UNIVERSITY OF NAIROBI

DEPARTMENT OF COMPUTING & INFORMATICS

RECOGNIZING BRAIN TUMOR USING CONVOLUTIONAL NEURAL NETWORKS

BY

JAPHETH OTIENO OWINY

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Declaration

Declaration by the student

This is a totally original piece of work that has not been submitted to any other university for the purpose of earning a degree. Without the express, previous, and explicit consent of both the author and The University of Nairobi, no part of this project may be replicated in any form.

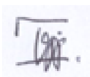
Signature:  Date: 27^{th} July 2022

Japheth Owiny

P52/36385/2020

Declaration by supervisor

This project report has been submitted for examination with my approval as the University Supervisor.

 Signature: Date: 29^{th} July 2022

Prof. Elisha Toyne O. Opiyo

Department of Computing and Informatics

University of Nairobi

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Abstract

A brain tumor is a collection of abdominal cells in the brain that, if left untreated, can cause permanent brain damage and even death. In order to stop the progression of this life-threatening malignant tumor, early detection and treatment are essential. Conventionally, brain specialists find any tumor abnormalities by physically studying medical images such as MRI images. This is how they detect any tumors. However, due to the cost of educating trained staff as well as other normal human limits such as lack of speed and exhaustion, a delayed or mistaken identification of the tumor may result, which in turn may lead to a delay in the initiation of treatment.

In recent years, machine learning has been utilized in the diagnosis of human illnesses such as fetal malformations and abnormalities in red blood cells. Convolutional neural networks are the focus of this research as a potential way to detect brain tumors from MRI scans. Because of the limited amount of time available, the focus of this research is on the detection and identification of tumors as either benign or malignant. Benign and malignant tumors are the most prevalent types of cancerous tumors that can be discovered and rectified at an early stage. The primary purpose of this research is to construct a deep learning model that is capable of classifying MRI images as either benign or malignant based on their examination.

In total, 3920 different MRI image samples were utilized for the project. The image dataset was divided into a training set and a testing set. A hyper-parameter tuning for the model was performed with the following settings for model training: 0.001 learning rate, 36 epochs, 80 steps per epoch, and an 80-step batch size. The model achieved an accuracy of 98.6 percent, with a precision of 99 percent and a recall of 98 percent, respectively.

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Abbreviations

CNN- Convolutional neural Network

RESNET- Residual Neural Network

MRI- Magnetic Resonance Imaging

ML - Machine Learning

ReLU - Rectified linear activation function

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CHAPTER ONE: INTRODUCTION

1.1 Background of the study

An abnormal mass of cells in your brain is known as a tumor. The structure of your skull, which protects your brain, is extremely hard. In such a constrained environment, any expansion can pose a challenge. Tumors of the brain can be cancerous or benign (benign). It is possible for benign or malignant tumors to create an increase in the pressure in your skull. This can lead to brain damage and even death, so be careful (Healthline, 2020).

Quick Facts about brain tumors: Primary brain tumors currently affect 700,000 individuals in Africa, and an additional 85,000 will be diagnosed by 2022, according to the World Health Organization. Brain tumors can be lethal, have a considerable influence on quality of life, and have a profound effect on the patient and their family members. There is no racial or ethnic group that is spared from this menace.

There are around 70% benign and 30% malignant brain tumors. Females account for 58% of all brain tumor cases, compared to 42% of cases in men. For non-malignant tumors, meningiomas account for 38.3 percent of all tumors and 54.5 percent of all non-malignant tumors; for malignant tumors, the figure is 14.5 percent of all tumors and 48.6 percent of all malignant tumors, respectively (National Brain Tumor Society.2020).

Patients with primary brain tumors have a median age at diagnosis of 60 years, and a survival rate of 75.2% is the average for all patients with main brain tumors. Life expectancy decreases with age and type of tumor. The five-year survival rate for patients with benign brain tumors is on average 91.7%. (Alfred Yungs, 2019).36 percent of individuals with malignant brain tumors had a 5-year relative survival rate following diagnosis.

Just 7.2% of patients with glioblastoma, the most prevalent kind of primary malignant brain tumor, should expect to live for more than five years. Malignant brain tumor (brain cancer) deaths in 2020 are expected to total 18,020, with 10,190 deaths in men and 7,830 deaths in women (Web Cavenee, 2021).

Medical imaging, surgical robots, hospital efficiency, and brain tumor detection and segmentation are all being revolutionized by artificial intelligence. From its present valuation of $4.9 billion USD, the AI healthcare market is predicted to reach $45.2 billion USD by 2026. (Forbes Technology Council, 2020).Rapid and accurate diagnosis may soon become possible thanks to the superiority of deep learning in detecting disease from X-ray, MRI and CT images.

1.2 Problem statement

A brain tumor, when it has progressed to its later stages, is one of the diseases that poses the greatest risk of death, and it can strike anyone of any age, gender, or color. Can result in the development of cancer if it is not discovered and treated in its early stages, which can lead to an untimely death. It is generally believed that spotting problems early on and fixing them is the most effective way to stop the growth of tumor cells.

Although specialists are able to physically interpret MRI scans and identify anomalies at an early stage, training to become a specialist can take many years and a significant amount of money. In addition, past research that looked into the use of MRI scans in an emergency setting revealed that mistakes or missed diagnoses were made, which led to mortality in some of the patients.

1.3 Research objectives

General objective:

1. To recognize brain tumor using convolutional neural networks

Specific objectives:

1. To acquire the right dataset that will be used to recognize brain tumors.
2. Split the brain tumor dataset into training (75%) and test set (25%)
3. Extract specific features from the images through manipulation techniques.
4. Classify brain tumor as either benign or malignant
5. Asses the trained model performance in classification of brain tumor

1.4 Significance of the study

A primary brain tumor affects an estimated 700,000 Africans today, and an additional 85,000 will be diagnosed with one by the year 2022. Brain tumors can be lethal, have a considerable influence on quality of life, and have a profound effect on the patient and their family members. There is no racial or ethnic group that is spared from brain cancer.

Magnetic resonance (MR) image segmentation is a critical procedure for selecting the right treatment at the right time for patients with brain malignancies. There are several ways to lower the expense of cancer diagnosis, and MRI image detection using CNN are one of the best ways to identify and locate brain tumors quickly and accurately.

CHAPTER TWO: LITERATURE REVIEW

This section discusses brain tumors, convolutional neural networks, related work, research gaps, and a proposed model.

2.0 Brain Tumor

These aberrant cell growths are known as brain tumors. Brain tumors can be different sizes and shapes. It is possible to have cancerous brain tumors that appear to be benign or malignant. Secondary brain tumors are cancers that originate elsewhere in the body and then spread to the brain (secondary, or metastatic, brain tumors).
The rate of growth of brain tumors varies. Your neurological system may be affected by a brain tumor in a variety of ways, depending on its size and location. By type, size, and location, therapies for brain tumors differ.

2.1 Brain tumor types

Glioblastoma

Glioblastoma is a brain or spinal cord malignancy. Glioblastoma arises in nerve-supporting astrocytes. Glioblastoma can occur at any age, but in older adults. Headaches, nausea, vomiting, and seizures can worsen.
Glioblastoma, often called glioblastoma multiform, is typically incurable. Cancer treatments may delay progression and relieve symptoms.

Diagnosis

Brain scan: Doctors ask about symptoms during neurological examinations to diagnose glioblastoma. The ability to see, hear, balance, coordinate, exert force, and react can all be tested. The location of a brain tumor may be indicated by problems in one or more of these regions. MRIs. Brain tumors can be diagnosed via imaging studies. Brain tumors are diagnosed using MRI functional scans and MR spectroscopy, or spectroscopy of magnetic resonance.
CT and PET scans are among the others (PET).Tissue sampling (biopsy). Depending on your situation and tumor location, a needle biopsy can be done before or during glioblastoma surgery. A lab analyzes suspicious tissue to determine cell kinds and aggressiveness.
Tests on tumor cells can reveal mutations. This tells your doctor your prognosis and therapy alternatives.

Treatment

Glioblastoma treatments:
Glioblastoma surgery. Neurosurgeons remove glioblastoma. The tumor must be completely removed. Because glioblastoma invades normal brain tissue, excision is impossible. Most people get post-surgery therapy to target leftover cells.

Irradiation: Radiation therapy kills cancer cells with X-rays or protons. You recline on a table during radiation therapy as a machine directs beams to your brain.
Radiation therapy may be coupled with chemotherapy following surgery. Radiation therapy and chemotherapy are alternatives to surgery for some patients.

Chemotherapy: Chemotherapy kills cancer cells. During surgery, tiny chemotherapeutic wafers may be inserted in the brain. Slowly dissolving wafers attack cancer cells.
During and after radiation therapy, temozolomide (Temodar) is typically given following surgery. If glioblastoma recurs, additional treatment may be recommended. Other chemotherapy is often given through an arm vein. TTF treatment TTF disrupts tumor cell growth with an electrical field. TTF utilizes scalp-adhesive pads. A portable gadget generates the electrical field. After radiation therapy, TTF is coupled with chemotherapy.
Drug targeting. Targeted treatments target cancer cell defects that promote growth. Drugs target abnormalities, killing cancer cells.
Bevacizumab targets glioblastoma cell signals that cause new blood vessels to develop and feed cancer cells. Bevacizumab may be an option for recurrent or unresponsive glioblastoma.
Trials. New therapy clinical trials. These studies let you try the latest treatments, but side effects are unknown. Ask your doctor about clinical trials.
Palliative support. Palliative care focuses on relieving pain and other disease symptoms. Palliative care professionals provide extra assistance to you, your family, and your other doctors. Palliative care can be utilized during surgery, chemotherapy, or radiation therapy.

Glioma
Brain/spinal cord tumors are known as gliomas. Gland-supporting cells, known as glial cells, are the origin of most gliomas.

Cancer is caused by three types of glial cells. A tumor's genetic characteristics and the type of glial cell that is causing it can help determine how aggressive the tumor will be and what treatments will be most effective.

Glioma types:
Astrocytic tumor, anaplastic astrocytoma, and glioblastoma.
Epidermomas, such as subcutaneous anaplastic and myxopapillary
There are oligodendrogliomas, anaplastic oligodendrogliomas, and anaplastic oligoastrocytoma in this group.

Gliomas can be life-threatening depending on their location and growth pace.
Gliomas are the most prevalent type of brain tumor.
Depending on the type of glioma, treatment and prognosis can be affected. Glioma treatment options include surgery, radiation, chemotherapy, targeted therapy, and clinical trials.***Symptoms***
Symptoms vary by tumor kind, size, location, and growth pace.
Glioma symptoms include:
Headache, nausea/vomiting, Confusion or brain deterioration, Dementia, Mood swings, Balance issues, UTI, Blurred vision, double vision, or peripheral vision loss, Speech problems, Unprecedented seizures.

Causes
Gliomas' cause is unknown, like other primary brain tumors. Some variables may raise brain tumor risk.
Risks
Gliomas' cause is unknown, like other primary brain tumors. Some variables may raise brain tumor risk. Risk factors:
Age raises brain tumor risk. Gliomas are most frequent in 45-65-year-olds. Any age can get a brain tumor. Children and young adults are more likely to develop ependymomas and pilocytic astrocytomas.
Radioactivity. Ionizing radiation increases brain tumor risk. Ionizing radiation includes cancer treatments and atomic bombs.
Radiation from power lines and microwave ovens has not been demonstrated to enhance glioma risk.
Meningioma

Meningioma is a brain and spinal cord tumor that develops in the meninges. Although not strictly a brain tumor, it can compress neighboring brain, nerves, and arteries. Most head tumors are meningiomas. Most meningiomas grow slowly, frequently without symptoms. Their impact on brain tissue, nerves, or arteries might induce impairment. Meningiomas are more common in women and older ages, but can occur at any age.
Most meningiomas grow slowly and without symptoms, so they may be watched over time.

Symptoms
Meningioma symptoms are usually gradual and modest at first. Signs and symptoms depend on where the tumor is in the brain or spine. Double vision or blurriness Morning headaches Hearing loss or ringing in the ears Memory loss of smell Seizures Arm or leg weakness Language problems

2.2 Machine learning

If ever wondered how to construct AI that can learn from data without being explicitly programmed, machine learning is the answer.
An algorithm is a set of statistical processing processes in data science. When it comes to machine learning, computers are tasked with 'teaching' themselves to recognize patterns and features in vast volumes of data in order to anticipate future outcomes. As it analyses more data, a smarter algorithm will produce more accurate conclusions and predictions (IBM, 2020).
It is the goal of machine learning to develop applications that can learn from past experiences and improve their decision-making and forecast accuracy over time.

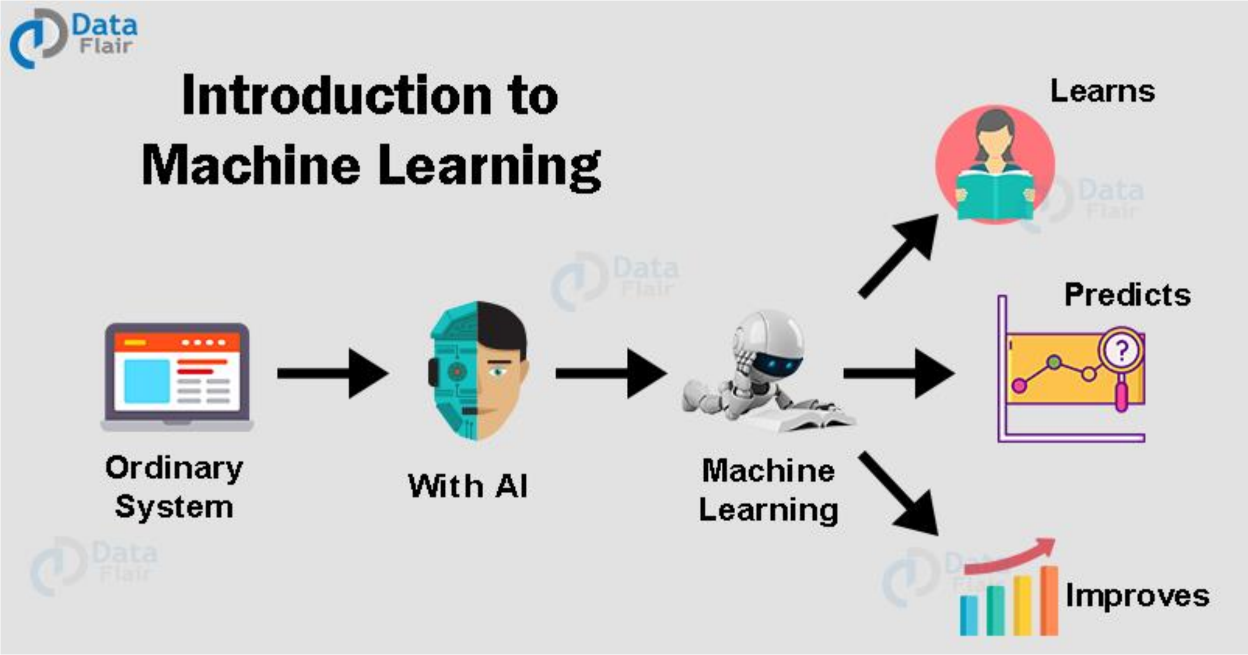


Figure 1: Data flair machine learning introduction

2.2.1 What machine learning does;

We can create intelligent systems capable of self-decision with the use of Machine Learning.
Statistical analysis and pattern matching are the methods used by these algorithms to learn from previous data.
Once the data is understood, it predicts the outcomes based on that data.
Algorithms for machine learning rely on data as their foundation.
We may use previous data to train machine learning algorithms, which in turn allows us to generate new data.
The advanced idea of Machine Learning known as Generative Adversarial Networks, for example, learns from previous photos and then uses that knowledge to generate new images.
Speech and text synthesis can also benefit from this.

Machine Learning, on the other hand, has opened up a wide range of applications for data science.
Computer science, mathematics, and statistics all come together in machine learning.
In order to get meaningful conclusions from data, we need statistics.
The development of machine learning models relies on mathematics, while the implementation of those models relies on computer science.
Building models alone, on the other hand, will not enough.
To get accurate results, you'll need to fine-tune and optimize your model.
To achieve the best possible outcome, optimization approaches use hyper parameter adjustment.
A wide range of industries rely on machine learning. Static systems can gain intelligence by utilizing this technology.
Intelligent products are created using the data's accumulated expertise.

2.2.2 How machine learning works;

Machine learning creates artificial intelligence (AI) programs that learn from experience and improve over time.
Algorithms in the field of data science are statistical processes. Algorithms are 'trained' to recognize patterns and features in massive amounts of data and use this information to create predictions. The algorithm becomes better at making predictions and conclusions as it analyzes more data (IBM, 2020). The focus of machine learning is on applications that learn and improve over time.
Machine learning helps us create intelligent, autonomous systems. Through statistical analysis and pattern matching, these algorithms learn from past data. Then it predicts results based on the learned data. Machine learning algorithms rely on data. Training machine learning algorithms with past data creates more data.

Generative Adversarial Networks, an advanced Machine Learning concept, learn from previous images to generate more images. Speech and text synthesis use this method. Machine Learning offers huge data science application potential.Machine Learning mixes CS, Math, and Stats. Data inference requires statistics.

Computer science is used to implement algorithms and develop machine learning models. Modeling isn't enough. Optimize and tweak the model for accurate results. Hyperparameters are tuned for optimization. Every field uses ML. It gives static systems intelligence. With data understanding, intelligent products are built.

Machine learning;

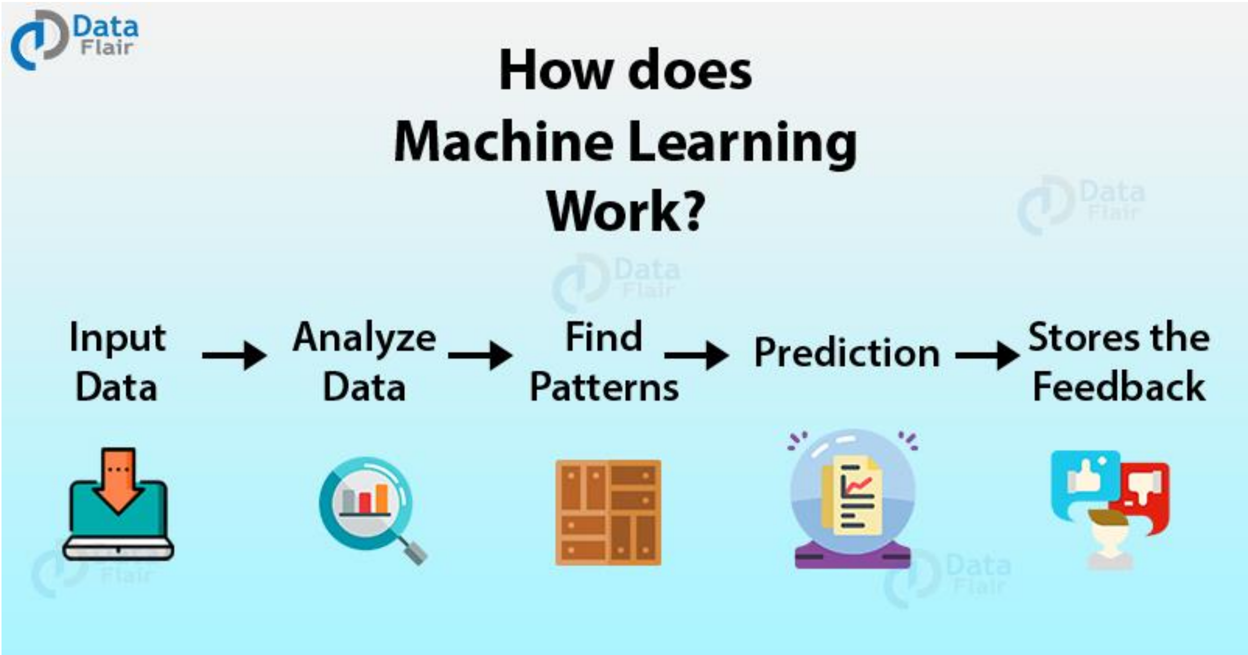


Figure 2: Data flair machine learning steps

2.3. Deep learning

It is a type of machine learning known as deep learning (all deep learning is machine learning, but not all machine learning is deep learning). Deep learning techniques are used to build artificial neural networks that mimic the functions of the human brain. In order to alter and improve the outcomes, deep learning models necessitate enormous amounts of data, which must be processed through multiple layers of computation.

There are no supervised or semi-supervised deep learning models. Reinforcement learning has the potential to be extremely complex. Computer vision, natural language processing (including speech recognition), and self-driving cars are all benefiting from advances in convolutional and recurrent neural networks (CNNs and RNNs).

2.4 Neural Networks

Algorithms for machine learning modeled after the brain are known as neural networks. Neuronal networks can learn from data and make predictions or classifications, just like neurons in our own brains.

New patterns can be discovered using nonlinear statistical models that have complex input-output interactions. Images are recognized by artificial neural networks. Speech is recognized by artificial neural networks.

2.4.1 Architecture of neural networks

Artificial Neural Networks work like our neurons. Three layers:
INPUTS
The input layer of an ANN accepts text, numbers, audio files, image pixels, etc.

Hidden Layers
Hidden layers are in the ANN model. A perceptron can have one or several hidden layers. These hidden layers do math on input data and recognize patterns.

Output layer
The middle layer's rigorous computations are output in the output layer. Parameters and hyper parameters affect a neural network's performance. These settings determine ANN output. Weights, biases, learning rate, batch size, etc. ANN nodes have weight. Each network node is weighted. A transfer function calculates the inputs and bias weighted sum.

2.4.2 Artificial Neural Networks

Artificial Neural Networks have two types:

Feedback Neural Network and Feedforward ANN
Feedforward ANNs have one-way information flow. Information flows from input to hidden to output. This neural network is feedback-free. These neural networks are used for classification, image recognition, etc. in supervised learning. They're used when data isn't consecutive.
AI feedback Loops are component of feedback ANNs. Recurrent neural networks are used to retain memories. Sequential or time-dependent data is best for these networks.
Handwritten Character Recognition; Speech Recognition; Signature Classification; Facial Recognition

2.5 Convolutional Neural Networks

Deep Learning Convolutional Neural Networks learn the image's attributes through filters. This helps them understand the image's essential objects and distinguish between images.
The neural network learns the properties that distinguish cats from dogs so it can readily identify between cats and dogs.
Convolutional Neural Network's capacity to pre-process data distinguishes it from other Machine Learning techniques. Pre-processing data may not require many resources.
Cold-start filters may need manual engineering, but with training they can adapt to learnt features and develop their own. CNN evolves as data grows.

2.5.1 How do CNNs work?

CNNs perform similarly to fully linked NNs. Convolutional networks learn from input and biases. Every network neuron receives an input and does a dot product. Non-linear.
Ending scoring function is unique. This function includes neural network layer scores. A loss function to evaluate model performance. Convolutional neural networks assume input as an image, unlike ordinary neural networks.

This assumption simplifies architectural definition. Unlike a simple neural network's linear structure. Neurons have length, width, and height. Images in the CIFAR 10 dataset are 32x32x3, but the final output is 1x1x10.

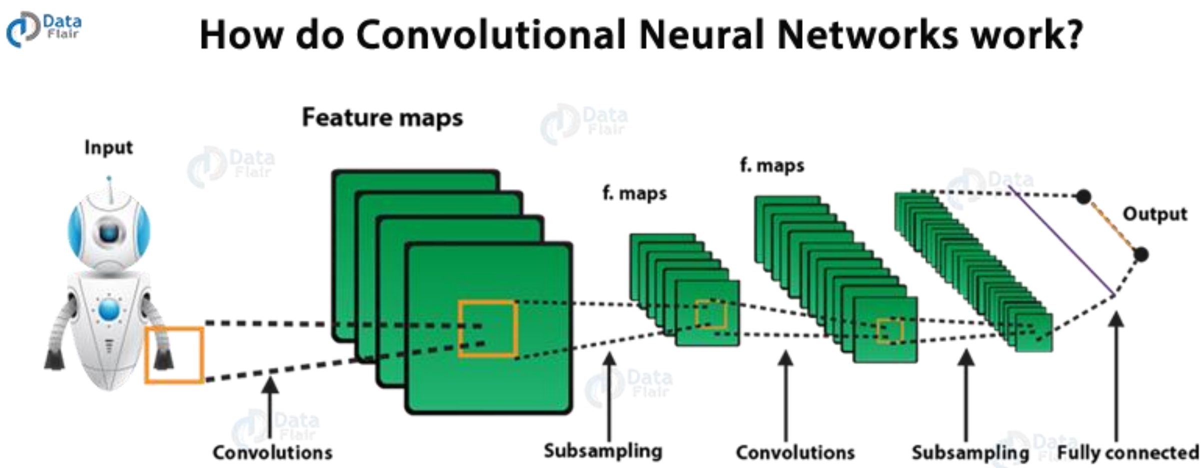


Figure 4: CNN operation
The CNN architecture is:

INPUT – As described above, a typical CIFAR 10 image is 32x32x3, where depth specifies the number of channels (RGB).
The CONV layer computes the dot product between neuron weights and input picture regions. Here, 32x32x12 represents the neural network's 12 filters.
The final layer is RELU, which activates our dot product. This result's size remains constant.
The fourth POOL layer samples image width and height. This makes it 16x16x12.
●Fully connected layer computes class score, resulting in 1x1x10 volume. CIFAR-10 has 10 categories.

2.5.2 CNN **Uses**

CNNs were developed for image recognition and are used for classifying, segmenting, and localizing pictures in computer vision.

Videos have a temporal dimension, unlike photographs. While more sophisticated than photos, CNNs can handle streaming visual inputs. Convolutional networks are used with LSTM and Boltzmann Machines for managing visual input.
CNNs are used for semantic parsing, sentence modeling, prediction, and classification in Natural Language Processing.
Google uses CNNs, RNNs, and LSTMs for speech recognition.
CNNs are also utilized in drug development to uncover molecule-protein interactions and potential treatments.

2.5.3 Examples of CNN Architectures

Classic network architectures (included for historical purposes)

- LeNet-5, AlexNet, VGG 16

Modern network architectures

- Inception, ResNet, ResNeXt, Dense Net

2.6 Image analysis and CNNs

Medical image analysis is the science of applying image analysis tools to solve medical problems. It's a leading engineering and medical research area. Medical image analysis has increasingly used machine learning methods.
These machine learning algorithms extract condensed information to increase medical image analysis systems' performance over older methods that use handmade features. Deep learning has provided state-of-the-art findings in pattern recognition and computer vision research.
CNN's applications include medical image recognition, segmentation, classification, and CAD. Medical image analysis aids radiologists and doctors in diagnosis and therapy. CADx and CAD rely on medical image analysis, making performance critical since it affects clinical diagnosis and therapy. Medical image analysis requires good accuracy, F-measure, precision, recall, sensitivity, and specificity. Medical image analysis requires a strategy suited to large data analysis since digital clinical images are growing rapidly.

2.6.1 Segmentation

Segmentation divides a picture into distinct non-overlapping sections based on pixels or fundamental properties like color, contrast, and texture. Segmentation minimizes an image's search area by splitting it into object and background classes. Image segmentation represents the image so it may be used and examined easily.
Medical picture segmentation extracts shape, volume, organ position, and anomalies.

2.6.2 Abnormality detection/classification

Abnormality detection in medical pictures identifies diseases like tumors. Detecting anomalies traditionally takes human labor and time. Automated abnormality detection systems are gaining popularity.

2.6.3 CAD (CADx)

Computer-aided detection (CADe) or computer-aided diagnosis (CADx) systems are used in radiology to help interpret medical images. These include machine learning, computer vision, and image processing in the medical imaging field. In clinical practice, a typical CADe system acts as a second reader, providing additional information about the abnormal location.
CADe's core components include pre-processing, feature extraction, feature selection, and classification.

2.6.4 Image retrieval

Hospitals make extensive use of computers and digital information systems. A large number of medical images are generated by PACSs. A large number of medical images are generated at hospitals and radiology departments, resulting in enormous image archives. These solutions are needed to standardize the generation and management of large databases, and they must be automated. A patient's condition, stage, and diagnosis can be determined more quickly and accurately if similar examples are used. Medical images need classification and retrieval strategies.
CBIR systems built on LESVP utilize reduced feature vectors, classification trees, and regression trees to analyze skin lesions. This technique retrieves brain MRIs for the diagnosis of Alzheimer's disease using BoVWs and SIFT.

2.7 Metrics Evaluation

Accuracy, F1-score, precision, recall, and sensitivity, specificity, and dice coefficient are all metrics used to assess medical image analysis systems. These measurements are as follows:

Evaluation Metrics	**Formulae**
Accuracy (TPR)	$(TP + TN)N$
Sensitivity (TNR)	$(TP + FN)/TP$
Specificity	$(TN + FP)/TN$

Precision	$(TP + FP)/TP$
Recall	$(TP + FN)/TP$
F1-score	$2((precision * recall)/(precision + recall))$
ROC	$calculatestheareaundertheROC$

Table 1: Evaluation metrics

where, TP (true positive) represents the number of correctly recognized cases as defected, FP (false positive) represents the number incorrectly recognized cases as defected, TN (true negative) represents the number of correctly recognized cases as non-defected and FN (false negative) represents the number of incorrectly recognized cases as non-defected.

2.8 Neurology and CNNs

Deciphering hospital electronic data could change modern medicine, but the hurdles are great. Deep learning has changed medical machine learning with new algorithms and technology. Due to mild neurological symptoms, clinical neurosciences will profit from these advances.

Deep learning algorithms have revolutionized medical image segmentation for quantitative evaluation of neuroanatomy and vasculature, connectome mapping for the diagnosis of autism, ASD, and ADHD, and mining of microscopic EEG signals.

New diagnostic and prediction tools are being created using deep learning in clinical neuroscience. Clinical diagnosis relies on subtle symptoms and advanced neuroimaging modalities, making deep learning techniques intriguing in neuroscience.

Deep learning was developed through computational and open-source research. Graphics processing units have cut training time from months to days, expanding algorithm architectures. Rapid and high-throughput experimentation improves algorithms.

TensorFlow, Keras, PyTorch, Caffe, and others have made it easier to collaborate on cutting-edge research and applications. Deep learning has changed medical research and patient treatment.

2.9 Related work

Here is a summary and analysis of recent studies.

Component analysis can detect brain cancers in MRI images (Padole & Chaudhari, 2018). Combining Normalized cut (Ncut) and mean shift algorithms can automatically detect brain tumor surface area.

(Roy & Bandyopadhyay,2019) assessed the brain tumor utilizing symmetric analysis [7]. This method's quantitative analysis helps diagnose disease.

El-Dahshan et al. studied classification and segmentation approaches and concluded that MRI of the human brain needs computer-aided diagnosis. The authors created a hybrid intelligent machine learning system for MRI brain tumor detection. A neural network and feedback pulse segment the images. A feed-forward neural network with backpropagation classifies abnormal and normal images. The tests use 101 MRI scans of a human brain, 87 abnormal and 14 normal. This technique's accuracy was 98%.

Abdel-Maksoud et al. combined K-means clustering with fuzzy C-means to segment images. Thresholding and segmentation helped spot the tumor accurately. Fuzzy c-means reduced calculation time and increased accuracy. The suggested technique's performance, processing time, and accuracy were compared to existing methods. Experiments showed the method's usefulness by improving segmentation quality and accuracy with minimal run time.

Multimodal Brain Tumor Image Segmentation Benchmark (BRATS). Twenty segmentation algorithms were trained on 65 multi-contrast MRI scans of glioma patients. Separate methods were shown to be optimal for distinct tumor subregions.

(Mahalakshmi & Velmurugan,2019) used particle swarm optimization to detect brain tumors. Conversion, implementation, selection, and extraction make up the algorithm. The suggested PSO algorithm measures brain MRI images.

(Elamri & Planque, 2020) suggested a 3D convolutional neural network-based approach for segmenting GBM tumors. The authors proposed generalizing CNNs to get 3D filters for increased robustness and geographical information. The presented CNN design increased effective data size, reduced model variance, and improved accuracy to 89%.

Pereira et al. developed an automatic segmentation algorithm employing 3*3 CNN kernels. These kernels permitted deeper architecture design and reduced overfitting. Using intensity normalization and data augmentation as preprocessing steps improved MRI image segmentation. The BRATS 2013 database validates this method. The above work still needs accuracy improvements. Optimized WCA approaches can remedy this.

Dong et al., established a fully automatic technique for segmenting brain tumors using U-Net. The tests used LGG and HGG BRATS 2015 datasets. Experiments showed the recommended technique worked. Five-fold cross-validation validated the technique. This approach may segment tumor pictures for specific patients without any intervention.

Havaei et al. developed an automatic brain tumor segmentation method utilizing deep neural networks (DNN). This DNN approach uses global and local contextual features. Two-phased training eliminates imbalanced tumor labeling.

Shen et al. extended fuzzy C-means (FCM) to build a robust segmentation technique. Neighborhood attractiveness is determined by the placement and qualities of nearby pixels. Neural network technology optimizes this attraction. Classifier accuracy isn't improved. FCM-based techniques with varying noise levels justify the approach. The current MRI segmentation approach.

Kazerooni et al. updated the standard GVF method to segment MRI brain tumors. Active contour evolution uses scaled edge maps. This method is improved using threshold-based edge detection. Bspline snakes represent active contour. Bspline snake captures corners and has local control. This method improves GVF accuracy by 30%. Currently enhancing the approach's efficiency, security, and robustness in noise, but the detection rate hasn't changed.

Chen et al. segmented MRI images using fuzzy clustering and MRF. Fuzzy clustering used gray-level data to remove disruptions. It's based on multi-scale decomposition's coarse image. MRF improves image fidelity and reduces noise. MAP-MRF combines geographical limitations and gray level data.

(Josephine, 2018) segmented brain picture using symmetry. This effort aims to automatically detect tumor site and edge. Experiments use real photos. Experiments highlight the algorithm's flexibility and convenience. It recognizes tumors in T1, T2-weighted MRI brain imaging. Current classification approaches exclude benign and malignant tumors.

(Par Knur and HarishKundra, 2019) updated the intelligent water droplets algorithm. IWD detects brain cancers using MRI scans. SVM classifier improves intelligent water droplets algorithm. SVM classifies cancer and non-cancer MRI cells. SVM classifier receives IWD output. MATLAB measures the system's performance. It boosts accuracy by 20%. Execution time is 1.5 s.

2.10 Research gap

Many techniques have been proposed for classification of brain tumors in MR images, including fuzzy clustering means (Raghavan,2018), support vector machine (Zanaty,2019), artificial neural network (ANN), knowledge-based techniques (Kong, 2020), and expectation-maximization (Vijakumar, 2018) algorithm technique.
A general brain tumor detection procedure includes pre-processing the picture to reduce noise and artifacts, segmenting the image to identify likely tumor regions, and collecting usable features from the tumor regions.

Despite advantages, current approaches can't accurately forecast brain tumors. This study aims to improve brain tumor detection accuracy and reduce computation time using convolutional neural networks.
In this project, a mixture of biologically inspired RESNET and RESUNET models will classify healthy and infected tumor tissues for a vast library of medical images. The trained model will include clinical decision support tools for primary screening and diagnosis.

2.11 Proposed Model

The graphic below shows how applying RESNET and RESUNET models improves diagnosis and localization.

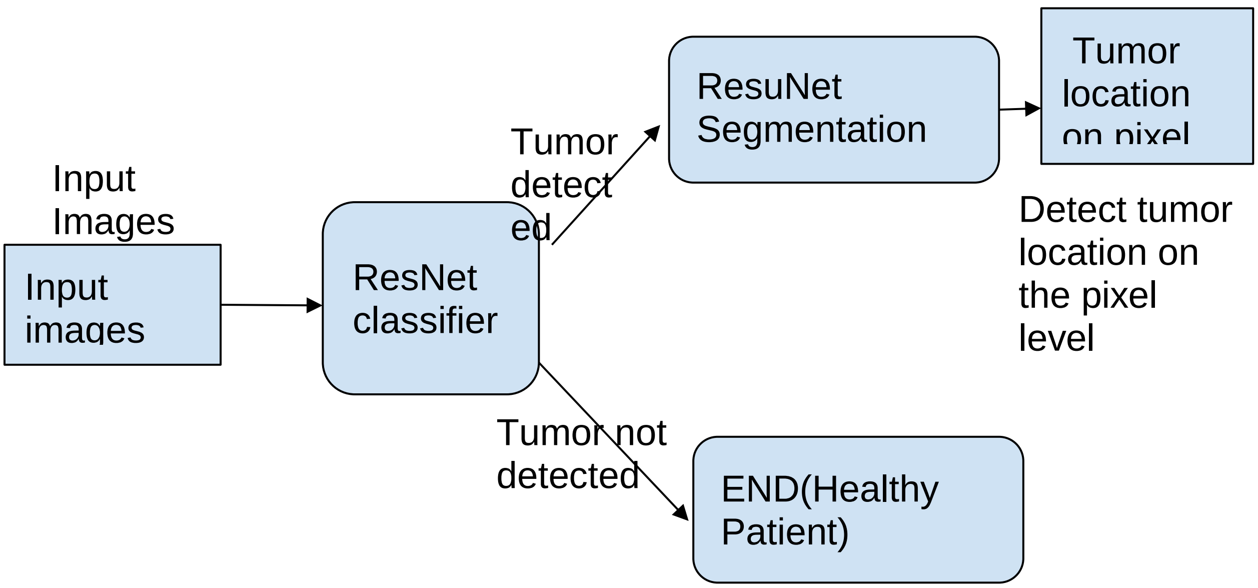


Figure 5: Proposed model

CHAPTER THREE: METHODOLOGY

3.0 Introduction

This section describes the study's concepts, guidelines, rules, and processes. The study targeted brain tumors. The idea is to use Convolutional neural networks to forecast and segment brain tumors based on data attributes.
The Cancer Imaging Archive provided the research dataset (TCIA)..

3.1 Research design

This section addresses data gathering, visualization, image processing, data analysis, research quality, validity, reliability, and ethics.

3.2 Data collection

The dataset includes brain MR images with manual FLAIR masks. Cancer Imaging Archive provided the images (TCIA). They relate to 3929 TCGA lower-grade glioma patients with FLAIR sequencing and genomic cluster data. Data.csv contains tumor and patient genomic groupings.

3.3 Image processing

This entails enhancing images or extracting relevant information from them. This includes converting 3D photos to 3D for faster processing. All the photographs will then be turned to grayscale and augmented to add more.

3.3.1 Data split

Randomly split the dataset comprising negative and positive attributes into training and testing sets. Shuffling eliminates training bias. The remaining 15% is used to test the model's performance.

3.3.2 Feature extraction

New features from old ones will reduce the number of image features. CNN architecture will be utilized to extract features because it can learn automatically even for little features across a wide space. CNN creates features. Feature extraction creates a m * m layer across the feature map.

3.4 Data analysis

We'll apply transfer learning, deep learning classification, and ResUNet segmentation.

3.4.1 Transfer learning

Pre-trained machine learning networks are reused for comparable tasks. Transfer is useful since using pretrained models can minimize training time.

Steps to transmit learning.
Freeze CNN's first-layer weights.
Train the newly added dense layers (with randomly initialized weights) Initialize CNN with pre-trained weights
Retrain CNN at a slow rate. Learning rate prevents aggressive weight changes.

3.4.2 ResNet Classification learning

ResNet seeks to eliminate vanishing gradients as CNN models go deeper. Network performance suffers from vanishing gradient.
ResNet classifiers will detect tumors. Asses ResNet model performance.

3.4.3 Segmenting Resunet

ResUNet combines UNet and residual blocks to eliminate vanishing gradient descent. UNET uses fully convolutional networks adjusted for segmentation tasks.
Image segmentation extracts pixel-level information from images.
Segmentation will train a neural network to create a pixel-wise picture mask.
Every input pixel's loss function will be formulated.
Softmax function is applied to every pixel to turn segmentation into a classification problem where every pixel is classified.
Mask is the model's output.

3.5 Research validity, reliability.

The trained ResNet classifier and ResUNet segmentation model will be assessed and validated. Accuracy, precision, recall, specificity, F1-score, ROC score will be measured.

Evaluation Metrics	**Formulae**
Accuracy (TPR)	$(TP + TN)N$
Sensitivity(TNR)	$(TP + FN)/TP$
Specificity	$(TN + FP)/TN$
Precision	$(TP + FP)/TP$
Recall	$(TP + FN)/TP$
F1-score	$2((precision * recall)/(precision + recall))$
ROC	$calculatestheareaundertheROC$

Table 2: research quality and validity table

Another criterion that is utilized during the assessment process is the computation time. This refers to the total amount of time that is necessary for image processing, segmentation, features extraction, features reduction, classification, and evaluation. The amount of time spent computing or processing data should be kept to a minimum, provided that this does not compromise the reliability of the classification.

3.6 Analysis tools

Python and Google Colab Notebook will be used for processing and Analysis. Google Colab Notebook offers TensorFlow with TPU that accelerates operations on TensorFlow graphs and 64GB of high bandwidth memory on a single board. It also has all the libraries pre-installed making work easier. This saves on time and computation costs.

3.7 Ethical considerations

The brain MRI and masked images are HIPAA complaints and the images will then be de-identified. This means that the privacy of the patient information is protected, there is physical and electronic security of patient health information and specifies the patients’ rights to approve the use and access of medical information.

The research will be carried out in accordance with the use agreement of the Brain MRI dataset.

CHAPTER FOUR: SYSTEMS ANALYSIS AND DESIGN

4.0 Introduction

This part entails functional and non- functional requirements and discusses further systems design and architecture. The chapter also models the data flow, use case diagram, sequence diagram and class diagram.

4.1 Requirement Analysis

Functional requirements

Functional requirements that are described in the systems are:

i. System should accept images from users as input.
ii. The system should be able to extract specific features from images provided.
iii. The systems should detect and localize brain tumor from the image provided.
iv. The system should display a response whether brain tumor is detected or not and the exact tumor location.

Non-functional Requirements

i. The system should be able to adapt gradually and improve based on the training data set.
ii. The system should be secure to prevent unauthorized personnel and changes to the model parameters.
iii. The system should be able to adjust its weights accordingly when new dataset is provided.
iv. To avoid over training, the system should store model weights every time a prediction is made.
v. The system should not be complex that it results model overfitting.

4.2 Systems Design

Modules

Patient Registry

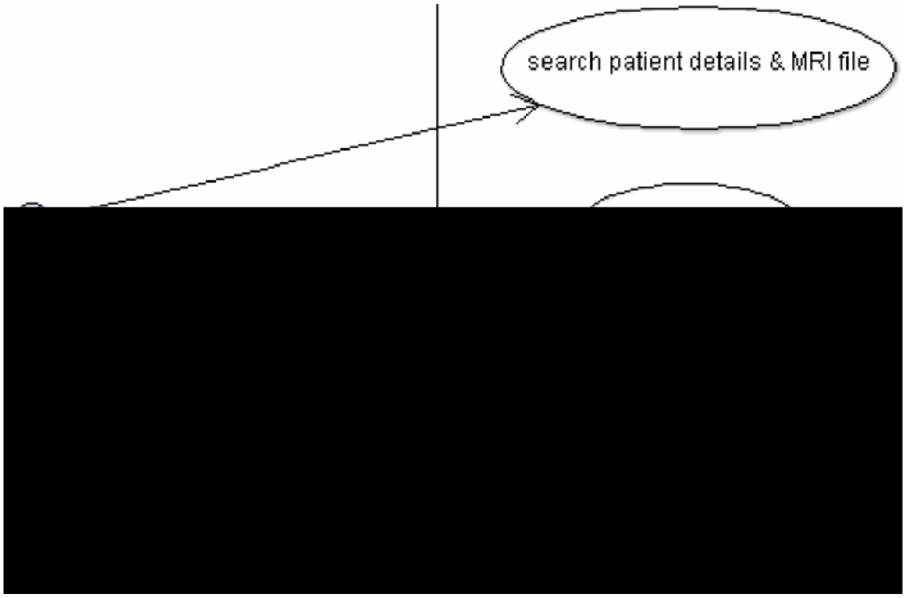
a. Add patient detail
b. Update patient detail
c. Delete patient detail

Tumor identification

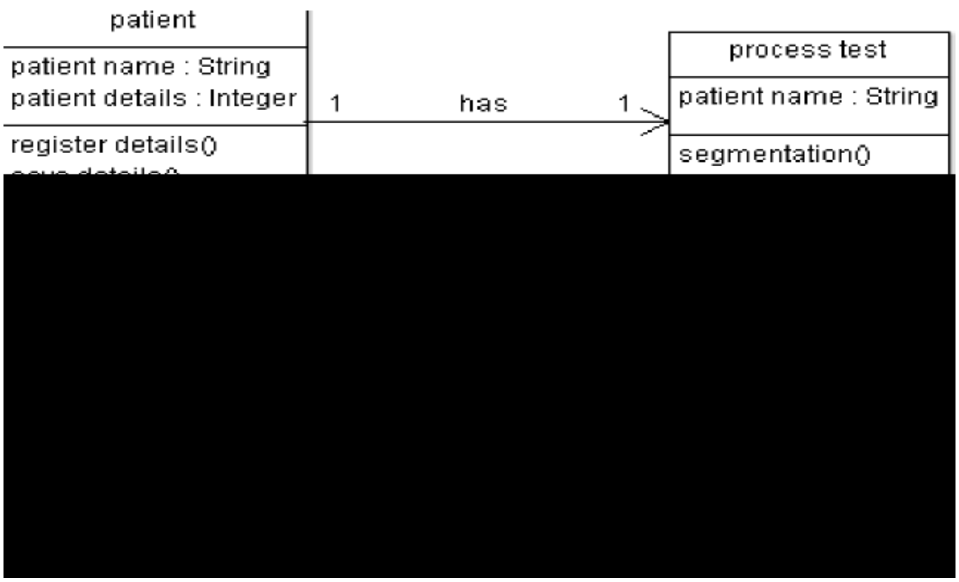
a. Detection
b. Segmentation

Use case Diagram

Represents participants involved in the model design. These participants have different responsibilities. These participants are medical experts and a developer.



Class diagram Report



4.3 Platform Requirement

Supportive operating systems:

WINDOWS 10 PRO

Software Requirement:
Python, Google Colab

4.4 Libraries

Libraries to be imported for systems development

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import zipfile
import cv2
from skimage import io
import tensorflow as tf
from tensorflow.python.keras import Sequential
from tensorflow.keras import layers, optimizers
from tensorflow.keras.applications import DenseNet121
from tensorflow.keras.applications.resnet50 import ResNet50
from tensorflow.keras.layers import *
from tensorflow.keras.models import Model, load_model
from tensorflow.keras.initializers import glorot_uniform
from tensorflow.keras.utils import plot_model
from tensorflow.keras.callbacks import ReduceLROnPlateau, EarlyStopping, Mode
lCheckpoint, LearningRateScheduler
from IPython.display import display
from tensorflow.keras import backend as K
from sklearn.preprocessing import StandardScaler, normalize
import os
import glob
import random
from google.colab import files #library to upload files to colab notebook
```

4.5 Hardware Requirement

Basic Hardware Requirement for Development
PROCESSOR: AMD A12

RAM: 12GB

MONITOR: 14'
KEYBOARD: STANDARD KEYBOARD
MOUSE: STARNDAD MOUSE

CHAPTER FIVE: RESULTS AND EVALUATION

5.0 Overview

This section describes the model's outcome. The model was segmented using RESUNET and classified using a Convolutional neural network. Performance evaluation compares segmentation and classification against other models.

5.1 Experiment setup

Image processing uses Jupyter Notebook and Python libraries NumPy, Pandas, OpenCV. Used Python 3.6 with Anaconda. CNN, TensorFlow, and Keras were used with a Google Colab TPU for model training and testing.

5.2 Dataset

This research used brain tumor MR images from The Cancer Imaging Archive (TCIA) for 110 patients in The Cancer Genome Atlas (TCGA) lower-grade glioma collection with FLAIR sequencing and genomic cluster data.
The tumor- and non-tumor-labeled dataset is separated into Training and Testing sets.
3929 Brain MRI scans show brain tumor locations.

5.3 Image preprocessing

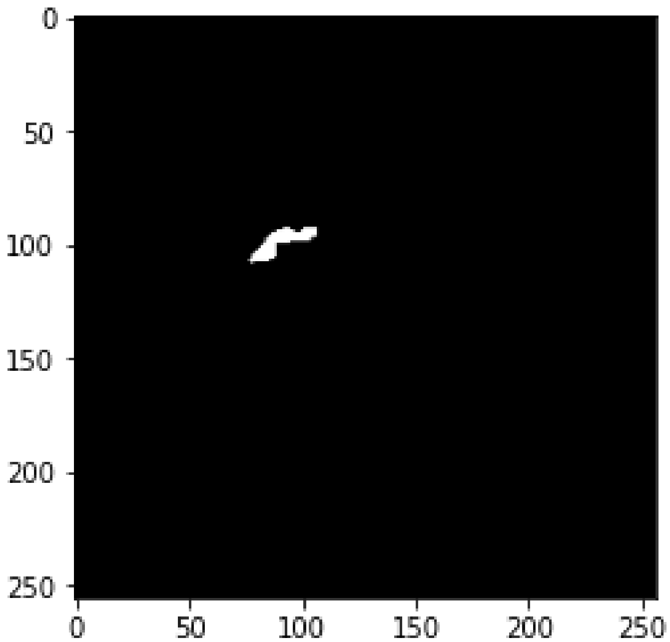
5.3.1 Tumor segmentation

Segmenting images extracts pixel-level information. This trains a neural network to create a pixel-by-pixel image mask. Modern image segmentation approaches use deep learning, CNN, FCNs, and deep encoders-decoders.
ResUNet encodes images into vectors and decodes them back into images.
Every input pixel has a loss function.
Softmax function is then applied to every pixel, making segmentation a classification problem where every pixel is classified.

5.3.2 Masking

Image segmentation model output.

Assigning pixel values to coordinates represents a mask. Flattening the image into a 1-D array yields [255, 0, 0, 255] for the mask. Index makes a mask.



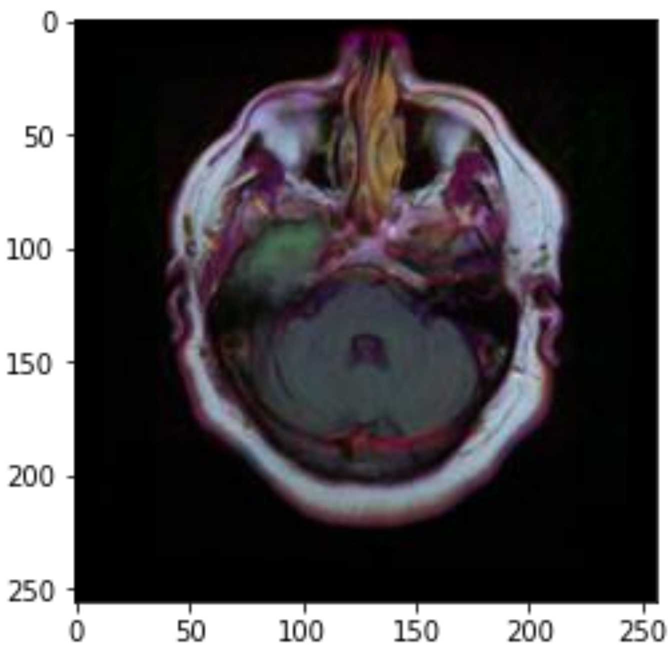


Figure shows a mask a corresponding image.

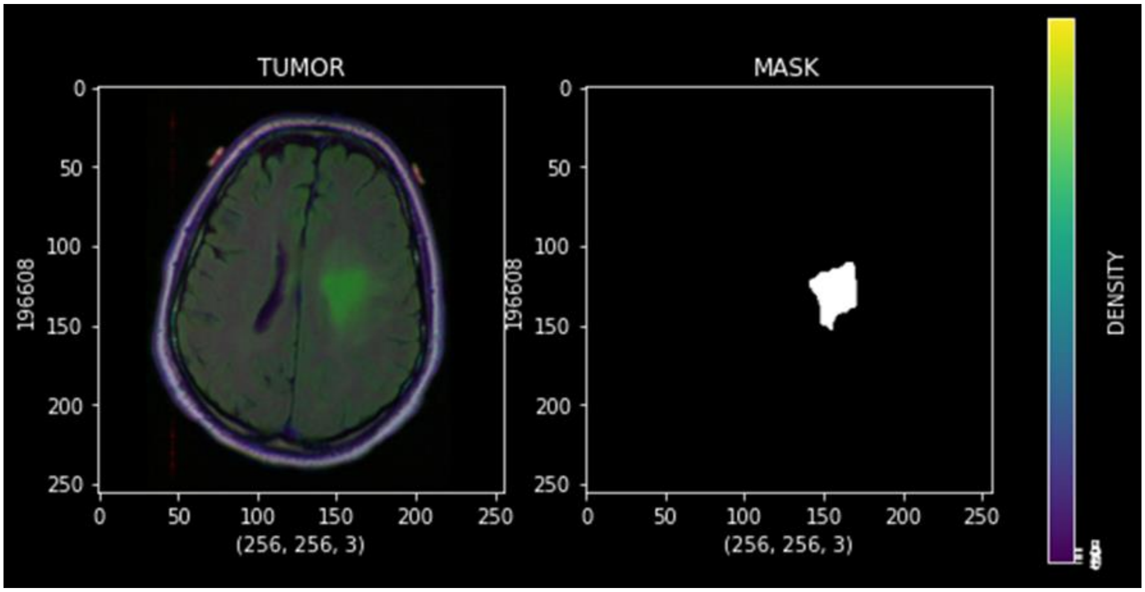
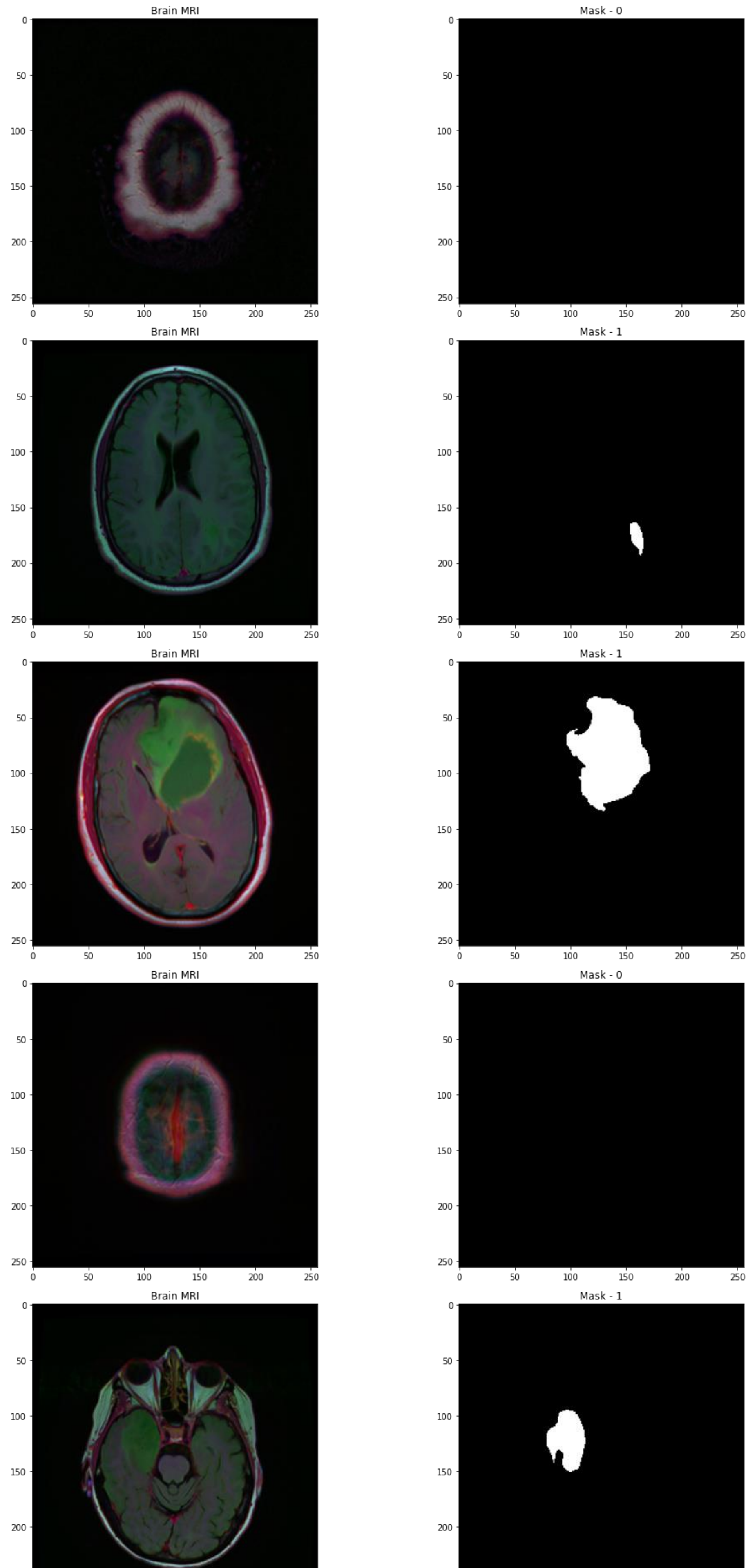
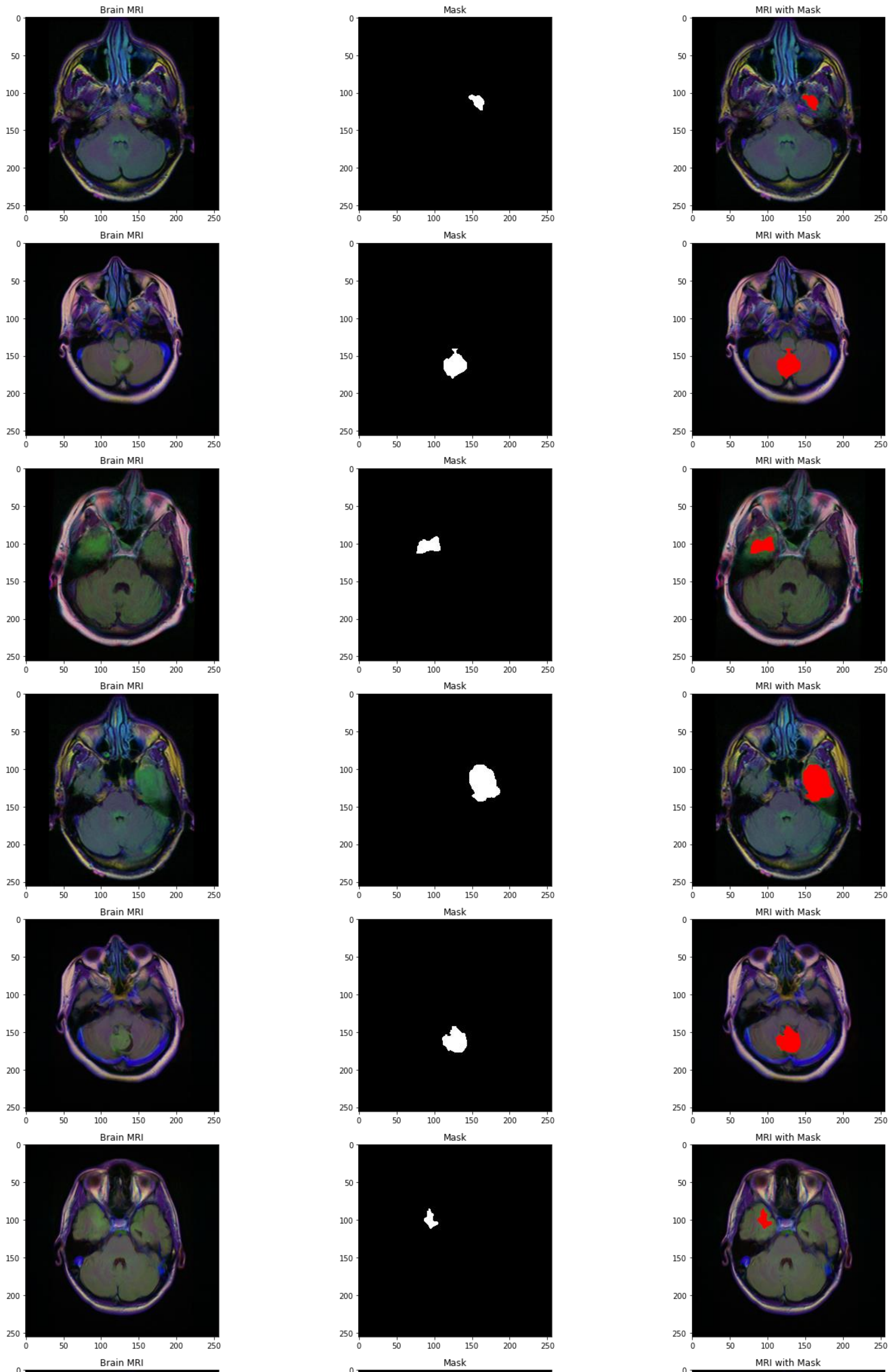


Figure : Brain MRI with corresponding Masks


Brain MRI
Mask - 0
Brain MRI
Mask - 1
Brain MRI
Mask - 1
Brain MRI
Mask - 0
Brain MRI
Mask - 1


Brain MRI
Mask
MRI with Mask

5.4 Part 1: Model building and Trainning.

Calculations were made to determine the total number of parameters, the total number of trainable parameters, and the total number of non-trainable parameters while the model was being trained. The outcomes are detailed in the table that follows;

Total number of Parameters	23,587,712
Number of trainable parameters	**23,534,592**
Non-trainable parameters	**53,120**

Confusion Matrix

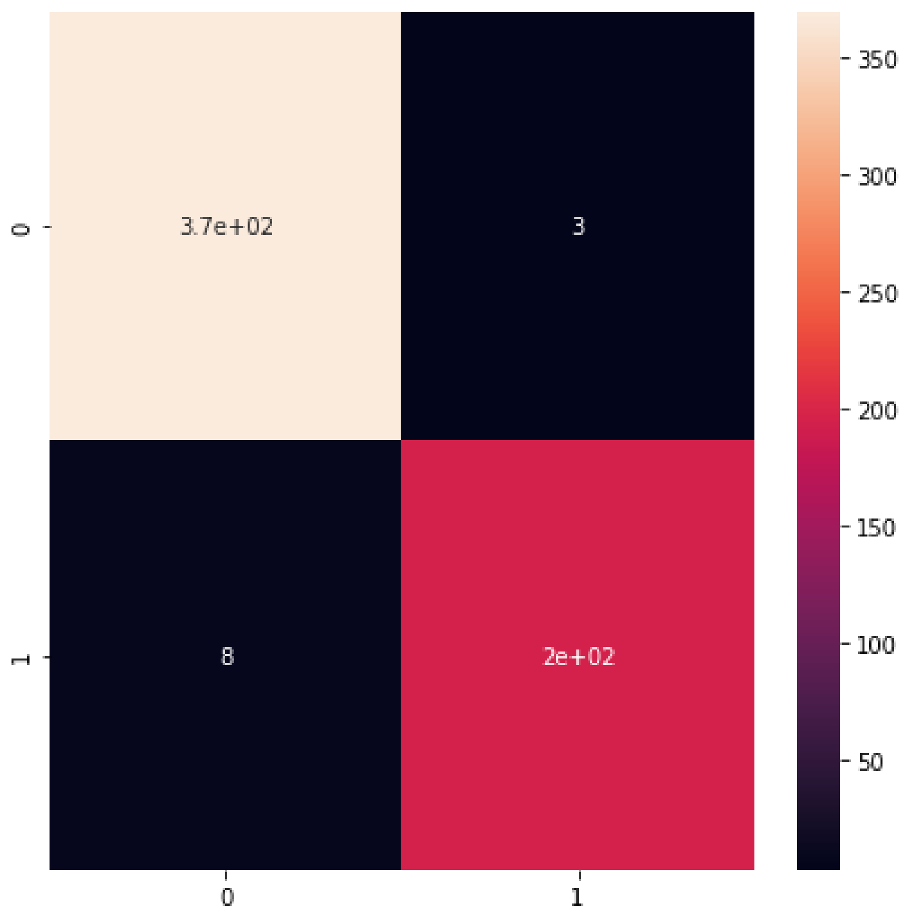


Table for confusion score

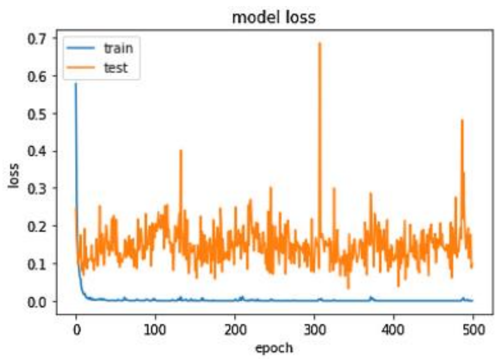
	Predicted (YES)	**Predicted (NO)**
Actual (YES)	365	2
Actual (NO)	9	200

Table: **Table for metrics and performance**

Metrics	**Score**
True positive, TP	**365**
True negative, TN	**200**
False positive, FP	**2**
False negative, FN	**9**
Accuracy score	**0.98**
Precision	**0.98**
Recall	**0.98**
F1-score	**0.97**
Precision	0.99

F1-score

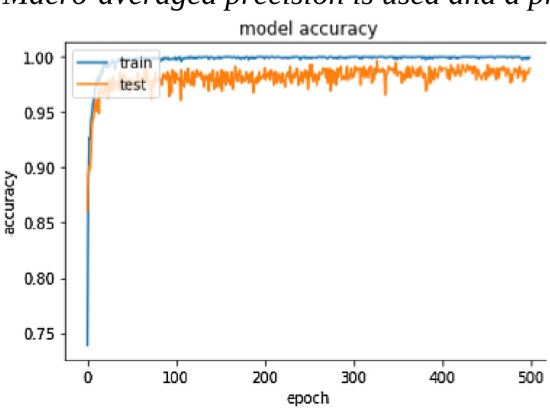
Macro-averaged FI score is used and a score of 97% is achieved.



(d) loss

Precision

Macro-averaged precision is used and a precision of 99% is achieved.



(a) accuracy

5.5 Part ii: Building a segmentation model to localize Brain Tumor

Parameters were also computed for the RESUNET segmentation model

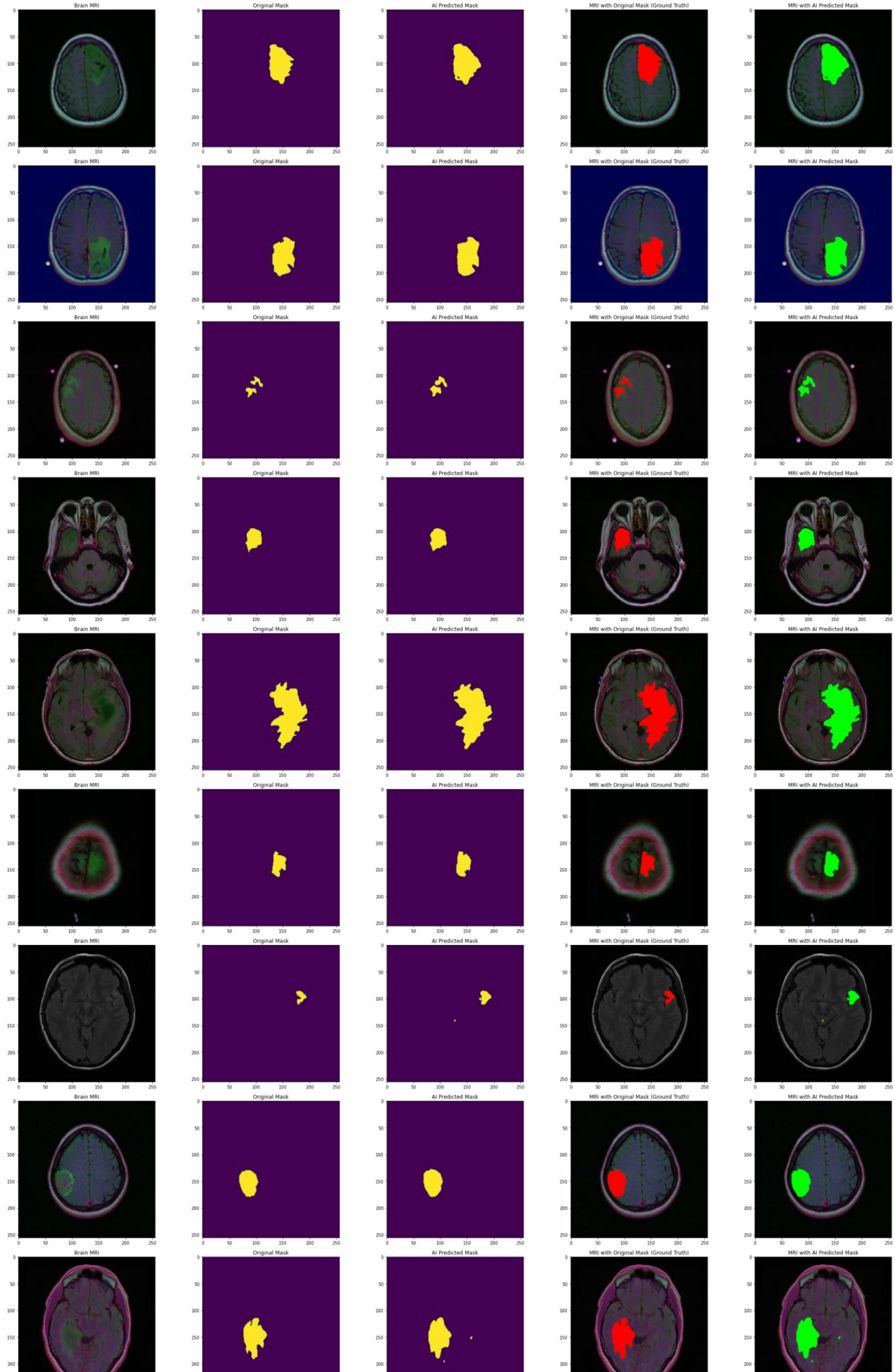
Total number of Parameters	1,206,465
Number of trainable parameters	1,202,177
Non-trainable parameters	4,288

Table for confusion score

	Predicted (YES)	**Predicted (NO)**
Actual (YES)	365	2
Actual (NO)	9	200

Table: **Table for metrics and performance**

Metrics	**Score**
True positive, TP	**365**
True negative, TN	**200**
False positive, FP	**2**
False negative, FN	**9**
Accuracy score	**0.98**
Precision	**0.98**
Recall	**0.98**
F1-score	**0.97**
Precision	0.99



Brain MRI
Original Mask
AI Predicted Mask
MRI with Original Mask (Ground Truth)
MRI with AI Predicted Mask
Brain MRI
Original Mask
AI Predicted Mask
MRI with Original Mask (Ground Truth)
MRI with AI Predicted Mask
Brain MRI
Original Mask
AI Predicted Mask
MRI with Original Mask (Ground Truth)
MRI with AI Predicted Mask
Brain MRI
Original Mask
AI Predicted Mask
MRI with Original Mask (Ground Truth)
MRI with AI Predicted Mask
Brain MRI
Original Mask
AI Predicted Mask
MRI with Original Mask (Ground Truth)
MRI with AI Predicted Mask
Brain MRI
Original Mask
AI Predicted Mask
MRI with Original Mask (Ground Truth)
MRI with AI Predicted Mask
Brain MRI
Original Mask
AI Predicted Mask
MRI with Original Mask (Ground Truth)
MRI with AI Predicted Mask
Brain MRI
Original Mask
AI Predicted Mask
MRI with Original Mask (Ground Truth)
MRI with AI Predicted Mask
Brain MRI
Original Mask
AI Predicted Mask
MRI with Original Mask (Ground Truth)
MRI with AI Predicted Mask

5.6 Model comparison.

A comparison of the performance of existing models and the proposed model utilizing the same TCIA dataset corresponding to 110 patients is presented in this section.

No	Paper name	Year	Method	Accuracy
1	The ACM Segmentation and ANN-LM Classification Techniques in diagnosing tumors.	2016	FCM + Artificial N. N	93.74% (Jaccard index)
2	The identification and classification of MRI images of brain tumors through the use of DWT and probabilistic neural networks as feature extraction tools.	2017	Probability Neural Network	95.33%
3	Detecting MRI images through component analysis	2018	Component Analysis	95.21%
4	Utilizing symmetric analysis for both the detection and measurement of tumors obtained from the Brain MRI.	2019	Symmetric Analysis	96.31%
5	Glioblastoma (GBM) tumor segmentation using three-dimensional convolutional neural networks.	2020	3D Convolutional Neural Networks	89.21%
6	**Proposed model**	**2021**	**ResNet and ResUNet**	**98.6%**

5.7 Summary

Performance metrices with a short method description and their accuracies have been shown. It is also evident that applying both ResNet and ResUNet model to detect and localize tumor provides a much-improved accuracy.

CHAPTER SIX: CONCLUSION AND FUTURE WORKS

6.0 Future Works

For effective classification, there is a requirement for the collection of additional data. In the future, a mobile or online platform will need to be developed to communicate with the API that has been generated to assist users who are not technically savvy in interacting with the prediction model and API. It is also necessary for the model and API to be hosted on a cloud platform in order to support speedier processing.

6.1 Conclusion

Automated detection and segmentation from MR images of brain tumors has been studied utilizing basic image processing techniques. In order to detect brain tumors utilizing RESNET and RESUNET, the use of a CNN should be adopted. CNN for brain tumor detection using RESNET and RESUNET has much improved accuracy hence should be adapted.

REFERENCES

Osman AFI (2019) A multi-parametric MRI-based radiomics signature and a practical ML model for stratifying glioblastoma patients based on survival toward precision oncology. Front Comput Neurosci 13:58

S. Mahalakshmi and T. Velmurugan, "Detection of brain tumor by particle swarm optimization using image segmentation", Indian Journal of Science and Technology, vol. 8, no. 22, 2019.

A. Kaur, “An automatic brain tumor extraction system using different segmentation methods,” Second International Conference on Computational Intelligence & Communication Technology (CICT), 2020.

Gupta, Gaurav and Vinay Singh. “Brain Tumor segmentation and classification using Fcm and support vector machines.” (2018).

Anam Mustaqeem, Ali Javed, Tehseen Fatima, “An Efficient Brain Tumor Detection Algorithm Using Watershed & Thresholding Based Segmentation”, I.J. Image, Graphics and Signal Processing, 2019, 10, 34-39.

Seetha, J & Selvakumar Raja, S. (2018). “Brain Tumor Classification Using Convolutional Neural Networks. Biomedical and Pharmacology Journal”. 11. 1457-1461. 10.13005/bpj/1511.

Mariam Saii, Zaid Kraitem, “Automatic Brain tumor detection in MRI using image processing techniques”, Biomedical Statistics and Informatics, Vol. 2, No. 2, pp. 73-76, 2018

Gupta, M. P., and Shringirishi, M. M., Implementation of brain tumor segmentation in brain MR images using k-means clustering and fuzzy c-means algorithm. International Journal of Computers & Technology 5(1):54–59, 2019.

Louis, D. N., Ohgaki, H., Wiestler, O. D., Cavenee, W. K., Burger, P. C., Jouvet, A., Scheithauer, B. W., and Kleihues, P., The 2007 classification of tumours of the central nervous system. Acta

Neuropathol. 114(2):97–109, 2020.

Menze, B. et al., The multimodal brain tumor image segmentation benchmark (BRATS). IEEE Trans. Med. Imag. 34(10):m1993–m2024, 2020.
Tustison, N. J. et al., N4ITK: Improved n3 bias correction. IEEE Trans. Med. Imag. 29(6):1310–1320, 2018.

Balafar, M. A., Ramli, A. R., Saripan, M. I., and Mashohor, S., Review of brain MRI image segmentation methods. Artif. Intell. Rev. 33(3):261–274, 2018.

Ejaz, K., Rahim, M. S. M., Rehman, A., Chaudhry, H., Saba, T., and Ejaz, A., segmentation method for pathological brain tumor and accurate detection using MRI. Int. J. Adv. Comput. Sci. Appl. 9(8): 394–401, 2018.

Shen, S., Sandham, W., Granat, M., and Sterr, A., MRI fuzzy segmentation of brain tissue using neighborhood attraction with neural-network optimization.IEEE Trans. Inf. Technol. Biomed. 9(3):459–467, 2019

Havaei M, Davy A, Warde-Farley D et al (2017) Brain tumor segmentation with deep neural networks. Med Image Anal 35:18 –31

Naceur MB, Saouli R, Akil M, Kachouri R (2018) Fully automatic brain tumor segmentation using end-to-end incremental deep neural networks in MRI images. Comput Methods Programs Biomed 166:39–49

Pereira S, Pinto A, Alves V, Silva CA (2018) Brain tumor segmentation using convolutional neural networks in MRI images. IEEE Trans Med Imaging 35: 1240–1251

AlBadawy EA, Saha A, Mazurowski MA (2018) Deep learning for segmentation of brain tumors: Impact of cross-institutional training and testing. Med Phys 45:1150–1158

Rios Velazquez E, Meier R, Dunn WD Jr et al (2019) Fully automatic GBM segmentation in the TCGA-GBM dataset: prognosis and correlation with VASARI features. Sci Rep 5:16822

Appendix

Gantt chart for the list of activities

	Dec - April	***April 6th 2021***	***April - May***	***May - June***	***June - July***	***July***	***August***
Proposal preparation							
Proposal presentation							
Data acquisition							
Model analysis							
Generating report							
Project submission							
Project presentation							

List of tasks and resources

Task	Duration(days)	begin	End	Predecessors	Resource Names
Data Acquisition	3	4/12/21	4/14/21		laptop;medical expert;Datas...
Scaling and color conversion	3	4/15/21	4/19/21	1	laptop;python;Google Colab...
Image enhancement	2	4/20/21	4/21/21	2	laptop;python;Google Colab
Image Restoration	10	4/22/21	5/5/21	3	Dataset;Computer vision pa...
Color image processing	2	5/6/21	5/7/21	4	python;Computer vision pac...
Wavelenght and multi reso...	10	5/6/21	5/19/21	1;2;3;4	python;Google Colab;Comp...
Image compression	6	5/20/21	5/27/21	6	python;Google Colab;Comp...
Morphologial processing	5	5/28/21	6/3/21	5;6;7	Computer vision package;py...
Segmentation	10	6/4/21	6/17/21	8	Google Colab;python;Tenso...
Object Recognition	15	6/18/21	7/8/21	9	Google Colab;Tensorflow;Ke...