

BRAIN TUMOR DETECTION USING DEEP LEARNING TECHNIQUES

A PROJECT REPORT

Submitted by

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In partial fulfillment of the requirements for the award of the degree of

MASTER OF COMPUTER APPLICATIONS



**Thangal Kunju Musaliar College of Engineering
Kerala**

DEPARTMENT OF COMPUTER APPLICATIONS

MAY 2022

DECLARATION

I undersigned hereby declare that the project report **BRAIN TUMOR DETECTION USING DEEP LEARNING TECHNIQUES**, submitted for partial fulfillment of the requirements for the award of degree of Master of Computer Applications of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by me under supervision of Prof.JASMIN M R. This submission represents my ideas in my own words and where ideas or words of others have been included, I have adequately and accurately cited and referenced the original sources. I also declare that I have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in my submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for the award of any degree, diploma or similar title of any other University.

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22/05/2022



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C E R T I F I C A T E

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ABSTRACT

An automatic efficient system for brain tumor classification assists doctors in interpretation of medical images and supports decision of specialists in an early stages of tumor growth. Accurate and precise brain tumor MR images classification plays important role in clinical diagnosis and decision making for patient treatment. The need for a tumor detection program, thus, overcomes the lack of qualified radiologists. This process is difficult due to the wide variety of tumor tissues in the presence of different patients, and, in most cases, the similarity within normal tissues makes the task difficult. The key challenge in MR images classification is the semantic gap between the low-level visual information captured by the MRI machine and the high-level information perceived by the human evaluator. Processing of magnetic resonance images (MRI) is one among the parts of the image processing in medical field, which is the most emerging field from past few days. The tumor detection is often a preliminary phase. In the case study, Glioma, Meningioma, Pituitary tumor and No tumor types were classified using this method. The results reveal the effectiveness of the proposed method in classifying brain tumor via MRI images. EfficientNetB1 is the CNN architecture proposed here for the detection of brain tumor.

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List of Abbreviations

ROI	Region of interest
GA	Genetic Algorithm
FFT	Fast Fourier Transform
RBR	Rectangular box region
CT	Computed Tomography
SVM	Support Vector Machines
CRF	Conditional Random Field
ROC	Receiver operating system
DWT	Discrete Wavelet Transform
ELM	Extreme Learning Machines
CNN	Convolutional Neural Network
CE-MRI	Contrast-enhanced MRI images
KELM	Kernel Extreme Learning Machines
DCNN	Deep Convolutional Neural Network
FCNN	Fully Convolutional Neural Network
MRMR	Minimal-Redundancy-Maximal-Redundancy

Chapter 1

Introduction

Brain tumor is one of the most rigorous diseases in the medical science. An effective and efficient analysis is always a key concern for the radiologist in the premature phase of tumor growth. Histological grading, based on a stereotactic biopsy test, is the gold standard and the convention for detecting the grade of a brain tumor. The biopsy procedure requires the neurosurgeon to drill a small hole into the skull from which the tissue is collected. There are many risk factors involving the biopsy test, including bleeding from the tumor and brain causing infection, seizures, severe migraine, stroke, coma and even death. But the main concern with the stereotactic biopsy is that it is not 100% accurate, which may result in a serious diagnostic error followed by a wrong clinical management of the disease. Detection plays a critical role in biomedical imaging. The brain tumor analyzation, classification, and identification are critical issues for a neurologist who is using CAD (computer-aided diagnosis) as a supportive tool for a medical operation. There are three noticeable kinds of brain tumors: meningioma, pituitary, and glioma. The proposed method efficiently detected the tumor type from the brain MRI image.

Automated defect detection in medical imaging using machine learning has become the emergent field in several medical diagnostic applications. Studies in the recent literature have also reported that automatic computerized detection and diagnosis of the disease, based on medical image analysis, could be a good alternative as it would save radiologist time and also obtain a tested accuracy. Furthermore, if computer algorithms can provide robust and quantitative measurements of tumor depiction, these automated measurements will greatly aid in the clinical management of brain tumors by freeing physicians from the burden of the manual depiction of tumors. In the past,

machine learning (ML) techniques were considered as the foundation for the purpose to take over classification and mining tasks. Recently the less accuracy in prediction models and critical nature of the medical data analyzation force researchers toward new methods of brain tumor detection to improve classification accuracy. Consequently, deep learning (DL); a sub-field of machine learning, has become the center of attraction because it is capable to provide efficient prediction models by using extensive data such as images and text. Apart from it, predicting the model on a large dataset, deep learning is capable to provide the concluded results. The accuracy of prediction models and data analysis through DL techniques mainly rely on the data sample and its training as it needs more accurate data for better outcomes. The accuracy of prediction models and data analysis through DL techniques mainly rely on the data sample and its training as it needs more accurate data for better outcomes. To overcome shortcomings in training of data samples, transfer learning can be applied to secure better performance. Transfer learning is a DL technique in which trained features of large data can be deployed to small data sets where the large data is called a source or base dataset and small data is named as target data set.

1.1 Problem Definition

Diagnosing brain tumor is usually undergoes a complicated and time-consuming process. Here present a model for the automatic detection of brain tumor using better architecture along with high accuracy. By using pre-trained CNN models on large scale datasets, important features can be learned which can be used in image classification. The image can be classified into four classes glioma, meningioma, pituitary and no tumor.

1.2 Objective

The main goal of project is:

- Developing a deep learning model for the detection of brain tumor type.
- Training the deep learning model with data set using pre-trained CNN architectures
- Testing the model and find its accuracy.
- Implementing the model with higher accuracy using Gradio.

Chapter 2

Literature Survey

Literature review is the comprehensive study and interpretation of literature that relates to a particular topic. When one uses literature review research questions are identified, then one seek to answer this research questions by searching for and analyzing relevant literature. Some importance of literature reviews is that new insights can be developed by the re-analyzing the results of the study. A literature review is both a summary and explanation of the complete and current state of knowledge on a topic as found in academic books and journal articles. There are two kinds of literature reviews you might write at university: one that students are asked to write as a stand-alone assignment in a course, and the other that is written as part of an introduction to, or preparation for, a longer work, usually a thesis or research report. The focus and perspective of your review and the kind of hypothesis or thesis argument you make will be determined by what kind of review you are writing. One way to understand the differences between these two types is to read published literature reviews or the first chapters of theses and dissertations in your own subject area. Analyses the structure of their arguments and note the way they address the issues.

2.1 Purpose of the Literature Review

1. It gives readers easy access to research on a particular topic by selecting high quality articles or studies that are relevant, meaningful, important and valid and summarizing them into one complete report.
2. It provides an excellent starting point for researchers beginning to do research in a new area. by

forcing them to summarize, evaluate, and compare original research in that specific area.

3. It ensures that researchers do not duplicate work that has already been done.
4. It can provide clues as to where future research is heading or recommend areas on which to focus.
5. It highlights the key findings.
6. It identifies inconsistencies, gaps and contradictions in the literature.
7. It provides a constructive analysis of the methodologies and approaches of other researchers.

2.2 Related Works

Neelum Noreem et al.[1] used two pretrained deep learning models i.e. Inception-v3 and DenseNet201 are used. With the help of these two models, two different scenarios of brain tumor detection and its classification were evaluated. The features were concatenated and passed to softmax classifier to classify the brain tumor.

A.Rehman et al.[2] proposed a three step preprocessing, which enhance the quality of MRI images, along with a new Deep Convolutional Neural Network (DCNN) architecture for effective diagnosis of glioma, meningioma, and pituitary. The architecture uses batch normalization for fast training with a higher learning rate and ease initialization of the layer weights. The proposed architecture is a computationally lightweight model with a small number of convolutional, max-pooling layers and training iterations. The model accomplished an accuracy of 97.72 percentage overall. But the dataset used is minimal hence data augmentation needed.

M.Sajjad et al.[3] proposed the architecture (structure) of the CNN is evolved using Genetic Algorithm(GA), unlike existing methods of selecting a deep neural network architecture which are usually based on trial and error or by adopting predefined common structures. The results, in the case study, 90.9 percent accuracy for classifying three Glioma grades was obtained. Using a network architectures that performs well on some data may lead to poor results for another set of data. Therefore, it is necessary to compare different network architectures to reach the desired objective.

O.Charron et al.[4] discussed a new method that open new dimensions for readers to explore the concerned area of research. Through the entire review process, it has been observed that the com-

combination of Conditional Random Field (CRF) with Fully Convolutional Neural Network (FCNN) and CRF with DeepMedic or Ensemble are more effective for the segmentation of tumor from the brain MRI images.

S.Pereira et al.[5] used a technique for automatic classification of brain tumor from MR images using an SVM-based classifier. To improve the accuracy of the classifier, features are extracted using fast Fourier transform (FFT) and reduction of features is performed using Minimal-Redundancy-Maximal-Relevance (MRMR) technique. This technique has obtained an accuracy of 97.84 percentage.

K.V.A.Muneer et al.[6] proposed a grading system has two main stages: ROI extraction, and glioma grade prediction. Additionally, an interpretation of predictions stage that serves as prediction quality assessment, and use it for two purposes. First, to evaluate if regions indicative of tumor grade are the most relevant ones for classification. Second, to identify possible problems with the method (e.g. focus on spurious patterns) and devise strategies to obtain better classifiers.

S.Banerjee et al.[7] used Novel ConvNet models, which are trained from scratch, on MRI patches, slices, and multi-planar volumetric slices. The suitability of transfer learning for the task is next studied by applying two existing ConvNets models (VGGNet and ResNet) trained on ImageNet dataset, through fine-tuning of the last few layers. LOPO testing, and testing on the holdout dataset are used to evaluate the performance of the ConvNets. Results demonstrate that the proposed ConvNets achieve better accuracy in all cases where the model is trained on the multi-planar volumetric dataset. Unlike conventional models, it obtains a testing accuracy of 95 percentage for the low/high grade glioma classification problem.

L.Zhou et al.[8] discussed a method to investigate the effect of transfer learning on computed tomography (CT) images for the benign and malignant classification on renal tumors and to attempt to improve the classification accuracy by building patient-level models. Five image-level models were established for each of the Slice, region of interest (ROI), and rectangular box region (RBR) datasets. Then, two patient-level models were built based on the optimal image-level models. The network's performance was evaluated through analysis of the receiver operating characteristic (ROC) and five-fold cross-validation.

E.Deniz et al.[9] proposed transfer learning and deep feature extraction methods are used which adapt a pre-trained CNN model to the problem at hand. AlexNet and Vgg16 models are consid-

ered in the presented work for feature extraction and AlexNet is used for further fine-tuning. The obtained features are then classified by support vector machines (SVM). Extensive experiments on a publicly available histopathologic breast cancer dataset are carried out and the accuracy scores are calculated for performance evaluation. The evaluation results show that the transfer learning produced better result than deep feature extraction and SVM classification.

M.R Ismael et al.[10] discussed a framework for classification of brain tumors in MRI images that combines statistical features and neural network algorithms. This algorithm uses region of interest (ROI).focus on feature selection by using a combination of the 2D Discrete Wavelet Transform (DWT) and 2D Gabor filter techniques.

A.Pashaei et al.[11] used Extreme Learning Machines (ELM), are a kind of learning algorithm that consists of one or more layers of hidden nodes. These networks are used in various fields such as classification and regression. Then a kernel ELM (KELM) classifies the images based on these extracted features. Datasets consists of three types of brain tumors including meningioma, glioma and pituitary tumor in T1-weighted contrast-enhanced MRI (CE-MRI) images. The results of this ensemble of CNN and KELM (KE-CNN) are compared with different classifiers such as Support Vector Machine, Radial Base Function, and some other classifiers. These comparisons show that the KE-CNN has promising results for brain tumor classification.

N.Abiwinanda et al.[12] mainly focused on developing a CNN model for classifying brain tumors in T1-weighted contrast-enhanced MRI images. The proposed system consists of two significant steps. First, preprocess the images using different image processing techniques and then classify the preprocessed image using CNN. The experiment is conducted on a dataset of 3064 images which contain three types of brain tumor (glioma, meningioma, pituitary)The proposed system exhibited satisfying accuracy on the dataset and outperformed many of the prominent existing methods.

Chapter 3

Methodology

Brain tumor is a mass or growth of abnormal cells in brain. Many different types of brain tumors exist. Some brain tumors are noncancerous (benign), and some brain tumors are cancerous (malignant). Brain tumors can begin in the brain (primary brain tumors), or cancer can begin in other parts of the body and spread to the brain as secondary (metastatic) brain tumors. The growth rate as well as the location of a brain tumor determines how it will affect the function of your nervous system. Brain tumor treatment options depend on the type of brain tumor, as well as its size and location.

Three noticeable types of brain tumors are:

Glioma Tumor: Glioma is a type of tumor that occurs in the brain and spinal cord. Gliomas begin in the gluey supportive cells (glial cells) that surround nerve cells and help them function. Three types of glial cells can produce tumors. Gliomas are classified according to the type of glial cell involved in the tumor, as well as the tumor's genetic features, which can help predict how the tumor will behave over time and the treatments most likely to work.

Meningioma Tumor: A meningioma is a tumor that arises from the meninges — the membranes that surround the brain and spinal cord. Although not technically a brain tumor, it is included in this category because it may compress or squeeze the adjacent brain, nerves and vessels. Meningioma is the most common type of tumor that forms in the head.

Pituitary Tumor: Pituitary tumors are abnormal growths that develop in the pituitary gland. Some pituitary tumors result in too much of the hormones that regulate important functions of the body. Some pituitary tumors can cause the pituitary gland to produce lower levels of hormones.

3.1 Proposed system

To overcome the limitations of traditional Brain tumor detection, the method of automatically detecting Brain tumor is developed with better accuracy. Traditionally, The brain tumor analysis, classification, and identification are critical issues for a neurologist who is using CAD (computer-aided diagnosis) as a supportive tool for a medical operation. Automated diagnostic methods have been developed in recent years as an alternative to expert diagnosis. Deep learning-based image processing has been shown to be effective in automated diagnosis of brain tumor. However, deep learning typically requires a large number of labelled samples for training, which is time consuming and expensive to obtain in medical applications as it requires the input of human experts. Transfer learning, where a model is pre-trained for a task on an existing labelled database is adapted to be reused for a different but related task, is a common workaround to this issue. In the paper, models presented based on the applications of deep learning and convolutional neural networks based on transfer learning that are capable of classifying automatically that the patient has brain tumor or not. The proposed methodology uses EfficientNetB1 deep transfer learning algorithms that extracts the features from the MRI image that describes the presence of tumor.

3.2 System Architecture

The main purpose of the project is the detection of brain tumor by input some MRI of brain images, the proposed algorithm can detect whether it is a tumor affected brain MRI image or not. This study uses a well-known convolutional neural network model EfficientNetB1 for diagnosis of brain tumor. Brain tumor can diagnose effectively by using pre-trained models for image classification.

- Training the data set
- Evaluation of the model

- Implementing the model using Gradio

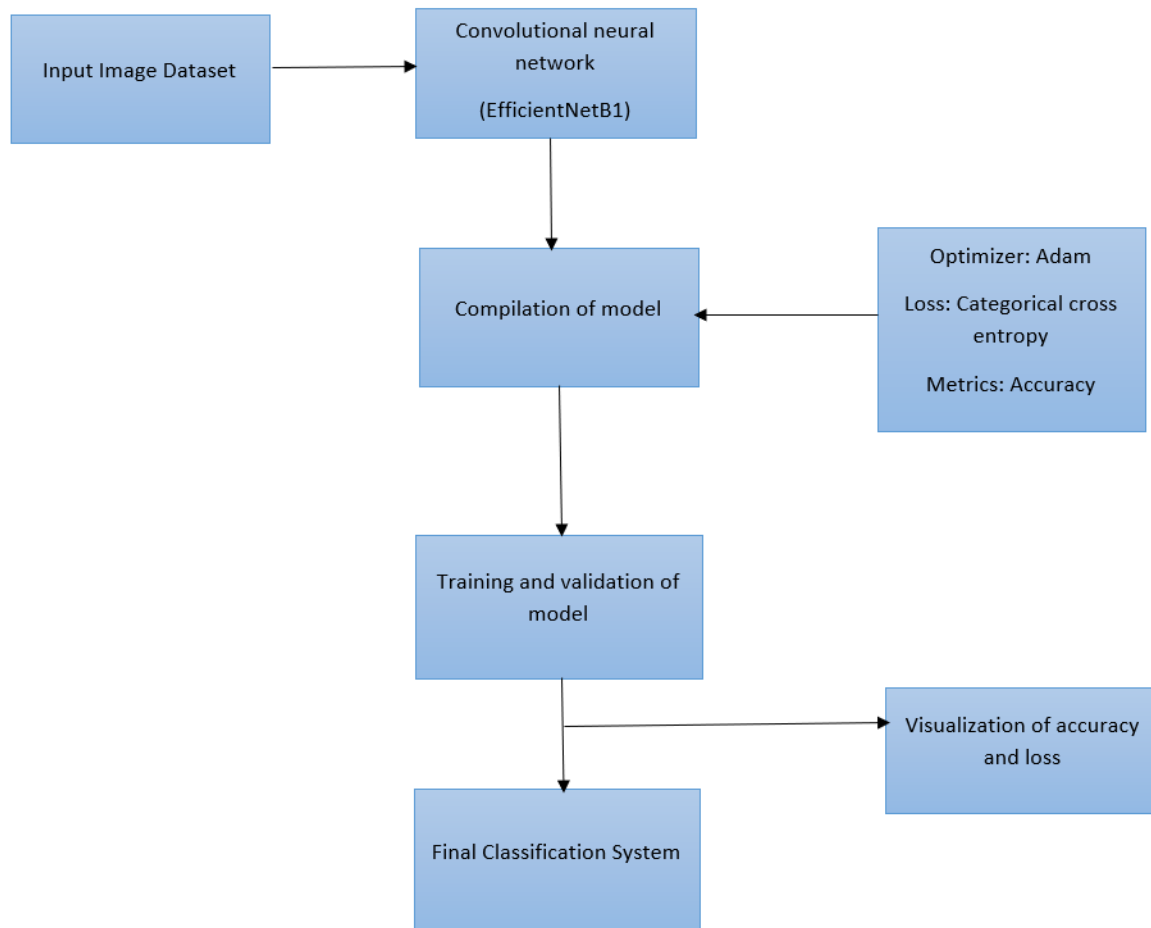


Figure 3.1: System Architecture

3.2.1 Data set

The dataset used for brain tumor is based on a brain MRI dataset which is released on the Kaggle website. All the images are MRI consisting of the RGB format. The Keras open-source deep learning framework along with the TensorFlow backend is employed to build and train the Convolutional Neural Network. The dataset obtained consisted of the training, testing and validating images, each divided by the glioma, meningioma, pituitary and no tumor MRI images. A total of

approximately 10000 brain MRI images are present. The data is modified into the training and validation set to enhance the system and increase efficiency. A total of around 80 percentage images are included in the training set and similarly, a total of 20 percentage images are allocated to the validation set in order to improve the overall accuracy.

3.2.2 Convolutional Neural Network: EfficientNet B1

EfficientNet is a convolutional neural network architecture and scaling method that uniformly scales all dimensions of depth/width/resolution using a compound coefficient. Unlike conventional practice that arbitrary scales these factors, the EfficientNet scaling method uniformly scales network width, depth, and resolution with a set of fixed scaling coefficients. The compound scaling method is justified by the intuition that if the input image is bigger, then the network needs more layers to increase the receptive field and more channels to capture more fine-grained patterns on the bigger image.

3.2.3 Compilation of model

The compilation is the final step in creating a model. Once the compilation is done, then move on to training phase. Compilation of a model includes loss, optimizer and metrics.

Optimizer

Optimization is an important process which optimize the input weights by comparing the prediction and the loss function. Optimizer used in this model is Adam Optimizer. Adam is a first-order-gradient-based algorithm of stochastic objective functions, based on adaptive estimates of lower-order moments. Adam is one of the latest state-of-the-art optimization algorithms being used by many practitioners of machine learning. The first moment normalized by the second moment gives the direction of the update.

Loss

Loss function is used to find error or deviation in the learning process. Keras requires loss function during model compilation process. The proposed model uses categorical cross entropy loss

function. Categorical crossentropy is a loss function that is used in multi-class classification tasks. These are tasks where an example can only belong to one out of many possible categories, and the model must decide which one. Formally, it is designed to quantify the difference between two probability distributions.

Metrics

Metrics is used to evaluate the performance of your model. It is similar to loss function, but not used in training process. Accuracy is a metric that generally describes how the model performs across all classes. It is useful when all classes are of equal importance. It is calculated as the ratio between the number of correct predictions to the total number of predictions.

3.2.4 Training the model

Another performance enhancing method in deep models especially in CNNs which is named as transfer learning. Transfer learning is the idea of overcoming the isolated learning paradigm and utilizing knowledge acquired for one task to solve related ones. There are three different transfer learning approaches in CNNs. These are feature extractor, fine-tuning and pre-trained models. The study, used fine tuning approach which is motivated by observing in early layers of CNNs have more generic features such as edges, colors. The models used in the proposed system is EfficientNetB1. The model is trained and it is saved as H5 files.

3.2.5 Testing the model

The proposed EfficientB1 model is tested with testing data images for classifying the brain tumor from MRI images. Testing accuracy is most important performance matrix of classification algorithm. The accuracy of proposed model is high. Another most important performance matrix used is precision and recall.

3.2.6 Implementing the model in Gradio

Here, we developed a basic API using Gradio where user can upload MRI image which is to be detected and the system predicts the tumor type.

3.3 EfficientNetB1 Architecture

EfficientNet is a convolutional neural network architecture and scaling method that uniformly scales all dimensions of depth/width/resolution using a compound coefficient. Unlike conventional practice that arbitrary scales these factors, the EfficientNet scaling method uniformly scales network width, depth, and resolution with a set of fixed scaling coefficients. The compound scaling method is justified by the intuition that if the input image is bigger, then the network needs more layers to increase the receptive field and more channels to capture more fine-grained patterns on the bigger image.

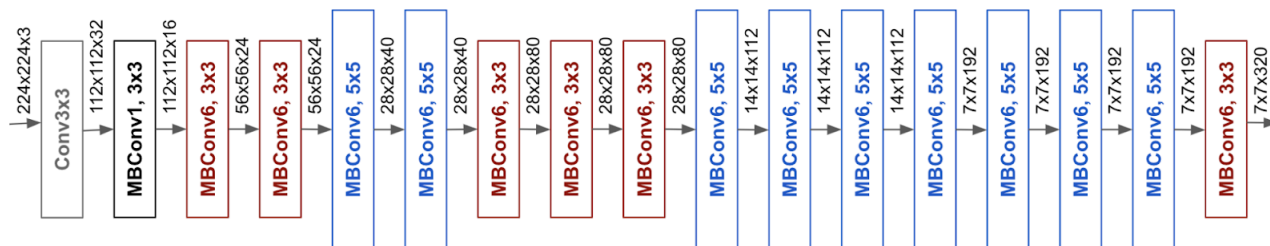


Figure 3.2: EfficientNetB1 architecture

EfficientNet using three techniques: (1) increasing the network depth, (2) increasing the channel width, and (3) increasing the resolution of input images. The effectiveness of model scaling also relies heavily on the baseline network. So, to further improve performance, we have also developed a new baseline network by performing a neural architecture search using the AutoML MNAS framework, which optimizes both accuracy and efficiency (FLOPS). The resulting architecture uses mobile inverted bottleneck convolution (MBConv), similar to MobileNetV2 and MnasNet, but is slightly larger due to an increased FLOP budget. We then scale up the baseline network to obtain a family of models, called EfficientNets. This model takes input images of shape (224, 224, 3). The first observation is that this model is composed of repeated MBConv1 and MBConv6 blocks. These are basically different types of MBConv block. The second observation is that inside each block the number of channels is increased or expanded (through a larger number of filters), each type can have several variants depending on the filter size used in the convolutional layers inside the block (which can be 3x3 or 5x5).

Stage i	Operator $\hat{\mathcal{F}}_i$	Resolution $\hat{H}_i \times \hat{W}_i$	#Channels \hat{C}_i	#Layers \hat{L}_i
1	Conv3x3	224×224	32	1
2	MBConv1, k3x3	112×112	16	1
3	MBConv6, k3x3	112×112	24	2
4	MBConv6, k5x5	56×56	40	2
5	MBConv6, k3x3	28×28	80	3
6	MBConv6, k5x5	14×14	112	3
7	MBConv6, k5x5	14×14	192	4
8	MBConv6, k3x3	7×7	320	1
9	Conv1x1 & Pooling & FC	7×7	1280	1

Table 3.1: Pre-trained EfficientNetB1 architecture

3.4 Gradio

Gradio is an open-source python library which allows you to quickly create easy to use, customizable UI components for ML model, any API, or any arbitrary function in just a few lines of code. We can integrate the GUI directly into our Python notebook, or we can share the link to anyone. Then use the Gradio functions to build an image classification model. Finally, deploy the web application so that it can be accessed using a browser.

Benefits of using Gradio:-

- Enables you to create demos of your machine learning model. These demos can be used to present ideas to clients, users, and team members before the actual application is implemented.
- Gradio allows the collection of feedback from the user. A developer can, therefore, make the necessary improvements.
- When using Gradio, you can easily identify bugs and errors in the model. This enables you to remove the bugs before production.
- Gradio has an easy setup which makes it easier to build models of machine learning apps.
- Gradio enables you to permanently deploy an application on online servers.

- Gradio generates a public link that enables other users to interact with the application remotely.

3.5 Software requirements and specification

The software used for the project:

- Python
- Google Colaboratory

1. PYTHON

Python is an object-oriented programming language created by Guido Rossum in 1989. It's ideally designed for fast prototyping of complicated applications. It has interfaces to several OS system calls and libraries and is protractile to C or C++. several massive corporations use the Python programming language embody NASA, Google, YouTube, BitTorrent, etc. Python programming is widely utilized in AI, natural language Generation, Neural Networks and other advanced fields of computer science. Python is programming language open supply, high-level artificial language developed by Guido van Rossum within the late Eighties and presently administered by Python Software Foundation. It came from the ABC language that he helped produce early on in his career. Python is a powerful language that you can use develop games, write GUIs, and develop web applications. It's a high-level language. Reading and writing codes in Python is far like reading and writing regular English statements. As a result, they're not written in the machine-readable language, Python programs got to be processed before machines can run them. Python is an understood language. This implies that each time a program is run, its interpreter runs through the code and interprets it into machine-readable byte code. Python is an object-oriented language control users to manage and management data structures or objects to make and run programs. Everything in Python is, in fact, top-notch. All objects, data types, functions, methods, and classes take an equal position in Python. Programming languages are created to satisfy the requirements of programmers and users for an efficient tool to develop applications that impact lives, lifestyles, economy, and society. they assist build lives better by increasing productivity, enhancing communication, and rising potency. Languages die and become obsolete once they fail to live up to expectations and are replaced and superseded by languages that are more powerful. Python programming language artificial language that has stood the test of time and has remained relevant

across industries and businesses and among programmers, and individual users. It's a living, thriving, and extremely helpful language that's extremely recommended as a primary programming language for those that want to dive into and experience programming. Python version 3.7 is used.

- Python is Interpreted : Python is processed at runtime by the interpreter. You do not need to compile your program before executing it. This is similar to PERL and PHP.
- Python is Interactive : You can actually sit at a Python prompt and interact with the interpreter directly to write your programs.
- Python is Object-Oriented : Python supports Object-Oriented style or technique of programming that encapsulates code within objects.
- Python is a Beginners Language : Python is a great language for the beginner level programmers and supports the development of a wide range of applications from simple text processing to WWW browsers to games.
- An easy and intuitive language just as powerful as those of the major competitor
- Open source, so anyone can contribute to its development
- Code that is as understandable as plain English

2. Google Colaboratory

Google Colab was developed by Google to provide free access to GPU's and TPU's to anyone who needs them to build a machine learning or deep learning model. Google Colab can be defined as an improved version of Jupyter Notebook. Jupyter Notebook is an application that allows editing and running Notebook documents through a web browser or an Integrated Development Environment (IDE). Instead of files, it will work with Notebooks. Notebook documents can include executable lines of code along with text, images, figures, tables, graphs, equations, and much more graphical data. In simple words, Notebook documents are a way of creating human-readable executable documents. In a Notebook, cells are the building blocks. Everything in a Notebook is composed of cells. There are two types of :

- Text cell :- A text cell can contain text, images, links and much more. You can double-click a text cell to edit its contents. The text cell supports Markdown markup language.
- Code cell:- A code cell contains the executable code. A code cell has a run button to its left that

lets you execute the contents of the cell. When you run a cell the output is displayed under the cell. Google Colab provides tons of exciting features that any modern IDE offers, and much more. Some of the most exciting features are listed below.

- Interactive tutorials to learn machine learning and neural networks.
- Write and execute Python 3 code without having a local setup.
- Execute terminal commands from the Notebook.
- Import datasets from external sources such as Kaggle.
- Save Notebooks to Google Drive.
- Import Notebooks from Google Drive.
- Free cloud service, GPUs and TPUs.
- Integrate with PyTorch, Tensor Flow, Open CV.
- Import or publish directly from/to GitHub.

Chapter 4

Result And Discussion

An automated system for brain tumor detection is beneficial for people living in remote areas. Convolutional Neural Network (CNN) have been quite successful in disease identification. Also by using pre trained CNN models on large scale datasets, important features can be learned which can be used in image classification. The efficiency of the model is rated high which in turn can be trusted by the patients. This can further help doctors to ease out their task and will also save their time. After the model is constructed, compile the neural net using a categorical cross entropy selected as loss function, Adam used as the optimizer, batch size is given 64. Different approaches are used for avoiding over fitting. Firstly, the dropout method was used after fully connected layers. Secondly, Early stopping is used for avoiding overfitting.

4.1 Training and Validation results

Training gives optimized results, with high accuracy of 99.86 percentage for EfficientNetB1 and corresponding loss of 0.0023 for training with 20 epochs. For EfficientNetB1 its, 98.97 percentage accuracy for validation. The given table 4.1 shows model's training and testing accuracy.

4.2 Performance metrics

The below table indicates the performance metrics to calculate accuracy based on the classification results. The most important performance matrix is precision. Precision is the fraction of

Model	Training Accuracy	Testing Accuracy
EfficientNetB1	99.8	99.3

Table 4.1: Accuracy of EfficientNetB1

relevant instances among the retrieved instances of classification techniques. The precision value of the proposed EfficientNetB1 model.

True Positive (TP)

- The predicted value matches the actual value
- The actual value was positive and the model predicted a positive value

True Negative (TN)

- The predicted value matches the actual value
- The actual value was negative and the model predicted a negative value

False Positive (FP)

- The predicted value was falsely predicted
- The actual value was negative but the model predicted a positive value
- Also known as the Type 1 error

False Negative (FN)

- The predicted value was falsely predicted
- The actual value was positive but the model predicted a negative value
- Also known as the Type 2 error

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

Recall is also one of the most common performance metrics to estimate the performance of the classification model. The recall is the fraction of the total amount of relevant instances that were actually the retrieved instance of the classification algorithm.

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

In statistical analysis of binary classification the f1 score is a measure for testing accuracy. It considers both the precision and the recall of the classification algorithm to compute the f1 score.

$$\text{F1score} = \frac{2 \times \text{precision} \times \text{Recall}}{\text{precision} + \text{Recall}}$$

The support is the number of samples of the true response that lie in that class. Performance metrics of EfficientNetB1 model is shown in table 4.2. The outcomes of the most common performance matrix such as classification accuracy, precision, recall and f1 score Also figure 4.3 shows sample images from dataset and final prediction.

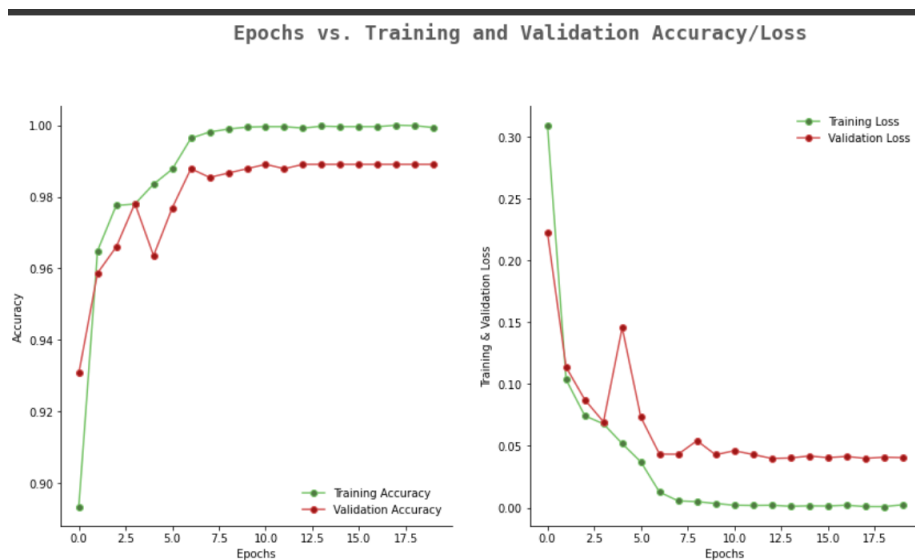


Figure 4.1: Epochs vs. Training and Validation Accuracy/Loss

	precision	recall	f1-score	support
0	0.99	0.99	0.99	503
1	0.99	1.00	1.00	470
2	0.99	0.98	0.98	542
3	0.99	0.99	0.99	543
accuracy			0.99	2058
macro avg	0.99	0.99	0.99	2058
weighted avg	0.99	0.99	0.99	2058

Table 4.2: Performance metrics of EfficientNetB1

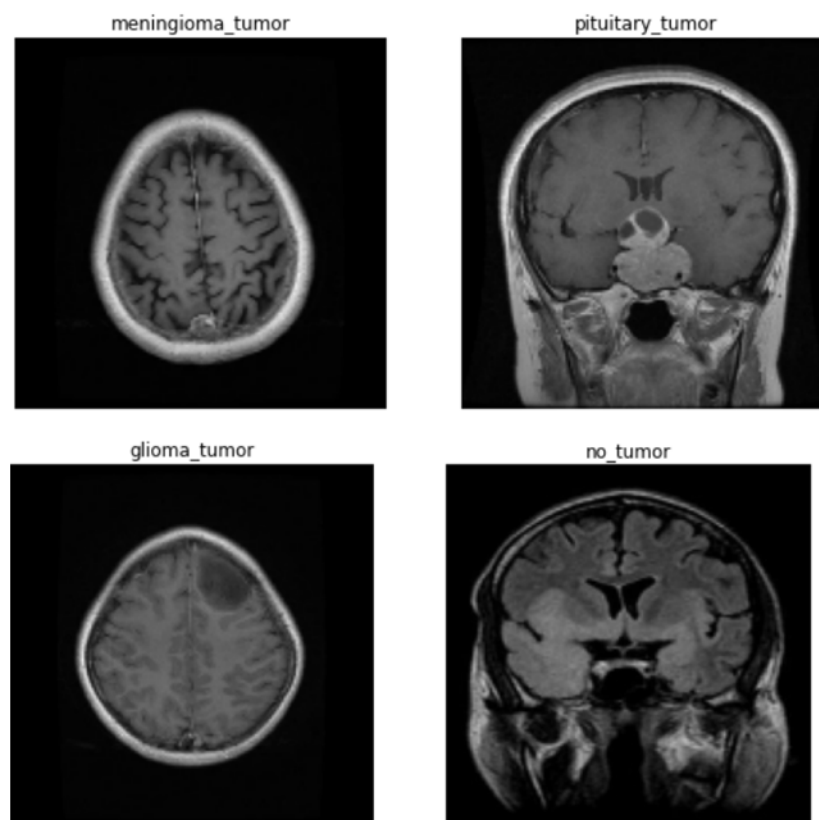


Figure 4.2: Data Samples

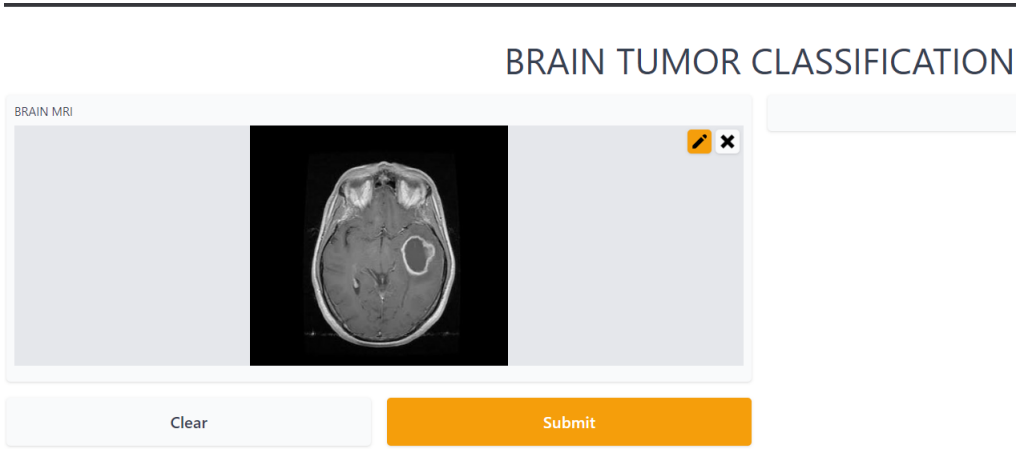


Figure 4.3: Input image

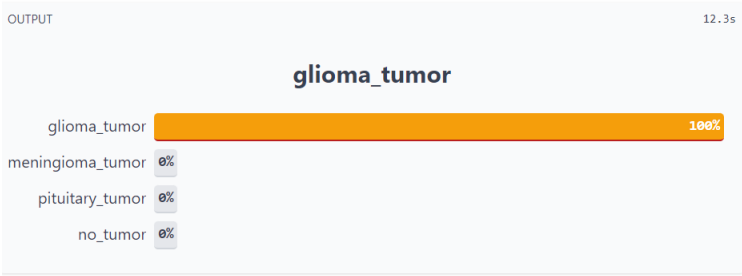


Figure 4.4: Output image of EfficientNetB1

Chapter 5

Conclusion

It is concluded that the proposed deep learning model, EfficientNetB1, classifies the brain MRI images for tumor type detection in a very accurate manner. The loss of the model is minimized while training and the accuracy simultaneously increased through each epoch stages in order to yield distinct results for classifying the tumor types. The deep neural networks is not subjected towards over fitting, thus the results obtained will always remain coherent. The proposed model predicts effectively whether a given sample of brain MRI images has tumor or normal.

5.1 Advantages

The main merits of proposed model are:

- No need of an expert knowledge to identify the tumor type.
- The system provide more accuracy and efficiency for detecting tumor.
- Early diagnosis of disease.

5.2 Future Enhancement

This project has an immense scope in the field of medicine and health care and can be continued for other such insightful innovations. Future work will be concentrated on improving the architectures used and other deep learning models other than this. This study can be extended to diagnose the stages of brain tumor in patients which has affected many people across the globe.

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APPENDICES

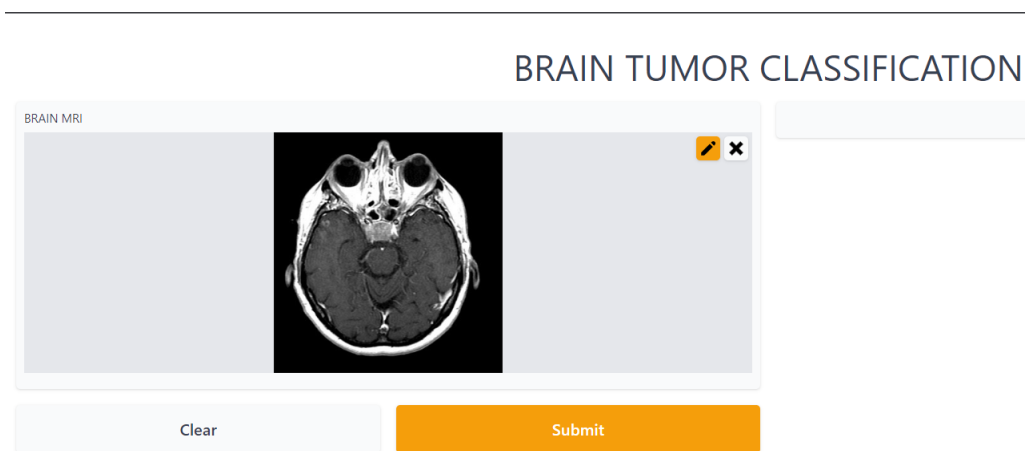


Figure A.1: Input image

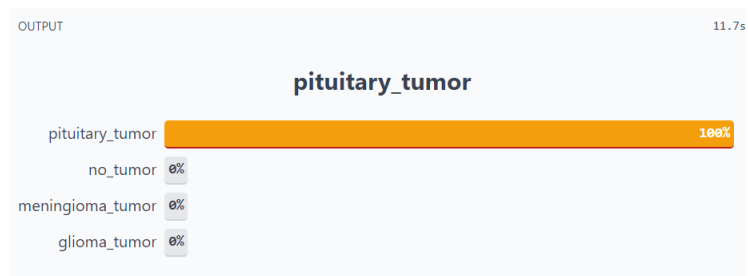


Figure A.2: Output image

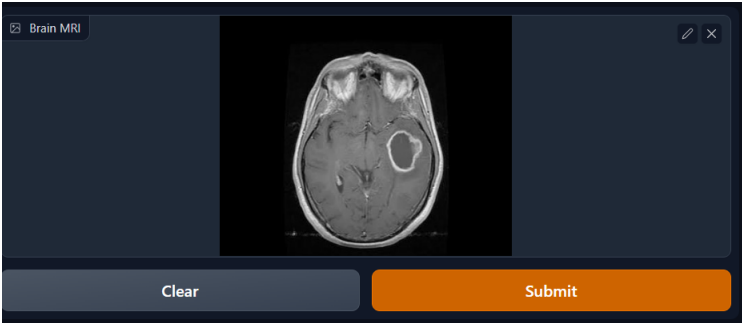


Figure A.3: Input image

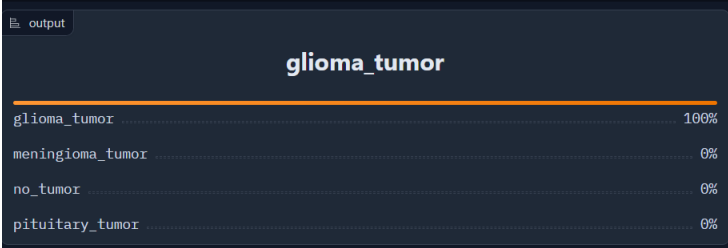


Figure A.4: Output image

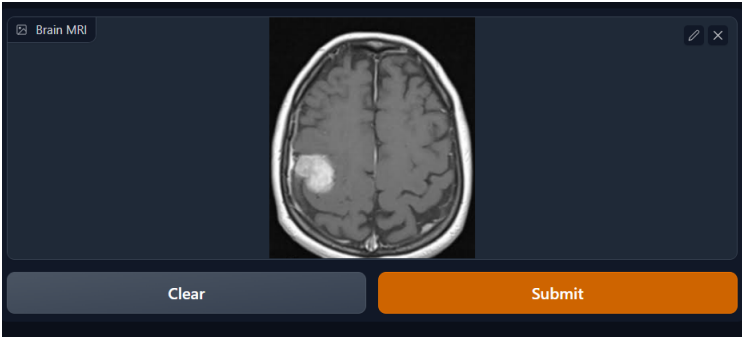


Figure A.5: Input image

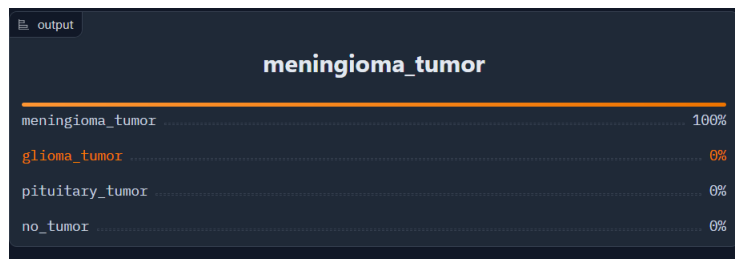


Figure A.6: Output image

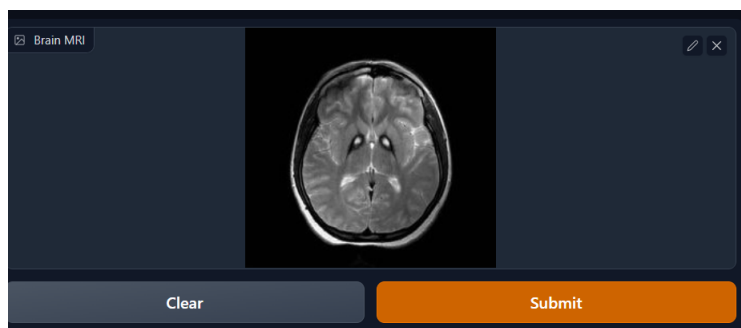


Figure A.7: Input image

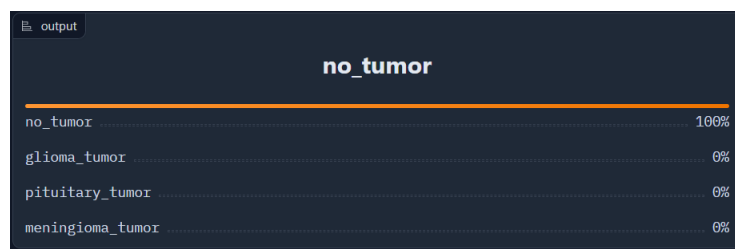


Figure A.8: Output image