BRAIN TUMOR DETECTION AND CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK

MD. SHAFIN SHAHARIA

MIMUSA RAHMAN MEEM

A THESIS SUBMITTED

FOR THE DEGREE OF BACHELOR OF SCIENCE

DEPARTMENT OF ELECTRONICS AND COMMUNICATIONS ENGINEERING

PROGRAM OF INFORMATION AND COMMUNICATIONS ENGINEERING

EAST WEST UNIVERSITY

SPRING 2022

CANDIDATE DECLARATION

This is to certify that the work presented in this thesis paper, titled "**Brain Tumor Detection and Classification Using Convolutional Neural Network**", is the outcome of the investigation and research carried out by the following students under the supervision of Rizwan Shaikh, Lecturer, Department of Electronics and Communications Engineering (ECE), East West University.

It is also declared that neither this thesis book nor any part thereof has been submitted anywhere else for the award of any degree, Bachelor of science or other qualifications.

MD. SHAFIN SHAHARIA

ID:2016-3-50-022

MIMUSA RAHMAN MEEM

ID:2016-1-50-024

SUPERVISOR APPROVAL

This thesis book titled "**BRAIN TUMOR DETECTION AND CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK**" submitted by Md. Shafin Shaharia, ID:2016-3-50-022 and Mimusa Rahman Meem, ID:2016-1-50-024 has been accepted as satisfactory in particular fulfilment of the requirement for the degree B.Sc. in Information and Communications Engineering in Spring, 2022.

Supervisor:

Rizwan Shaikh

Lecturer

Department of Electronics and

Communications Engineering

(ECE)

East West University

ACKNOWLEDGEMENT

ABSTRACT

MRI images are commonly utilized in medical science to detect brain tumors. Some types of brain tumors are fatal. As a result, it's critical to figure out which one is lethal so that treatment may begin as soon as possible. MRI images are frequently used to detect brain tumors, which are manually detected by the radiologist and doctor. It might be a lengthy procedure at times. If there is a big amount of data on this, we can use it in Machine Learning and create a model that will identify it automatically by training and testing itself with that data using Convolutional Neural Networks. That will be a huge aid in the field of medicine.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF ABBREVIATIONS

CNN	Convolutional neural network
CSF	Cerebrospinal fluid
BPNN	Backpropagation Neural Network
DNN	Deep neural network
LDA	Linear Discriminant analysis
PCA	Principal of component Analysis
LS-SVM	Least Squares Support Vector Machines
CT	Computed Tomography
WM	White Metter
GM	Grey Metter
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
RBF	Radiant Basis Function
FCM	Fuzzy C mean
MRI	Magnetic Resonance Imaging
ReLU	Rectified linear unit
GA	Gaussian Blur
DCNN	Deep neural convolution network

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

Medical imaging techniques are used to examine the interior of the human body in order to diagnose medical conditions. And one of the most difficult and lucrative issues in the field of Picture Processing is medical image categorization. Tumor identification or cancer detection is one of the most common medical image categorization issues. Physicians have been using improved technologies to identify tumors that are more uncomfortable for patients in recent years. CT (Computed Tomography) and MRI (Medical Reasoning Imaging) scans are two practical ways for analyzing anomalies in different sections of the body. Due to a growing requirement for rapid and impartial evaluation of vast volumes of medical data, MRI-based medical image processing for brain tumor investigations has gotten a lot of interest recently. The analysis of such a wide variety of picture formats necessitates the use of advanced computational quantification and visualization software. Since a result, automated brain tumor diagnosis from MRI scans will be critical in this scenario, as it will eliminate the need for human data processing.

1.2 BRAIN TUMOR

A brain tumor is a mass of tissue in which cells multiply at an uncontrollable rate. It comes from a variety of cells, both inside and outside the brain. Primary tumors are those that begin in the brain and spread to other areas of the body, whereas secondary tumors are those that spread to other parts of the body.[2]

Tumors can have a variety of sources, depending on the cells or origins acquired from various types of tumors. Gangliogliomas, for example, are tumors that contain neoplastic neurons and are often grade I or low-grade tumors, indicating that the tumor is well-differentiated and grows slowly.[2]

Meningioma is another example, starts in the meninges (the three membranes that surround the brain and spinal cord). It can be grade I, II, or III, and it covers the brain and spinal cord or III, and it grows slowly.[2]

Finally, there are two types of brain tumors: benign (noncancerous) and malignant (cancerous) (cancerous). Malignant tumors in the brain can swiftly spread to other brain tissues, worsening the patient's health. When the majority of the cells become too old or damaged to function, they are

destroyed and replaced by the addition of additional cells if old and damaged cells are not removed. It's possible that issues will arise when creating new cells.[3]

The development of new cells is frequently the result of the production of more cells. The growth or tumor is referred to as a mass of tissue. Because of the size, shape, location, and kind of tumor in the brain, brain tumor detection is extremely challenging. It is difficult to diagnose brain tumors in the early phases of their development because it is impossible to correctly quantify the tumor's size and resolution.[3]

However, if the tumor is detected and treated early in the tumor's development, the chances of the patient being treated are very good. As a result, tumor treatment is determined by the type of tumor.[3]

The tumor was diagnosed in a timely manner. The signs and symptoms of a brain tumor include headaches that can be both severe and chronic muscle pain, disorientation, and cognitive issues, to name a few.[3]

1.3 MOTIVATION

A medical examination, together with computer tomography or magnetic imaging, is frequently used to make the diagnosis. One of the most frequent and crucial ways for diagnosing and analyzing the patient's brain is MRI imaging, which produces reliable pictures of the brain. Due to its stronger contrast in soft tissue in humans, MRI pictures yield superior findings than other imaging techniques such as Computed Tomography (CT) in the field of Medical Detection Systems (MDS).[3]

Chemotherapy, radiation, tom therapy, and surgery are all options for treatment (craniotomy). Although brain tumors are very uncommon, with only 1.4 percent of new occurrences per year.

In the year, mortality related to brain injuries increased in developed countries. Over the last few decades, the number of tumors has climbed. Computer-assisted disease diagnosis has gained popularity in recent years, and it is assisting clinicians in making quick decisions. [2]

1.4 OBJECTIVES

Convolutional Neural Networks are one such technique (CNN) to extract geographical and temporal information from the supplied dataset that is required to diagnose the condition. A Convolutional Neural Network is a form of neural network where picture datasets are handled by a network that specializes in image datasets. This neural network's essential premise is a convolution procedure between the kernel and the image from which the features will be extracted All neural networks are capable of learning.[2]

The weights matrix is iteratively updated in all neural networks to learn. The ideal kernel values for all layers of the CNN model must be found here. As a result, the kernel values serve as the model's weights, and the ideal kernel values are gradually acquired by backpropagation and gradient descent. The backward calculation of derivatives of the loss function with regard to weights and biases is known as backpropagation. Gradient descent is the process of updating the weights on a regular basis so that the loss or error decreases with each iteration.[2]

A convolutional layer is frequently combined with a pooling layer, and numerous such convolutional layer-pooling layer pairings can be connected. For the final learning process, we can have a few Dense layers and dropout layers. Dropout layers are used to solve the problem of overfitting. The classification duty is done by the final output layer, which might contain either one neuron for a binary classification task or more than one for a multi-class classification task. Capsule networks, a sort of neural network that can contain spatial information as well as the likelihood of an item appearing in a picture, are gaining popularity and have been employed in several recent research.[2]

1.5 THESIS CONTRIBUTION

We present a system that uses a Convolutional Neural Network to predict the existence of a tumor in the brain or near the brain using a machine learning technique based on MRI scans of patients. A Convolutional Neural Network (CNN) is a Deep Learning algorithm that recognizes an input picture by assigning relevance (learnable weights and biases) to various aspects/objects in the image. In comparison to other classification methods, it needs less preparation steps. The design of a ConvNet is inspired by the organization of the Visual Cortex and is akin to the connection pattern of Neurons in the Human Brain. For feature extraction and analysis, we used the Sequential model of the Convolutional Neural Network (CNN). We also used kernel, ReLu and sigmoid as activation function. This model can aid medical workers in detecting tumors which is more than 98%correct and classified it with93%accuracy to providing appropriate therapy to patients at the appropriate time.

1.6 KEYWORDS

Brain tumor, Detection, Classification, CNN, Brain MRI

CHAPTER 2

UNDERLYING RESEARCH

2.1 TUMOR

A tumor or an excrescence is a growth of abnormal fleshly towel. Cancerous and noncancerous excrescences live. Excrescences develop when cells in the body peak and expand too snappily. The body typically regulates cell growth and division. To replace aged cells or to fulfill new conditioning, new cells are generated. Damaged or no longer needed cells die to make way for healthy reserves. An excrescence can arise if the balance of cell growth and death is disintegrated. Excrescences can be caused by problems with the vulnerable system. Tobacco kills further people than any other chemical in the terrain. [4]

Figure 2.1: Body Tumor [48]

Other cancer threat factors include benzene and other chemicals and poisons, inordinate sun exposure, inheritable diseases, rotundity, radiation exposure, contagions, and environmental

poisons similar as some poisonous mushrooms and a form of bane that may develop on peanut shops.[4]

Excrescences that are known to be caused or associated to contagions include

• Burkitt carcinoma (Epstein- Barr contagion)

• Cervical Cancer (Mortal papillomavirus)

• Utmost anal cancers (Mortal papillomavirus)

• Some throat cancers, including soft palate, base of lingo and tonsils (Mortal papillomavirus)

• Some vaginal, vulvar, and penile cancers (Mortal papillomavirus)

• Some liver cancers (Hepatitis B and hepatitis C contagions)

• Kaposi sarcoma (Mortal herpesvirus 8)

• Adult T- cell leukemia/ carcinoma (Mortal T- lymphotropic contagion- 1)

• Merkel cell melanoma (Merkel cell polyomavirus)

• Nasopharyngeal cancer (Epstein- Barr contagion)

Some cancers affect one coitus further than the other. Some are more current in youths or the senior. Diet, terrain, and family history are among the others. [4]

2.2 BRAIN TUMOR

A brain tumor is a grouping of abnormal cells in the brain that forms a mass. Your brain is defended by a hard cranium. Any expansion in such a small area might induce issues. Cancerous(malignant) or noncancerous brain excrescences live (Benign). The pressure inside your cranium might rise when benign or nasty excrescences grow. This can affect in endless brain damage and indeed death.[5]
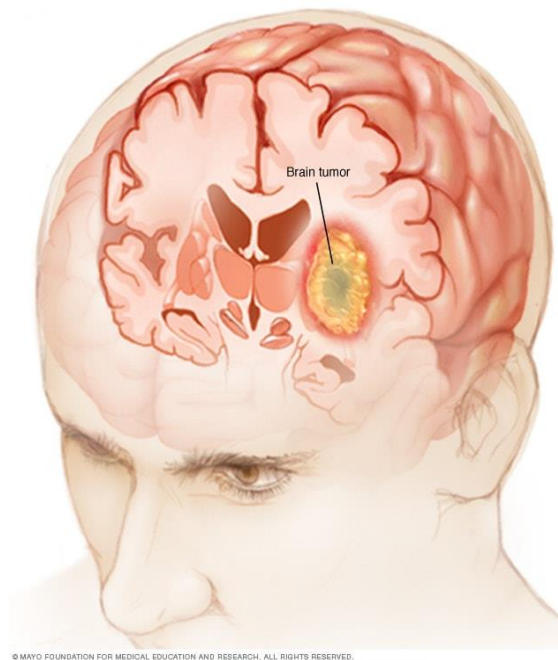
Figure 2.2: Brain Tumor [49]

Primary and secondary brain excrescences are distinguished in similar way like birth of a primary brain excrescence is in the brain. Numerous benign primary brain excrescences live. A secondary brain excrescence, also known as a metastatic brain excrescence, develops when cancer cells from another organ, similar as your lung or bone, resettle to your brain.[5]

Though benign brain excrescences can beget a variety of problems, they aren't nasty, meaning they develop sluggishly and infrequently spread to other corridor of the body. They also tend to have more well-defined boundaries, making surgical excision easier, and they infrequently return following junking. Nasty brain excrescences, on the other hand, are cancerous, develop snappily, and can spread to other regions of your brain or central nervous system, posing a life-changing hazard.[5]

2.3 TYPES OF BRAIN TUMOR

2.3.1 PRIMARY BRAIN TUMOR

Primary brain cancers arise from the brain. They may arise from your Meninges, the membranes that compass your brain, whim-whams cells, and glands like the pituitary and pineal, are all exemplifications of brain cells. Primary excrescences can be nasty or benign. Glioma and meningioma are the most current forms of brain excrescences in grown-ups.[5]

2.3.2 GLIOMAS

Gliomas are excrescences that form when glial cells multiply. These cells are responsible for maintaining the structure of your central nervous system, furnishing nutrients, drawing cellular waste, and breaking down dead neurons.

Gliomas can arise from a variety of glial cells. Astrocytic excrescences, which start in glial cells, include the following

• Astrocytomas, which arise in the brain stem.

 • Oligodendroglial malice are common in the anterior temporal lobes.

 • Glioblastomas, the most aggressive kind of brain cancer, arise from supporting brain towel.[5]

2.3.3 MORE VARIATION OF PRIMARY BRAIN TUMOR

Primary brain Excrescences also include:[5]

 • Pituitary excrescences are generally inoffensive.

 • Pineal gland excrescences can be benign or cancerous.

 • Ependymomas are benign excrescences that grow on the skin.

• Although Craniopharyngiomas are substantially plant in youths and are benign, they can beget clinical symptoms similar as visual abnormalities and early puberty.

 • Primary nasty tubercles of the central nervous system

 • Brain primary origin cell excrescences, which can be benign or nasty

 • Meningiomas are excrescences that start in the meninges.

• Schwannomas are cancerous excrescences that arise from Schwann cells, which induce the defensive covering for your jitters (myelin jacket).

 According to a exploration that divided actors into men and women, meningioma are detected more constantly in women than in men. Schwannomas affect both men and women inversely. Although these excrescences are generally benign, their size and placement might produce difficulties. Cancerous meningiomas and schwannomas are uncommon, yet they can be deadly.[5]
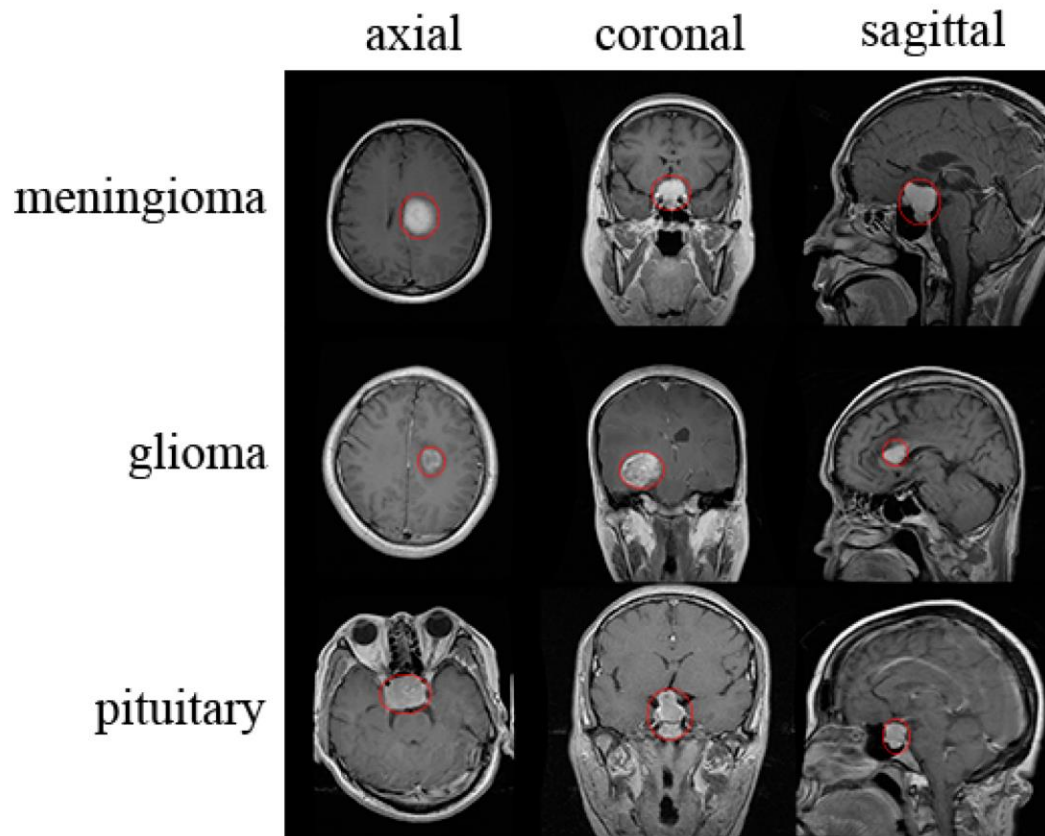
Figure 2.3: Variation of Primary Tumor[50]

2.3.4 SECONDARY BRAIN TUMOR

The maturity of brain malice are secondary brain excrescences. They begin in one region of the body and spread to the brain, or metastasis. The following conditions can spread to the brain

• Pulmonary cancer

• Ovarian cancer

• Renal cancer

• Cutaneous cancer

 Secondary brain excrescences are always cancerous. Excrescences that are benign don't spread from one section of the body to another.[5]
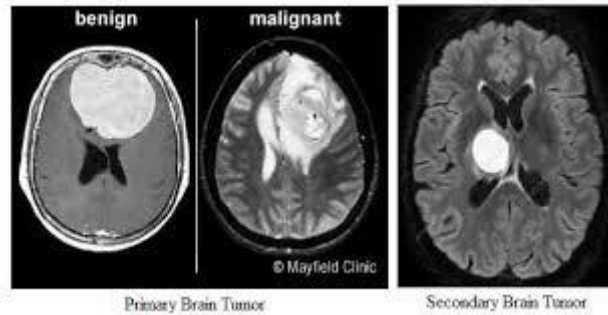
Figure 2.4: Primary and Secondary Brain Tumor[51]

2.4 RISK FACTOR

2.4.1 Family background

Only around 5 to 10 of all malice are heritable or genetically inherited. A genetically inherited brain excrescence is extremely rare. However, talk to your croaker, If you or someone in your family has been diagnosed with a brain excrescence. Your croaker can relate you to a inheritable counselor.[5]

2.4.2 Age

Utmost forms of brain excrescences grow in peril as people come aged.[5]

2.4.3 Exposure to chemicals

Certain chemicals, similar as those plant in a work setting, can raise your chance of developing brain cancer. A list of conceivably cancer- causing substances present in workplaces is kept by the National Institute for Occupational Safety and Health.[5]

2.4.4 Radiation exposure

Brain cancers are more common in those who have been exposed to ionizing radiation. High-radiation cancer remedy can expose you to ionizing radiation. Nuclear fallout might potentially beget you to be exposed to radiation. The Fukushima and Chernobyl nuclear power factory disasters show how individualities might be exposed to ionizing radiation.[5]

2.4.5 No previous exposure to chickenpox

According to a exploration published in Cancer Medicine in 2016, having had chickenpox as a sprat is linked to a 21 dropped chance of getting glioma.[5]

2.5 SYMPTOMS

The symptoms of a brain excrescence vary depending on the excrescence's position and size. Some excrescences insinuate brain towel and induce direct injury, while others put pressure on the girding brain. When a developing excrescence puts pressure on your brain towel, you will witness symptoms. A typical sign of a brain excrescence is headaches. You could have headaches that(5)

• Are worst first thing in the morning

• Take place when you are sleeping

• Are exacerbated by coughing, sneezing, or physical exertion

May also encounter:[5]

• Puking

• Double vision or muddled vision

• Confusion

• Storms (Especially in grown-ups)

• A branch or a portion of the face that's weak

• A shift in internal capacity

 Other common signs and symptoms are:[5]

• Clumsiness

• Memory problems

• Confusion

• Jotting or reading difficulties

• differences in hail, tasting, or smelling

• Doziness and loss of knowledge are exemplifications of lowered alertness.

• Swallowing problems

• Vertigo or dizziness

• Hanging eyelids and uneven pupils are exemplifications of eye issues.

• Changeable moves

• Temblors in hands

• Loss of equilibrium

• Bladder or bowel control problems

• Chinking or impassiveness on one side of the body

• Difficulty communicating or comprehending what others are saying

• Mood, personality, feelings changes

• Walking difficulties

• Facial, arm, or leg muscular weakness

2.6 BRAIN TUMOR DIAGNOSIS

A physical test and a review of your medical history are used to diagnose a brain excrescence. A thorough neurological evaluation is part of the physical examination. Your croaker will do a test to determine whether your cranial jitters are healthy. These are the jitters that fan out from your brain.[5]

An ophthalmoscope, which is a device that flashes a light through your pupils and onto your retinas, will be used by your croaker to examine the innards of your eyes. This enables your croaker to see how your pupils respond to light. It also allows your croaker to see directly into your eyes to check for any optical whim-whams blowup. Changes in the optical whim-whams can do as pressure inside the cranium rises.[5]

 Croaker may also assess:

• Muscular power

• Collaboration

• Memory

• Capacity to calculate mathematically

 Following the physical examination, your croaker may define farther testing. Some exemplifications are:[5]

2.6.1 CT scan of the head

CT reviews allow your croaker to acquire a further thorough picture of your body than an X-ray scanner can give. It's possible to negotiate this with or without discrepancy. In a CT checkup of the head, discrepancy is created by employing a specific color that allows croakers to see particular structures, similar as blood highways, more easily.[5]
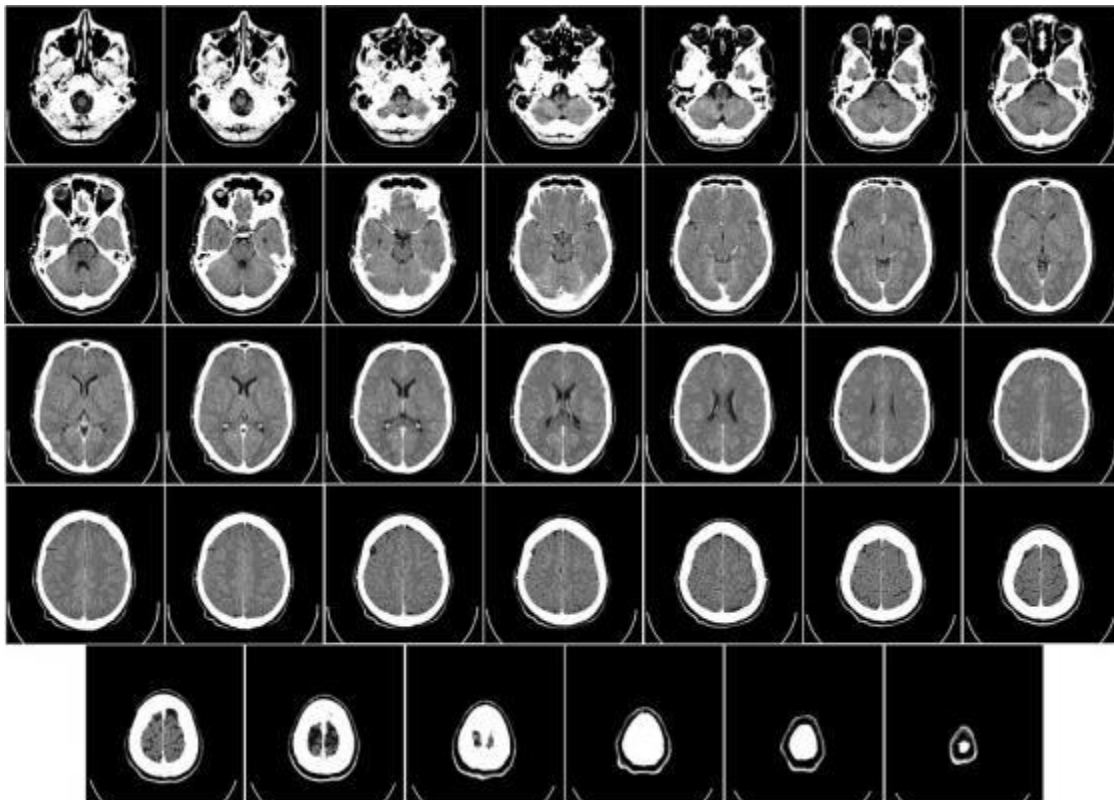
Figure 2.5: Various Image of CT Scan [52]

2.6.2 MRI scan of the brain

A special color can be used during a head MRI to help your croaker in detecting malice. An MRI differs from a CT checkup in that it doesn't use radiation and frequently produces far more detailed images of the brain's armature.[5]
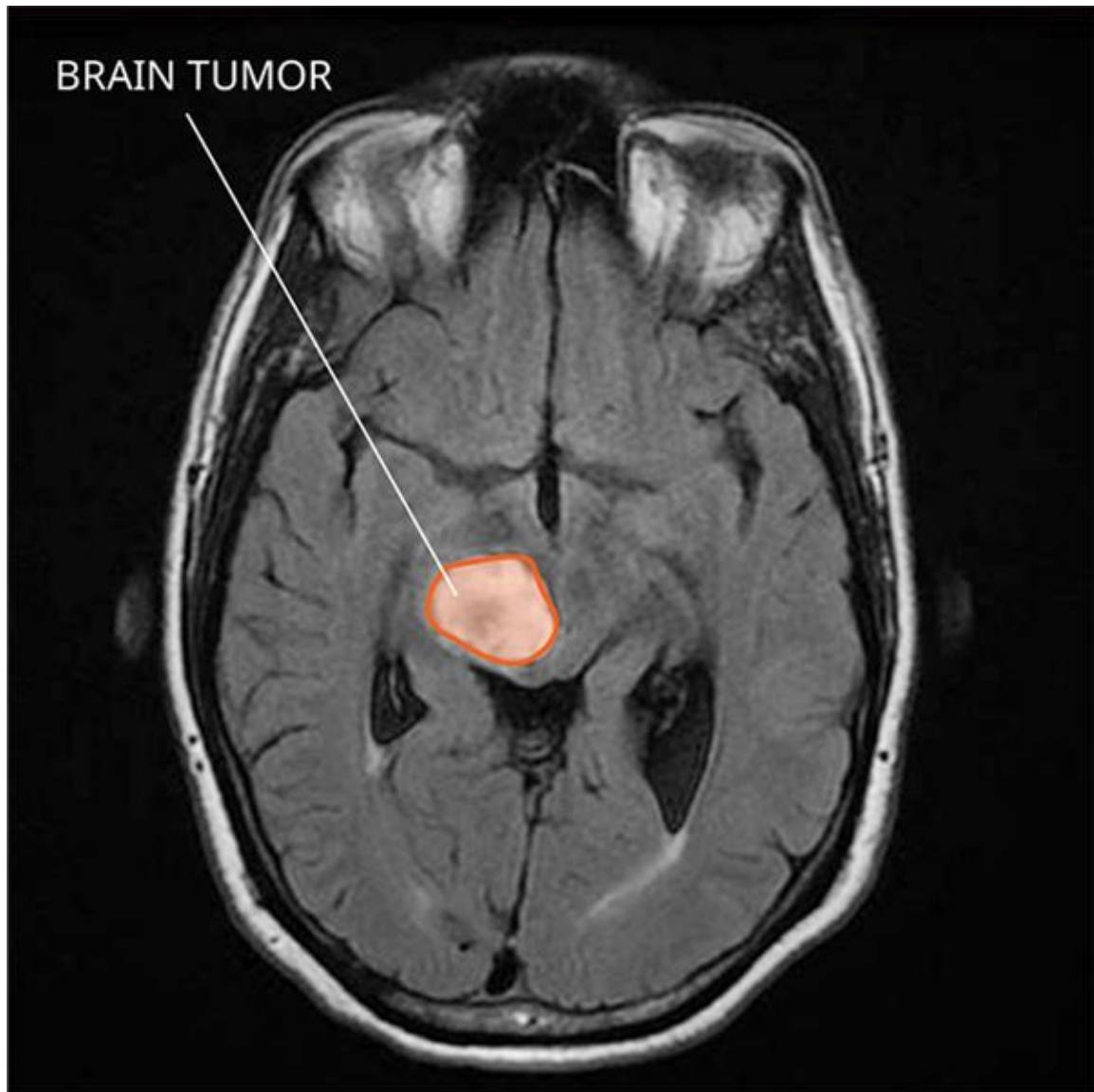
Figure 2.6: MRI Image[53]

2.6.3 Angiography

A color is fitted into your roadway, generally in the groin area, for this disquisition. The color goes to your brain's highways. It enables your croaker to examine the blood inflow to the malice. This knowledge is helpful during surgery.[5]

2.6.4 X-rays of the skull

Brain excrescences can produce breaks or fractures in the bones of the cranium, which can be detected with technical X-rays. Calcium deposits, which are sometimes seen within excrescences, can also be detected using these X-rays. Still, calcium deposits may be present in your rotation, If your cancer has spread to your bones.[5]

2.6.5 Biopsy

During a vivisection, a little bit of the excrescence is removed. It'll be examined by a specialist known as a neuropathologist. The excrescence cells will be linked as benign or nasty after the vivisection. It'll also reveal if your cancer started in your brain or away in your body.[5]

2.7 TREATMENT

The following factors impact brain excrescence treatment:[5]

• The excrescence's kind

• The excrescence's confines

• The excrescence's exact position

• Your general well- being

Surgery is the most frequent remedy for nasty brain excrescences. The ideal is to remove as important cancer as possible while avoiding detriment to the brain's healthy regions.[5]

While the placement of certain excrescences allows for safe excision, others may be at a region where only a small portion of the excrescence may be removed. Indeed, partial brain cancer excision can be profitable.[5]

Infection and hemorrhage are two pitfalls of brain surgery. Surgical junking of clinically hanging benign excrescences is also performed. Metastatic brain excrescences are treated according to the original cancer's norms.[5]

Other curatives, including as radiation remedy and chemotherapy, can be coupled with surgery. After neurosurgery, physical remedy, occupational remedy, and speech remedy can all help you recover.[5]

CHAPTER 3

LITERATURE REVIEW

Aryan Methil, 2021[64]; he suggested brain tumor detection using deep learning and image processing in this conference article. He trains the model using a dataset of 3762 photos that he divided into multiple subsets. He shifted 20 percent width to the left or right and 20 percent height to the top or bottom by resizing all photos to 150X150 pixels and rotating them between -30 and +30 degrees. To train and validate, divide the dataset into two parts: 70% and 30%. All of the work was completed using the ResNet 101v2 CNN model. Transfer learning was also crucial there, with a sufficient accuracy of 97 percent, 98.55 percent for training recall, and 99.73 percent validation.

Masoumeh-Halimeh Siar and Mohammad Teshhnehlab, 2019[65]; They suggested a method for detecting brain tumors using a deep neural network and a machine learning algorithm in their research. The approach is mostly based on a feature extraction algorithm and CNN. They utilized 1666 photos as a training dataset and 226 images as a test dataset. They classified 94 percent of the data using the CNN softmax classifier, 97.34 percent using the RBF classifier, and 94.24 percent using the DT classifier.

Krizhevsky et al. 2012[66]; achieve high quality results in image classification based on transmission learning solutions in training a large, deep convolutional neural network to divide 1.2 millions of high resolution images in the ImageNet LSVRC-2010 competition in 1000 different competitions. In the test data, you found 1 and 5 error scores of 37.5% and 17.0% much better than the previous state of the art. You also added a different version of this model the ILSRC-2012 competition also achieved a high pass rate of 5 winning marks of 15.3%, compared to up to 26.2% achieved by entering the second best place. The neural network, which had 60 million 650,000 parameters and neurons, comprising five layers of flexibility, some of them followed by layers of mass integration, as well as three fully integrated layers in the last 1000 Softmax. To make training faster, he used non-saturating neurons and a more efficient GPU implementation of convolution. To reduce overcrowding in fully integrated layers use a newly developed method called dropout which has proved to be very effective and successfully.

Simonyan & Zisserman, 2014[67]**:** investigating the impact of the depth of the convolutional network accuracy is the setting for seeing the big picture. These findings were their

foundation Submission of ImageNet Challenge 2014, where their team won first and second place on local performance tracks and sections respectively. Their main contribution was caution depth-based network testing using structures with very low convolution (3×3). filters, indicating that significant improvements in pre-art configuration can be achieved by pushing depth into 16-19 weight layers after training the smaller VGG versions with layers of low weight.

Pan & Yang, 2010[68]; the survey focused on classification and reviewing current progress pass on learning about problems of separation, retreat and integration. In this study, see discussed the relationship between transfer learning and other machine learning related techniques such as background familiarity, multi-tasking learning and sample selection, as well mutual flexibility. They also explored some of the future problems that could arise in transferring learning research. In this is the subject of the survey, they reviewed a few current trends in transfer learning.

Szegedyet al.2015[69]; proposed a comprehensive construction of a coded neural network Inception, which was responsible for setting up a new art form of segregation once and for all acquisition in ImageNet Large Scale Visual Challenge 2014 (ILSVRC14). IA key feature of this structure is the improved use of computer resources inside network. This is achieved by a carefully designed design that allows for maximum depth and network coverage while maintaining a compact budget. His results appear to be the same present strong evidence that the expected little frame is easily accessible dense building blocks are an effective way to improve neural networks of computer vision.

He et al., 2015b[70]; introduced ResNet, which uses connects with the bulk normalization .Introduced a residual learning framework to facilitate the training of existing networks much deeper than those used before. You have obviously redesigned the layers as read residual functions in reference to the layer input, instead of reading the non-reference functions. He has provided ample evidence that the remnants are easy to make improve, and can get accuracy to the greatest depth. In the ImageNet database explored residual nets at depths of up to $152—8 \times$ depth than VGG nets but still and low complexity. The set of residual nets receives 3.57% error in ImageNet test set. This result won first place in the ILSVRC 2015 dividing work presented analysis to CIFAR-10 with 100 and 1000 layers.

Muhammad Sajjad, et.al[71]; has proposed a new CNN-based a brain tumor that has multiple scales in this paper. An in-depth reading method was used in the beginning to separate the plant regions in the MR image. In addition, the proposed system was well trained using I data growth in the second step. However, where a multi-stage brain tumor is to be performed using MRI, the issue of lack of data was avoided. With it finally, the distortion of the brain tumor was is done using augmented data and using a VGG-19 CNN model previously trained in it. The test was

performed on real and augmented data and as a performance metric metrics namely sensitivity, clarity and accuracy has improved.

Komal Sharma[72]; Automatic medical disability diagnosis imaging has become a emerging field in several medical fields diagnostic applications. Automatic detection of the plant inside Magnetic Resonance Imaging (MRI) is as important as it is provides information about abnormal tissues it is necessary to plan treatment. Normal how to detect impairment in brain magnetic resonance images are human experiments. This method does not work with a large amount of data. Thus, automatic plant detection methods are developed as they can save the radiologist's time.

Natarajan et al. [73]; the proposed method using a Median filter for preliminary analysis of Brian MRI image, the separation used threshold separation as well morphological activities and then image extraction the procedure is used to find the region of interest in the brain MRI image.

Uchita and Lalit[74]; unplanned MRI brain unsupervised learning method for neural network classification. MRI brain images are processed first which includes the removal of the audio edge and the division of the plant part. Self Organizing Maps (SOM) is used to divide the mind as normal or abnormal, i.e. whether it contains or not tumor

A. Batra and G. Kaushik [75]; raise the combination FCM clustering algorithm and SVM classifier for plant separation in accordance with BCFCM of bias field adjustment and HAAR waveform modification of feature background. The proposed approach reaches 98.2 percent accuracy, 97.5 percent sensitivity, 100 percent specificity, 100 percent of the good predictable value and similarity of 98.7 dice coefficient. Intelligent Automatic Brain Tumor Model Diagnosis presented by M. B. M. Amien et al. which classifies MRI images as normal, edema, cancer, or not segregation . The sound is deleted and the image difference is developed in the processing phase through a number of steps. The texture elements are extracted and are a key component. PCA is used to reduce its size in the end stage. Finally, Back-Propagation Neural Network (BPNN) based on the Pearson coefficient of integration is used to differentiate brain images. The proposed model achieved the accuracy of 96.8%.

S M Kamrul Hasan, 2018[76]; Proposed Nearest-Neighbor Re-sampling Based Elastic-Transformed (NNRET) Net Deep CNN framework has been trained in 285 glioma patients of the BRATS 2017 MR dataset located at MICCAI 2017. The framework has been tested in patients 146 using the same Dice performance metrics (DSC) and Intersection over Union (IoU) and

surpassing the older U-net model. Traditional U-net 'separates' voxels rather than merges. In this study, the deconvolution layer is replaced up sampling layer over two layers of convolution, sampling layer followed by amplification of elastic trans formation. The DSC rose from 0.86 to 0.87.

Ying Zhuge , Andra V Krauze , Holly Ning[77]; Two previous imaging techniques have been used for MRI imaging. The N4ITK method was used to correct the bias of the bias. A novel method based on stiffness was developed so that the tissue types had the same degree of stiffness in different studies of the same MRI protocol. high-grade (HGG), based on double-factor verification. The proposed method took approximately 10 h of 50,000 repetitive training, and approximately 30 s of standard MRI scanning on the BRATS 2013 database with a size of $160 \times 216 \times 176$, using the DELL PRECISION workstation T7400.

Sang Hee Ahn , Adam Unjin Yeo 2016[78]; In this paper 70 liver and brain cancer patients were used.They were described by hand by three experienced doctors as referral structures. The atlas and the default sections for in-depth learning were developed in accordance with MIM Maestro 6.5 and the deep neural convolution network (DCNN). Clearly, in the case of the abdomen, DSC, VOE, and RVD showed a significant difference of 21.67, 25.11, 28.80% respectively.

Devendra Somwanshi; Ashutosh Kumar 2015[79]; In this paper, we have explored the various functions of its Entropy segregation of the tumor and its detection in various MRI images. Different limit values are available based on the specific definition of entropy. I threshold values depend on the different function of the entropy also affecting different results. Therefore in the review we found that the automatic detection of brain tumor and classification from MRI images are one of the most effective areas for research.

Nilesh Bhaskarrao Bahadure 2014[80]; They have used a flexible comparator enhancement based on adjusted sigmoid performance. The source database of the MR brain image, as well as the algorithm used to perform MR brain segregation. Figure 1 provides a flow diagram of the algorithm. As experimental images, a variety of MR brain scans were used, including T1-weighted MR images with 1740 Repetition Time (TR) and 20 Echo Time (TE). examined the results produced by the proposed method which is divided into the component results of the three classes of WM, GM, and CSF

CHAPTER 4

THEORY OF OPERATION

4.1 ARTIFICIAL INTELLIGENCE

Artificial intelligence (AI) is the emulation of mortal intellect in robots that have been trained to suppose and act like humans. The expression may also relate to any machine that demonstrates mortal-suchlike characteristics like literacy and problem- working.[6]

Artificial intelligence is innovated on the idea that mortal intellect may be described in such a manner that a computer can simply duplicate it and do tasks ranging from simple to sophisticated. Artificial intelligence's points include bluffing mortal cognitive processes. To the extent that they can be primarily characterized, experimenters and inventors in the field are making suddenly quick progress in bluffing tasks similar as literacy, logic, and perception.[6]

Artificial intelligence's finest point is its capacity to reason and take conduct that have the stylish possibility of reaching a certain ideal. Machine literacy is a subset of artificial intelligence that relates to the notion of computer programs learning from and conforming to new data without the backing of humans. Deep literacy algorithms allow for this independent literacy by absorbing large volumes of unshaped data including textbook, prints, and videotape.[6]

The simulation of mortal intellect in machines is known as artificial intelligence. Artificial intelligence aims to ameliorate literacy, thinking, and perception. Artificial intelligence is being employed in a variety of fields, including banking and healthcare. Weak AI is more straightforward and concentrated on a particular job, whereas strong AI handles more complicated and mortal-suchlike conditioning.[6]

4.1.1 APPLICATION OF ARTIFICIAL INTELLIGENCE

Artificial Intelligence's use and appeal are growing by the day. Artificial intelligence refers to a system's or program's ability to think and learn from its experiences. AI applications have advanced dramatically in recent years, with applications in practically every industry. The greatest artificial intelligence applications in the real world are recognized here:[7]

- E-Commerce AI Applications: AI-powered Assistants, Personalized Shopping, and Fraud Prevention
- Artificial Intelligence in Education: Automated Administrative Tasks to Assist Educators, Smart Content Creation, Voice Assistants, Personalized Learning

- Autonomous vehicles, spam filters, facial recognition, and recommendation systems are examples of AI applications in the lifestyle.
- Navigational Applications of Artificial Intelligence:
- Carrying products in hospitals, factories, and warehouses, cleaning offices and huge equipment, and inventory management are all examples of AI applications in robotics.
- Artificial Intelligence in Human Resource Management
- Artificial Intelligence Applications in Healthcare
- Agriculture Artificial Intelligence Applications
- Artificial Intelligence Applications in Gaming
- Automobile Artificial Intelligence Applications
- Artificial Intelligence Applications in Social Media: Instagram, Facebook, and Twitter
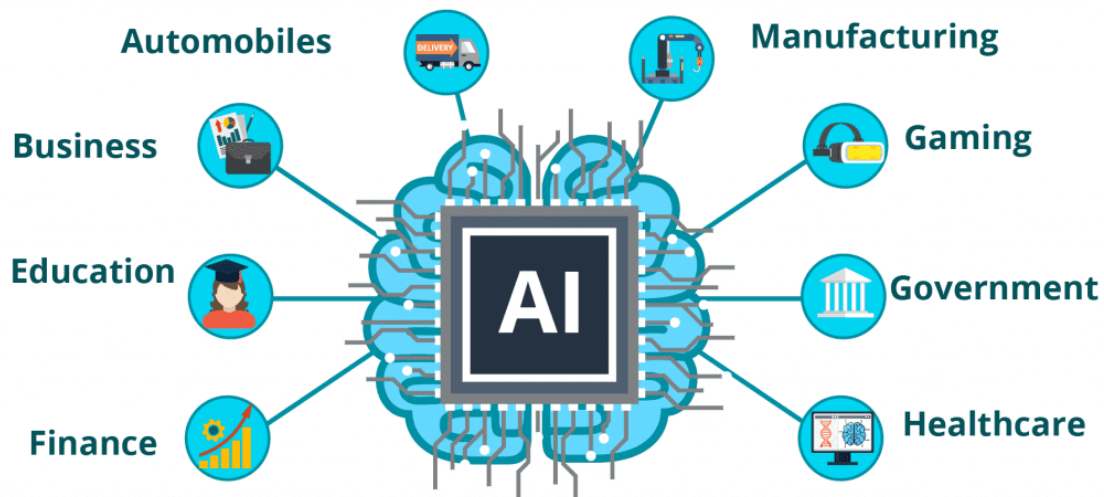- Artificial Intelligence Applications in Finance

Figure 4.1: Application of Artificial Intelligence[54]

The use of machine-learning algorithms and software, or artificial intelligence (AI), to replicate human cognition in the analysis, display, and interpretation of complicated medical and health-care data is referred to as artificial intelligence in healthcare. AI refers to computer algorithms' capacity to estimate conclusions based purely on input data. The major goal of health-related AI applications is to investigate the connections between clinical procedures and patient outcomes. Diagnostics, treatment protocol creation, medication research, customized medicine, and patient monitoring and care are all areas where AI systems are being used. The capacity to gather data, process it, and deliver a well-defined output to the end-user distinguishes AI technology from

traditional healthcare solutions. Machine learning and deep learning are used by AI to do this. These mechanisms are capable of recognizing patterns in behavior and developing their own logic. Machine learning models must be trained with large volumes of data in order to provide relevant insights and predictions. In two ways, AI algorithms differ from humans: algorithms are literal: once a goal is set, the algorithm learns exclusively from the input data and can only understand what it has been programmed to do, and some deep learning algorithms are black boxes; algorithms can predict with extreme precision, but offer little to no comprehensible explanation to the logic behind their decisions apart from the data and type of algorithm used.[8]

4.2 MACHINE LEARNING

Machine learning (ML) is a kind of artificial intelligence e AI) that allows software programs to ameliorate their vaticination delicacy without being expressly designed to do so. Machine literacy algorithms estimate new affair values using once data as input.[9]

 Machine Learning is significant because it allows businesses to see trends in client gesture and company operating patterns while also aiding in the creation of new goods. Machine literacy is at the heart of numerous of moment's most successful businesses, like Facebook, Google, and Uber. For numerous businesses, machine literacy has come a pivotal competitive isolation.[9]
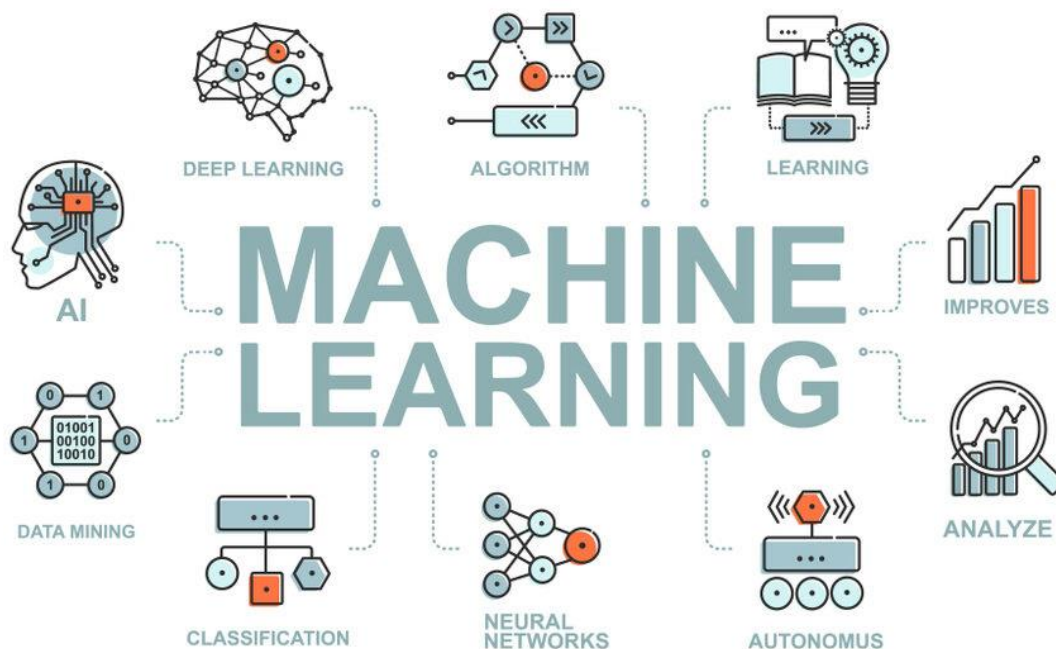

Figure 4.2: Versatility of Machine Learning[55]

4.3 CATEGORY

Traditional machine literacy is constantly classified by how an algorithm learns to ameliorate its vaccination delicacy. supervised learning, unsupervised learning, semi-supervised learning, and Reinforcement learning are the four abecedarian methodologies. The algorithm that data scientists employ is determined on the kind of data they wish to read.[9]

• Supervised learning: In supervised literacy, data scientists give algorithms with labeled training data and specify the variables they want the computer to look for connections between. The algorithm's input and affair are both handed.[9]

• Unsupervised learning: Machine literacy algorithms that train on unlabeled data are known as unsupervised literacy. The program looks for applicable connections between data sets. The data used to train algorithms, as well as the vaticinations or suggestions they give, are all destined.[9]

•Semi-supervised learning: Semi-supervised literacy is a mongrel of the two former approaches to machine literacy. Although data scientists may feed an algorithm largely labeled training data, the model is allowed to explore the data and establish its own knowledge of the set.[9]

• Reinforcement learning: Reinforcement literacy is a fashion that data scientists use to train a machine how to finish a multi-step process with precisely specified criteria. Data scientists design an algorithm to perform a task and give it with positive or negative feedback as it figures out how to do so. But, for the utmost part, the algorithm chooses which conduct to take on its own.[9]
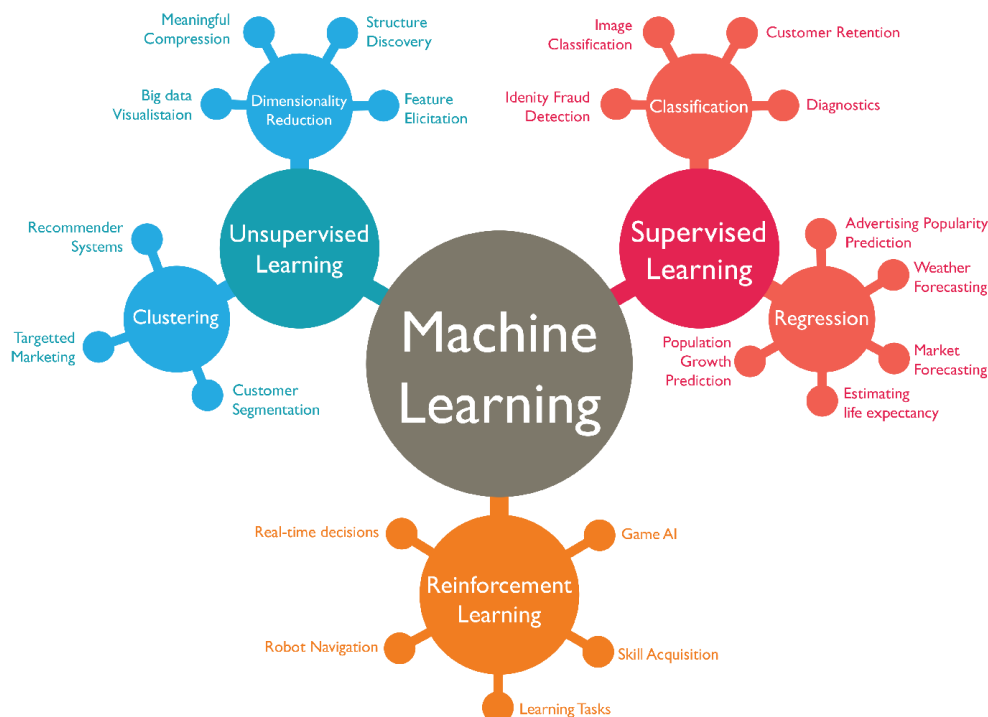
Figure 4.3: Category of Machine Learning[56]

To train the model fed labeled photos, we employed supervised learning. The categorization of the given image may subsequently be determined using supervised learning.

Image classification is a supervised learning problem in which a model is trained to recognize a collection of target classes (things to identify in photographs) using labeled sample photos. Raw pixel data was used as the input to early computer vision algorithms.[10]

A training set is used in supervised learning to educate models to produce the desired output. This training dataset contains both right and incorrect outputs, allowing the model to improve over time. The loss function is used to assess the algorithm's correctness, and it is adjusted until the error is suitably minimized.[11]

When it comes to data mining, supervised learning may be divided into two sorts of problems: classification and regression. Here we use only classification. An algorithm is used to correctly classify test results into certain groups. It detects certain items in the dataset and tries to come to some judgments about how they should be labeled or described. Linear classifiers, support vector machines (SVM), decision trees, k-nearest neighbor, and random forest are some of the most used classification techniques.[11]

4.4 DEEP LEARNING

Deep learning (also known as deep structured learning) is a type of machine learning technology that uses artificial neural networks to learn representations. There are three types of learning: supervised, semi-supervised, and unsupervised.[12]

Deep learning refers to a type of machine learning techniques that employ numerous layers to extract higher-level characteristics from raw data. Lower layers in image processing, for example, may recognize edges, whereas higher layers may identify human-relevant concepts like numerals, characters, or faces.[12]

Deep-learning architectures such as deep neural networks, deep belief networks, deep reinforcement learning, recurrent neural networks, and convolutional neural networks have been used in fields such as computer vision, speech recognition, natural language processing, machine translation, bioinformatics, drug design, medical image analysis, climate science, material inspection, and board game programs, producing results that are comparable to, and in some cases superior to, traditional methods.[12]

In deep learning, the word "deep" refers to the employment of numerous layers in the network. A linear perceptron cannot be a universal classifier, but a network with a nonpolynomial activation function and one hidden layer of unlimited width may, according to early research. Deep learning is a recent variant that involves an infinite number of layers of bounded size, allowing for practical application and optimization while maintaining theoretical universality under moderate circumstances. For the sake of efficiency, trainability, and understandability, deep learning layers are also allowed to be heterogeneous and stray substantially from physiologically informed connectionist models, hence the "structured" portion. [12]
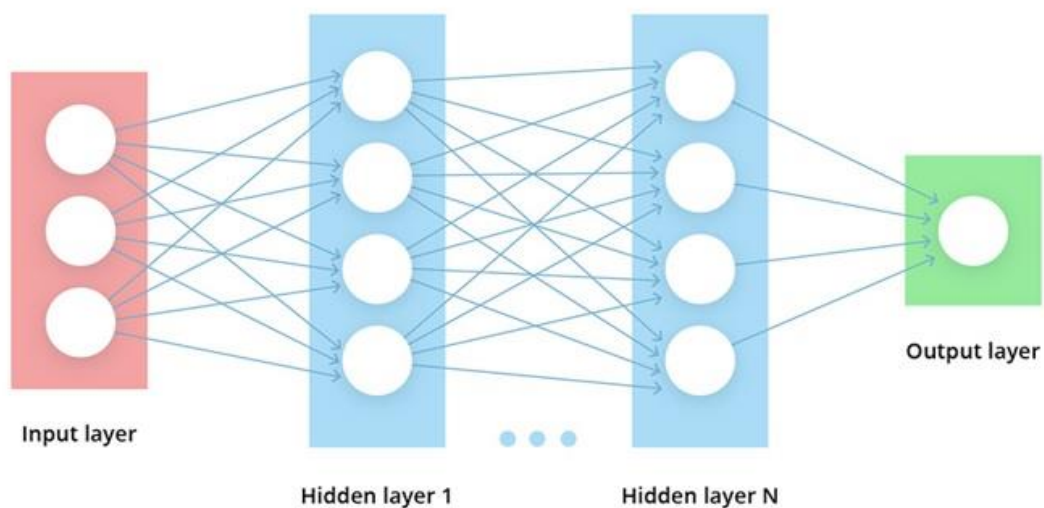
Figure 4.4:Layers of Deep Learning[57]

4.5 DIFFERENCE

Deep Learning is a subset of Machine Learning, as previously stated, although there are numerous distinctions between the two. The volume of data input into the system is one of the primary disparities between the two. Large amounts of data feed a Machine Learning system better, however there comes a threshold of diminishing returns: [13]

Deep Learning systems are capable of processing large amounts of data. The relevance of Deep Learning is growing increasingly relevant and common in companies across verticals as data is created at a rate that exceeds our expectations. [13]

The type of algorithms utilized is another significant distinction between Machine Learning and Deep Learning. Machine Learning use simple algorithms to explain why a certain prediction occurred. Deep Learning, on the other hand, employs a number of sophisticated algorithms that make it hard to comprehend why a certain prediction happened. There's no doubting that predictions made by Deep Learning systems are more accurate than those made by Machine Learning systems.[13]

4.6 IMPORTANCE

As more data is put into a deep learning system, it improves, and it flourishes with certain use cases. However, much as Artificial Intelligence and Machine Learning systems have limits, providing a Deep Learning system with relevant data does not guarantee a solution to each problem. Machine Learning Algorithms can outperform Deep Learning Algorithms in some situations.[13]

Deep Learning's applications have grown critical in a variety of fields, including Natural Language Processing (NLP), Computer Vision, Pattern Recognition, and others.[13]

Natural Language Processing powers clever digital assistants like Alexa, Siri, and other speech programs that we use every day. Voice instructions may be converted into text using these technologies. The algorithm would then go through all of the dictionaries and build sentiment from these terms in order to provide users with suitable replies. With the introduction of Deep Learning, advances in NLP are happening at a breakneck speed.[13]

USE:

Nowadays deep learning is using for so many aspects some of them are: [14]

- Customer satisfaction.
- Translation services
- Colorizing black-and-white photographs and videos
- Recognized languages
- Self-driving cars.

- Computer vision
- Generation of text
- Image caption generation.
- Sentiment-based news aggregator.
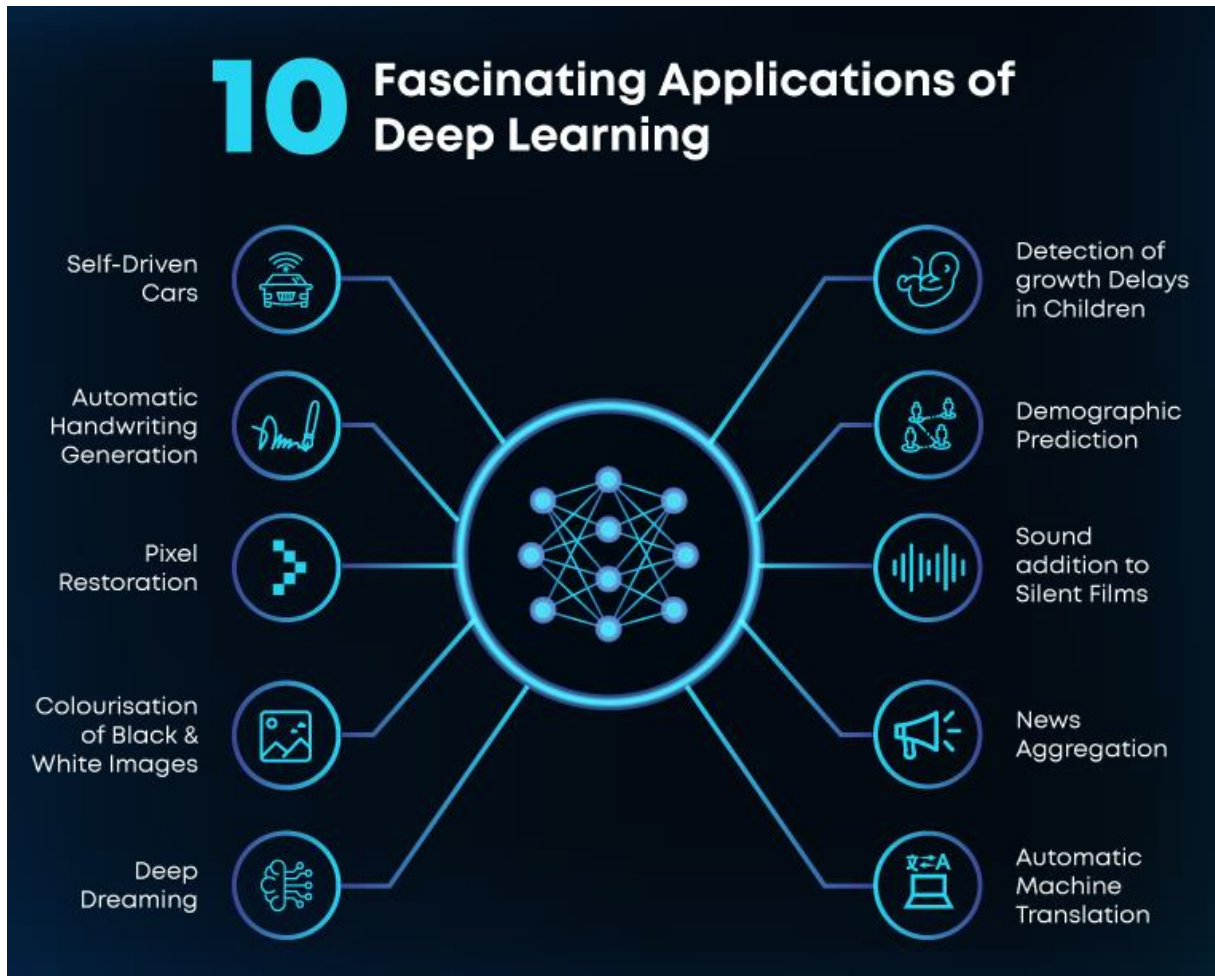- Robots with deep learning capabilities.

Figure 4.5: Application of Deep Learning[58]

In this model we use computer vision and image caption generation to classify the tumor and obtaining the desire output.

The field of computer vision is concerned with analyzing and comprehending pictures and video. It's used to teach computers how to "see" and use visual information to do tasks that humans can do. Computer vision models are created to interpret visual input using features and contextual information discovered during training. This allows models to evaluate photos and videos and apply their findings to prediction or decision-making tasks.[15]

Image processing and computer vision are not the same thing, even though they both deal with visual input. Modifying or altering photos to generate a new outcome is what image processing entails. Optimizing brightness or contrast, boosting resolution, obscuring sensitive information, or cropping are all examples of this. The distinction between image processing and computer vision is that the former does not always need content recognition.[15]

Using deep learning and computer vision, image caption generator recognizes the context of a picture and annotates it with appropriate captions. It involves identifying an image with English keywords using datasets generated during model training. The imaginate dataset is used to train the Xception CNN model. Image feature extraction is handled by Xception. These attributes will be put into the LSTM model, which will create the picture description.[16]

4.7 NEURAL NETWORK

A neural network is a set of algorithms that attempts to detect underlying relationships in a batch of data using a method that mimics how the human brain works. In this context, neural networks are systems of neurons that might be biological or artificial. [17]
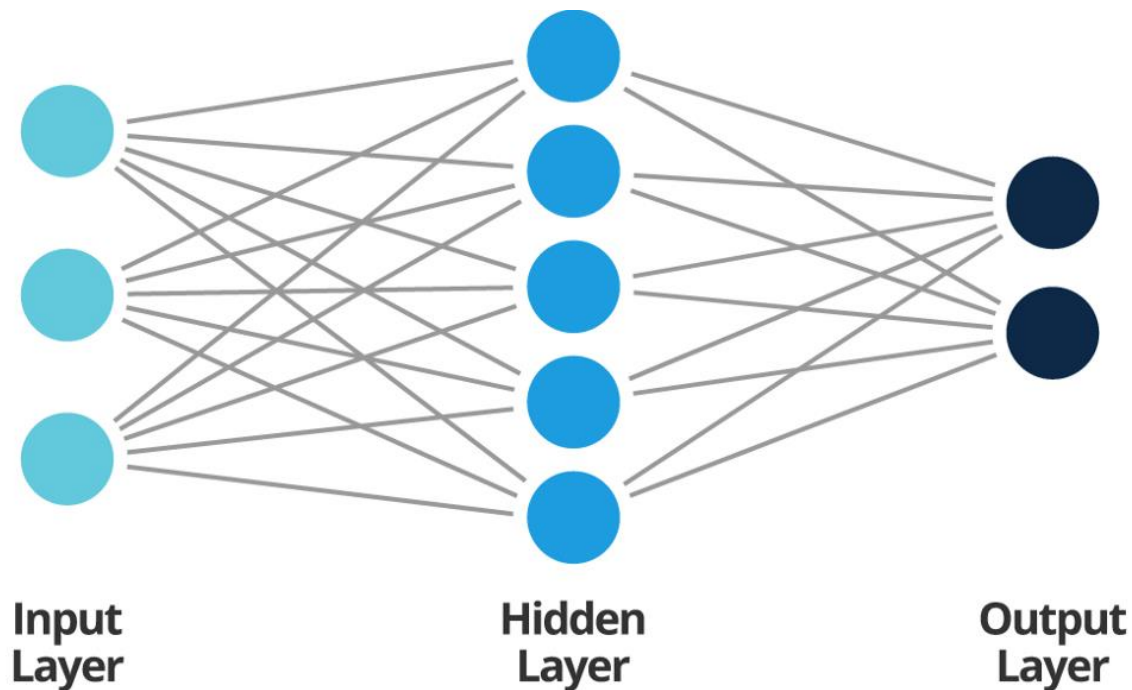

Figure 4.6: Layers of Neural Networks[59]

An input layer, a processing layer, and an output layer are the three basic components. Different criteria might be used to weight the inputs. There are nodes and connections between these nodes within the processing layer, which is concealed from view, that are designed to be equivalent to neurons and synapses in an animal brain. [17]

Perceptions are organized in linked layers in a multi-layered perceptron (MLP). Input patterns are collected by the input layer. The output layer contains classifications or output signals that input patterns can be mapped to. For example, the patterns may include a list of amounts for technical indications concerning a security, with possible outputs of "YES," "NO," or "SOMETHING ELSE."[17]

The input weightings are fine-tuned via hidden layers until the neural network's margin of error is as little as possible. Hidden layers are thought to infer prominent aspects from the input data which have predictive potential for the outputs. This is how feature extraction works, and it's comparable to how statistical approaches like principal component analysis work. [17]

Our brain tumor photos are 64x64 pixels in size. Each neuron in the first layer receives one pixel as input. Neurons in one layer communicate with neurons in the next layer via channels. Weight is a numerical number applied to each of these channels. The inputs are multiplied by the relevant weight before being provided as input to the hidden layer neurons. The bias is a numerical value assigned to each of these neurons, which is subsequently added to the input total. This value is then sent via the activation function, which is a threshold function. The output of the activation function decides whether or not a certain neuron is stimulated.[18]

Over the channels, an active neuron communicates data to the neurons of the following layer. Forward propagation is the process of sending data through a network in this manner. The neuron with the greatest value fires in the output layer, determining the output. The figures are only estimates. To determine the inaccuracy in prediction, the expected output is compared to the actual output. The error magnitude indicates the direction and magnitude of adjustment required to lessen the mistake. This data is then transmitted backwards across our network. Back propagation is the term for this. The weights are now modified depending on this information.[18]

With numerous inputs, this cycle of forward and reverse propagation is repeated recursively. This approach is repeated until our weights are set to the point where the network can accurately predict the kind of tumor in the majority of cases. Our training program is now complete. NN may take hours or even months to teach, but when contrasted to its scope, time is an acceptable trade-off. After pre-processing MRI pictures, several trials demonstrate that the neural network classification technique, notably CNN(Convolutional Neural Network), outperformed the Support Vector Machine(SVM) and Random Forest Field.[18]

4.8 TRANSFER LEARNING

The reuse of a previously learned model on a new issue is known as transfer learning. It's particularly popular in deep learning right now since it can train deep neural networks with a small amount of data. This is especially beneficial in data science since most real-world situations do not require millions of labeled data points to train complicated models. [19]

In computer vision, neural networks typically aim to identify edges in the first layer, forms in the middle layer, and task-specific properties in the latter layers. The early and intermediate layers are utilized in transfer learning, whereas the subsequent layers are just retrained. It makes use of the labeled data from the job it was trained on.[19]

We strive to transfer as much information as possible from the previous task the model was trained on to the new task at hand in transfer learning. Depending on the situation and the data, this knowledge might take many different forms.[19]

Transfer Learning

Pretrained Model

Small dataset → **Medium Compute resources and less training time** → **Trained neural network on the custom dataset**
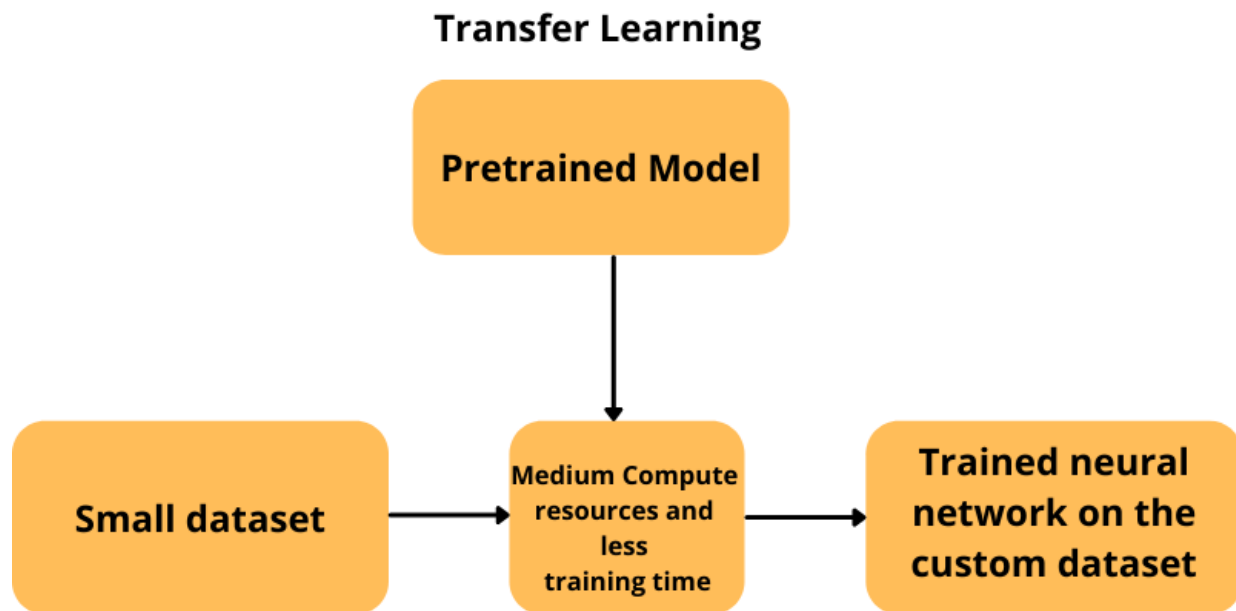
Figure 4.7: Transfer Learning[60]

Transfer learning offers various advantages, but the most important ones are reduced training time, improved neural network performance (in most circumstances), and the lack of input requirements. To train a neural network from start, a lot of data is usually required, but access to that data isn't always possible – this is when transfer learning comes in useful. Because the model has previously been trained, a good machine learning model may be generated with relatively little training data via transfer learning. This is especially useful in natural language processing, where huge labeled datasets require a lot of expert knowledge. Additionally, training time is lowered because building a deep neural network from start on a challenging job can take days or even weeks.[19]

MAIN BENEFITS OF TRANSFER LEARNING

Better initial model

Higher accuracy after training

Higher learning rate

Faster training

Figure 4.8: Benefits of Transfer Learning[61]

Neural networks may now use substantially less input thanks to transfer learning. We are effectively transferring the knowledge' that a model has learnt from a previous task to our present one through transfer learning. Because the two jobs aren't completely disjointed, we can use whatever network parameters the model has acquired during its extended training without having to do it ourselves. Transfer learning has been shown to improve model accuracy while reducing training time; less data, less time, greater accuracy. Inductive transfer learning, transductive transfer learning, and unsupervised transfer learning are the three types of transfer learning.[18]

The majority of prior works concentrated on the settings. Furthermore, depending on what to transfer in learning, each of the techniques to transfer learning may be grouped into four settings. The instance-transfer strategy, feature-representation-transfer approach, parameter transfer approach, and relation acknowledge-transfer approach are all examples of these approaches. Pre-training is a process in which smaller networks converge and are subsequently utilized as initializations for bigger, deeper networks. While it makes sense, pre-training is a time-consuming and arduous procedure that necessitates training a complete network before it can act as a foundation for a deeper network.[18]

4.9 MRI

MRI is a non-invasive imaging technique that creates three-dimensional detailed anatomical pictures. It is frequently employed in the detection, diagnosis, and monitoring of diseases. It works by stimulating and detecting changes in the rotational axis of protons contained in the water that makes up biological tissues.[20]

Figure 4.9: MRI Machine[62]

Magnetic resonance imaging (MRI) uses powerful magnets to create a strong magnetic field that compels protons in the body to align with it. Protons are activated and spin out of equilibrium when a radiofrequency current is pulsed through the body, pushing against the magnetic field's attraction. The MRI sensors can measure the energy produced as the protons realign with the magnetic field when the radiofrequency field is switched off. The quantity of energy released and the time it takes for the protons to realign with the magnetic field vary depending on the environment and the chemical makeup of the molecules. These magnetic fields allow doctors to distinguish between different types of tissues.[20]

A patient is put within a huge magnet to produce an MRI image and must remain very motionless during the imaging process to avoid blurring the image. To accelerate the speed at which protons realign with the magnetic field, contrast medications (typically containing the element Gadolinium) may be administered intravenously to a patient before or during the MRI. The brighter the picture, the faster the protons realign.[20]

MRI scanners are especially well adapted to imaging non-bony bodily components and soft tissues. They vary from computed tomography (CT) in that they do not employ x-rays, which emit harmful ionizing radiation. MRI images the brain, spinal cord, and nerves, as well as muscles, ligaments, and tendons, considerably more clearly than normal x-rays and CT; as a result, MRI is frequently used to imaging knee and shoulder problems.[20]

MRI can distinguish between white and grey matter in the brain and may also be used to diagnose aneurysms and malignancies. MRI is the imaging modality of choice when frequent imaging is

necessary for diagnosis or therapy, especially in the brain, because it does not use x-rays or other radiation. MRI, on the other hand, is more costly than x-ray imaging or CT scanning.[20]

Functional Magnetic Resonance Imaging is one type of specialized MRI (fMRI.) During various cognitive activities, this is utilized to study brain architecture and identify which parts of the brain "active" (consuming more oxygen). It's utilized to further our understanding of brain organization and might be a new benchmark for determining neurological state and neurosurgical risk.[20]

4.10 ACTIVATION FUNCTION

In a neural network, an activation function specifies how the weighted sum of the input is turned into an output from a node or nodes in a layer. The activation function is sometimes known as a "transfer function." The activation function is referred to as a "squashing function" if its output range is restricted. Nonlinearity in the layer or network architecture refers to the fact that many activation functions are nonlinear.[21]

The activation function chosen has a significant influence on the neural network's capabilities and performance, and multiple activation functions may be utilized in different portions of the model. Although networks are designed to employ the same activation function for all nodes in a layer, the activation function is applied within or after the internal processing of each node in the network.[21]

There are three sorts of layers in a network: input levels that receive raw domain information, hidden layers that take input from one layer and transfer output to another layer, and output layers that produce predictions. The activation function is usually the same for all concealed levels. Depending on the sort of prediction required by the model, the output layer will often utilize a different activation function than the hidden layers.[21]

Activation functions are usually differentiable, which means that for a given input value, the first-order derivative may be determined. This is necessary because neural networks are usually trained using the backpropagation of error procedure, which requires the derivative of prediction error to update the model's weights. In neural networks, there are many distinct types of activation functions, albeit possibly only a few are employed in practice for hidden and output layers.[21]

4.10.1 Hidden Layers Activation

In a neural network, a hidden layer takes input from another layer (for example, another hidden layer or an input layer) and outputs to another layer (such as another hidden layer or an output layer). In general, a hidden layer does not interact directly with input data or provide outputs for a model. Hidden layers can be zero or more in a neural network. There are three activation functions you might wish to think about using in hidden layers: [21]

- Logical (Sigmoid)
- Rectified Linear Activation (ReLU)
- Hyperbolic Tangent (Tanh)

This is not a full list of hidden layer activation functions, but they are the most prevalent.[21]

4.10.2 Output Layers Activation

In a neural network model, the output layer is the layer that directly produces a prediction. An output layer is present in all feed-forward neural network architectures. There are three activation functions that we might wish to consider using in the output layer: [21]

- LineaR
- Softmax
- Logical (Sigmoid)

Although this is not a full list of activation functions for output layers, it is the most prevalent.[21]

4.11 CONVOLUTIONAL NEURAL NETWORK

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning system that can take an input picture, assign relevance (learnable weights and biases) to various aspects/objects in the image, and distinguish between them. In comparison to other classification methods, ConvNet requires substantially less pre-processing. While basic approaches need hand-engineering of filters, ConvNets can learn these filters/characteristics with enough training.[22]

The design of a ConvNet is inspired by the organization of the Visual Cortex and is akin to the connection pattern of Neurons in the Human Brain. Individual neurons can only respond to stimuli in a small area of the visual field called the Receptive Field. A group of similar fields can be used to cover the full visual field. For brain tumor detection and classification, we employed the Convolutional Neural Network architecture in our study.[22]

Convolutional neural networks are used for image categorization, image processing, and face identification, among other things. It's a 3D structure with specialized NN that analyzes RGB layers in a picture. It analyzes one image at a time, detects and extracts essential elements, and then utilizes them to categorize the image, unlike others. Convolutional Neural Networks (ConvNets) learn mid- and high-level representations or abstractions from incoming training data automatically. The convolutional layer is the most important component of a CNN design. It also has multiple other levels, some of which are listed below: [18]

- Input Layer-It takes in the raw pixel value of input image.
- Convolutional Layer- It is the first layer to extract features from an input image. Convolution preserves the relationship between pixels by learning image features using small squares of input data. It is a mathematical operation that takes two inputs such as image matrix and a filter or kernel to generate a feature map Convolution of an image with different filters can perform operations such as edge detection, blur and sharpen by applying filters.[18]
- Activation Layer-It produces a single output based on the weighted sum of inputs.
- Pooling layer-When the photos are too huge, the Pooling Layers section would lower the number of parameters. Spatial pooling (also known as subsampling or down sampling) decreases the dimensionality of each map while still retaining critical data. There are several forms of spatial pooling: [18]

  o Max Pooling – using the feature map's biggest element.

  o Average Pooling - the feature map's components are averaged.

  o Sum Pooling – calculating the total of all feature map components
- Fully Connected Layer-We flattened our matrix into a vector and sent it into a fully connected layer, similar to a neural network, to create the FC layer. The column vector (x1, x2, x3,...) will be created from the feature map matrix. We integrated these attributes to generate a model using the fully linked layers. Based on the training set, categorizing the input picture into several classes. [18]
- The Dropout Layer- The Dropout Layer prohibits network nodes from co-adapting to one another.[18]
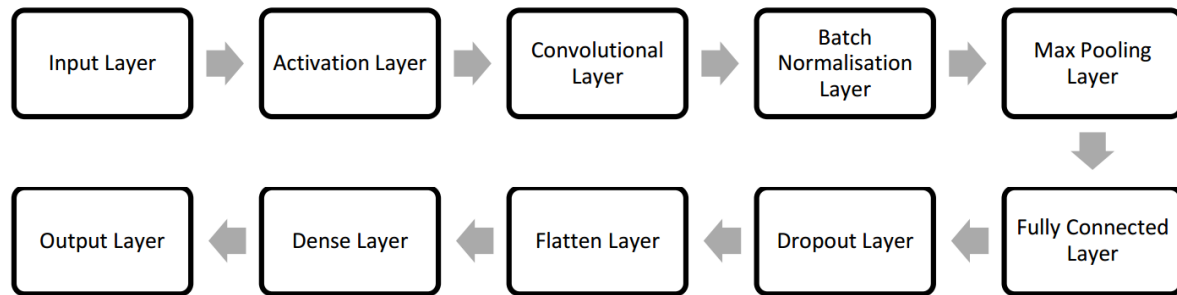
Figure 4.10: CNN Layers [18]

Advantages [18]

- It is considered as the best ml technique for image classification due to high accuracy.
- Image pre-processing required is much less compared to other algorithms.

- It is used over feed forward neural networks as it can be trained better in case of complex images to have higher accuracies.
- It reduces images to a form which is easier to process without losing features which are critical for a good prediction by applying relevant filters and reusability of weights
- It can automatically learn to perform any task just by going through the training data i.e. there no need for prior knowledge
- There is no need for specialized hand-crafted image features like that in case of SVM, Random Forest etc.

Disadvantages [18]

- It needs a huge amount of training data.
- It necessitates a suitable model.
- It's a time-consuming and exhausting process.
- While convolutional networks have been around for a while, their success has been restricted due to the size of the network under consideration. It needs a huge amount of training data.
- It necessitates a suitable model.

CHAPTER 5

METHODOLOGICAL IMPLEMENTATION

5.1 HARDWARE REQUIREMENTS

To complete this thesis, we will need certain hardware that will aid in the smooth execution of the required software. Such as:

- Processor: AMD Ryzen 5 3600 6-Core Processor @ 3.59 GHz
- Installed memory (RAM): 16.0 GB
- System type: 64-bit Operating System
- Operating System: Windows 10

5.2 SOFTWARE REQUIREMENT

Here we have used Python which is a high level, general purposed, interpreted programming language. Its design philosophy prioritizes code readability with extensive indentation. Python is garbage-collected and dynamically typed. It works with a variety of programming paradigms, including structured (especially procedural), object-oriented, and functional programming. Because of its extensive standard library, it is frequently referred to as a "batteries included" language.[23] We utilized Python 3.6, which was published in the final quarter of 2016. Python was chosen over MATLAB for the following reasons:

- Python code is smaller and easier to read than MATLAB code.
- The data structure of Python is superior than that of MATLAB.
- It's free and open source, with additional visual packages and data sets.

We utilized Anaconda to construct a virtual environment that seeks to ease package management and deployment for scientific computing (data science, machine learning applications, large-scale data processing, predictive analytics, and so on). Data-science software for Windows, Linux, and macOS are included in the release.[24]

The online dataset was obtained using Kaggle.

In case of programming syntax issues, GitHub and Stackoverflow were used as resources.

OpenCV (Open Source Computer Vision) is a library of programming functions aimed at real-time computer vision, such as reading and writing images, modifying image quality, removing noise with Gaussian Blur, performing binary thresholding on images, converting the original image consisting of pixel values into an array, changing the image from RGB to grayscale, and so on. It is open source, easy to use, and supports C++, Java, C, and Python. Cam Scanner or

Instagram, GitHub, or a web-based control repository are some of its most common applications.[18]

For creating and analyzing deep learning models, we utilized Keras, a powerful and easy-to-use free open source Python toolkit. It covers the fast numerical calculation libraries Theano and TensorFlow, allowing neural network models to be defined and trained in just a few lines of code.[25]

Tensorflow, especially Tensorflow 1.14, was employed here. It's an open source artificial intelligence package that builds models using data flow graphs. It enables programmers to build large-scale neural networks with several layers. Classification, perception, understanding, discovering, prediction, and creation are some of the most common uses for TensorFlow with cudatool 10 and cudnn 7.8 .[26]

NumPy (Numerical Python) is an open-source package for the Python programming language that we utilized. It is utilized in scientific computing and array manipulation. It also has high-level capabilities for working with arrays in addition to its multidimensional array object.[27]

In this case, we've used the Sequential model. A sequential approach is suited for a simple stack of layers with one input and one output tensor for each layer.[28]

Adam served as an optimizer for us. An optimizer is a function or algorithm that changes the weights and learning rate of a neural network. As a result, it aids in the reduction of total loss and the improvement of accuracy.[29] The Adam optimizer produces better results than other optimization algorithms, takes less time to compute, and requires fewer tuning parameters.[30]

We utilized Matplotlib, a Python tool that allows you to create static, animated, and interactive visualizations. Matplotlib makes both easy and difficult tasks feasible.[31]

As an activation function, we employed ReLu. The ReLu function allows us to identify and show the status of the model findings, as well as improve the model's computational efficiency.[32]

5.3 IMAGE ACQUISITION FROM DATASET

Images can be in the form of.csv (comma separated values) files,.dat (data) files in grayscale, RGB, or HSV, or simply a.zip file, like in the case of our online Kaggle dataset. It contains 1500 images for 'YES', 1500 images for 'NO', 826 images for 'Benign' and 247 images for 'Malignant' tumors.

5.4 DATA AUGMENTATION

Grey scaling (converting RGB/BW to greyscale), reflection (vertical/horizontal flip), Gaussian blur (reducing image noise), histogram equalization (increasing global contrast), rotation (may not preserve image size), translation (moving the image along the x or y axis), and linear

transformations like random rotation (0-10 degrees), horizontal and vertical shifts, and horizontal and vertical flips are all examples of data augmentation. When just a few training examples are available, data augmentation is used to teach the network the appropriate invariance and resilience qualities.[18]

5.5 IMAGE PRE-PROCESSING

Rescaling, noise reduction, Binary Cross entropy, and activation functions like 'ReLu' and optimizer 'Adam' are all part of our pre-processing (edge based methodology). The image's memory space is scaled in the first phase of pre-processing by scaling the 64X64, RGB of the pixels in the range 0-255 and reshaping using the 'Flatten' filter. 'Dense' to keep the layers together. Because the shape of the brain is not segmented as tumor here, these produce better outcomes than the Median filter.

5.6 SEGMENTATION

Brain tumor segmentation is the technique of using MRI scans or other imaging modalities to separate tumor tissues (Region of Interest - ROI) from normal brain tissues and solid brain tumors. Its mechanism is based on identifying similar types of subjects within an image and grouping them together by either calculating the similarity measure between the objects and grouping the objects with the highest similarity or calculating the dissimilarity measure between the objects and separating the most dissimilar objects in the space. Bi-clusters (2 sub-parts) and multi-clustered (more than 2 sub-parts) algorithms are two types of segmentation algorithms.[18]

Binary Crosse trophy (through Region Growing technique) may be used to detect the tumor region from a brain imaging, which transforms an RGB/Gray scale image to a binary image depending on the set threshold values. The drawbacks of this method are that binary pictures lose texture and the threshold value varies depending on the image. As a result, we're seeking for a more sophisticated segmentation technique that uses Otsu Binarisation, such as the watershed algorithm (with cv2 library).

5.7 FEATURE EXTRACTION

 A mathematical statistical process for extracting the quantitative parameter of resolution changes/abnormalities that are not evident to the human eye is known as feature extraction. Entropy, RMS, Smoothness, Skewness, Symmetry, Kurtosis, Mean, Texture, Variance, Centroid, Central Tendency, IDM (Inverse Difference Moment), Correlation, Energy, Homogeneity, Dissimilarity, Contrast, Shade, Prominence, Eccentricity, Perimeter, Area, and many other characteristics are examples of such characteristics.[18]

Identifying anomalies is what Feature Extraction is all about. We'll need to extract certain features from photos since we'll be using a classifier to classify the images, and these characteristics will be used to train the classifier. In this feature extraction, we employed the CNN's' sequential' model.

5.8 MODEL CONSTRUCTION

To construct the model we use "Sequential Model". A sequential approach is suited for a simple stack of layers with one input tensor and one output tensor for each layer.[33]
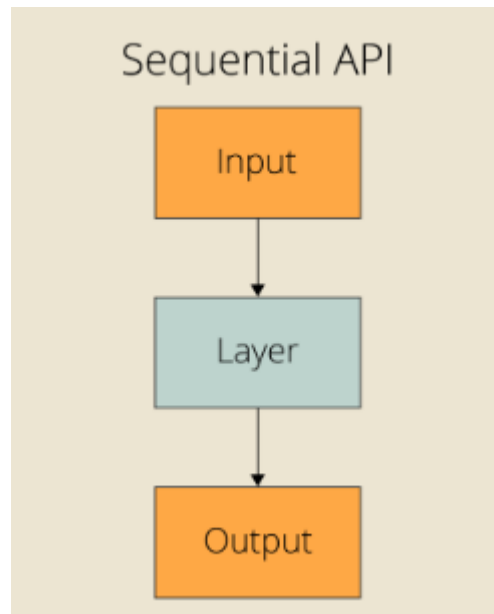
Figure 5.1: Sequential API[63]

We used the library tensorflow and keras. Keras, a sophisticated and easy-to-use free open source Python toolkit, was used to create and analyze deep learning models. It covers the Theano and TensorFlow rapid numerical computation libraries, which allow neural network models to be constructed and trained in a few lines of code. [25] Tensorflow, specifically Tensorflow 1.14, was used in this project. It's an open source artificial intelligence tool that uses data flow graphs to generate models. It allows programmers to create multi-layer, large-scale neural networks. TensorFlow is commonly used for classification, perception, comprehension, discovery, prediction, and invention. [26]

We used NumPy (Numerical Python), which is an open-source library for the Python programming language. It's used in array manipulation and scientific computing. In addition to its multidimensional array object, it includes high-level features for working with arrays. [27]

We used Matplotlib, a Python library for creating static, animated, and interactive graphics. Matplotlib makes both simple and complex tasks possible. [31]

For us, Adam worked as an optimizer. An optimizer is a function or method that modifies a neural network's weights and learning rate. As a consequence, it helps to reduce overall loss while also improving precision. [29] The Adam optimizer outperforms other optimization methods in terms of performance, computation time, and tweaking parameters. [30]

We used softmax as activation function. Softmax is a mathematical function that transforms a vector of integers into a vector of probabilities, with the probability of each value proportional to the vector's relative scale. The softmax function is most commonly used as an activation function in a neural network model in applied machine learning. The network is set up to produce N values, one for each classification task class, and the softmax function is used to normalize the outputs, turning them from weighted sum values to probabilities that total to one. Each number in the softmax function's output is interpreted as the likelihood of belonging to each class. Softmax is a mathematical function that transforms a vector of integers into a vector of probabilities, with the probability of each value proportional to the vector's relative scale.[34]

We used ReLu as a model activation function. We may use the ReLu function to detect and display the status of model discoveries, as well as to enhance the model's computational efficiency. [32]

5.9 TRAINING AND TESTING

Train/Test is a technique for determining your model's correctness. Because you split the data set into two sets: a training set and a testing set, it's termed Train/Test. Training accounts for 80% of the budget, while testing accounts for 20%. The training set is used to train the model. The testing set is used to test the model. The term "train the model" refers to the process of developing a model. Testing the model entails determining its correctness.[35]

We used 'x_train, y_train ', x_test, y_test to train and test the dataset where the training batch size is 16. The batch size is a hyperparameter that specifies how many samples must be processed before the internal model parameters are updated.[38] x train: The initial sequence's training phase (x) x test: The initial sequence's test section (x) y train: The second sequence's training phase (y) y test: The second sequence's test section (y)[36] Here the test size is 20% and the training size is 80%. The random state was zero. The verbose was one.

By enabling you to visually separate logical elements of the pattern and add comments, the verbose option helps you to construct regular expressions that appear prettier and are more legible.[38] verbose=0 will show you nothing (silent). verbose=1 will show you an animated progress bar like this:

Figure 5.2: Verbose Progress Bar

Here epochs was 15. The number of epochs is a hyper parameter that controls how many times the learning algorithm runs over the whole training dataset. Each sample in the training dataset has had the chance to change the internal model parameters once each epoch. There are one or more batches in an epoch. The batch gradient descent learning algorithm, for example, is named after an epoch with only one batch.[38]

We get the loss and accuracy from x test and y test. Accuracy is a metric for evaluating the performance of a classification model. In most cases, it's given as a percentage. The number of forecasts when the anticipated value is identical to the real value is known as accuracy. For a specific sample, it is binary (true/false). During the training phase, accuracy is frequently graphed and monitored, however the value is frequently related with the total or final model accuracy. Loss is more difficult to understand than accuracy. A loss function, also known as a cost function, considers the likelihood or uncertainty of a forecast based on how much it differs from the real value. This provides a more nuanced picture of the model's performance.[39]
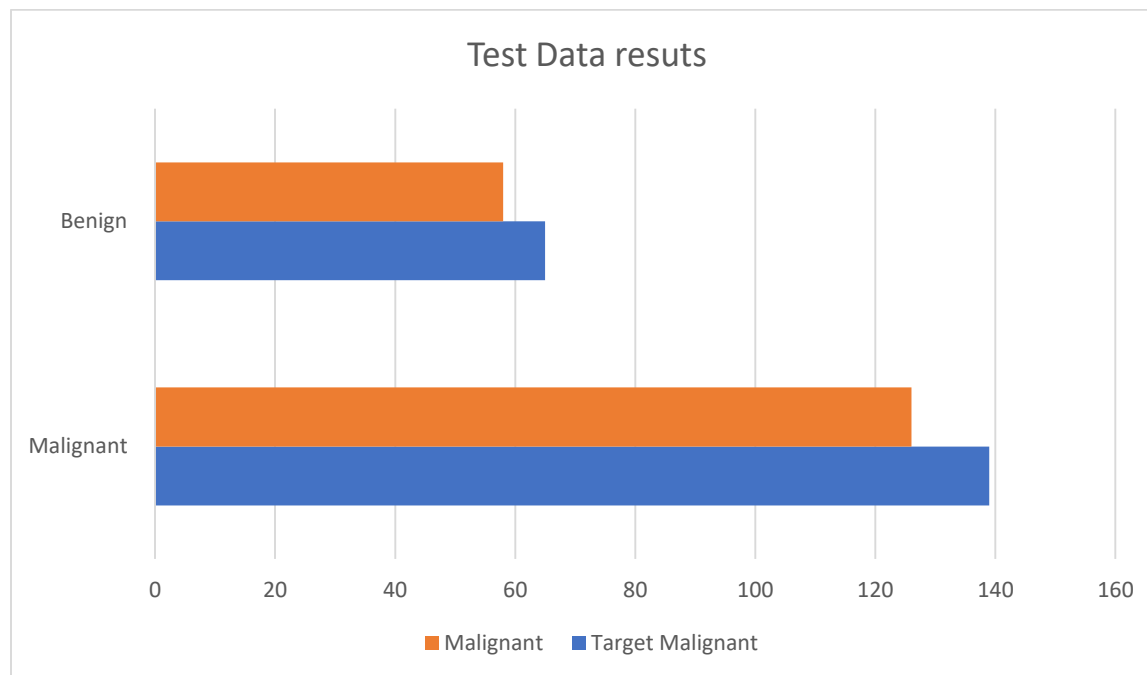
Figure 5.3: Test Data Result

CHAPTER 6

EXPERIMENTAL RESULT AND EVALUATION

To detect tumors at the user's end, we created a web app that requires the user to input an MRI image and then provides an output by detecting and classifying it.

We utilize the flask library to create a web application. Flask is a compact and lightweight Python web framework that provides essential tools and capabilities for building online applications in Python. Because you can construct a web application rapidly using only a single Python file, it allows developers greater flexibility and is a more accessible framework for beginning developers. Flask is also extendable, and it doesn't require complex boilerplate code or a certain directory structure to get started.[40]

We used tensorflow.python.keras.preprocessing to import and analyze the picture. The flask.templating package contains the render template Flask method. The render template function is used to create output from a template file that is based on the Jinja2 engine and located in the application's templates folder. This is how we utilized it.[41] If you provide it a filename werkzeug. secure filename will return a secure version of that file. This filename may then be securely kept and provided to os on a conventional file system.[42]

We use the program to submit some MRI photos and obtain the results.

When we access the web app, it looks like this:
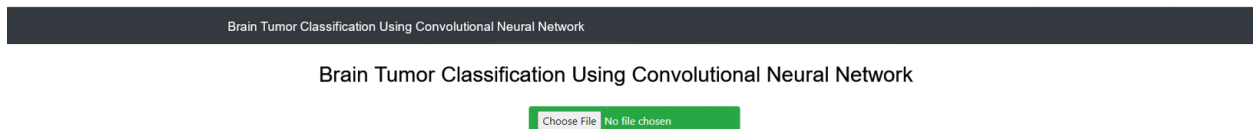
After that, we choose one image from the dataset.
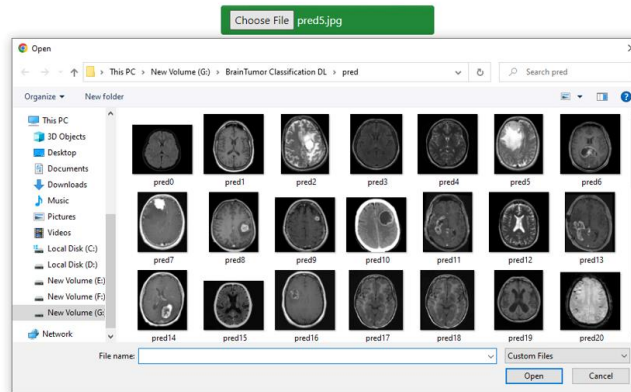
After that, we place it in the upload box.
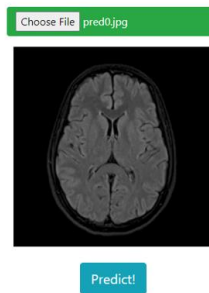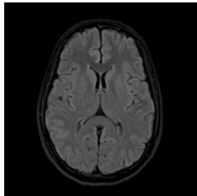
If it predicts, it will then respond.
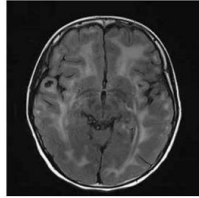

We uploaded some images like these and got the result like these.
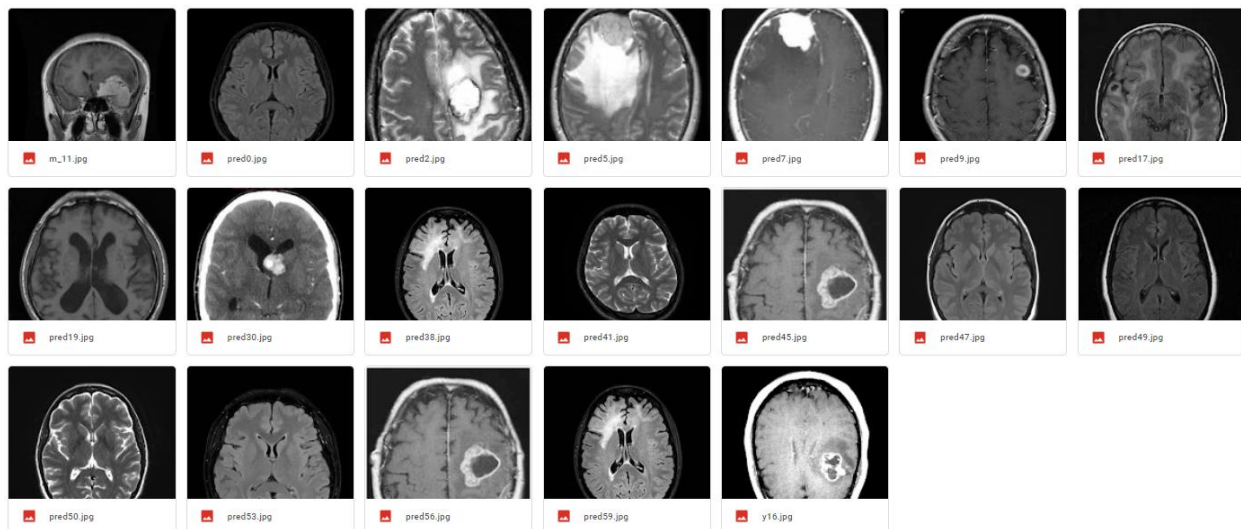
Brain Tumor Classification Using Convolutional Neural Network

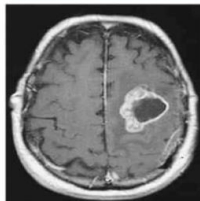Result: No Brain Tumor

Brain Tumor Classification Using Convolutional Neural Network

Result: Yes Brain Tumor Class-Malignant

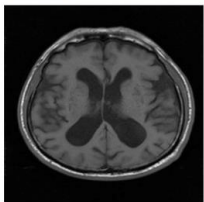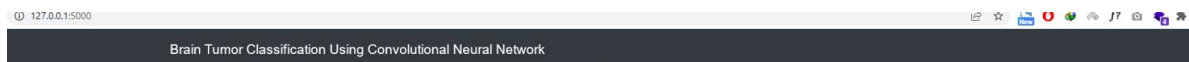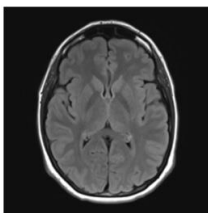Brain Tumor Classification Using Convolutional Neural Network

Choose File pred9.jpg
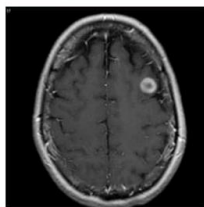
Result: Yes Brain Tumor Class-Benign

Brain Tumor Classification Using Convolutional Neural Network

Choose File pred19.jpg

Result: No Brain Tumor

Brain Tumor Classification Using Convolutional Neural Network
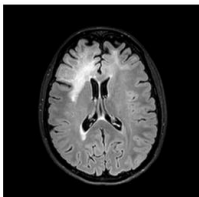
Choose File pred47.jpg
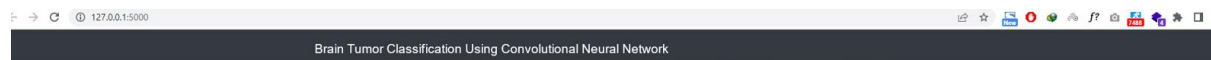
Result: No Brain Tumor

Brain Tumor Classification Using Convolutional Neural Network

Choose File pred38.jpg

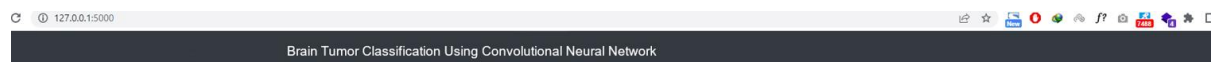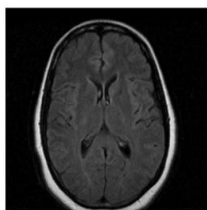Result: Yes Brain Tumor Class-Malignant

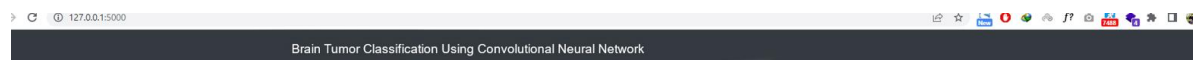Brain Tumor Classification Using Convolutional Neural Network

Result: Yes Brain Tumor Class-Benign

Brain Tumor Classification Using Convolutional Neural Network
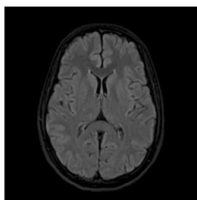
Result: No Brain Tumor

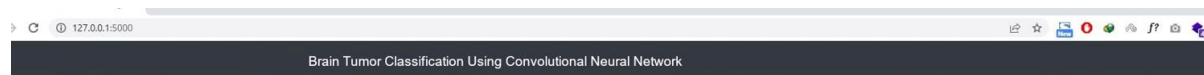Brain Tumor Classification Using Convolutional Neural Network

Result: No Brain Tumor

Brain Tumor Classification Using Convolutional Neural Network

Result: Yes Brain Tumor Class-Malignant

Brain Tumor Classification Using Convolutional Neural Network

Result: Yes Brain Tumor Class-Malignant

Brain Tumor Classification Using Convolutional Neural Network
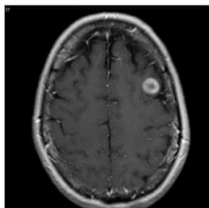
Result: Yes Brain Tumor Class-Benign

6.1 ACCURACY AND LOSS FUNCTION

A machine learning algorithm is optimized using a loss function. The loss is calculated using training and validation data, and its meaning is determined by how well the model performs in these two sets. It's the total number of mistakes committed in each training or validation set for each example. The loss value indicates how well or poorly a model performs after each optimization iteration. An accuracy metric is used to interpretably quantify the algorithm's performance. The accuracy of a model is generally calculated as a percentage once the model parameters have been defined. It's a metric for how close your model's forecast is to the actual data.[44] We acquired a 98 percent accuracy rate for detecting whether or not there is a tumor in the brain MRI picture. When a tumor is detected in an MRI scan, the system classifies it as Malignant or Benign, with a 93 percent accuracy rate.
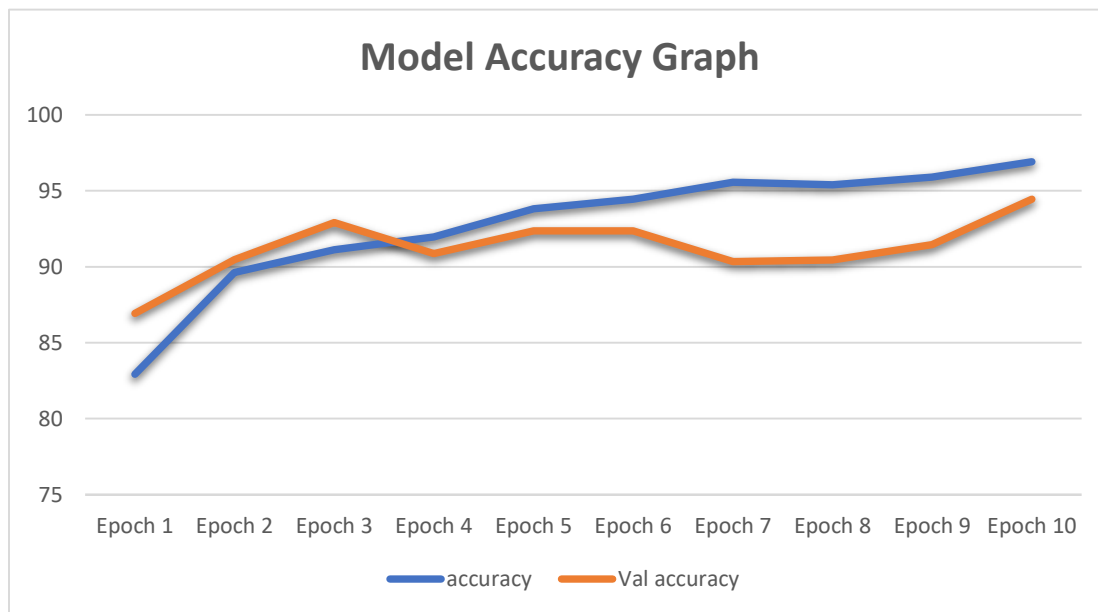
Figure 6.1: Model Accuracy Graph
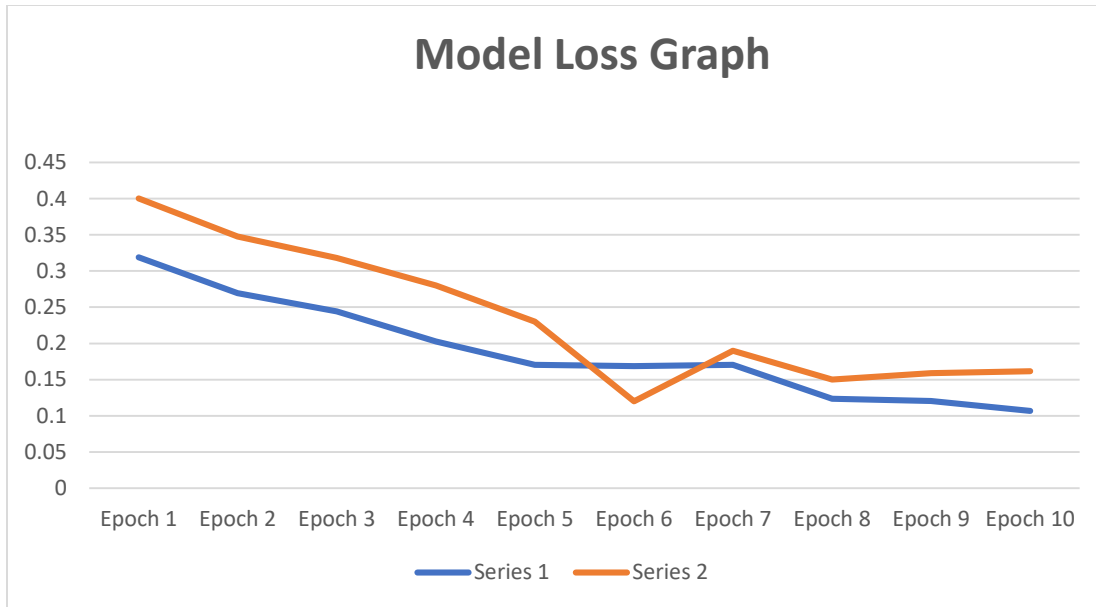
Figure 6.2: Model Loss Graph

6.2 LIMITATIONS

There were a lot of data sets while we were looking for data sets of brain tumor MRI pictures. In this thesis, we use the kaggle dataset. Then, in order to classify the tumor, we'll need a separate dataset for malignant and benign tumors. However, there were a lot of MRI scans in this case. We had to deal with a lack of MRI images of categorized brain tumors even on the internet. If we wish to improve the accuracy of a machine learning model, we must give it a huge dataset. As a result, having a large dataset is critical. Despite having a huge dataset, our model's accuracy rate of classification is affected. and it was a challenge we had to deal with when we were creating this.

CHAPTER 7

CONCLUSION AND FUTURE STRATEGY

7.1 CONCLUSION

We intend to use MRI scanning pictures to detect brain tumors in our thesis. We utilize the Kaggle data set for our dataset. We utilize the sequential model after preprocessing the dataset. We import various libraries, including cv2, os, tensorflow, keras, PIL, numpy sklearn, and others, then utilize those datasets with x train y train to train the model. ReLu is used as an activation function, and Adam is used as an optimizer. This model training takes 15 epochs. We used x test y test to train 80% of the dataset and test 20% of it.

Following training and testing, we used a web application to make detection easier for the user. For the we app, we utilize the flask library .The user interface of the online app allows the user to upload a picture from their smartphone. The web program then responds by determining whether or not there is a tumor in the photograph. If a tumor is detected, it will be classed as either malignant or benign. According to the model, the online app has a 98 percent accuracy rate in identifying tumors and a 93 percent accuracy rate in classifying them. We are limited in our ability to classify brain tumors due to a lack of data. In the future, we'd want to work with the VV16 model and the ResNet architecture. We aim to receive more varied results in the future so that we can compare them and see what the differences are.

7.2 FUTURE STRATEGY

For this thesis, we would like to include VGG16 and resnet 50 in the future. VGG16 is a convolutional neural network (CNN) architecture that won the 2014 ILSVR(Imagenet) competition. It is regarded as one of the best vision model architectures ever created. The most distinctive feature of VGG16 is that, rather than having a huge number of hyper-parameters, they concentrated on having 3x3 filter convolution layers with a stride 1 and always utilized the same padding and maxpool layer of 2x2 filter stride 2. Throughout the design, the convolution and max pool layers are arranged in the same way.[44] VGG16 is a convolutional neural network (CNN) architecture that won the 2014 ILSVR(Imagenet) competition. It is regarded as one of the best vision model architectures ever created. [45]

The ResNet-50 model is a 50-layer convolutional neural network (CNN). A Residual Neural Network (ResNet) is a type of Artificial Neural Network (ANN) that builds a network by stacking residual blocks on top of each other. [46] In 30 epochs, the ResNet-50 is 81 percent accurate, while in 100 epochs, the MobileNet is 65 percent accurate. However, as can be seen in MobileNet's

training performance, its accuracy is improving, and it can be assumed that the accuracy will increase more if the training is done for a larger number of epochs. [47]

There are some others work plan we want to do in future like as:

- The number of images can be increased. The bigger the number of the images is- the better the model is trained.
- Now we are using 2D images but we want to work on 3D images in future.
- More traditional classifiers can be applied to get more increased accuracy. We plan to Improve our accuracy up to 99% in future work models.
- We will try to classify the tumor if its other classification except benign or malignant after the detection of the tumor.
- We will try to put more variations of deep learning methods can be tested in Future
- We want to train our model with improved data set like RIDER where the total number of images in this dataset is 70,220 from 19 patient and Repository of Molecular Brain Neoplasia Data where the total number of images in this dataset is 110,020 from 130 patient.
- We are planning to build mobile apps on android and iOS for brain tumor detection and classification beside our web app which will be easier for user to detect more easily.
- We want to develop our model in which the model will show the tumor size and guess the weight and show the spread possibility with percentage of development or spread of previous test.

REFERENCE

1. https://www.google.com/search?q=EWU+LOGO&rlz=1C1CHBF_enBD926BD926&tbm=isch&source=iu&ictx=1&vet=1&fir=vAibcxRLYY1TvM%252Cybq6nzFgdEw3CM%252C_%253BCVBdYLEDxt8i7M%252CKOHcXCBxNOPhLM%252C_%253B3LDdlP0N5ckY4M%252CAnVhN8GGD4asQM%252C_%253Bsbf2FpDjfqWo5M%252CKOHcXCBxNOPhLM%252C_%253B5rND9U8Z32o0NM%252CKOHcXCBxNOPhLM%252C_%253Bq4d4dbkzcREa0M%252C8abPPsWWXXmndM%252C_%253BabfRw3gtbWmsMM%252CE5iBPtPC14SX4M%252C_%253BnsHat0YAhZWG4M%252CwEpiYZAkOBwLEM%252C_%253BC80OIY_jhz4MMM%252CqAENTysK_IhzzM%252C_%253BkLGQ4dfwMzfllM%252C5fDyd1MMr1zq1M%252C_%253BULnqdwMwtWsNlM%252CZ84BAdBZfATLkM%252C_%253BaQ45c6eY_0YJoM%252CBOEUakqAccoqwM%252C_%253Bd8Z9OcaS3_YSmM%252CBOEUakqAccoqwM%252C_%253BnB_WStLPDY2UFM%252ChDkPusXzSCIHUM%252C_&usg=AI4_-kSLLs8Wsk9hVLTtJdclK4TVuroTZg&sa=X&ved=2ahUKEwjp2tfBlPD3AhUlRWwGHaiTBjMQ9QF6BAgCEAE#imgrc=vAibcxRLYY1TvM&imgdii=Vm_3GIKFCfsrCM

2. https://www.researchgate.net/publication/350936156_Brain_Tumor_Detection_using_Deep_Learning_and_Image_Processing

3. https://www.researchgate.net/publication/338797226_Brain_Tumor_Detection_Using_Deep_Neural_Network_and_Machine_Learning_Algorithm

4. https://medlineplus.gov/ency/article/001310.htm

5. https://www.healthline.com/health/brain-tumor

6. https://www.investopedia.com/terms/a/artificial-intelligence-ai.asp

7. https://www.simplilearn.com/tutorials/artificial-intelligence-tutorial/artificial-intelligence-applications

8. https://en.wikipedia.org/wiki/Artificial_intelligence_in_healthcare

9. https://www.techtarget.com/searchenterpriseai/definition/machine-learning-ML

10. https://developers.google.com/machine-learning/practica/image-classification#:~:text=Image%20classification%20is%20a%20supervised,the%20input%20to%20the%20model.

11. https://www.ibm.com/cloud/learn/supervised-learning

12. https://en.wikipedia.org/wiki/Deep_learning

13. https://aipatasala.com/blogs/importance-of-deep-learning-how-deep-learning-is-useful-in-realtime

14. https://bernardmarr.com/10-amazing-examples-of-how-deep-learning-ai-is-used-in-practice/

15. https://www.run.ai/guides/deep-learning-for-computer-vision

16. https://www.analyticsvidhya.com/blog/2021/12/step-by-step-guide-to-build-image-caption-generator-using-deep-learning/

17. https://www.investopedia.com/terms/n/neuralnetwork.asp#:~:text=A%20neural%20network%20is%20a,organic%20or%20artificial%20in%20nature.
18. GR_15 AUTOMATIC BRAIN TUMOR DETECTION AND CLASSIFICATION ON MRI IMAGES USING MACHINE LEARNING TECHNIQUES by SHREYASI GHOSH, Sayeri Biswas and Jitsona De; 2020
19. https://builtin.com/data-science/transfer-learning
20. https://www.nibib.nih.gov/science-education/science-topics/magnetic-resonance-imaging-mri
21. https://machinelearningmastery.com/choose-an-activation-function-for-deep-learning/#:~:text=An%20activation%20function%20in%20a,a%20layer%20of%20the%20network.
22. https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53
23. https://en.wikipedia.org/wiki/Python_(programming_language)
24. https://en.wikipedia.org/wiki/Anaconda_(Python_distribution)
25. https://machinelearningmastery.com/tutorial-first-neural-network-python-keras/
26. https://www.exastax.com/deep-learning/top-five-use-cases-of-tensorflow/
27. https://phoenixnap.com/kb/install-numpy
28. https://keras.io/guides/sequential_model/
29. https://www.analyticsvidhya.com/blog/2021/10/a-comprehensive-guide-on-deep-learningoptimizers/#:~:text=An%20optimizer%20is%20a%20function,loss%20and%20improve%20the%20accuracy.
30. https://www.analyticsvidhya.com/blog/2021/10/a-comprehensive-guide-on-deep-learning-optimizers/
31. https://matplotlib.org/
32. https://www.askpython.com/python/examples/relu-function
33. https://keras.io/guides/sequential_model/
34. https://machinelearningmastery.com/softmax-activation-function-with-python/
35. https://www.w3schools.com/python/python_ml_train_test.asp#:~:text=Train%2FTest%20is%20a%20method,model%20using%20the%20training%20set.
36. https://realpython.com/train-test-split-python-data/
37. https://www.geeksforgeeks.org/verbose-in-python-regex/#:~:text=VERBOSE%20%3A%20This%20flag%20allows%20you,the%20pattern%20%20and%20add%20comments.
38. https://machinelearningmastery.com/difference-between-a-batch-and-an-epoch/
39. https://machine-learning.paperspace.com/wiki/accuracy-and-loss
40. https://www.digitalocean.com/community/tutorials/how-to-make-a-web-application-using-flask-in-python-3
41. https://www.fullstackpython.com/flask-templating-render-template-examples.html
42. https://tedboy.github.io/flask/generated/werkzeug.secure_filename.html
43. https://intellipaat.com/community/368/how-to-interpret-loss-and-accuracy-for-a-machine-learning-model

44. https://towardsdatascience.com/step-by-step-vgg16-implementation-in-keras-for-beginners-a833c686ae6c#:~:text=VGG16%20is%20a%20convolution%20neural,vision%20model%20architecture%20till%20date.
45. https://www.analyticsvidhya.com/blog/2017/08/10-advanced-deep-learning-architectures-data-scientists/
46. https://viso.ai/deep-learning/resnet-residual-neural-network/
47. https://analyticsindiamag.com/mobilenet-vs-resnet50-two-cnn-transfer-learning-light-frameworks/
48. https://www.medicinenet.com/what_exactly_is_a_tumor/article.htm
49. https://www.mayoclinic.org/diseases-conditions/brain-tumor/symptoms-causes/syc-20350084
50. https://www.mdpi.com/2076-3417/10/6/1999/htm
51. https://ieeexplore.ieee.org/document/9563299
52. https://www.itnonline.com/content/ct-scans-may-increase-risk-brain-cancer
53. https://www.cancer.gov/rare-brain-spine-tumor/tumors/diffuse-midline-gliomas
54. https://leverageedu.com/blog/applications-of-artificial-intelligence/
55. https://www.eurixgroup.com/eurix-machine-learning-2/
56. https://www.wordstream.com/blog/ws/2017/07/28/machine-learning-applications
57. https://databricks.com/glossary/deep-learning
58. https://www.google.com/search?q=use+of+deep+learning&tbm=isch&ved=2ahUKEwilg-60yv_3AhVak9gFHRQvCbUQ2-cCegQIABAA&oq=use+deep+learning&gs_lcp=CgNpbWcQARgBMgYIABAeEAcyBggAEB4QBzIGCAAQHhAIMgQIABAYMgQIABAYMgQIABAYOgQIABBDOggIABAeEAgQB1CmCVi4EGD6NWgAcAB4AIABBmgGIAegFkgEDMC41mAEAoAEBqgELZ3dzLXXdpei1pbWfAAQE&sclient=img&ei=n7aQYuW3H9qm4t4PlN6kqAs&bih=912&biw=1920&rlz=1C1CHBF_enBD926BD926#imgrc=sXfARb227I0hCM
59. https://towardsai.net/p/machine-learning/how-to-build-and-train-your-first-neural-network-9a07d020c4bb
60. https://debuggercafe.com/transfer-learning-using-efficientnet-pytorch/
61. https://research.aimultiple.com/transfer-learning/
62. https://www.philips.co.in/healthcare/solutions/magnetic-resonance
63. https://developpaper.com/three-methods-of-constructing-neural-network-with-keras/
64. https://www.researchgate.net/publication/350936156_Brain_Tumor_Detection_using_Deep_Learning_and_Image_Processing
65. https://www.researchgate.net/publication/338797226_Brain_Tumor_Detection_Using_Deep_Neural_Network_and_Machine_Learning_Algorithm
66. Fine-Grained Classification of Product Images Based on Convolutional Neural Networks (scirp.org)
67. Robustness Augmentation of Deep Learning Model Based on Pixel Change (scirp.org)

68. [Automated Classification of Lung Diseases in Computed Tomography Images Using a Wavelet Based Convolutional Neural Network (scirp.org)](#)

69. [(PDF) Deep Learning (researchgate.net)](#)

70. [Review of He et al. 2015 *Deep Residual Learning for Image Recognition* (neural.vision)](#)

71. [Multi-grade brain tumor classification using deep CNN with extensive data augmentation - ScienceDirect](#)

72. [IJCA - Brain Tumor Detection based on Machine Learning Algorithms (ijcaonline.org)](#)

73. [A structural MRI study of human brain development from birth to 2 years - PubMed (nih.gov)](#)

74. [Brain Tumour Detection Using Unsupervised Learning Based Neural Network (researchgate.net)](#)

75. https://ieeexplore.ieee.org/abstract/document/8343231

76. [A Modified U-Net Convolutional Network Featuring a Nearest-neighbor Re-sampling-based Elastic-Transformation for Brain Tissue Characterization and Segmentation - PubMed (nih.gov)](#)

77. [Brain tumor segmentation using holistically nested neural networks in MRI images - PubMed (nih.gov)](#)

78. [Comparative clinical evaluation of atlas and deep-learning-based auto-segmentation of organ structures in liver cancer - PubMed (nih.gov)](#)

79. https://ieeexplore.ieee.org/abstract/document/7939554

80. https://www.hindawi.com/journals/ijbi/2017/9749108/

PYTHON FOR MODEL BUILDING:

9.1 Training Model

```python
import cv2
import os
import tensorflow as tf
from tensorflow import keras
from PIL import Image
import numpy as np
from sklearn.model_selection import train_test_split
from keras.utils import normalize
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D
from keras.layers import Activation, Dropout, Flatten, Dense
from keras.utils import to_categorical
from keras.optimizers import Adam

import matplotlib.pyplot as plt

image_directory='dataset/'

no_tumor_images=os.listdir(image_directory+ 'no/')
yes_tumor_mali_images=os.listdir(image_directory+ 'mali/')
yes_tumor_beni_images=os.listdir(image_directory+ 'beni/')


dataset=[]
label=[]

INPUT_SIZE=64



for i , image_name in enumerate(no_tumor_images):
    if(image_name.split('.')[1]=='jpg'):
        image=cv2.imread(image_directory+'no/'+image_name)
        image=Image.fromarray(image,'RGB')
        image=image.resize((INPUT_SIZE,INPUT_SIZE))
        dataset.append(np.array(image))
        label.append(0)


for i , image_name in enumerate(yes_tumor_mali_images):
    if(image_name.split('.')[1]=='jpg'):
        image=cv2.imread(image_directory+'mali/'+image_name)
```

```python
        image=Image.fromarray(image,'RGB')
        image=image.resize((INPUT_SIZE,INPUT_SIZE))
        dataset.append(np.array(image))
        label.append(1)

for i , image_name in enumerate(yes_tumor_beni_images):
    if(image_name.split('.')[1]=='jpg'):
        image=cv2.imread(image_directory+'beni/'+image_name)
        image=Image.fromarray(image, 'RGB')
        image=image.resize((INPUT_SIZE,INPUT_SIZE))
        dataset.append(np.array(image))
        label.append(2)

dataset=np.array(dataset)
label=np.array(label)


x_train, x_test, y_train, y_test=train_test_split(dataset, label, test_size=1,
random_state=0)

# print(x_train.shape)
# print(y_train.shape)

# print(x_test.shape)
# print(y_test.shape)

x_train=normalize(x_train, axis=1)
x_test=normalize(x_test, axis=1)

y_train=to_categorical(y_train , num_classes=3)
y_test=to_categorical(y_test , num_classes=3)



# Model Building
# 64,64,3

model=Sequential()

model.add(Conv2D(32, (3,3), input_shape=(INPUT_SIZE, INPUT_SIZE, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Conv2D(32, (3,3), kernel_initializer='he_uniform'))
model.add(Activation('relu'))
```

```python
model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Conv2D(64, (3,3), kernel_initializer='he_uniform'))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Flatten())
model.add(Dense(64))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(3))
model.add(Activation('softmax'))

model.compile(loss='categorical_crossentropy',optimizer='adam',
metrics=['accuracy'])


model.fit(x_train, y_train,
batch_size=16,
verbose=1, epochs=15,
validation_data=(x_test, y_test),
shuffle=False)


model.save('BrainTumor10EpochsCategorical.h5')


plt.xlabel('batch size')
plt.ylabel('accuracy')


plt.legend()
plt.show()
```

9.2 Testing Model

```python
import cv2
from keras.models import load_model
from PIL import Image
import numpy as np

model=load_model('BrainTumor10EpochsCategorical.h5')

image=cv2.imread('E:\\BrainTumor detection and Classification
DL\\pred\\pred45.jpg')
```

```python
img=Image.fromarray(image)

img=img.resize((64,64))

img=np.array(img)

input_img=np.expand_dims(img, axis=0)

result=model.predict_classes(input_img)

print(result)
```

9.3 Web Application

```python
import os
import tensorflow as tf
graph=tf.get_default_graph()
import numpy as np
from tensorflow.python.keras.preprocessing import image
import cv2
from keras.models import load_model
from flask import Flask, request, render_template
from werkzeug.utils import secure_filename


app = Flask(__name__)


model =load_model('BrainTumor10EpochsCategorical.h5')
print('Model loaded. Check http://127.0.0.1:5000/')


def get_className(classno):
    if classno==0:
        return "No brain Tumor"
    elif classno==1:
        return "Yes Brain Tumor Class-Malignant"
    elif classno==2:
        return "Yes Brain Tumor Class-Benign"




def getResult(img):
```

```python
        image=cv2.imread(img)
        image = Image.fromarray(image, 'RGB')
        image = image.resize((64, 64))
        image=np.array(image)
        input_img = np.expand_dims(image, axis=0)
        result=model.predict_classes(input_img)
        return result


@app.route('/', methods=['GET'])
def index():
    return render_template('index.html')


@app.route('/predict', methods=['GET', 'POST'])
def upload():
    if request.method == 'POST':
        f = request.files['file']

        basepath = os.path.dirname(__file__)
        file_path = os.path.join(
            basepath, 'uploads', secure_filename(f.filename))
        f.save(file_path)
        value=getResult(file_path)
        result=get_className(value)
        return result
    return None


if __name__ == '__main__':
    app.run(debug=True)
```