

Approval

We certify that we have read the thesis submitted by Chauncy Yarngo Gibson titled

"Unlocking the Potential of Deep Convolutional Neural Networks for Accurate Diagnosis of BrainTumors" and that in our combined opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Sciences.

Examining Committee	Name-Surname	Signature
Head of the Committee:	Prof.Dr. Bulent Bilgehan	....
Committee Member*:	Assis.Prof.Dr. Ali Serener	Ali Serener.......................
Supervisor:	Assoc.Prof.Dr. Sertan Serte	....

Approved by the Head of the Department

17/2/2023

Prof.Dr.Bulent Bilgehan

Head of Department

Approved by the Institute of Graduate Studies

...../...../20...

Prof. Dr.KemalHüsnü Can Başer

Head of the Institute

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Chauncy Yarngo Gibson

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Chauncy Yarngo Gibson

Abstract

Unlocking the Potential of Deep Convolutional Neural Networks for Accurate Diagnosis of BrainTumors

Gibson, Chauncy

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Brain tumors are dangerous formation of bad cells within the brain, they cause serious health issues and it is more effectively treated when discover early. Medical Imaging Technology is the most used and most efficient way of detecting brain tumors. This research is about utilizing deep convolutional neural networks as a tool for Diagnosing medical imaging with an objective of detecting and classifying brain tumors. This research takes several deep convolutional neural network models and adopts the models for the task of classifying Normal brain MRI scans from Abnormal brain MRI scans. Three Datasets were use for the proposed of adopting and testing the convolutional neural networks models. Two of the datasets are binary structure datasets contain positive and negative classes, the third dataset is amulticlass structure dataset contains four classes. After adopting and testing, high results were observed of some models up to 100% test accuracy on the binary structure datasets and up to 97.0% on the multiclass structure dataset. This researchshows the effectiveness of deep Convolutional Neural Networks for the used in medical imaging technology for diagnosing medical imaging, with the objective ofdetecting and classifying brain tumors. Also shows that Artificial Intelligent system is and will continue to play an important role in the medical world.

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Abbreviations

TRNC:	Turkish Republic of North Cyprus
MNE:	Ministry of National Education
DCNN:	Deep Convolutional Neural
NetworksCNN:	Convolutional Neural Networks
MRI:	Magnetic Resonance Imaging
RELU:	Rectified Linear Unit
VGG:	Visual Geometry Group
TP:	True Positives
TN:	True Negatives
FP:	False Positives
FN:	False Negatives

CHAPTER I
Introduction

The brain is a vital organ in the human body, it and the spinal cord serves has the central point for the nervous system and coordinate all nerves activities (Janig & Habler, 2000). According to Kollias, et al. (2009) the human brain consistsof three parts, the cerebrum, the brainstem and the cerebellum. The human brain is house within the skull a protective shell. A healthy human brain through the utilization of the three parts controls most of the activities within the human body and provides cognitive functions. Healthy human brain is a construct of healthy cells; these cells compose of various brain tissues which make up the brain (Kollias et al., 2009). One of the most harmful threat to the healthy state of the human brain are brain tumors (Krull et al., 2009). According to Cha (2006) brain tumors are lumps within the brain that are made up of abnormal tissues. The tumors develop in the brain from cancerous cells that can originate from other parts of the body or from abnormal brain tissues. Brain tumors serves has unwanted mass within the brain that can obstruct normal functions of the brain, create pressure within the skull which exert force on normal brain tissues causing complications which could lead to death. It is essential that brain tumors be detected for life saving medical intervention (Cha 2006).

With the inception of medical imaging technology, an image of various tissues within the brain can be view. With the viewing of these brain tissues, braintumors can now be identify from other tissues in the brain through an non invasive procedure. According to Khan, et al. (2018) medical imaging is a technique and a procedure that involves taking internal images of the human body for clinical evaluation, medical intervention, and to show how certain organs or tissues are functioning. Medical imaging use non-invasive means to produce internal tissues or organs images. Medical imaging technologies provide the ability to look deeper within hidden structures of the brain, by providing an image that is made up of features that defines the complex structure of tissues with in the brain (Khan et al.,2018).

With so many different types of medical imaging technologies with different specifications, the widely used medical imaging technology for the detection of brain tumors is Magnetic resonance imaging (MRI). A Medical Imaging Technology that uses Magnetic fields and Radio waves to form an imageof internal body systems (Saini & Singh, 2015). Since its introduction in the 1970sand 1980s, MRI has established itself as a flexible imaging method. MRI differs from most Medical imaging technologies in that it does not utilize X-rays or ionizing radiation and in comparison provides better image contrast of soft tissues.The images of MRI scans contain layers of detail features of scan internal tissues. For effective medical diagnosis to be carryout from the analysing of MRI images the layers of detail features of scan internal brain tissues needs to be interpret and healthy tissues classify from abnormal brain tissues. This is the diagnosing medical imaging process (Saini & Singh, 2015).

Diagnosing medical imaging is a complex process, careful and skilful analyses of medical images are required for interpretation and classification of internal tissues (Sarvamangal & Kulkarni, 2022). With the boost in digital computation in the 1970s, digital programs begin to assists in the process of diagnosing medical imaging. Using these artificial means made the process of interpretation, classification efficient and fast. Artificial methods through digital computation means are playing a vital role in diagnosing medical imaging, as digital computation means have been evolving over the last few decades so as the artificial methods use in medical imaging (Tang 2020).

As the years move by with significant advancement in computational technology, a shift from hard coded digital programs to smart digital programs that can predict outcomes base on patterns extracted from data is now the preferable artificial means for diagnosing medical imaging (Goldenberg et al., 2019). These smart digital programs use the properties of perception to learned from data, the perception of these smart digital programs give them a tool of intelligence. With the construct of intelligence within the smart digital programs, artificial intelligence methods can be use for much deeper analysis of medical imaging and is playing a critical role in diagnosing medical imaging (Goldenberg et al., 2019). The most widely used artificial intelligence method in recent years for the interpretation and classification of features within

Images are artificial neural networks. Artificial neural networks are model after the structure and function of Biological neural networks, they can be design to form a network of neurons or neural net and the network of neurons can be broken down into layers (Jain et al., 1996).

There are many different connection structure that layers of artificial neurons can be connected and arrange in. These different arrangements of layers of neurons can be used to classify different types of neural networks and their specifications. Due to Spatial locality and Translation invariance of features in images, deep convolutional neural networks are the profound choice for interpretation and classification of features within images (Rawat & Wang 2017).

Deep convolutional neural networks are artificial neural networks, design to utilize the properties of spatial locality and translation invariance of features in images through convolution (Rawat & Wang 2017). Deep convolutional neural networks are made up of several layers, from input to output consisting of the convolutional blocks to feed forward layers.

1.1 Statement of the Problem:

Brain tumors are the growth of chaotic cells that form within the brain, any growth within such a constrained area can lead to issues. Brain tumors cells can be cancerous in nature (malignant) or noncancerous (benign), because these cells don’t have the normal biological structure of other brain cells, they grow in an abnormal way forming lumps within the brain, that causes pressure inside the skull to rises, making them extremely harmful to the brain (Dolecek et al., 2015). Hundreds of thousands of people are affected by brain tumors globally and the number keeps rising (Yang et A1., 2022). There are multiple ways to detect brain tumors but the most effective is through Medical Imaging Technology (Liu et al., 2019). One of the most important issues in the world of medicine is early brain tumor detection and categorization. These developments in the field of medicine are especially important to patients because it aids in the choice of the most effective course of health treatment to preserve their lives. Research carryout by the World Health Organization (WHO) (2007) states that, accurate diagnosis of brain tumors includes identifying the presence of a tumor, determining its location within the brain, classifying it as cancerous or noncancerous, determining its grade (aggressiveness), and identifying the specific type of tumor.

Due to the complexity of the human brain, the generated MRI image of the human brain contains complex features and regions that need careful analysis for carrying out classifications. Deep convolutional neural networks can extract features even, extremely small and hidden features within MRI images of human brain scans to make predictions to detect, classify brain tumors (Khan et a1., 2020).

1.2 Purpose of the Study:

This research seeks to shed light on the vital importance of deep convolutional neural networks with respect to brain tumors detection from MRI images of brain scans. The research will shows that the vital images generated by Magnetic resonance imaging (MRI) technology of brain scans can be can be analyze by deep convolutional neural networks and that the neural networks can effectively classify an image with a tumor or no tumor. As a result, this research will deliver the following:

- Acquire three Data Sets for the study
- Utilize functional models of several deep convolutional neural networks architecture.
- Adapt various models to the Data Sets, through training.
- Test the various models and report the results.

1.3 Research Hypothesis

This research supports the claim of the effectiveness of deep convolutionalneural networks as an efficient means for brain tumors detection of brain scan images from Magnetic resonance imaging (MRI) technology.

1.4 Significance of the Study

To show the importance of deep convolutional neural networks, has they give an effective means of analyzing images of brain scans, extracting features thatlies within complex details that make up an image and making predictions with high accuracy base on those complex details.

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CHAPTER II

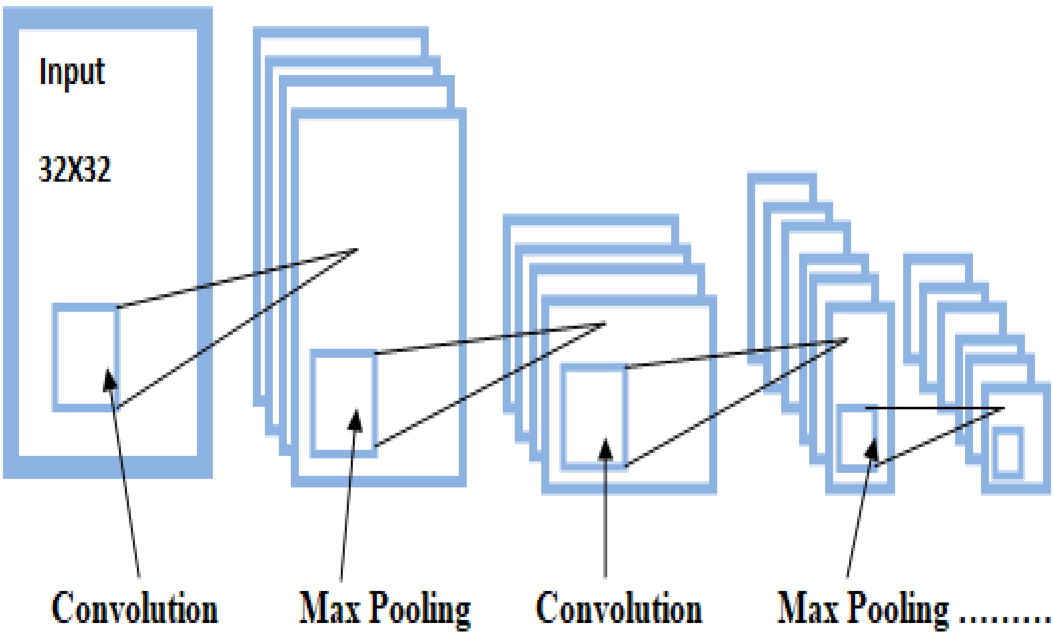
Literature Review

Deep CNNs are simply Convolution Neural Networks CNNs that have many layers. The additional layers allow the network to learn more complex patterns, but also make the network more computationally expensive to train.

2.1 Convolutional Neural Networks

A Convolutional Neural Network is a deep neural network that has layers that can convolve with incoming signals of multidimensional structure like an image, that have features that make up something meaningful and extract those features from that data using filters and those extracted features are propagated throughout the network for performing classification(Rawat & Wang 2017). The filters form a local receptive field of certain define dimension over a region in the multidimensional structure signal, the local receptive field set a small define region in the multidimensional structure signal that is made up of weights and biases that is then slide across the entire multidimensional structure signal extracting features. Weights and biases are tune to look for specific features. Convolutional Neural Network take two important properties of grid structure signals, the property of spatial locality and Translation invariance, also the ability to share weights and biases for easy learning. Spatial locality property states that the pixels that define certain feature in an image tend to be next to each other in that image (Chris Olah 2018). Translation invariance refers to the ability of a model to recognize an object regardless of its location in an image (Rawat & Wang 2017). It is on these principles that Convolutional Neural Networks convolves with incoming data to extract features to be propagated throughout the neural network. Convolutional Neural Networks can be broken into layers of convolution layers, pooling layers and fully connected layers with output. The pooling layers take the information from the output of the convolution layers and simplify it. The Convolutional layers perform convolution on incoming data. The two common type of pooling layer use in Convolutional Neural Networks are max pooling and average pooling layer (Karpathy 2018). Max pooling layer simple output the maximum values within certain region of specific dimensions of the convolutional layer output. Average pooling layer take the average within certain region of specific dimensions of the convolutional layer output. With fully connected layers the inputs of neurons are connected to all neurons in the previous layer. The final layer in the fully connected layers the output layer, carried out the classification of multidimensional input signals that have been propagated throughout the convolutional neural network. The composition of all these layers makes convolutional neural networks effective at learning complicated features by forming a feature map and from the feature map convolutional neural network classify two dimension signals like image with high accuracy.

Figure 1: *Convolutional Block*

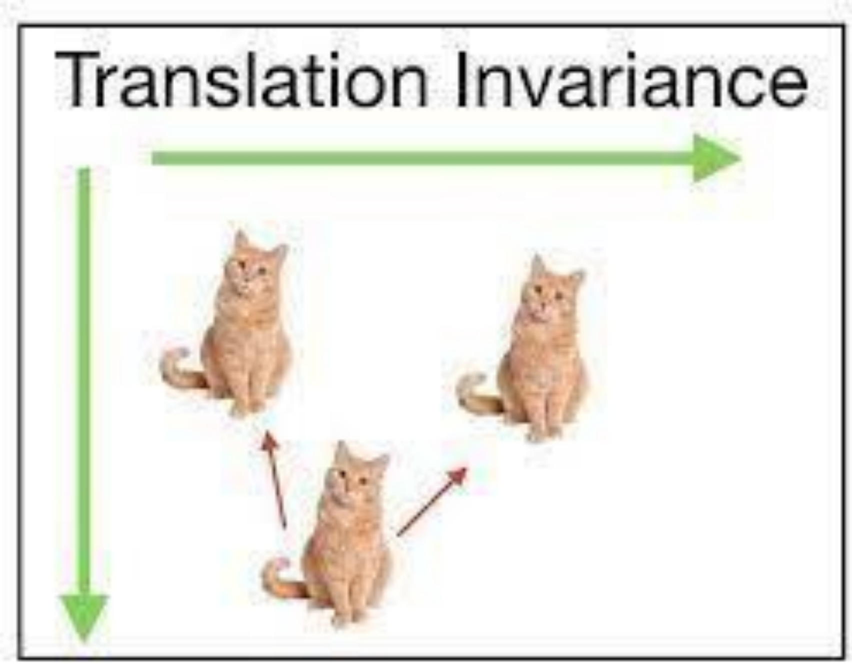


2.1.1 Signals of multidimensions

A multidimensional signals are signals compose of components that are define in more than one dimension, example a flat plane is compose by points define in two dimensions and a photo is compose by pixels define in two dimensions (Theodoridis et A1., 2002). An image is a multidimensional signals madeup of pixels. Convolutional neural networks are very effective in classifying imagesbecause they possess the properties of spatial locality and Translation

Invariance, set of pixels that characterizes a dog will be near one another in the image and the pattern that characterizes a dog is the same no matter where in the image the dog occurs.

Figure 2: *The pattern that characterizes this cat is the same no matter where in theimage the cat occurs(Wennberg et A1., 2021)*



2.1.2 Filters

In Convolutional Neural Network a Filter is a construct of weights and biasesthat is apply to a image and it will find all the places in the image where certain features lies (Cheon et al., 2019). The construct of weights and biases forms a local receptive field a window on the pixels of the image. The window of weights and biases move across the entire image computing a feature map. The process of moving the window of weights and biases across the image computing a feature mapis called convolution. The feature map is a map of features detected within the image. Features are meaningful construct that add up together to make up an image. The weights and biases of filters serves have parameters for detecting certain features.

Figure 3: *A 4x4 filter forming a local receptive field on a 8x8 image.*

0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
0.1	0.0	0.0	1.0	1.0	1.0	0.0	0.1
0.1	0.0	1.0	0.0	0.0	0.0	0.0	0.1
0.1	0.0	1.0	1.0	1.0	0.0	0.0	0.1
0.1	0.0	1.0	0.0	0.0	1.0	0.0	0.1
0.1	0.0	1.0	0.0	0.0	1.0	0.0	0.1
0.1	0.0	0.0	1.0	1.0	0.0	0.0	0.1
0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1

0.5	0.3	0.3	1.0
0.1	0.5	1.0	0.1
0.1	1.0	0.5	0.1
1.0	0.3	0.3	0.5

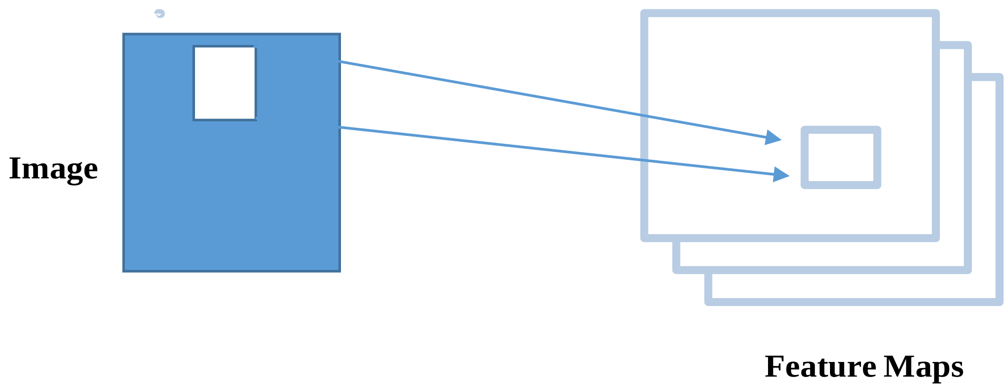
4x4 filter

8x8 image

2.1.3 Convolutional Layer

The convolution layer is made up of a set of filters that make up the core structure of a Convolutional Neural Network (Cheon et al., 2019). The set of filters that make up the convolutional layer serves as features detector, parameterize by weights and biases. The filters convolve with the input image to form feature maps that maintains the spatial information of the image. The feature maps will propagate to other layers in the Network.

Figure 4: *Convolution*



2.1.4 Pooling Layer

The pooling layer simplifies the outputs from the convolutional layer by generalizing the features in the feature map (Mamale & Garcia, 2012). The two most common pooling layers use in convolutional neural networks are max pooling andaverage pooling layers.

Max pooling layer

The max pooling layer extracts the highest pixel value within a region of some define dimension of the feature map. The region defines by some dimension, move across the entire feature map extracting the highest pixel values as its output.

Figure 5: *2x2 Max pooling with stride of two.*

0.0	0.1	0.1	0.0
0.2	1.0	0.2	0.1
1.0	0.0	1.0	0.2
1.0	0.0	1.0	0.0

4x4 Feature map

1.0	0.2
1.0	1.0

2x2 Max pooling

Average pooling layer

The average pooling layer extracts the average of all the pixels value within aregion of some define dimension of the feature map. The region defines by some dimension, move across the entire feature map extracting the average values as its output.

Figure 6: *2x2 Average pooling with stride 2.*

0.0	0.1	0.1	0.0
0.2	1.0	0.2	0.1
1.0	0.0	1.0	0.2
1.0	0.0	1.0	0.0

4x4 Feature Map

0.325	0.40
2.0	2.2

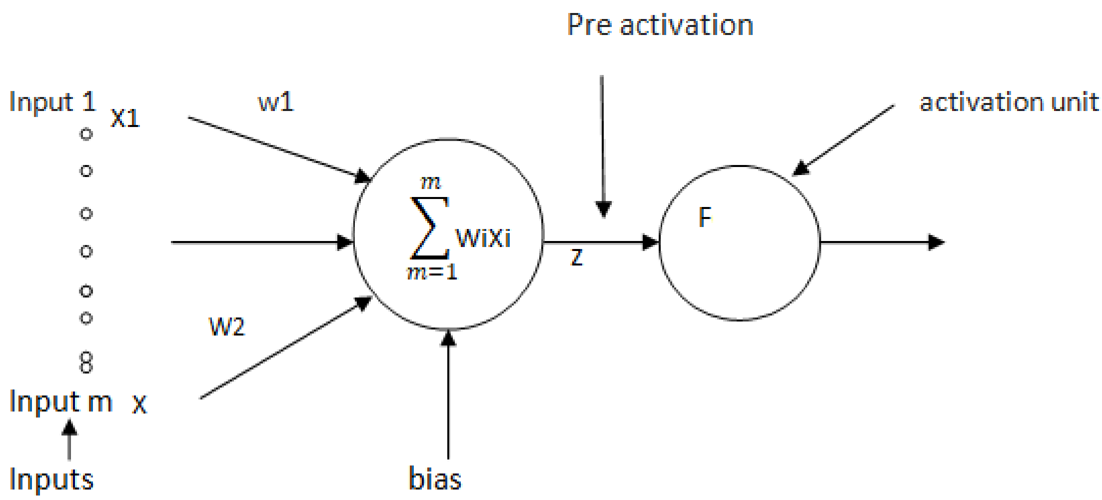
2x2 average pooling

2.1.5 Fully Connected Layer

The fully connect layer is the last part in the convolutional neural network; it is at this layer classification take place. The fully connected layer is made

Up of several connected neurons that form a neural network (Rawat & Wang 2017). The neuron is the basic element of a neural network; it has a bias, can have multiple inputs, an output and each input has a weight attach to it. The weights and bias perform a linear function on the input of a neuron which serve as pre-activation and is then process by an activation unit (Aggarwal 2018). The activation unit use in convolutional neural networks are rectify linear and nonlinear functions, with the most common being sigmoid, Relu and Softmax.

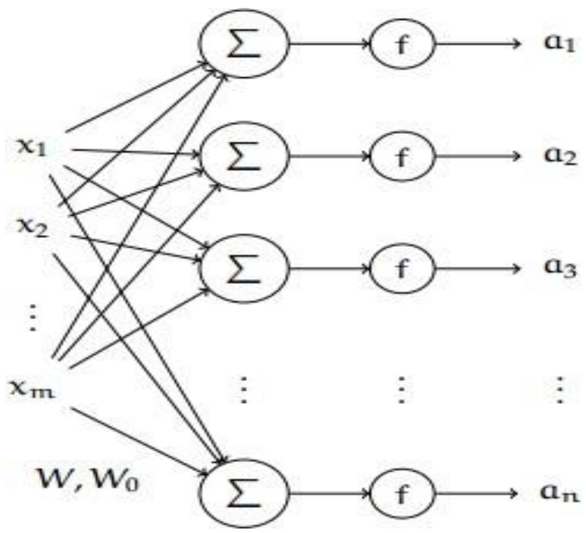
Figure 7: *A single Neuron.*



2.1.6 Neural Networks

Multiple connected neurons make up a neural network, they are structure into layers.In convolutional neural networks data flow one way, only in the forward direction makes them to be called feed-forward networks (Rawat & Wang 2017).

Figure 8: *Single Layer of neurons.*



2.1.7 Activation Units

Relu, Sigmoid and Softmax are the three common activation units use in convolutional neural networks. Relu activation unit is a common activation unit of hidden layer neurons, and sigmoid activation is common for binary classification (Yes or No) and softmax for multi – class classification. The hidden layers are layers of neuron between the input and output layer of the neural network.

Rectified Linear Unit(Relu)

The Rectified Linear Unit(Relu) is a linear activation function with a negative input cutoff

$$ReLU(z) = \begin{cases} 0 \; if \; z < 0 \\ z \; otherwise \end{cases} = \max(0, z)$$

Sigmoid Activation

The Sigmoid Activation function is a nonlinear function that has an S shape characteristic curve with output between 0 and 1.

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

Softmax Activation

A Softmax Activation function takes in the outputs of the last layer of the neural network and creates a probability distribution of it. The probability distribution represents the multi class classification of the network.

$$\sigma(z)i = \frac{e^{zi}}{\sum_{J=}^{K} e^{zj}}$$

2.1 Research Models

Specifications

Table1:*EfficientNetB0 Model*

Layer (type)	Output Shape	Number of parameters
Efficientnetb0 (Functional) 238_layers	(None, 1, 1, 1280)	4049571
GlobalAveragePooling2D	(None, 1280)	0
Flatten layer	(None, 1280)	0
dropout_layer	(None,1280)	0
Output_layer_Softmax	(None, 4)	5124

Table 2: *EfficientNetB1 Model*

Layer (type)	Output Shape	Number of parameters
Efficientnetb1 (Functional) 340_layers	(None, 1, 1, 1280)	6575239
GlobalAveragePooling2D	(None, 1280)	0
Flatten layer	(None, 1280)	0
dropout_layer	(None,1280)	0
Output_layer_Softmax	(None, 4)	5124

Table 3: *EfficientNetB2 Model*

Layer (type)	Output Shape	Number of parameters
Efficientnetb2 (Functional) 340_layers	(None, 1, 1, 1408)	7768569
GlobalAveragePooling2D	(None, 1408)	0
Flatten layer	(None, 1408)	0
dropout_layer	(None,1408)	0
Output_layer_Softmax	(None, 4)	5636

Table 4: *EfficientNetB3 Model*

Layer (type)	Output Shape	Number of parameters
Efficientnetb2 (Functional) 340_layers	(None, 1, 1, 1536)	10783535
GlobalAveragePooling2D	(None, 1536)	0
Flatten layer	(None, 1536)	0
dropout_layer	(None,1536)	0
Output_layer_Softmax	(None, 4)	6148

Table 5: *AlexNet Model*

Layer (type)	Output Shape	Number of parameters
Convolution layer_1	(None, 8, 8, 96)	34944
batch_normalization_1	(None, 8, 8, 96)	384
Max pooling_1	(None, 4, 4, 96)	0
Convolution layer_2	(None, 4, 4, 256)	614656
batch_normalization_2	(None, 4, 4, 256	1024
Max pooling_2	(None, 2, 2, 256)	0
Convolution layer_3	(None, 2, 2, 384)	885120
batch_normalization_3	(None, 2, 2, 384)	1536
Convolution layer_4	(None, 2, 2, 384)	1327488
batch_normalization_4	(None, 2, 2, 384)	1536
Convolution layer_5	(None, 2, 2, 256)	884992
batch_normalization_5	(None, 2, 2, 256)	1024
Max pooling_3	(None, 1, 1, 256)	0
Flatten layer	(None, 256)	0
Fully-Connect-layer_1	(None, 4096)	1052672
batch_normalization_6	(None, 4096)	16384
dropout_1	(None, 4096)	0
Fully-Connect-layer_2	(None, 4096)	16781312
batch_normalization_7	(None, 4096)	16384
dropout_2	(None, 4096)	0
Fully-Connect-layer_3	(None, 1000)	4097000
batch_normalization_8	(None, 1000)	4000
dropout_3	(None, 1000)	0
Output_layer_Softmax	(None, 4)	4004
batch_normalization_9	(None, 4)	16

Table 6: *VGGNET_16 Model*

Layer (type)	Output Shape	Number of parameters
vgg16 (Functional)	(None, 1, 1, 512)	14714688
Flatten	(None, 512)	0
Fully-Connect-layer_1	(None, 32)	16416
Fully-Connect-layer_2	(None, 16)	528
Output_layer_softmax	(None, 4)	68

Table 7: *VGGNET_19 Model*

Layer (type)	Output Shape	Number of parameters
Vgg19 (Functional)	(None, 1, 1, 512)	20024384
GlobalAveragePooling2D	(None, 512)	0
Flatten layer	(None, 512)	0
dropout_layer	(None,512)	0
Output_layer_Softmax	(None, 4)	2054

2.2 Related Research

The authors of this research (Akinyelu et A1., 2022) claimed that with the used of state of the art Convolutional Neural Network models, the detection of Braintumors from MRI images can be done with high accuracy. In their study, two different dataset types are examined utilizing cutting-edge CNN models. MRI images of both normal and affected brain scans are included in one dataset (binary), whereas all images of affected brain scans identified as glioma, meningioma, or pituitary are included in another dataset (multi-class). The models utilize for their studies, involves both random weight initialization and transfer learning using pre- trained weights from ImageNet. For a fair comparison, the experimental setting for each model in their study is the same. The EfficientNetB5 architecture surpasses all cutting edge models in the classification of normal and affected MRI images of brain scans in the binary dataset with the proposed methodologies in the study, with an accuracy of 99.75% and 98.61% accuracy for the multi-class dataset.

In (Febrianto et A1., 2020) the Authors describes Deep learning as a practicaland effective technique for classifying images and hypothesize it has a valuable tool for Brain tumor detection from MRI images. In their study to investigate their hypothesis, they tested two CNN models to evaluate which was the best one for classifying tumors in brain MRI images. After training CNN, they achieve prediction with an accuracy of up to 93%.

In (Siddique et A1., 2010) utilized a deep convolutional neural network (DCNN) to detect brain tumors from MR images. The dataset utilize in their study consists of 253 brain MRI scans, 155 of which had Brain tumors, according to their article. With an overall accuracy of 96%, their Deep Convolutional neural network model is able to identify the MRI images that include affected brains scans from normal brain scans. From their test dataset evaluations, they concluded that their model performed better for the diagnosis of brain tumors than the currentlyused traditional methods (Precision = 0.93, Sensitivity = 1.00, and F1-score = 0.97).

Additionally, the suggested model's average Cohen's Kappa, AUC, and precision-recall scores are 0.93, 0.91, and 0.95, respectively.

In (Rai et A1., 2020) emphasizes of the importance of early detection and classification of malignancies in the human brain from MRI images, stating how crucial it is for the diagnosis of such illnesses. Their study introduces the U-Net (LU-Net), a revolutionary Deep Neural network for tumor detection that has fewer layers and a simpler design. Their task entails the 27lassification of 253 high- resolution brain MRI images into normal and affected categories. First, the MRI images were downsized, cropped, pre-processed, and enhanced for quick and effective deep learning training. Utilizing five different statistical assessment metrics—Precision, Recall, Specificity, F-score, and Accuracy—the performance of the Lu-Net model is assessed and contrasted with that of other two model types, Le- Net and VGG-16. The CNN models were developed, tested, and validated on enhanced images using 50 sets of untrained data. Le-Net, VGG-16, and their proposed model U-Net (LU-Net) all received overall accuracy ratings of 88%, 90%, and 98%, respectively.

This paper (Qodri et A1., 2021) discuss, categorization of MRI-based brain cancers using deep learning and transfer learning. How Different domains, functions,and distributions can be utilize in training and research due to transfer learning. An open dataset was used in this study. 253 images total, 98 of which are brain imaging without tumors and 155 of which are tumor images, make up the dataset. The approaches used in this paper are Residual Network (ResNet), Neural Architecture Search Network (NASNet), Xception, DenseNet, and Visual Geometry Group (VGG). The research findings indicate that the ResNet50 model and VGG16 both achieve accuracy scores of 96%. The outcomes show that transfer learning is capable of handling medical imaging.

In (Bingol et A1., 2021), MRI images of brain tumors were detected using deep learning architectures Alexnet, Googlenet, and Resnet50. The Resnet50 architecture produced the highest accuracy rate. The Authors plan to use Future research to increase the accuracy value of 85.71 percent that was discovered through the testing. In the near future, they strive to create a novel approach based on convolutional neural networks. With that model, they aim to surpass all existing deeplearning techniques in accuracy.

In (Brindha et A1., 2021) the practicalization of Machine Learning and Deep Learning algorithms as a tool for Brain tumor detection from MRI images. A self- defined artificial neural network (ANN) and a convolution neural network (CNN) areused in this proposed study to detect the existence of brain tumors, and their performance is examined.

In (Sharma et A1., 2014) acknowledge using manual observations strategy with a lot of data is not practicable for Brain tumor detection from Mri images. Therefore, automated tumor identification techniques are needed in order to free up radiologist time. Due to the intricacy and variety of tumors, detecting brain tumors with an MRI is a challenging undertaking. In their study, they use machine learning techniques to find tumors in brain MRIs. The proposed study may be broken down into three sections: applying pre-processing techniques to brain MRI images, extracting texture features using a Gray Level Co-occurrence Matrix (GLCM), and classifying the results using a machine learning method.

In (Mohsen et A1., 2018) utilize deep neural networks for classifying a dataset of 66 brain MRIs into 4 categories normal, glioblastoma, sarcoma, and metastatic bronchogenic carcinoma tumors they employed a Deep Neural Network classifier, one of the Deep Learning architectures. Principal components analysis (PCA), a potent feature extraction method, the discrete wavelet transforms (DWT), and the classifier were coupled, and the evaluation of the performance was quite positive across all performance criteria.

CHAPTER III

Methodology

3.1 Utilize Deep CNN models

Seven deep Convolutional Neural Networks models were utilize in this study for the propose of showing the effectiveness of deep convolutional neural networksin the field of diagnosing medical imaging specifically for brain tumor detection from Magnetic resonance imaging (MRI) images. The models EffficientNetB0, EfficientNetB1, EfficientNetB2, EfficientNetB3, AlexNet, VGG-16, and VGG- 16 have been utitlize for the research. Below are the specifics of these architectures:

Table 8: *Utilize Models*

Propose Models	**Number of Layers**
EfficientNetB0	238
EfficientNetB1	340
EfficientNetB2	340
EfficientNetB3	385
AlexNet	8
VGGNET16	16
VGGNET19	19

3.1.1 EfficientNetB0

EfficientNetB0 is the baseline for all efficientNet models. EfficientNet is a deep convolutional neural network introduction by Mingxing Tan and Quoc V. Le (2019), that apply uniform scaling to the depth, width and resolution of the Network, to increase the accuracy. EfficientNet uses a fix scaling coefficient, to scale the width ofthe network, the depth of the network and the resolution of the network. This approach of scaling depth, width and resolution uniformly has led efficientnet modelsto achieved high accuracy at great depth. EfficientNetB0 has 238 layers that make upits convolutional block. Base on the needs of this research, GlobalAveragePooling layer was added after the EfficientNetB0 convolutional block, a flatten layer, a dropout layer and an output layer of two or four neurons with softmax for activation base on the dataset structure (binary or multiclass). Categorical CrossEntropy loss is used to determine the loss of the network on prediction and Adam an alternative of

Stochastic Gradient Descent is use to minimize the loss by finding optimum value for weights and bias that will be update through back propagation.

3.1.2 EfficientNetB1

EfficientNetB1 is several layers deeper than EfficentNetb0, it has 340 layers within its functional convolutional block. The model works on the same principle of uniform scaling of depth, width and resolution (Mingxing et A1., 2019). Base on the needs of this research, GlobalAveragePooling layer was added after the EfficientNetB1 convolutional block, a flatten layer, a dropout layer and an output layer of two or four neurons with softmax for activation base on the dataset structure(binary or multiclass). Categorical CrossEntropy loss is used to determine the loss of the network on prediction and Adam an alternative of Stochastic Gradient Descentis use to minimize the loss by finding optimum value for weights and bias that will be update through back propagation.

3.1.3 EfficientNetB2

EfficientNetB2 is similar to EfficientNetB1; it has 340 layers but more channels within its functional convolutional block. EfficienNetB2 output a total of 1408 channels (Mingxing et A1., 2019). The model works on the same principle of uniform scaling of depth, width and resolution. Base on the needs of this research, GlobalAveragePooling layer was added after the EfficientNetB2 convolutional block, a flatten layer, a dropout layer and a output layer of four neurons with softmax for activation. Categorical CrossEntropy loss is used to determine the loss of the network on prediction and Adam an alternative to Stochastic Gradient Descent is useto minimize the loss by finding optimum value for weights and bias that will be update through back propagation.

3.1.4 EfficientNetB3

EfficientNetB3 is a scaled version of EfficientNetB0, it has 385 layers and more channels within its functional convolutional block. EfficienNetB3 output a totalof 1536 channels. The model works on the same principle of uniform scaling of depth, width and resolution (Mingxing et A1., 2019). Base on the needs of this research, GlobalAveragePooling layer was added after the EfficientNetB3 convolutional block, a flatten layer, a dropout layer and an output layer of two or four neurons with softmax for activation base on the dataset structure (binary or multiclass). Categorical CrossEntropy loss is used to determine the loss of the network on prediction and Adam an alternative of Stochastic Gradient Descent is useto minimize the loss by finding optimum value for weights and bias that will be update through back propagation.

3.1.5 AlexNet

AlexNet is an 8-layer deep convolutional neural network (CNN) that has been trainedon over 1 million images from the ImageNet database, which contains over 15 million high-resolution images labeled with 22,000 classes. It has a structure of eightlayers, comprising of five convolutional layers, and three fully connected layers. Themax-pooling operation is placed between the 1st and 2nd convolutional layers, 2nd and 3rd convolutional layers and between the fully connected layers and the 5th convolutional layer (Krizhevsky et A1., 2012). One can import a pre-trained version of the network. The image input size for Alex network use in this research is 32 x 32,with a 3 color channel. Base on the needs of this research a flatten layer, a dropout layer and an output layer of two or four neurons with softmax for activation base on the dataset structure (binary or multiclass). Categorical CrossEntropy loss is used to determine the loss of the network on prediction and Adam an alternative of Stochastic Gradient Descent is use to minimize the loss by finding optimum value for weights and bias that will be update through back propagation.

3.1.6 VGGNET-16

VGG, which stands for Visual Geometry Group, is a deeper convolutional neural network (CNN) than AlexNet, with a greater number of layers. It has been trained onmore than 1 million images from the ImageNet database, which contains over 15 million high-resolution images labeled with 22,000 classes. One can import a pre- trained version of the network. VGGNET consist of VGG-16 or VGG-19 consisting of 16 and 19 layers (Simonyan et A1., 2014). VGG_16 has 13 convolutional layers with 512 output channels. Base on the needs of this research a flatten layer, a dropoutlayer and an output layer of two or four neurons with softmax for activation base on the dataset structure (binary or multiclass). Categorical CrossEntropy loss is used to determine the loss of the network on prediction and Adam an alternative of stochastic Gradient Descent to minimize the loss by finding optimum value for weights and bias that will be update through back propagation.

3.1.9 VGGNET-19

VGG19 is a variant of VGG with more layers, it has 19 convolutional layers. Its deeper architecture makes it more accurate and suitable for handling complex object recognition and data training tasks as compared to VGG16 (Simonyan et A1., 2014). A pre-trained version of the network, trained on over 1 million images from the ImageNet database, which contains over 15 million high-resolution images labeled with 22,000 classes, can be imported. Base on the needs of this research a flatten layer, a dropout layer and an output layer of two or four neurons with softmax for activation base on the dataset structure (binary or multiclass). Categorical CrossEntropy loss is used to determine the loss of the network on prediction and Adam an alternative of Stochastic Gradient Descent is use to minimize the loss by finding optimum value for weights and bias that will be update through back propagation.

3.2 Performance Metrics

Performance Metrics is a significant part in the machine learning design process; it gives the effectiveness of the machine learning model. There are multiple metric values that describe how effective a machine learning model is, the metrics use in this research are; sensitivity, precision, f1, classification accuracy and trainingaccuracy.

3.2.1 Confusion Matrix

The Confusion Matrix is a useful tool for evaluating the performance of a machine learning model. It is a table that compares the model's predicted classes to the actual classes, and it displays the results in terms of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). It provides a simpleand easy way to evaluate the effectiveness of a model (Müller et A1., 2016).

Figure 9: *Confusion Matrix*

		Actual		
		1	**0**	
Predicted	**1**	True Positives (TP)	False Positives (FP)	
	0	False Negatives (FN)	True Negatives (TN)	

3.2.2 Precision

The precision of a model is a measure of its ability to correctly identify positive instances, it is calculated by taking the ratio of the number of True Positives(TP) to the sum of True Positives (TP) and False Positives (FP).

P = TP/(TP + FP)

3.2.3 Sensitivity

The sensitivity or recall of a model is a measure of its ability to correctly identify all positive instances, it is calculated by taking the ratio of the number of True Positives (TP) to the sum of True Positives (TP) and False Negatives (FN).

SENS = TP/(TP + FN)

3.2.4 Specificity

The Specificity of a model is a measure of its ability to correctly identify negative instances, it is calculated by taking the ratio of the number of True Negatives (TN) to the sum of True Negatives (TN) and False Positives (FP).

Spe = TN / (TN + FP)

3.2.5 F1 Score

The f1 score of the model is the multiplication of 2 by the multiplication of precision and sensitivity divided by the sum of precision and sensitivity.

F1 = 2 * ((precision * sensitivity)/ (precision + sensitivity))

3.2.6 Classification Accuracy

The classification accuracy of the model is the sum of the True Positives (TP)and True Negatives (TN) divided by the sum of the True Positives (TP), False Positives (FP), False Negatives (FN) and True Negatives (TN).

Accuracy = TP + TN/ (TP + FP + FN + TN)

3.2.7 Training accuracy

The training accuracy of the model is how well the model can perform classification on the training data.

CHAPTER IV

DataSets

4.1 DataStructure

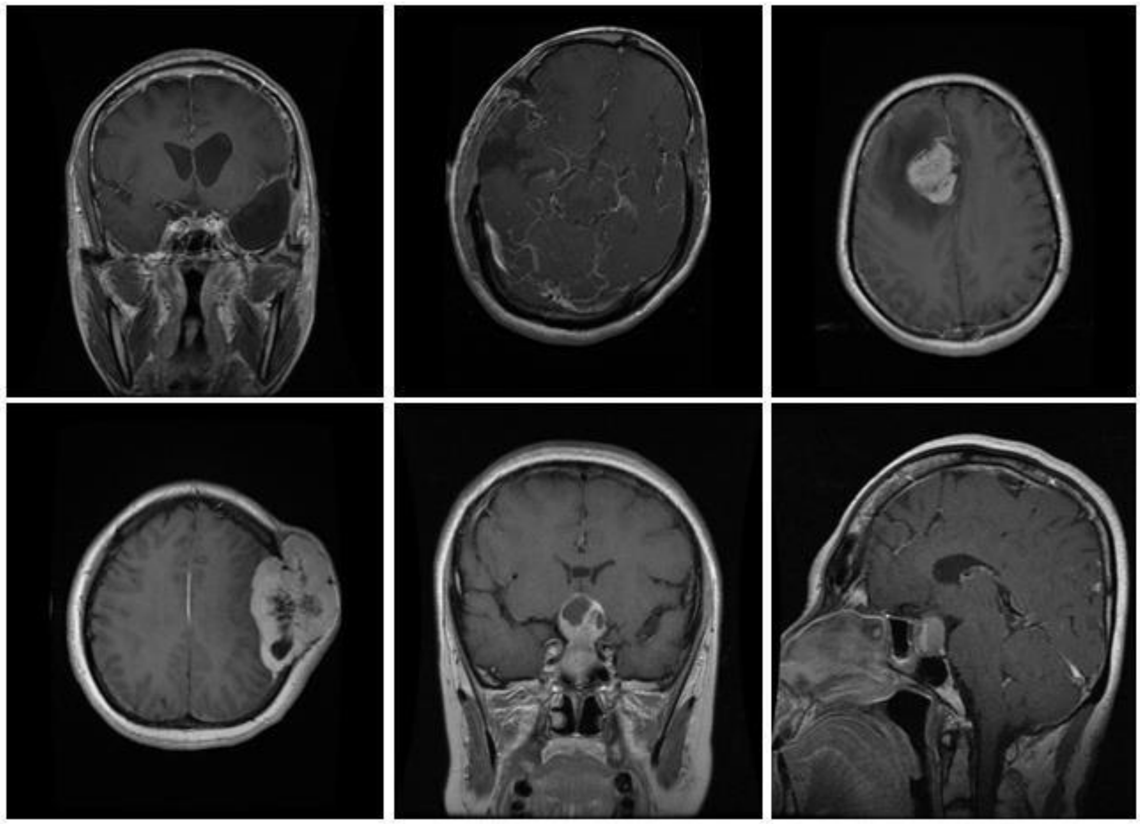
Table 9: *Datasets*

Binary Classification Datasets			Multiclass classification Dataset		
Dataset A	98 Negatives (Normal Brain scans) 155 Positives (Affected Brain scans)	Source Kaggle	**Dataset C** **Section 1** **Testing**	404(Normal Brain Scans) 300 (Affected with Glioma) 306(Affected with Meningioma) 300 (Affected with Pituitary)	Source Kaggle
Dataset B	1500 Negatives (Normal Brain scans) 1500 Positives (Affected Brain scans)	Source Kaggle	**Dataset C** **Section 2** **Training**	1595(Normal Brain Scans) 1321 (Affected with Glioma) 1339(Affected with Meningioma) 1457(Affected with Pituitary)	

Three datasets were collected and prepared for use. The datasets were labeledas Dataset A, Dataset B and Dataset C, in the order they were collected. Dataset A has two classes, one for pictures of brains with tumors and one for pictures without tumors, and a total of 253 brain scan images. Dataset B also has two classes, one for pictures of brains with tumors and one for pictures without tumors, and a total of 3000 brain scan images. Dataset C has four classes, one for pictures of brains withouttumors, and three for different types of brain tumors:

Glioma, Meningioma, and Pituitary tumors. This last dataset contains 7022 brain scan images, divided into atraining and testing section.

Figure 10: *Datasets Samples*



4.1.1 Data Sets

The research utilizes three datasets Dataset A, Dataset B and Dataset C in its study. A total of 10,276 images are use for training, testing and validating the models effectiveness.

4.1.1.1 Dataset A

Dataset A is a collection of MRI images of brain scans that is specifically designed for binary classification tasks. The dataset contains a total of 253 images, which are divided into two distinct classes: "normal" and "affected." The "normal" class, also referred to as the "negative" class, comprises 98 images of brain scans that have been determined to be free from any form of brain tumors. On the other hand, the "affected" class, also known as the "positive" class, Includes 155 images of brain scans that have been identified as containing signs of some sort of brain tumors.

4.1.1.2 Dataset B

Dataset B is a collection of MRI images of brain scans, specifically designed for binary classification tasks. The dataset contains a total of 3000 images, which are divided into two distinct classes: "normal" and "affected." The "normal" class, also referred to as the "negative" class, comprises 1500 images of brain scans that have been determined to be free from any form of brain tumors. On the other hand, the "affected" class, also known as the "positive" class, includes 1500 images of brain scans that have been identified as containing signs of some sort of brain tumor. Eachimage in the dataset has been specifically chosen and labeled to belong to one of these two classes. This dataset is useful for training and evaluating models that can automatically classify brain scans as normal or affected.

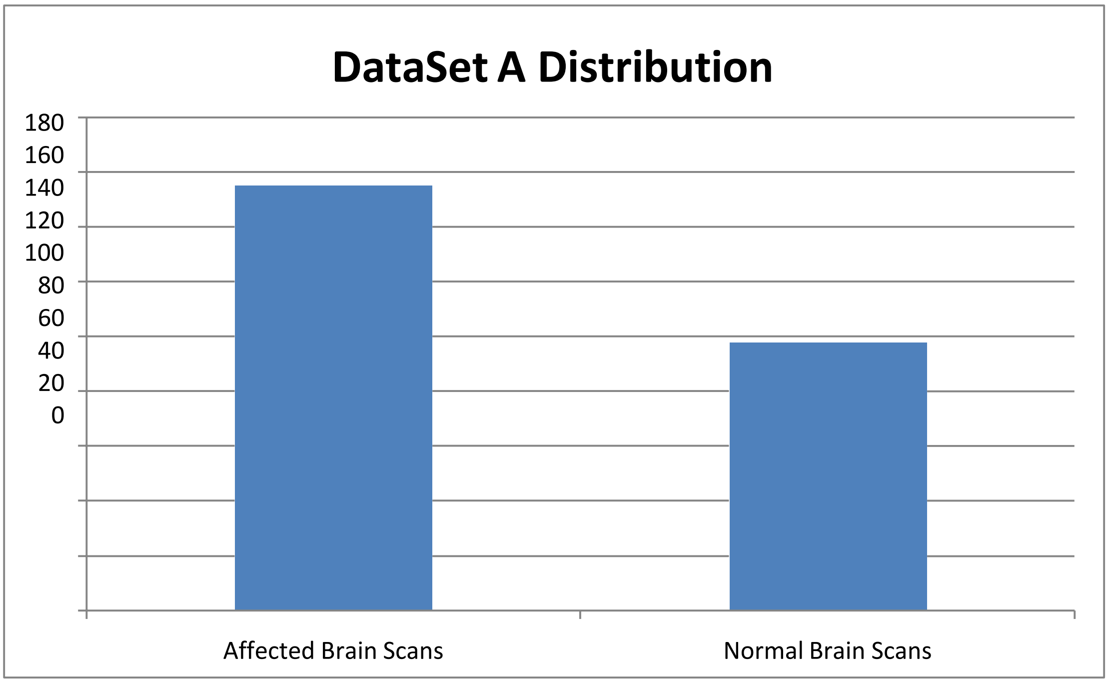
4.1.1.3 Dataset C

Dataset C is a collection of MRI images of brain scans, specifically designed for multiclass classification tasks. The dataset contains a total of 7022 images, whichare divided into two sections: a training set and a testing set. The training set is comprised of 5712 images and is used to train a model for the classification task. Thefour different classes of images in the training set are: "Normal" (i.e. brain scans without any tumors), "Glioma" (brain scans with a specific type of brain tumor), "Meningioma" (brain scans with a different type of brain tumor) and "Pituitary" (brain scans with tumors located in the pituitary gland). The testing set is made up of 1310 images, which is used to evaluate the performance of the trained model. The testing set also contains the same four classes of images as the training set. The goal of this Dataset is to be use for classification task to train a model that can accurately distinguish between these four different classes of brain scans, based on their visual features. This dataset is useful for training and evaluating models that can automatically classify brain scans into different tumor types, which is a common taskin medical imaging and the dataset may also be valuable for researchers studying brain tumors and the different types of tumors that can occur in the brain.

Table 10: *Dataset A data distribution*

Brain Scans Category	Class Data Distribution
Affected Brain Scans	**155**
Normal Brain Scans	**98**
Total	**253**

Figure 11: *Dataset A Distribution*

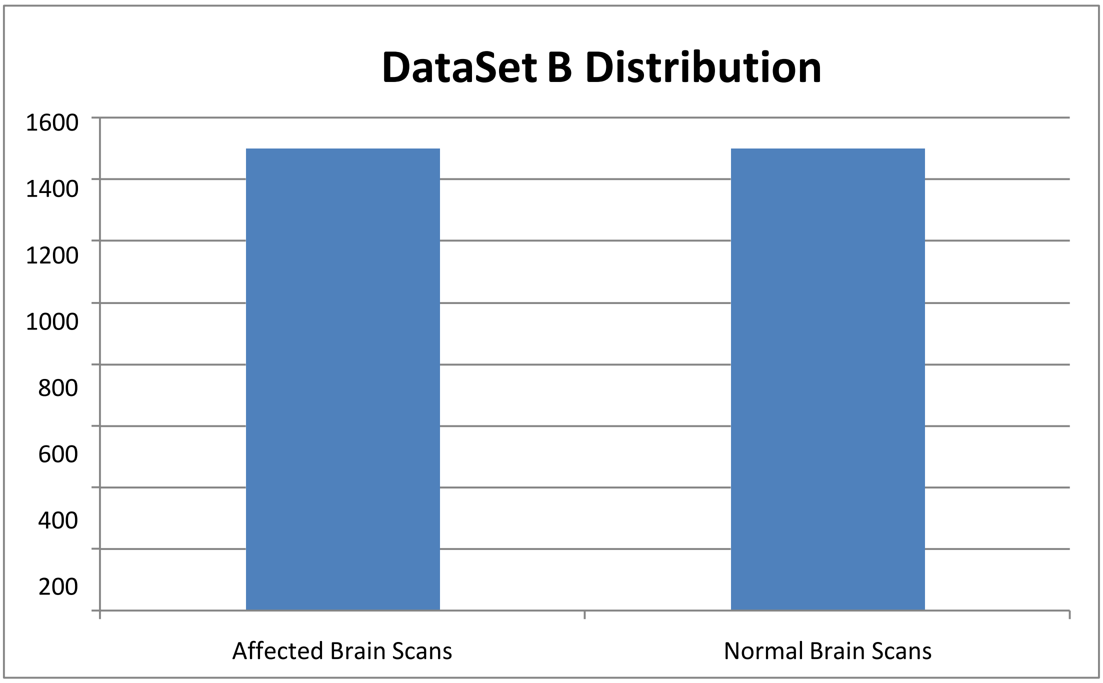


The Data Distribution in Table 10 and figure 11 shows the data distribution within Dataset A, the moderate imbalance of the dataset and shows that 61.3% of the data are affected, while 38.7% Data are normal.

Table 11: *Dataset B data distribution*

Brain Scans Category	**Classes Data Distribution**
Affected Brain Scans	**1500**
Normal Brain Scans	**1500**
Total	**3000**

Figure 12: *Dataset B Distribution*

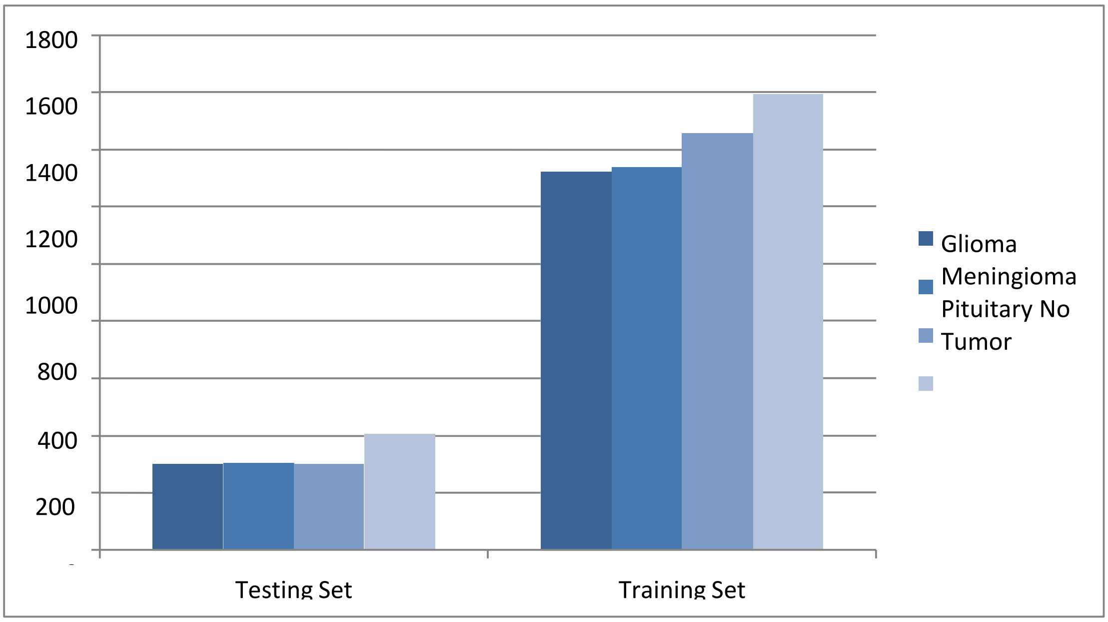


The Data Distribution in Table 11 and figure 12 shows the data distribution within Dataset B, the balance in Dataset B and shows that 50.0% of the data are affected, while 50.0% Data are normal.

Table 12: *Dataset C data distribution*

Brain Scans Category	Test Set Distribution	Training Set Distributio n
Affected with Glioma	**300**	**1321**
Affected with Meningioma	**306**	**1339**
Affected with Pituitary	**300**	**1457**
Normal Brain Scans	**404**	**1595**
Total	**1310**	**5712**

Figure 13: *Dataset C Distribution*



The Data Distribution in Table 12 and Figure 13 shows the data distribution within Dataset C, shows how moderately balance the Dataset training and testing section is.

4.2 Data Preprocessing

4.2.1 Image Resizing

In this study, seven convolutional Neural Network models were utilized to classify MRI brain images. Due to the computational power require by require by deep learning models on large images, image downsizing were use for the training of all deep learning models utilize in the study.

4.2.1 Normalization

Normalization is the process used to eliminate data from insignificant images and reduce data duplication. In this instance, the PCA (Principal Component Analysis) approach was used to normalize. Using PCA, a massive data variable is reduced to a tiny data variable while the majority of the data is preserved. Creating and combiningEigen flat fields to normalize the projection of Brain MRI images. Then, dynamic flat fields are used to decrease the systematic errors of intensity normalization projection. The Keras ImageDataGenerator class was used to complete this task. By turning rescaled input to a ratio that might be multiplied by each pixel, normalizationapproaches restrict data to a scale of 0 to 1.

CHAPTER V
Experiment One Binary Classifications

This chapter gives the findings of all utilize models in this research for classifications of MRI images of brain scans with a binary data structure.

For the binary classification experiment, Images from Dataset B serves as thetraining images for all deep convolution neural network models use in this research, for binary classifications of MRI images of brain tumors. Dataset A is use for the evaluation of the trained models.

5.1 Binary Classifications experiment data distribution

For the effectiveness of the experiment a total of 3000 MRI images of brain scans were used to trained each utilize deep convolutional neural network model anda total of 253 MRI images of brain scans were use for evaluations. The training images consists of 1500 negative images (Normal brain scans) and 1500 positive images(Affected brain scans). The evaluation images consists of 98 negative images(Normal brain scans) and 155

Table 13: *Training and evaluation data distribution*

Brain Scans Category	**Training**	**Evaluation**
Negative(Normal brain scans)	**1500**	**98**
Positive(Affected brain scans)	**1500**	**155**
Total	**3000**	**253**

5.2 Binary classification Experiment One Evaluations Results

Table 14: *Models Performance Experiment One.*

Models	AUC	ACC	SENSIVITY	SPEC	F1 score
EfficientNetB0	100%	100%	100%	100%	100%
EfficientNetB1	99.49%	99.60%	99.50%	99.40%	99.50 %
EfficientNetB2	99.35%	99.20%	99.50%	100%	99.00%
EfficientNetB3	98.42%	98.52%	98.50%	99.30%	98.50%
AlexNet	98.47%	98.81%	98.50%	98.10%	98.50%
VggNet16	97.87%	97.63%	98.0%	99.26%	97.50%
VggNet19	98.70%	98.42%	98.50%	100%	98.50%

Table 15: *Models precision on predicting Affected and Normal brain scans.*

Models	Normal Brain Scans Predicted Correctly	Affected Brain Scans Predicted Correctly
EfficientNetB0	100%	100%
EfficientNetB1	100%	99.4%
EfficientNetB2	98.0%	100%
EfficientNetB3	97.0%	99.3%
AlexNet	100%	98.1%
VggNet16	95.1%	99.3%
VggNet19	96.1%	100%

Figure 14: *Experiment One Evaluation Results Chart*

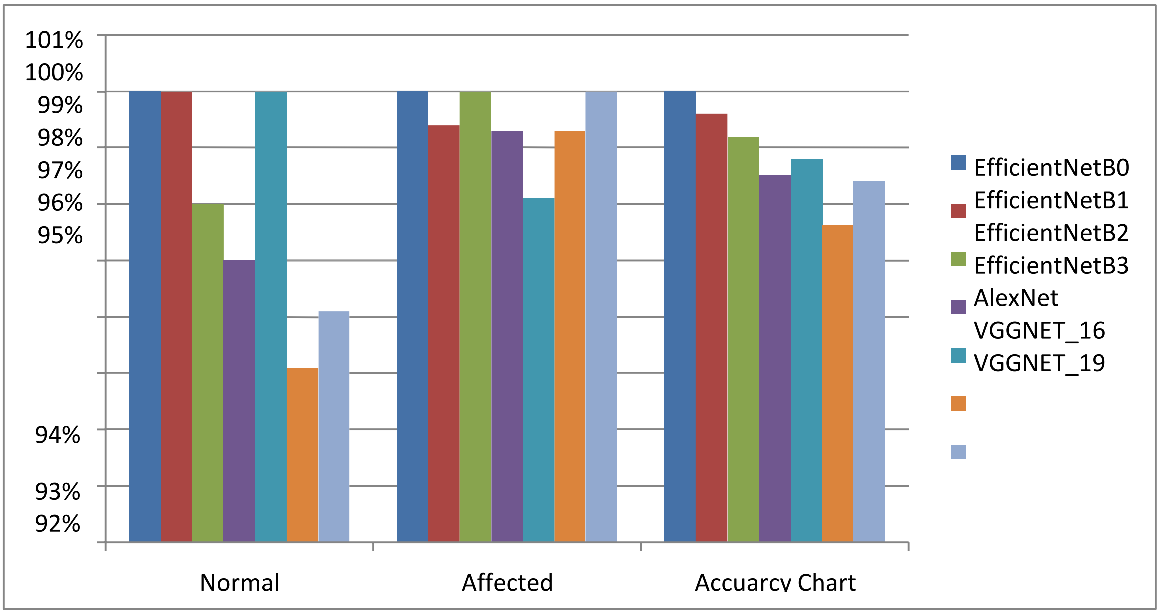


Table 16: *Binary Classification Dataset A and Dataset B.*

Worsks	Models	AUC	ACC	SENSIVITY	SPEC	F1 score
Binary Classification						
Md.Ahamed, A.Sardia(2022)	EffNet with Transfer Learning	--------	99.75%	99.76%	---	99.74%
DC Febrianto etal(2020)	2 covolution block,CNN	--------	93.38%	---------	-----	93.15%
Siddique, A.B.et al(2010)	DCNN (VGG16)	------	96.0%	-------	----	------
Rai, M.H. & Chatterjee, K.(2020)	LU-Net	--------	98.0%	100%	95%	98.0%
Qodri, K.N., Soesanti, I., & Nugroho.(2021).	ResNet50	--------	96.0%	94.0%	70%	-------
BINGOL, H., &ALATAS, B.(2021)	ResNet50	-------	85.71%	82.35%	87.5%	80.0%
Brindha, P.G et al. (2021)	CNN, method	--------	94.0%	--------	-------	89.40%
This study best Results	EFFNETB 0	100%	100%	100%	100%	100%

5.2.1 Binary Classification Experiment Evaluations Results Analysis.

The Evaluation results above presents the performance of several different models on the binary classification task. The models are EfficientNetB0, EfficientNetB1, EfficientNetB2, EfficientNetB3, AlexNet, VggNet16, and VggNet19. Each row in the tables represents a specific model, and the columns represent different evaluation metrics. These metrics are used in this research to evaluate the performance of the machine learning models, particularly in the context of this classification problem.

The EfficientNetB0 model achieved an AUC of 100%, an ACC of 100%, a SENSITIVITY of 100%, a SPEC of 100% and a F1 score of 100%. These are all outstanding results, indicating that the EfficientNetB0 model performed exceptionally well on the classification task. It correctly classified all of the examples in the test set, and was able to perfectly distinguish between positive and negative examples.

The other models also performed well on the classification task, with the EfficientNetB1 model achieving an AUC of 99.49%, an ACC of 99.60%, a SENSITIVITY of 99.50%, a SPEC of 99.40% and a F1 score of 99.50%. Similarly, the EfficientNetB2 model achieved an AUC of 99.35%, an ACC of 99.20%, a SENSITIVITY of 99.50%, a SPEC of 100% and a F1 score of 99.00%. EfficientNetB3, AlexNet and VggNet19 achieved similarly high results, with AUC and F1 scores in the 98-99% range. On the other hand, VggNet16 did not perform aswell as other models in the table. It achieved an AUC of 97.87%, an ACC of 97.63%, a SENSITIVITY of 98.0%, a SPEC of 99.26% and a F1 score of 97.50%.

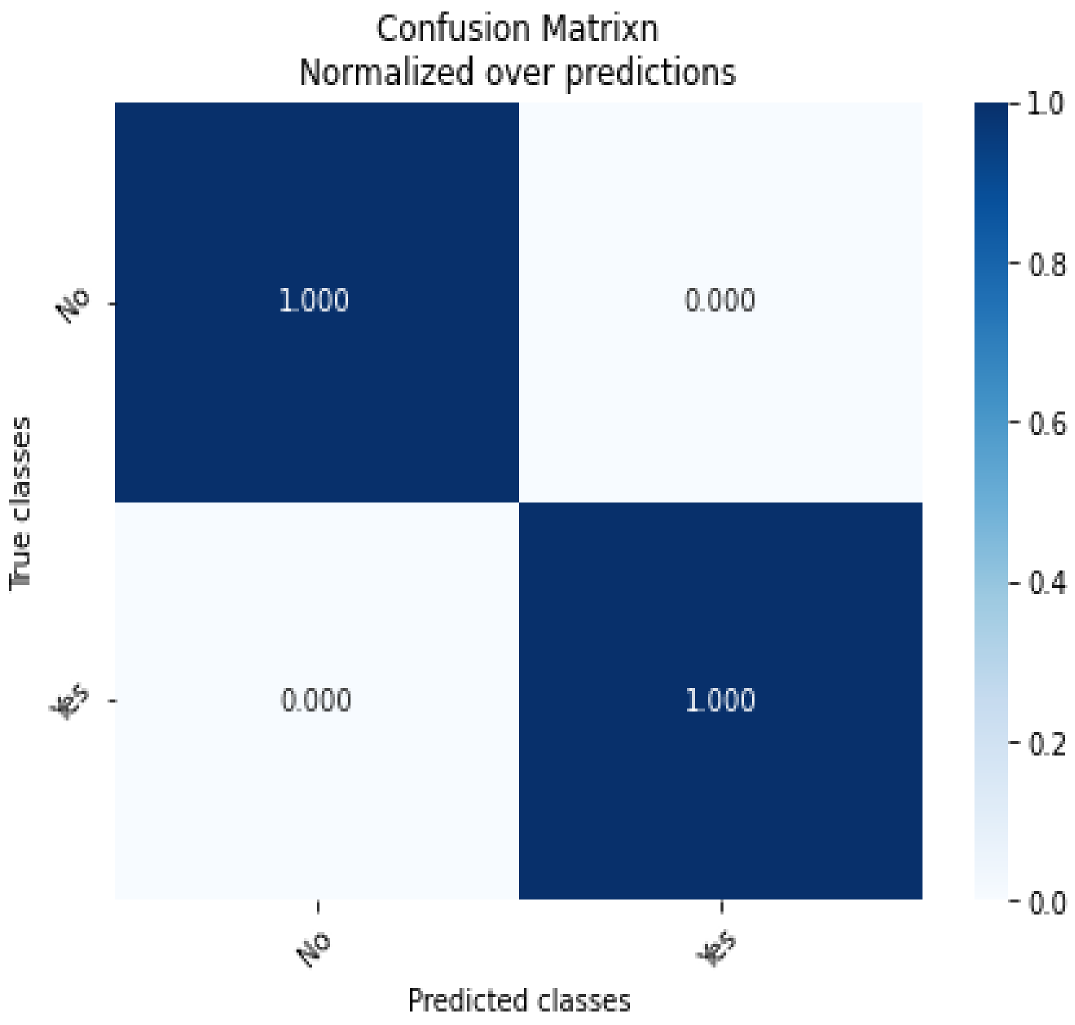
In conclusion, the results presented in this table indicate that all the models evaluated performed well on the binary classification task, with the EfficientNetB0 achieving the best results among all the models.

5.3 Binary Classification Experiment Analysis.

The experiment analysis of the binary classification data were carryout using confusion matrix for all models evaluation results.

5.3.1 EfficientNetB0 Experiment One Confusion Matrix

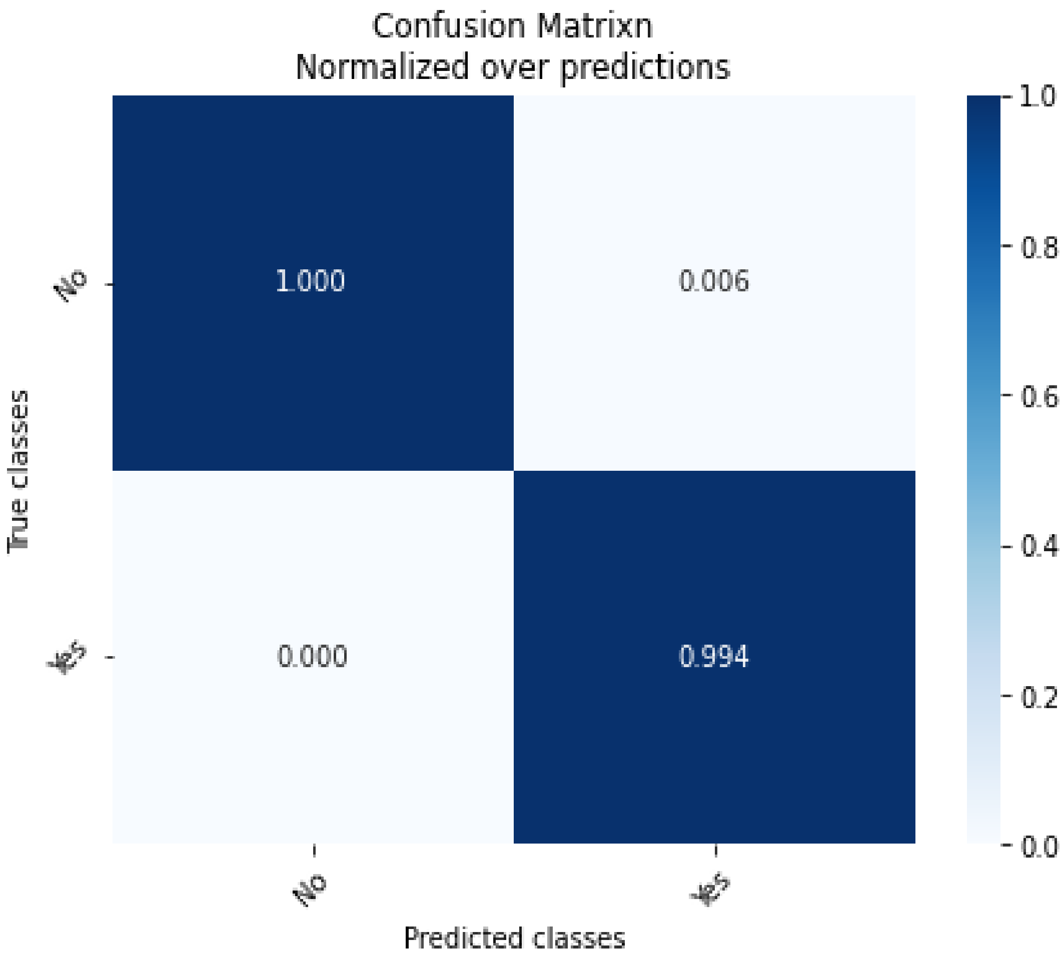
Figure 15: *Experiment One EfficientNetB0 Confusion Matrix*



The figure 15 shows the experiment confusion matrix of the EfficienNetB0, the confusion matrix shows how sensitive and precise the EfficientNetB0 model evaluated the evaluation data with 100% effectiveness.

5.3.2 EfficientNetB1 Experiment One Confusion Matrix

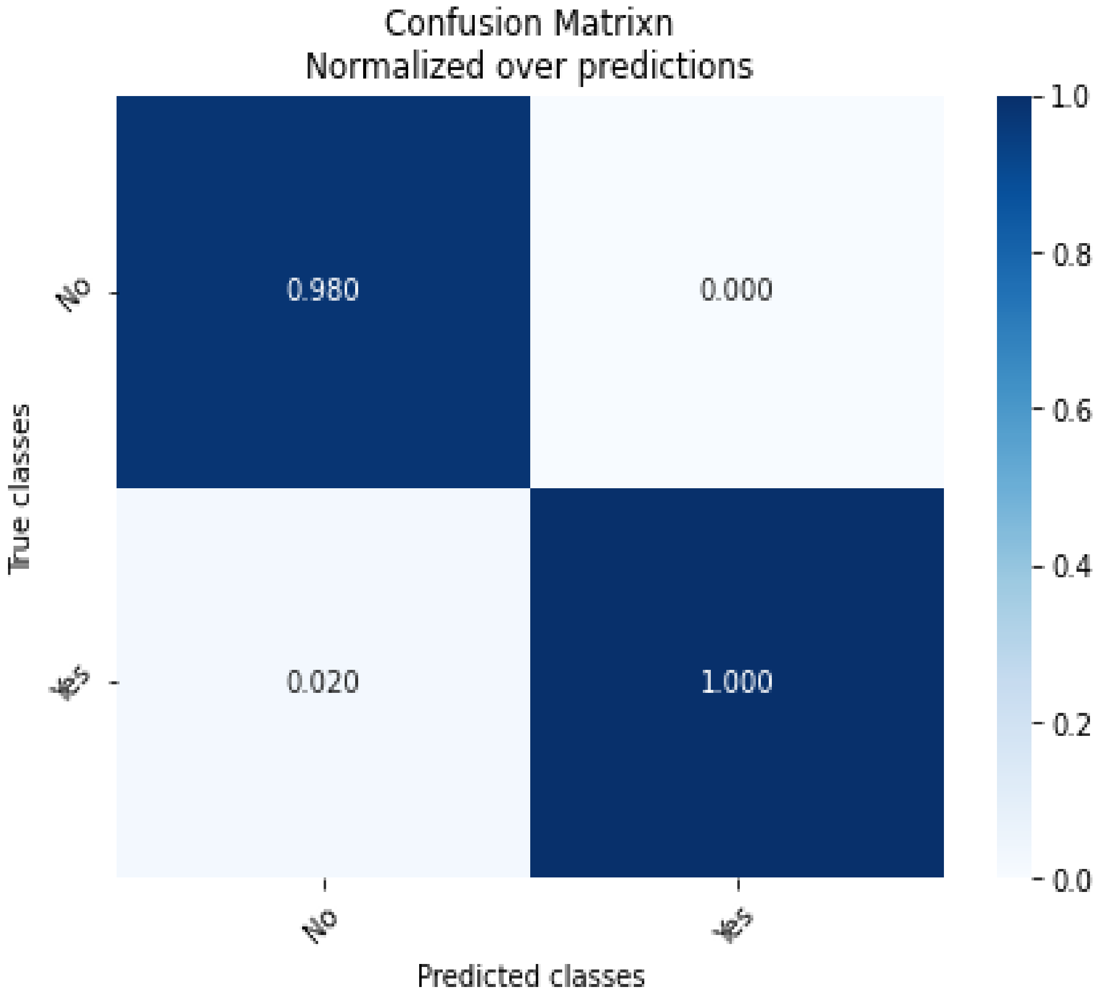
Figure 16: *Experiment One EfficientNetB1 Confusion Matrix*



The figure 16 shows that the EfficientNetB1 model has a high level of effectivenessin predicting normal brain scans, with 100% of the normal brain scans being correctly classified by the model. Additionally, the model has a high level of effectiveness in predicting affected brain scans, with 99.4% of the affected brain scans being correctly classified by the model. This indicates that the model is able toaccurately distinguish between normal and affected brain scans with a high degree ofprecision.

5.3.2 EfficientNetB1 Experiment One Confusion Matrix

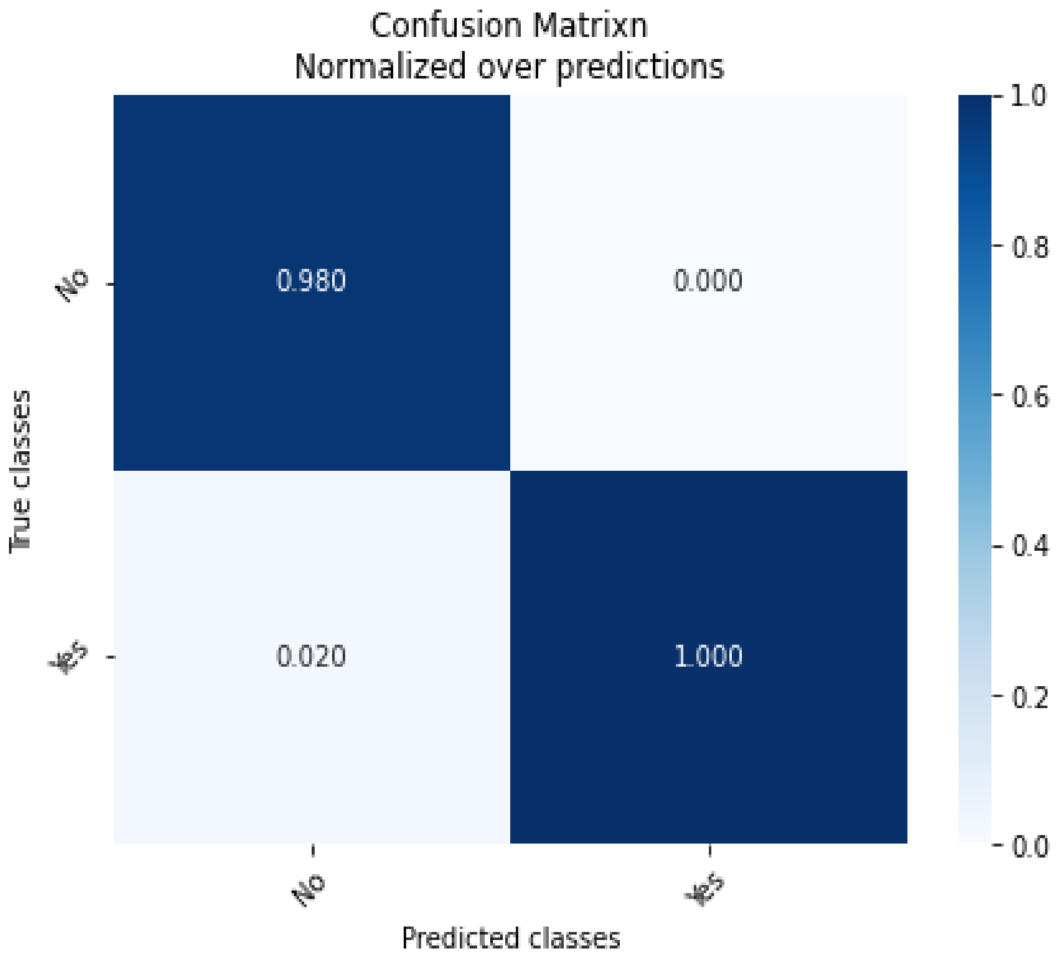
Figure 17: *Experiment One EfficientNetB2 Confusion Matrix*



The figure 17 shows that the EfficientNetB2 model has a high level of effectivenessin predicting normal brain scans, with 98.0% of the normal brain scans being correctly classified by the model. Additionally, the model has a high level of effectiveness in predicting affected brain scans, with 100% of the affected brain scans being correctly classified by the model. This indicates that the model is able toaccurately distinguish between normal and affected brain scans with a high degree ofprecision.

5.3.4 EfficientNetB3 Experiment One Confusion Matrix

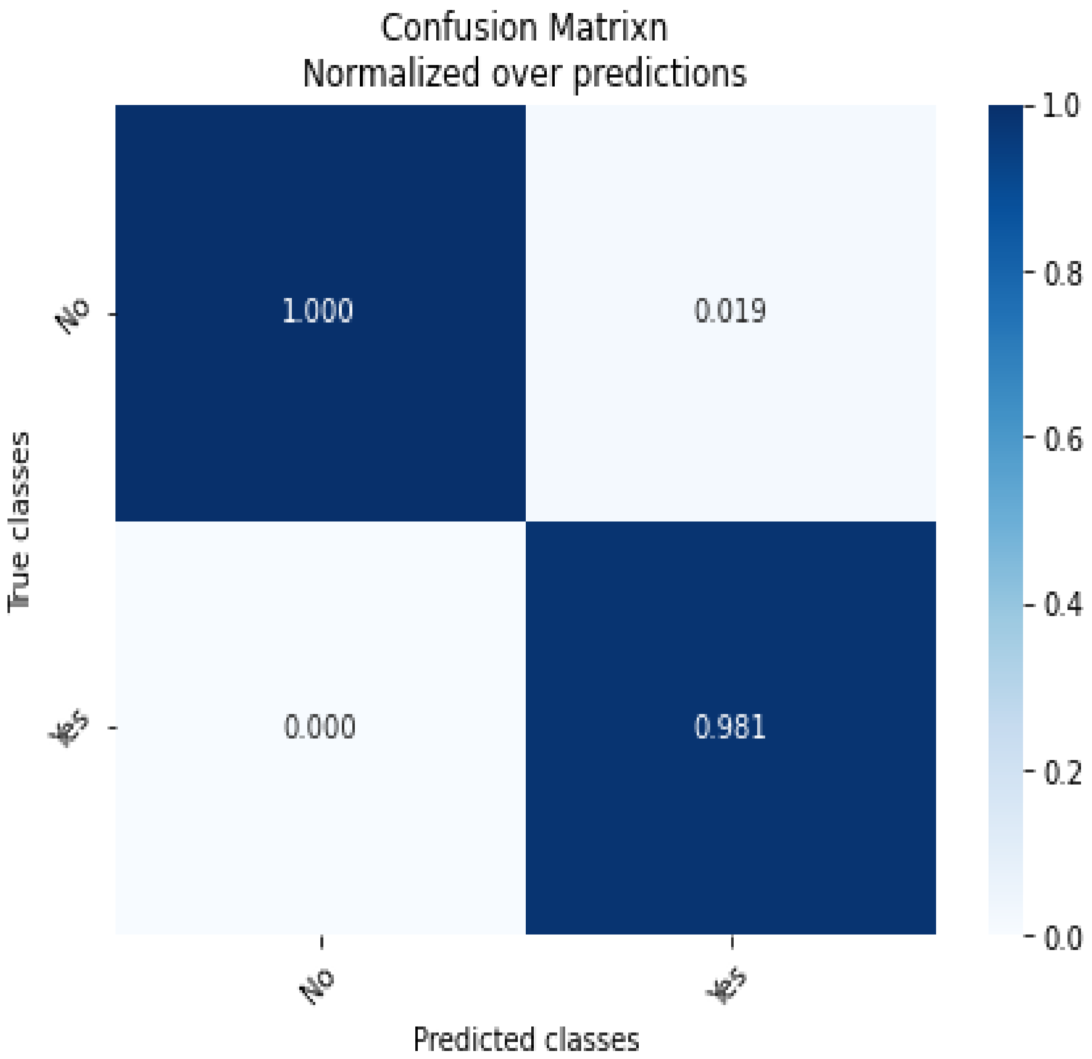
Figure 18: *Experiment One EfficientNetB3 Confusion Matrix*



The figure 18 shows that the EfficientNetB3 model has a high level of effectivenessin predicting normal brain scans, with 98.0% of the normal brain scans being correctly classified by the model. Additionally, the model has a high level of effectiveness in predicting affected brain scans, with 100% of the affected brain scans being correctly classified by the model. This indicates that the model is able toaccurately distinguish between normal and affected brain scans with a high degree ofprecision.

5.3.5 AlexNet Experiment One Confusion Matrix

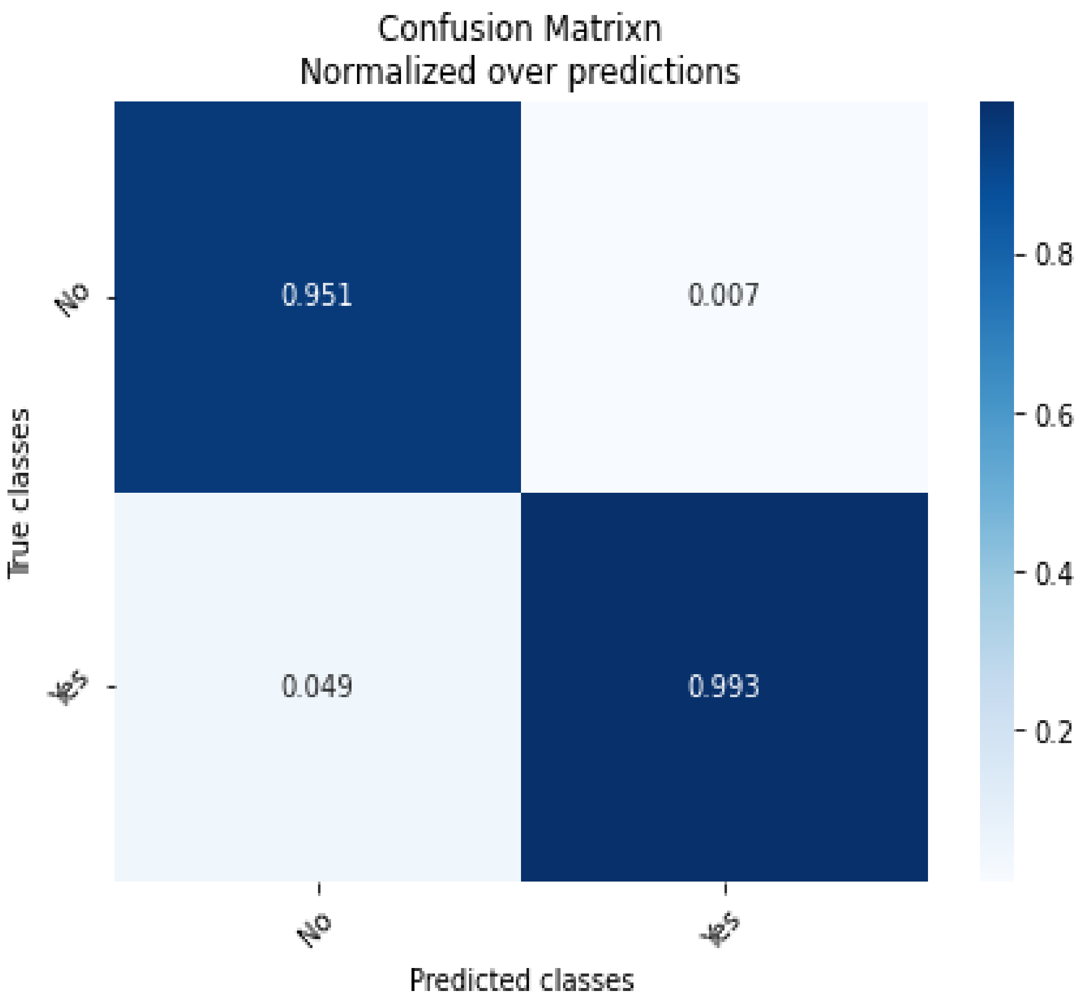
Figure 19: *Experiment One AlexNet Confusion Matrix*



The figure 19 shows that the AlexNet model has a high level of effectiveness in predicting normal brain scans, with 100% of the normal brain scans being correctly classified by the model. Additionally, the model has a high level of effectiveness in predicting affected brain scans, with 98.1% of the affected brain scans being correctly classified by the model. This indicates that the model is able to accurately distinguish between normal and affected brain scans with a high degree of precision.

5.3.6 VGGNET_16 Experiment One Confusion Matrix

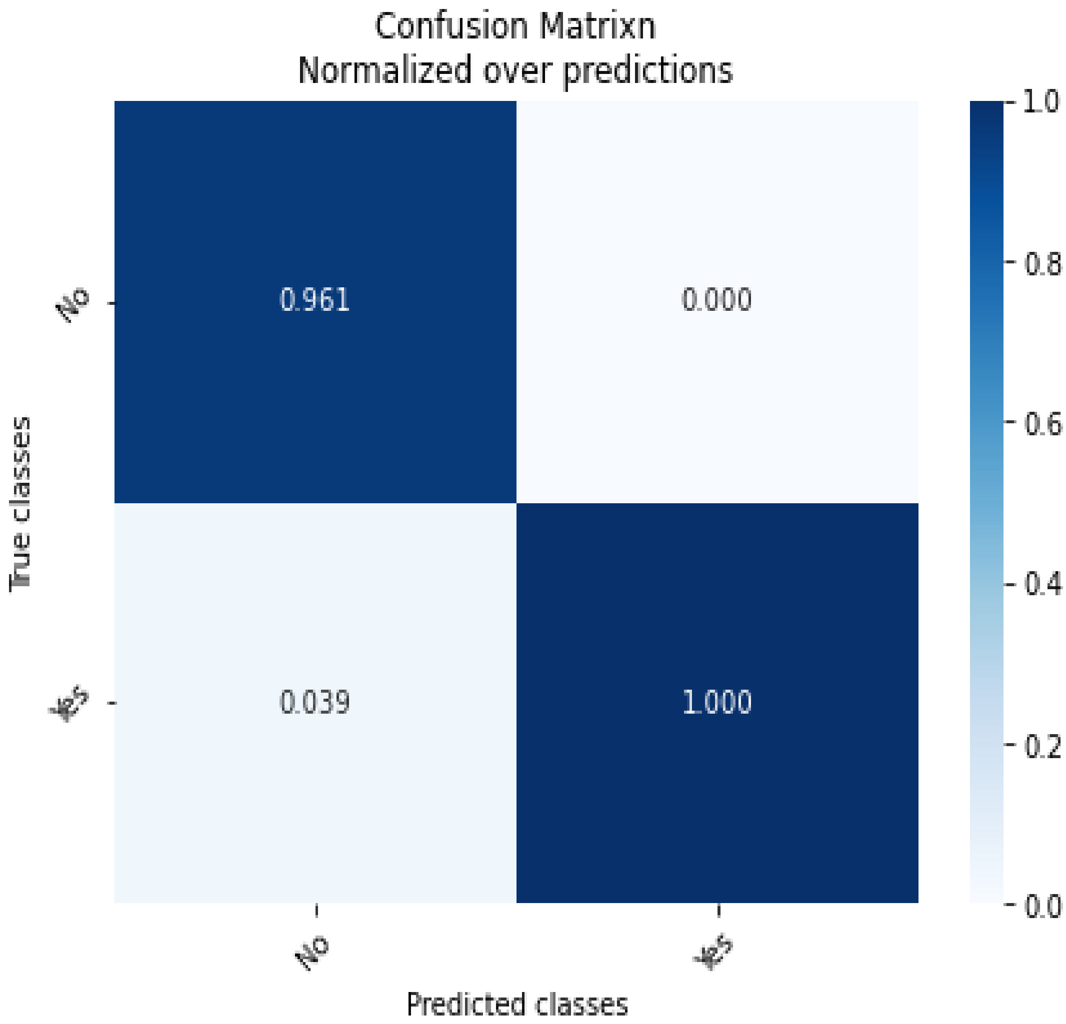
Figure 20: *Experiment One VGGNet_16 Confusion Matrix*



The figure 20 shows that the VGGNet_16 model has a high level of effectiveness inpredicting normal brain scans, with 95.1% of the normal brain scans being correctly classified by the model. Additionally, the model has a high level of effectiveness in predicting affected brain scans, with 99.3% of the affected brain scans being correctly classified by the model. This indicates that the model is able to accurately distinguish between normal and affected brain scans with a high degree of precision.

5.3.7 VGGNET_19 Experiment One Confusion Matrix

Figure 21: *Experiment One VGGNetB_19 Confusion Matrix*



The figure 21 shows that the VGGNet_19 model has a high level of effectiveness in predicting normal brain scans, with 96.1% of the normal brain scans being correctly classified by the model. Additionally, the model has a high level of effectiveness in predicting affected brain scans, with 100% of the affected brain scans being correctlyclassified by the model. This indicates that the model is able to accurately distinguish between normal and affected brain scans with a high degree of precision.

CHAPTER VI

Experiment Two Multiclass Classifications

This chapter gives the findings of all utilize models in this research for multiclass classifications of MRI images of brain scans.

For the multiclass classification experiment, Images from Dataset C training section serves as the training images for all deep convolution neural network modelsuse in this research, for multiclass classifications of MRI images of brain tumors. Dataset C testing section is use for the evaluation of the trained models.

6.1 Multiclass Classifications experiment data distribution

For the effectiveness of the experiment a total of 5712 MRI images of brain scans were used to trained each utilize deep convolutional neural network model anda total of 1310 MRI images of brain scans were use for evaluations. The training images consists of 1595 Normal brain scans, 1321 glioma tumor brain scans, 1339 meningioma tumor brain scans and 1457 pituitary tumor brain scans. The evaluationimages consists of 404 Normal brain scans, 300 glioma tumor brain scans, 306 meningioma tumor brain scans and 300 pituitary tumor brain scans.

Table 17: *Training and evaluation data distribution*

Brain Scans Category	**Training data**	**Evaluation data**
Normal brain scans	**1595**	**404**
Glioma brain tumor scans	**1321**	**300**
Meningioma tumor scans	**1339**	**306**
Pituitary tumor scans	**1457**	**300**
Total	**5712**	**404**

6.2 Multiclass Classification Experiment Evaluations

Table 18: *Models Performance Experiment Two.*

	AUC	ACC	SENSIVITY	SPEC	F1 score
EfficientNetB0	95.8%	96.57%	96.0%	95.66%	96.50%
EfficientNetB1	96.3%	97.0%	96.5%	96.12%	97.00%
EfficientNetB2	96.2%	96.8%	96.5%	95.94%	96.75
EfficientNetB3	93.1%	93.67%	93.2%	93.02%	93.25%
AlexNet	90.2%	90.62%	90.25%	90.28%	89.5%
VggNet16	85.8%	86.5%	85.75%	85.85%	85.5%
VggNet19	92.25%	92.45%	92.25%	92.26%	91.75%

Table 19: *Models precision on predicting Affected and Normal brain scans*

Model	Normal Brain Scans Predicted Correctly	Affected Brain Scans Predicted Correctly			
		Glioma	Meningioma	Pituitary	Total
EfficientNetB0	99.3%	98.2%	91.2%	98.4%	95.5%
EfficientNetB1	99.3%	96.6%	93.8%	97.7%	96.0%
EfficientNetB2	99.3%	97.8%	91.6%	98.0%	95.8%
EfficientNetB3	96.6%	85.5%	96.5%	96.3%	92.8%
AlexNet	97.8%	76.5%	96.6%	94.8%	89.2%
VggNet16	96.1%	81.4%	73.4%	89.7%	82.0%
VggNet19	98.3%	92.8%	92.0%	85.7%	90.2%

Figure 22: *Experiment Two Evaluation Results Chart*

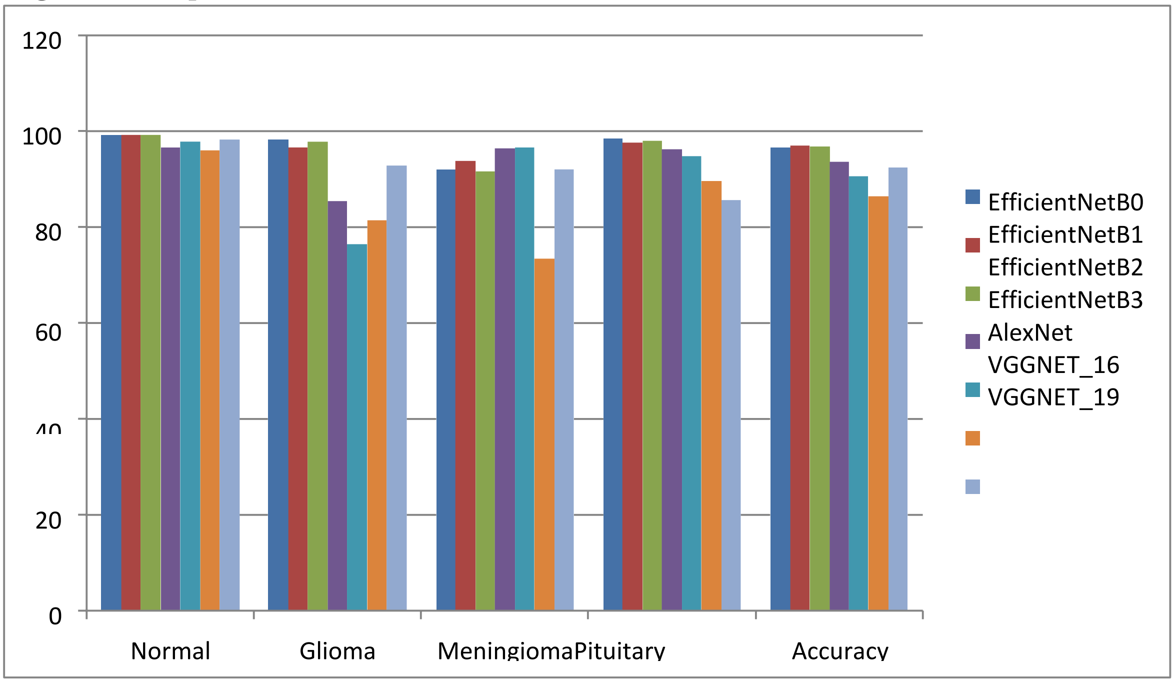


Table 20: ***Multiclass Classification Dataset C***

Multiclass Classification						
Md.Ahamed, A.Sardia(2022)	EffNet with Transfer Learning	--------	98.61%	98.33%	---	98.13%
Swati et al. (2019)	Fine Tuned VGG19	---------	94.8%	--------	------	-------
S. Deepak et al.(2019)	deep CNN-SVM	---------	97.1%	--------	-----	-------
This study best Results	EFFNETB 1	96.3%	97.0%	96.50%	96.12%	96.50%

6.2.1 Multiclass Classification Experiment Evaluations Results Analysis.

The Evaluation results above presents the performance of several different models on the multiclass classification task. The models are EfficientNetB0, EfficientNetB1, EfficientNetB2, EfficientNetB3, AlexNet, VggNet16, and VggNet19. Each row in the tables represents a specific model, and the columns represent different evaluation metrics. These metrics are used in this research to evaluate the performance of the machine learning models, particularly in the context of this classification problem.

EfficientNetB1 has an AUC of 96.3%, which indicates that it has a good ability to distinguish between the type of brain tumors and the normal class. Its ACC, Sensitivity, Specificity, and F1 scores are also high, at 97.0%, 96.5%, 96.12% and 97.0% respectively. This indicates that the model is able to correctly classify a high proportion of instances, and also performs well in terms of identifying positive instances while maintaining a high level of specificity.

EfficientNetB0 follows closely behind, with AUC of 95.8%, ACC of 96.57%, Sensitivity of 96.0%, Specificity of 95.66% and F1 score of 96.5%. EfficientNetB2 and B3 show similar performance, with AUC of 96.2% and 93.1%, ACC of 96.8% and 93.67%, Sensitivity of 96.5% and 93.2%, Specificity of 95.94% and 93.02% and F1 score of 96.75 and 93.25%.

On the other hand, AlexNet and VggNet16 performed lower than the EfficientNet models, with AUC of 90.2% and 85.8%, ACC of 90.62% and 86.5%, Sensitivity of 90.25% and 85.75%, Specificity of 90.28% and 85.85%, and F1 score of 89.5% and 85.5%. VggNet19 performed slightly better than AlexNet and VggNet16 with AUC of 92.25%, ACC of 92.45%, Sensitivity of 92.25%, Specificityof 92.26% and F1 score of 91.75%.

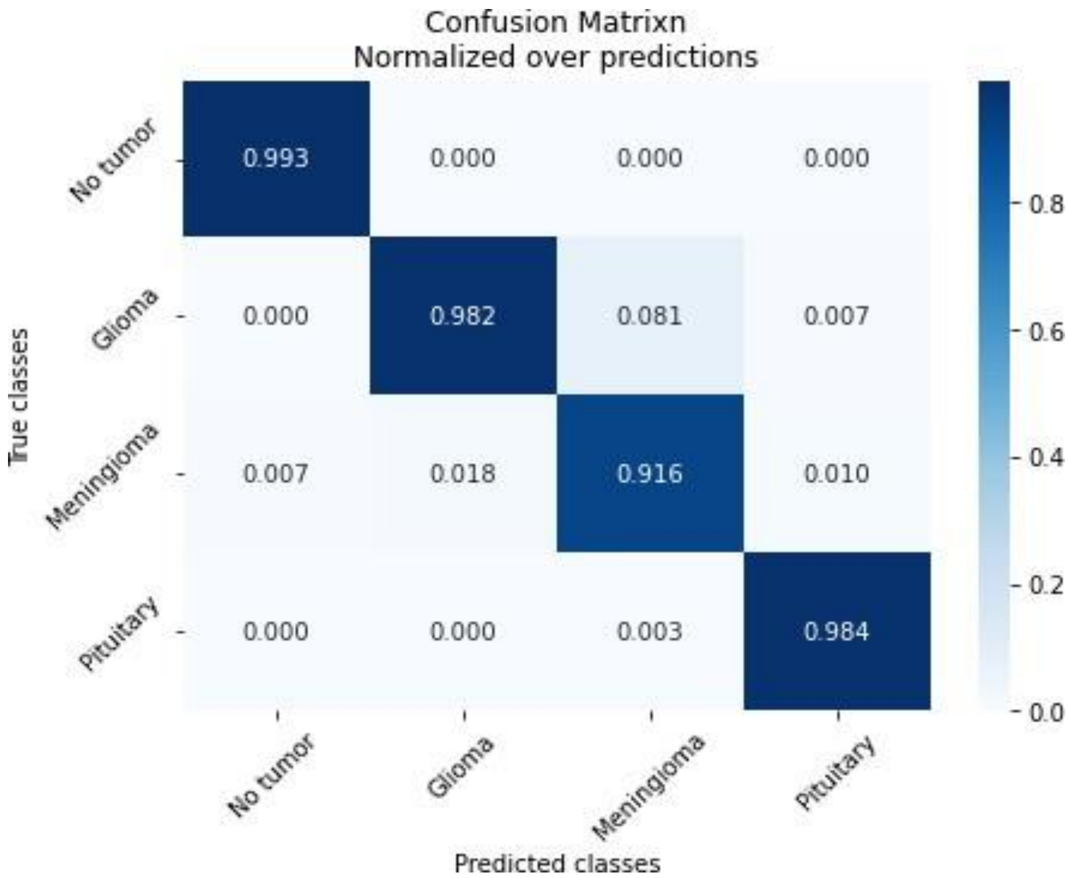
In conclusion, the results presented in this table indicate that all the models evaluated performed well on the binary classification task, with the EfficientNetB1 achieving the best results among all the models.

6.3 Multiclass Classification Experiment Analysis.

The experiment analysis of the Multiclass classification data were carryout using confusion matrix for all models evaluation results.

6.3.1 EffcientNetB0 Experiment Two Confusion Matrix

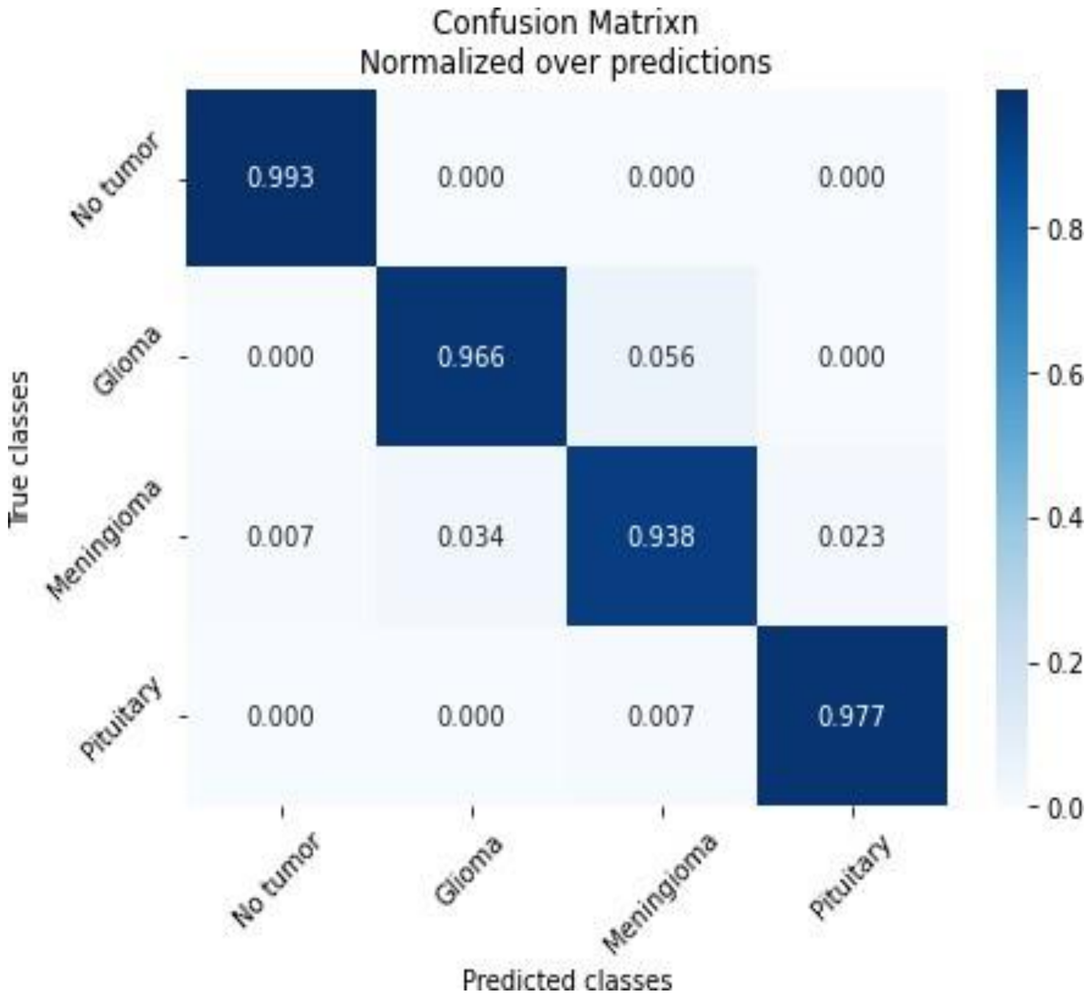
Figure 23: *Experiment Two EfficientNetB0 Confusion Matrix*



The figure 23 shows the experiment confusion matrix of the EfficienNetB0, the confusion matrix shows how sensitive and precise the EfficientNetB0 model evaluated the evaluation data with 99.3% effectiveness in predicting normal brain scans, 98.2% effectiveness in predicting glioma tumor brain scans, 91.6% effectiveness in predicting meningioma brain scans and 98.4% effectiveness in predicting pituitary brain scans.

6.3.2 EfficientNetB1 Experiment Two Confusion Matrix

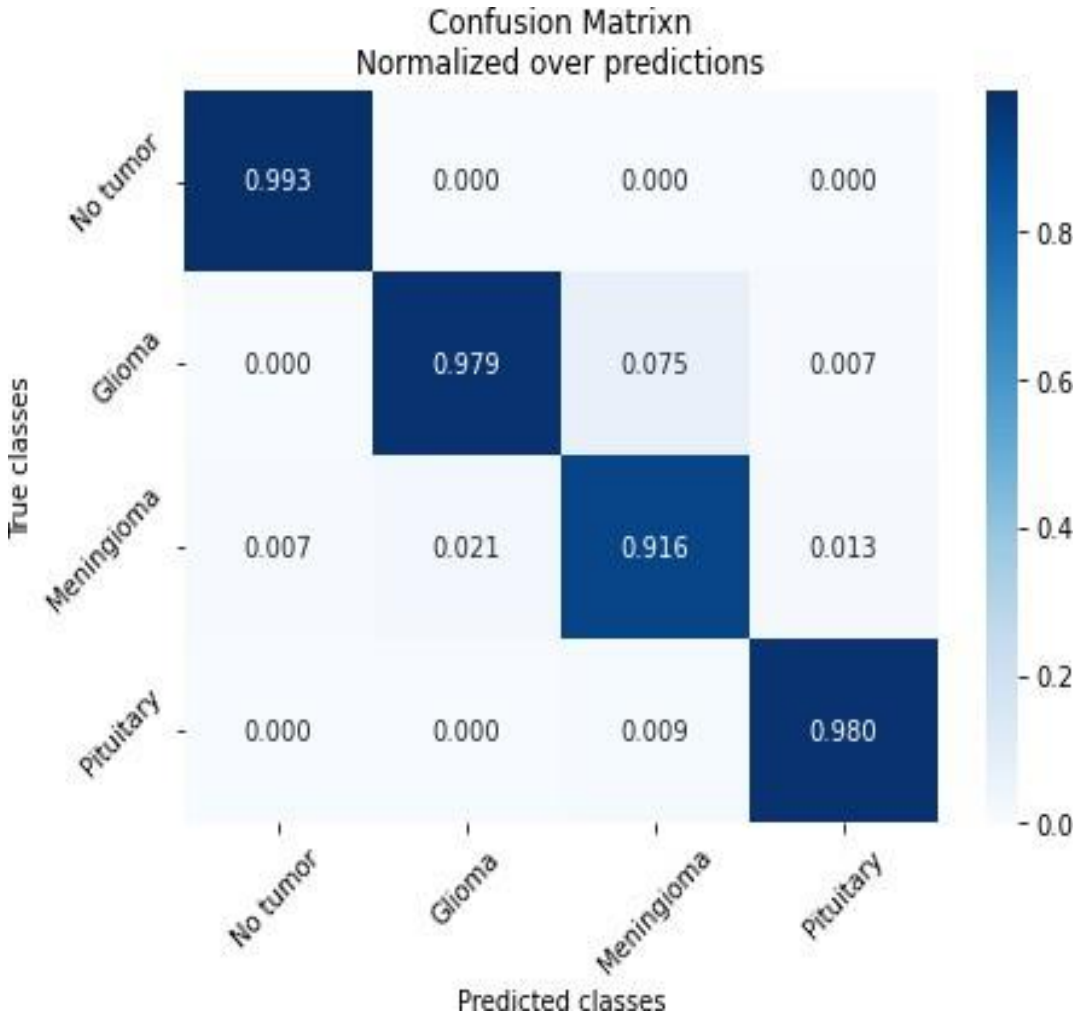
Figure 24: *Experiment Two EfficientNetB1 Confusion Matrix*



The figure 24 shows the experiment confusion matrix of the EfficienNetB1, the confusion matrix shows how sensitive and precise the EfficientNetB1 model evaluated the evaluation data with 99.3% effectiveness in predicting normal brain scans, 96.6% effectiveness in predicting glioma tumor brain scans, 93.8% effectiveness in predicting meningioma brain scans and 97.7% effectiveness in predicting pituitary brain scans.

6.3.3 EfficientNetB2 Experiment Two Confusion Matrix

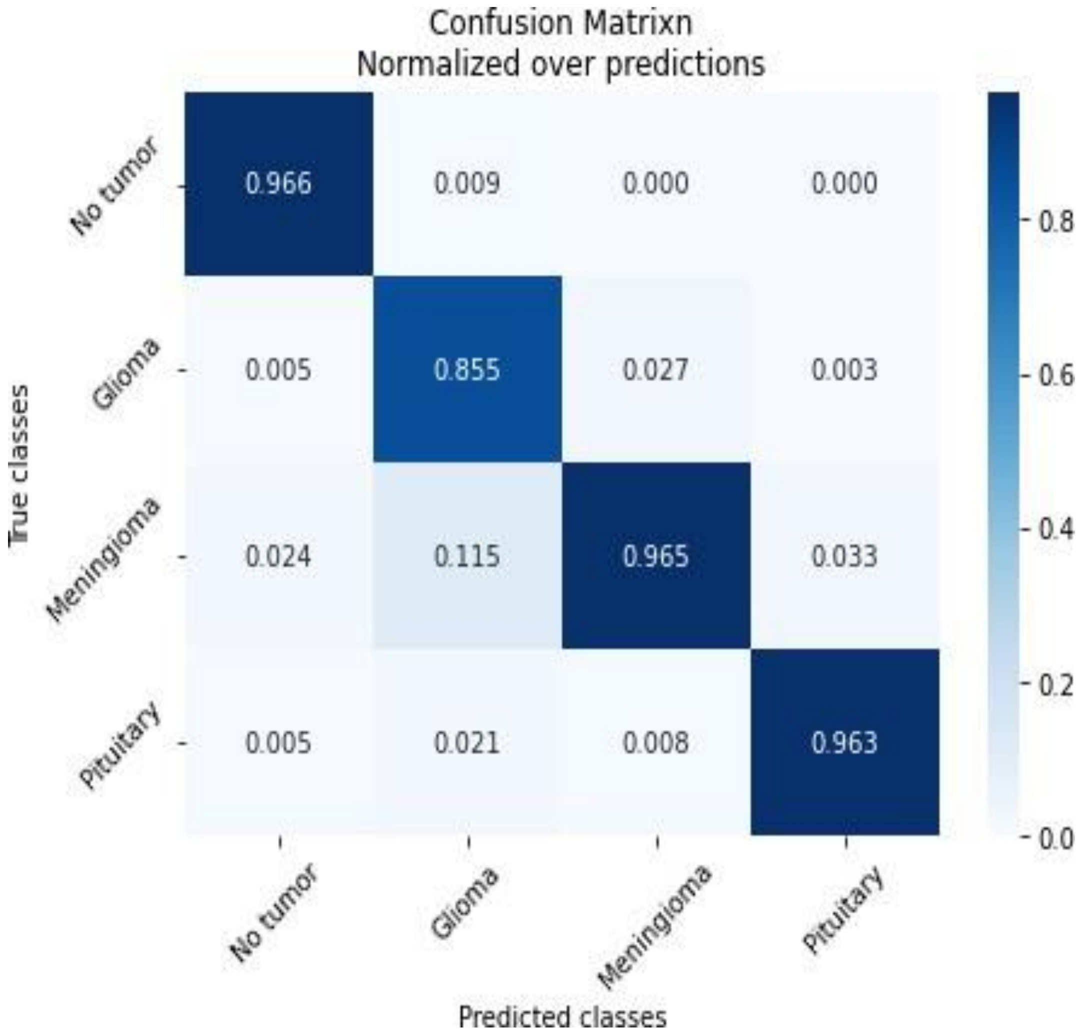
Figure 25: *Experiment Two EfficientNetB2 Confusion Matrix*



The figure 25 shows the experiment confusion matrix of the EfficienNetB2, the confusion matrix shows how sensitive and precise the EfficientNetB2 model evaluated the evaluation data with 99.3% effectiveness in predicting normal brain scans, 97.9% effectiveness in predicting glioma tumor brain scans, 91.6% effectiveness in predicting meningioma brain scans and 98.0% effectiveness in predicting pituitary brain scans.

6.3.4 EfficientNetB3 Experiment Two Confusion Matrix

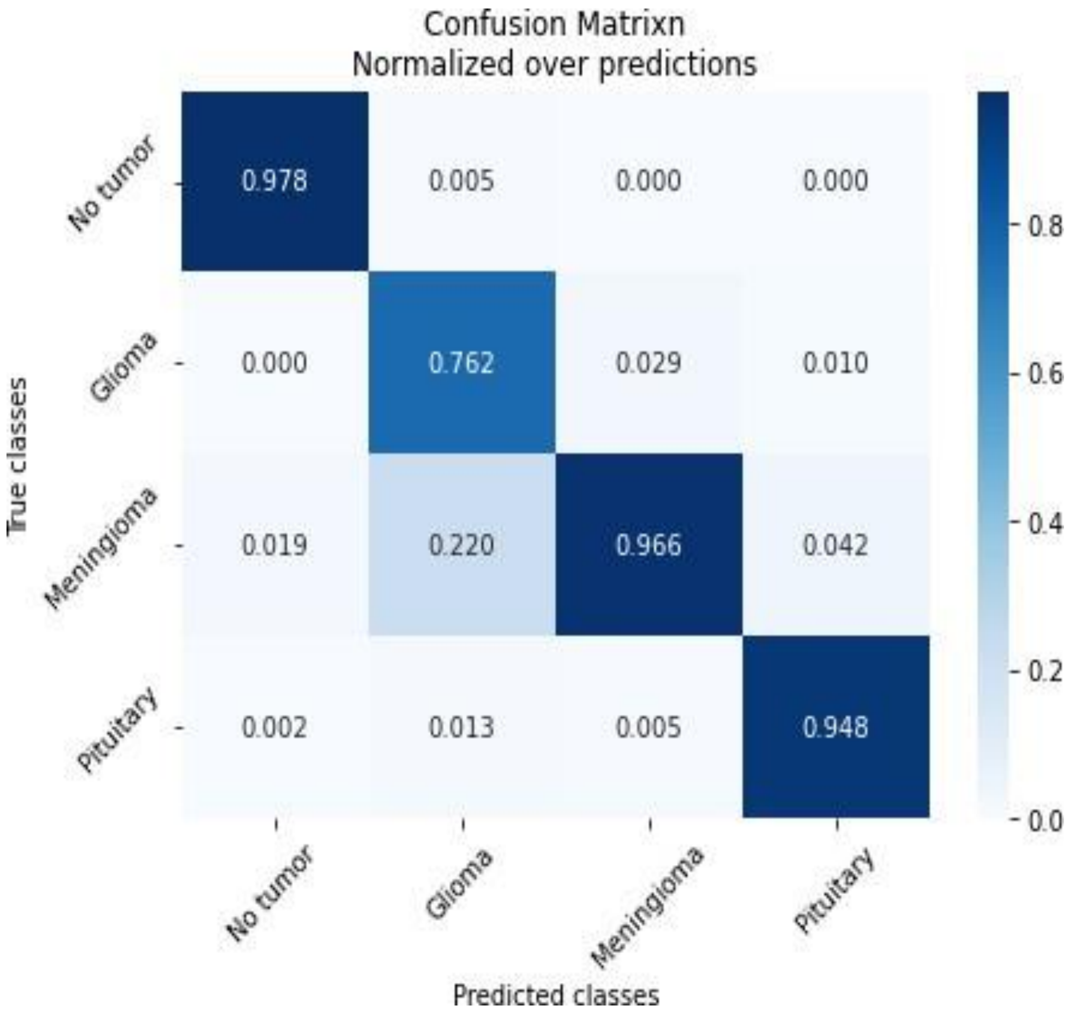
Figure 26: *Experiment Two EfficientNetB3 Confusion Matrix*



The figure 26 shows the experiment confusion matrix of the EfficienNetB3, the confusion matrix shows how sensitive and precise the EfficientNetB3 model evaluated the evaluation data with 96.6% effectiveness in predicting normal brain scans, 85.5% effectiveness in predicting glioma tumor brain scans, 96.5% effectiveness in predicting meningioma brain scans and 96.3% effectiveness in predicting pituitary brain scans.

6.3.5 AlexNet Experiment Two Confusion Matrix

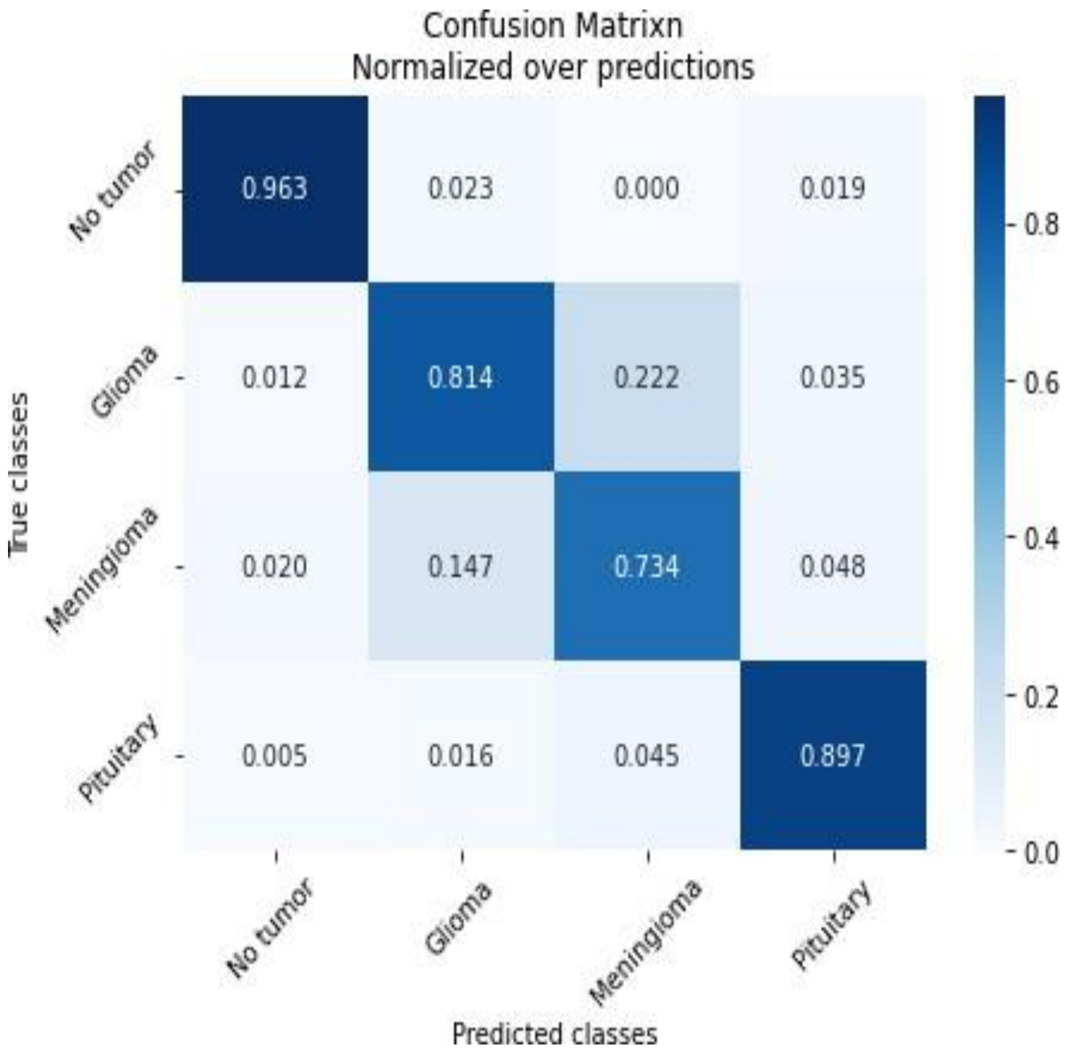
Figure 27: *Experiment Two AlexNet Confusion Matrix*



The figure 27 shows the experiment confusion matrix of the AlexNet, the confusionmatrix shows how sensitive and precise the AlexNet model evaluated the evaluation data with 97.8% effectiveness in predicting normal brain scans, 76.2% effectiveness in predicting glioma tumor brain scans, 96.6% effectiveness in predicting meningioma brain scans and 94.8% effectiveness in predicting pituitary brain scans.

6.3.6 VGGNET_16 Experiment Two Confusion Matrix

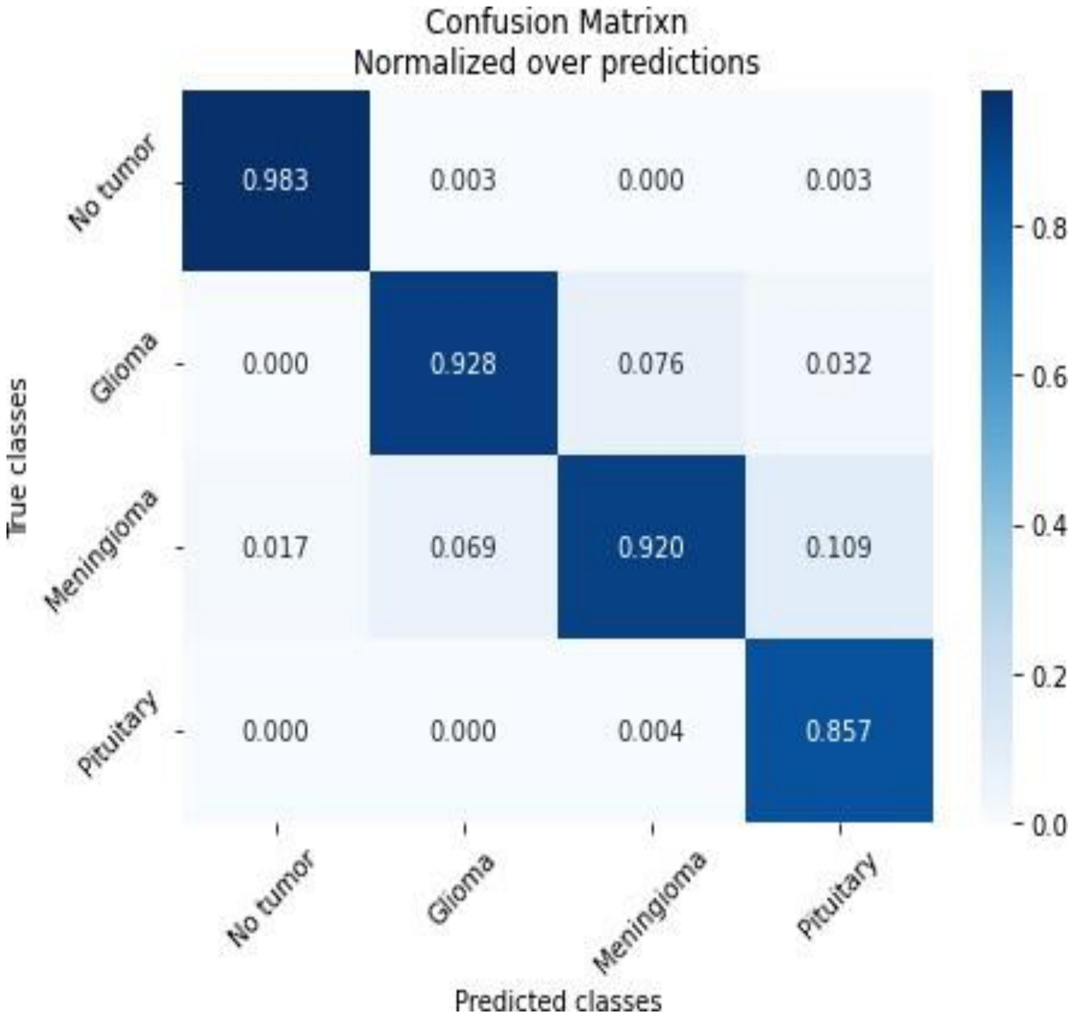
Figure 28: *Experiment Two VGGNet_16 Confusion Matrix*



The figure 28 shows the experiment confusion matrix of the VGGNet_16, the confusion matrix shows how sensitive and precise the VGGNet_16 model evaluated the evaluation data with 96.3% effectiveness in predicting normal brain scans, 81.4% effectiveness in predicting glioma tumor brain scans, 73.4% effectiveness in predicting meningioma brain scans and 89.7% effectiveness in predicting pituitary brain scans.

6.3.7 VGGNET_19 Experiment Two Confusion Matrix

Figure 29: *Experiment Two VGGNet_19 Confusion Matrix*



The figure 29 shows the experiment confusion matrix of the VGGNet_19, the confusion matrix shows how sensitive and precise the VGGNet_19 model evaluated the evaluation data with 98.3% effectiveness in predicting normal brain scans, 92.8% effectiveness in predicting glioma tumor brain scans, 92.0% effectiveness in predicting meningioma brain scans and 85.7% effectiveness in predicting pituitary brain scans.

CHAPTER VII

Conclusion

Brain tumors are hazardous to human health and early detection is essential for the patient's well-being and chances of recovery. Traditional methods for diagnosing brain tumors, such as manual examination of Magnetic Resonance Imaging (MRI) images, can be time-consuming and error-prone. Therefore, finding effective ways to diagnose brain tumors is crucial for improving patient outcomes. The study presented in this research shows how deep convolutional neural networks (CNNs) can provide an effective way of diagnosing brain tumors from MRI images. They can learn to extract relevant features from images and make predictions based on those features.

the CNN model achieved high accuracy in detecting brain tumors from MRI images. The study shows that using the EfficientNetB0, EfficientNetB1 and EfficientNetB2 models as the base system, it provides a good and effective way of diagnosing brain tumors on MRI images. With AUC of 100%, 99.49% and 99.35%, ACC of 100%, 99.60% and 99.20%, Sensitivity of 100%, 99.50% and 99.50% and Specificity of 100%, 99.40% and 100% respectively on the binary classifications and With AUC of 95.8%, 96.3% and 96.2%, ACC of 96.57%, 97.0% and 96.8%, Sensitivity of 96.5%, 96.0 % and 96.5% and Specificity of 95.66%, 96.12% and 95.94% respectively on the multiclass classifications, the model demonstrates a good accuracy in identifying the brain tumors on the images.

The results of the study demonstrate that deep CNNs are an effective method for detecting brain tumors from MRI images, which can help improve patient outcomes by enabling early detection. It also indicates that these models are efficient enough to be use in a clinical setting. This highlights the importance of continued research in the field of medical image technology and the use of artificial intelligence in medicine.

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Appendix

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