Multiclass Brain Tumor Detection and Improved Classification Using Convolutional Neural Network

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A thesis submitted for the degree of

BACHELOR OF SCIENCE IN COMPUTER SCIENCE AND ENGINEERING

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Gazipur, Bangladesh

June 2022

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Declaration

It is there by declared that the work presented in this thesis or any part of thesis has not been submitted elsewhere for the award of any degree or diploma.Information derived from the published and unpublished work of others has been acknowledged in the text and a list of references is given.

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Dedication

To our parents, our family members and all the teachers in our life.

Acknowledgements

In the name of Allah, the most Gracious, the most Merciful.Through our appreciation, We want to show our heartfelt gratitude to everyone who has been involved with this thesis, helped us with it, and made it a great experience for us. First and foremost, We want to express our gratitude to our supervisor, Associate Professor Md. Shafiqul Islam, Dhaka University of Engineering and Technology,Gazipur for his outstanding aid, support, and advice in the field of technology. After that, We express our cordial gratefullness to Khaleda Akhter Papry, Assistant Professor, Department of Computer Science and Engineering,for her courteous assistance and direction in completing this task. We are extended gratitude to our teachers, friends, Staff members of our department, who have their opinions and experiences through which we received the required information crucial for our thesis. We get dataset from this site(URL:https://github.com/sartajbhuvaji/brain-tumor-classification-dataset)MRI brain images.

We are grateful to our family for their patience and unconditional affection.

Abstract

Magnetic resonance imaging (MRI) is the most effective tool for diagnosing and classifying brain tumors. It provides detailed information on the anatomical structure of the brain. Various strategies for detecting malignancies from brain MRI have already been proposed. To identify any abnormalities in the brain, MRI must be analyzed by the sequence of operations like image pre-processing, separating, objects, feature extraction, detection and classifications. In this thesis, we propose a new classification algorithm for brain MRI images that can detect tumors and classify them as normal or different types of abnormalities. The feature extraction procedure was used to construct the classification method for detecting anomalies and brain malignancies using MRI pictures of the brain . An improved method is developed utilizing convolutional neural network (CNN) to separate the Tumors to increase the accuracy of detecting brain MRI abnormalities. CNN's technique consists of special neural networks that decide the weights through the training process and provide better image recognition when its neural network feature extraction becomes deeper (contains more layers). Experimental results show the improvement of our proposed method compared to the other classification method using CNN.

Contents

Declaration **i**

Dedication **ii**

Acknowledgements **iii**

Abstract **iv**

List of Figures **viii**

List of Tables **x**

List of Symbols **xii**

List of Abbreviations **xiii**

1 Introduction **1**

1.1 Introduction 1

1.2 Motivation 3

1.3 Problem Statement 4

1.4 Contribution 5

1.5 Thesis Organization 6

2 Literature Review **7**

2.1 Basic Concept of Brain Tumor 7

2.2 Basic concept of MRI 8

2.3 Image classification Model 13

2.3.1 Preprocessing 16

2.3.2 Segmentation 18

2.3.2.1 Intensity based segmentation 19

2.3.2.2 Thresholding based segmentation 20

2.3.2.3 Cluster based segmentation 20

2.3.3 Feature Extraction 21

2.3.3.1 Convolutional Neural Network 23

2.3.3.2 Discrete Wavelet Transform (DWT) 25

2.3.3.3 Principal Component Analysis (PCA): 27

2.3.3.4 Independent Component Analysis (ICA): 27

2.3.4 Classification 29

2.4 Literature Review of Classification Methods 33

2.5 Literature Review of Classification Methods for MRI 36

2.6 Discussion 39

3 CNN Based Classificaiton **40**

3.1 Introduction 40

3.2 Proposed Method 40

3.2.1 Pre-processing 41

3.2.1.1 Image Resize 42

3.2.1.2 Image filtering 42

3.2.1.3 Mean filter 43

3.2.1.4 Gaussian filter 43
3.2.1.5 Laplacian filter 44
3.2.1.6 Median filter 45
3.2.1.7 Data Augmentation 45
3.2.2 Feature Extraction & Classification 46
3.2.3 Convolutional Neural Network (CNN) 47
3.2.3.1 Convolution Layer 48
3.2.3.2 Padding 48
3.2.3.3 Rectifier Activation Function ReLU 49
3.2.3.4 Pooling Layer 50
3.2.3.5 Fully Connected Layers 50
3.2.3.6 Softmax 50
3.2.3.7 Adaptive Movement Estimation 50
3.2.3.8 Cross Entropy / Loss Function / Log Loss 51
3.2.3.9 Epochs 51
3.2.3.10 Batch Size 52
3.2.3.11 Training Accuracy 52
3.2.3.12 Validation Accuracy 52
3.3 Discussion 52

4 Experimental setup & Result Analysis 53

4.1 Experimental Setup 53
4.2 Dataset 55
4.2.1 Training data 55
4.2.2 Testing data 55
4.3 CNN Architecture 56

4.4 Accuracy Measurement 56

4.5 Experimental Result 59

4.6 Confusion Matrix & Classification Report 60

4.7 Conclusions And Future Work 61

References **62**

List of Figures

2.1 MRI Machine scans a patient 9

2.2 Normal Human Brain. 12

2.3 Different types Brain Tumors. 12

2.4 Algorithm for Classification Method [1] 16

3.1 Block Diagram of proposed Method for tumor detection and classification. 41

3.2 Original Image. 43

3.3 Mean Filter Image. 43

3.4 Gaussian Filter Image. 44

3.5 Laplacian Filter Image. 44

3.6 Median Filter Image. 45

3.7 Feature Extraction and Classification using CNN. 47

3.8 Architecture of CNN [2]. 48

3.9 softmax Function [3]. 51

4.1 sample of training dataset. 55
4.2 Sample of testing dataset. 56
4.3 sample of training dataset.. 56
4.4 Curve between Loss & Accuracy. 58
4.5 Curve between Loss & Validation Loss. 58
4.6 Curve of Loss_Accurary vs Validation Loss_Accuracy 58
4.7 Our Model predicted output. 59

List of Tables

4.1 Performance Matrix. 57

4.2 Comparision between Our model and other model 59

4.3 Confusion Matrix. 60

4.4 Classificaton report our proposed method. 60

List of Symbols

μ	mean
σ	variance
Ψ	wavelate
$\sum$	summation
∞	infinity

List of Abbreviations

CNN	Convolution Neural Network
MRI	Magnetic Resonance Imaging
CSF	Cerebrospinal fluid
KLT	Karhunen-Loeve Transform
CWT	Continuous Wavelet Transform
CT	Computed Tomography
LPT	Log-Polar Transform
GLCM	Gray level Cooccurrence Matrix
ANN	Artificial Neural Network
RBF	Radial basis functions
ICA	Independent Component Analysis
DWT	Discrete Wavelet Transform
FCM	Fuzzy C-Means
CNS	Central Nervous System
NLP	Natural Language Processing
PCA	Principal Component Analysis
KSvM	Kernel Support Vector Machine
SVM	Support Vector Machine
ROI	Region of Interest

Chapter 1

Introduction

1.1 Introduction

The technology and practice of creating visual representations of the interior of a body for clinical examination and medical intervention is known as magnetic resonance imaging (MRI). The main benefits of MRI over CT scan are that it delivers a more accurate image of the body. There are no radiation effects in the anatomical structure of tissues. As a result, It Brain imaging is widely used.

The systems for detecting brain tumors from MRI images rely on either factors of modified domain [1] or spatial values of an image [4]. Brain MRI image classification is critical for the investigation and interpretation of brain illnesses. Many strategies for developing an accurate classifier to discriminate between normal and pathological brain MRIs have been proposed [5–8]. A common method for classifying brain MRIs is feature extraction. Feature extraction entails reducing the input image's dimensionality and transforming the simpler collection of data for calculation. By assessing specific visual qualities, feature extraction eliminates unnecessary data. The collected features convert relevant visual attributes into feature vectors and help identify one pattern from another [9–12].

A brain MRI image segmentation approach is used to divide the image into relevant simplified areas with similar attributes or features. The characteristics used for segmentation are mostly determined by the feature extraction method. The most prevalent feature for tumor segmentation in brain MRIs is picture intensities. By grouping image pixels depending on intensity level, segmentation can easily distinguish diseased regions of the brain [10–12].

Our contribution of this work attempts to create a more powerful and precise classifier for distinguishing between malignant and benign brain MRIs. A novel way, an itemized por- trayal of the classifier, is also introduced with the purpose of having other researchers test and validate this strategy. To partition the brain tumor and extract features from MRI, this proposed method first used CNN as a feature extraction methodology. First and foremost, the suggested method employs the basic segmentation methodology. It then goes on to explain how to detect a brain tumor using a CNN feature extraction approach and a classification system. Following that, the method sorts the aberrant brain images into benign and malignant tumor categories.

Brain MRI picture segmentation is required for both detecting and appropriately diagnosing disorders. From our picture dataset, the segmentation procedure randomly chose two aberrant brain MRI images. The method then classifies the aberrant brain images based on their likelihood of including cancer tissues. A benign brain tumor is a non-cancerous mass of cells that grows slowly in the brain and tends to stay in one location. A benign tumor can be safely removed with the right procedure. The presence of malignant brain tumors indicates the presence of cancer. Malignancy spreads quickly and aggressively into surrounding tissues. The patient is frequently given radiotherapy or chemotherapy to kill the malignant cells in this scenario. The accuracy of detection is critical in improving symptoms. MRI images of neoplastic disorders that are rotation and scale invariant are used in the study. In MRI scans, it successfully detects both benign and malignant tumors.

In this thesis, first, we use the fundamental segmentation approach and CNN feature extraction method, as well as a classification algorithm, to detect brain tumors and categorize the tested brain into two categories: normal and abnormal, as well as benign and malignant tumors for abnormal brain. The major goal of this thesis is to use a CNN feature extraction approach and a classification system procedure for brain MRI images to detect a brain tumor and identify brain abnormalities. Our technique can successfully detect rotation and scale invariant MRI images of neoplastic disorders, which is significant.

1.2 Motivation

Automated brain tumor segmentation remains a difficult task. One of the reasons is that tumor features like size, form, and location are unknown unless the tumor's progression through time is explored and photos from prior scanning are accessible. All of the attributes listed are unknown when simply independent scanning is considered. As a result, typical pattern recognition approaches that rely on such qualities and are commonly utilized for item detection and extraction in medical and real-world photos are ineffective. Other information, like as the structure of a healthy human brain or tumor appearance in specific MR sequences, can be employed instead. On the other hand, this is a benefit over visual object detection, such as human or car detection, when the color and three backdrop scenes fluctuate. There has been a surge in interest in building such algorithms, with many computer vision research teams recently focusing on the automatic brain tumor identification challenge. Because of the wide range of brain tumor forms and their appearance in MR images, most state-of-the-art methods either focus on the most frequent tumor kinds, such as glioblastoma, or require a specialized training database to deal with a certain tumor type. Because multiple brain tumor segmentation algorithms use the same type of MR images , however, there has previously been no serious work in this sector for rotation and scale invariant images. We were inspired to write our thesis because of the above problem with existing approaches.

1.3 Problem Statement

Brain tumors are a diverse collection of central nervous system cancers that develop within or near the brain. A brain tumor has a significant impact on the body. Symptoms of the patient, surgical treatment choices, and the chances of getting a definitive diagnosis . The tumor's position in the brain also changes dramatically. The possibility of neurological toxicity that alters the patient's life quality. Brain cancers are currently detected using only after the beginning of neurological symptoms should imaging be performed. There are no early detection measures in place. Even in people who are known to be at risk for certain diseases forms of brain tumors based on their genetic makeup. Histopathological categorization as of now methods based on the tumor's anticipated cell type.

They've been in place for about a century and The World Health Organization updated them in 1999. They are satisfactory in many ways, but they do not allow for precise tumor behavior prediction in neither the individual patient nor the treatment process making decisions as precisely as patients do doctors wish for and require. Currently available imaging methods allow for precise anatomical delineation, and are the most important instruments for proving that the result of a brain injury is neurological symptoms of tumor.

There are many techniques for brain tumor detection. We have used CNN to detection and classify tumours in Brain MRI Image.

1.4 Contribution

The main contribution of this thesis is the use of a Convolutional Neural Network for feature extraction to detect and classify brain tumors in MRI images. The proposed approaches must be entirely automated, meaning they must be capable of detecting and segmenting brain tumors without requiring user interaction. The proposed procedures should be employed to treat neoplastic degenerative brain disorders first and foremost. The rotation and scale invariant MRI images, segmentation accuracy, and processing needs during the segmentation process should all be considered while developing algorithms. The thesis work can be summarized as follows:

- To improve the method of classification and feature extraction.
- To improve the image preprocessing technique.

- To use the CNN approach to extract features and classify brain MRI pictures.

1.5 Thesis Organization

There are four chapters in this thesis report. Basic Concepts of MRI, Brain MRI Imaging, Image Classification Model, Preprocessing, Segmentation, Feature Extraction, and Classification are all covered in Chapter 2. Chapter 3 focuses on our thesis's proposed technique and outlines the implementation specifics for the algorithms. Finally, Chapter 4 discusses the overall Experimental Method, the Analysis of the Results, and the Conclusion.

Chapter 2

Literature Review

Over the last decade, a variety of strategies for detecting tumors from brain MRI utilizing picture segmentation have been developed. The presented methodologies have generated an impressive concept. The main components that are demonstrated in the thesis study are highlighted in this chapter.

2.1 Basic Concept of Brain Tumor

Brain tumors are prevalent, and understanding the diagnosis and treatment by general healthcare practitioners is critical. It is primarily referred to as a heterogeneous group of malignancies that emerge from CNS cells. A brain tumor is a malignant or non-cancerous lump, or an abnormal proliferation of brain cells. Gliomas are the most common type of brain tumor, accounting for approximately 75% of all significant malignant brain tumors that develop in glial cells.The occurrence of primary brain tumors varies according to age, gender, and ethnicity. Malignant brain tumors, such as glioma, lymphoma, embryonic, and germ cell tumors, appear to be more common in men. Brain tumors, on the other hand, are more common in women, particularly meningiomas and pituitary tumors. Tumors in some functional sections of the brain can be found sooner on imaging, and they appear to be more focal in neurological symptoms than in other portions.

2.2 Basic concept of MRI

MRI may be a non-invasive imaging technique that uses no harmful radiation to form three-dimensional elaborate anatomical pictures. it's often wont to determine, diagnose, and track the progress of a sickness. It works by stimulating and detection changes within the movement axis of protons within the water that creates up biological tissues. The scan generates pictures of regions of the body that don't seem to be visible with X-rays, CT scans, or ultrasound thanks to a robust field of force and radio waves. Tumors, strokes, aneurysms, funiculus injuries, induration, and eye or sense organ abnormalities square measure among the conditions that may be diagnosed victimisation tomography. it is also ordinarily used in studies to assess brain form and performance, among alternative things. Associate in Nursing tomography scan creates a close cross-sectional image of interior organs and structures employing a powerful magnet, radio waves, and a pc. The scanner is typically formed sort of a long tube with a table within the middle into that the patient will slide. in contrast to CT scans and X-rays, Associate in Nursing tomography scan doesn't use doubtless dangerous radiation. [4].

Brain MRI Imaging: One of the active and versatile radio imaging techniques was MRI. Electromagnetic emission captures a human body's inside organ.

Figure 2.1 MRI Machine scans a patient

MRI is a non-invasive imaging technique that helps physicians detect anomalies in interior body structures such as bone and soft tissues. Unlike X-rays, the MRI imaging technique does not use hazardous radiation. When radio frequency impulses are applied to the human body, the hydrogen atoms in the body are arranged. The imaging parameters related to longitudinal relaxation time (T1) and transverse relaxation time (T2) can be changed with the aid of MRI technology to produce images with varying intensity (T2) [4]. The brain, chest, belly, and pelvis can all be imaged with MRI technology. It also aids in the diagnosis of many ailments by physicians.

MRI imaging is essential for early diagnosis of cerebral infections in the brain. The most common method for detecting white matter disease is MRI. CT imaging is unable to detect these conditions. The T1 and T2 relaxation durations are used to determine the intensity and contrast of MRI images [9]. The advantage are,MRI method has superior soft tissue imaging capabilities,MRI imaging has a high resolution,The signal-to-noise ratio is high. The downside is that MRI image acquisition takes longer than CT.

A brain tumor is a malignant or benign development of cells within the brain or skull. Tumors can form in the brain tissue itself (primary), or cancer can spread to the brain from elsewhere in the body (metastasis).Treatment methods differ depending on the type, size, and location of the tumor. Treatment goals may be curative or symptomatic relief. Many of the 120 different forms of brain tumors are treatable [9]. For many people, new medicines are extending their lives and enhancing their quality of life. The pressure inside your skull might rise when benign or malignant tumors get larger. This can result in brain damage, which can be fatal.A brain tumor occurs when the development of cells within the brain is aberrant. Cancerous (malignant) or non-cancerous brain tumors exist (benign). The tumor pictures are shown in Figure 2.2.

Normal Human Brain

The brain is the bulk of nerve tissue in an organism's front end. The brain integrates sensory information and guides muscular responses; it is also the learning center in higher animals. The human brain is made up of billions of cells called neurons and weighs about 1.4 kg (3 pounds).

Abnormal Human Brain

Any aberrant trait in brain functioning, anatomy, or metabolic levels is referred to as brain abnormalities. Genetic, parinatal compactions, developmental and traumatic problems, poisons, and diseases of the mother and/or child are just few of the etiologies of anomalies.

In medical image processing, CT and MRI imaging techniques are commonly employed. The segmentation process is carried out on MRI brain pictures in this study.

i. A computed tomography (CT) scan examines anatomical structures using an X-ray beam and a computer. It takes pictures of each slice as it slices the brain layer by layer. Your bloodstream may be infused with a dye (contrast agent). CT scans are particularly useful for examining changes in bone structures.

ii. A magnetic field and radio frequency waves are used in an MRI scan to provide a detailed image of the brain's soft tissues. It sees the brain in three dimensions, in cross-sections that can be taken from the side or from the top. Human bloodstream may be infused with a dye (contrast agent). The use of MRI to assess brain lesions and their consequences on the surrounding brain is extremely beneficial.

The borders of benign tumors are sharply defined, making surgical removal easier. Malignant tumors have an uneven boundary with finger-like extensions that penetrate normal tissue, making surgical excision more difficult.

Glioma: Glioma is a brain and spinal-cord tumor. Gliomas begin in the gluey supporting cells (glial cells) that surround and aid nerve cells operate. Glial cells can form tumors in three different ways Astrocytomas,Ependymomas,and Oligodendrogliomas . Gliomas are defined based on the type of glial cell that is involved in the tumor, as well as the tumor's genetic characteristics, which can help predict how the tumor will behave over time and the treatments that are most likely to work.

Meningioma: A primary central nervous system (CNS) tumor is a meningioma. This indicates that it starts in the brain or the spinal cord. Meningiomas are the most prevalent kind of primary brain tumor in the United States. Higher-

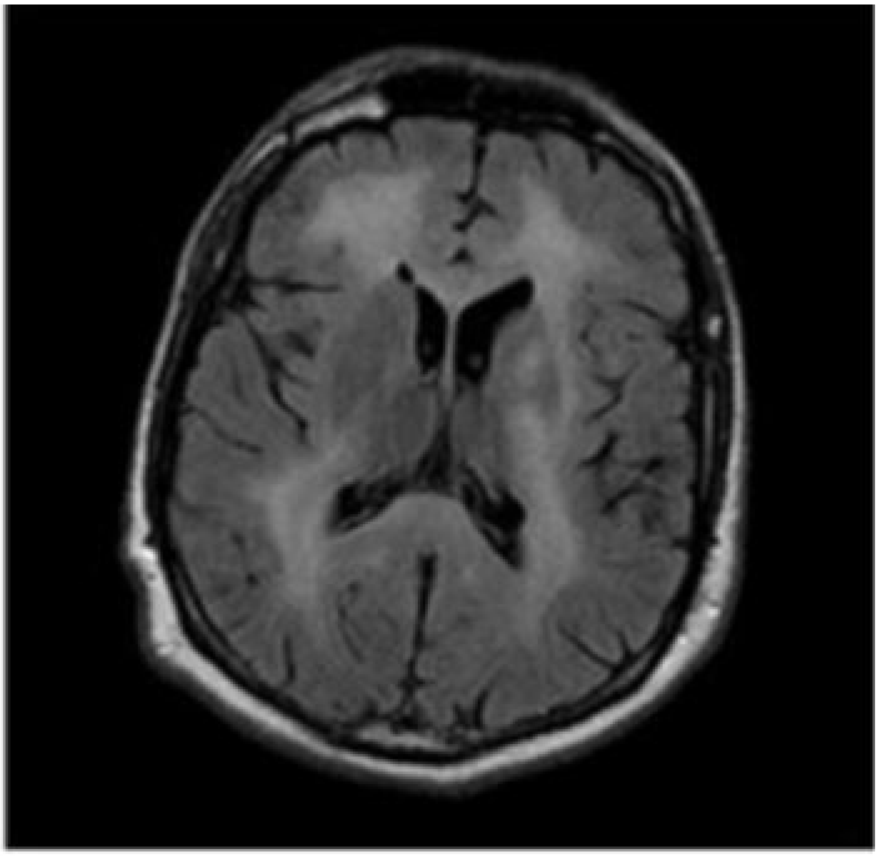


Figure 2.2 Normal Human Brain.

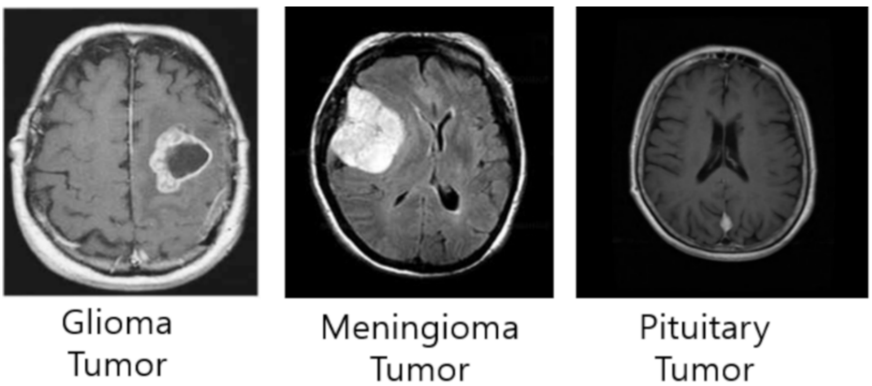


Figure 2.3 Different types Brain Tumors.

grade meningiomas, on the other hand, are extremely uncommon.In most of the cases Meningioma tumor are curable but in some froms of Meningioma are more aggresive.

Pituitary: Is a little, pea-sized gland beneath the hypothalamus at the base of your brain. The sella turcica, a little chamber beneath your brain, is where it resides. It's a portion of human endocrine system that produces numerous important hormones. Most of the Pituitary types tumor are non cancerous.

2.3 Image classification Model

Brain MRI categorization is critical for distinguishing between malignant and non-cancerous tumor states. The goal of image classification is to find a unique gray level (or color) for the characteristics in a picture that signify the distinction between objects or types of images. The spectral pattern existing within the data for each pixel is employed as the numerical foundation for categorisation.

Picture classification divides data into groups using numerical aspects of image features. Classification algorithms are built utilizing two processing phases: training and testing. Characteristic qualities of typical picture features are identified during the first training phase, and a unique description of each classification category, i.e. training class, is constructed based on them. These feature-space partitions are then employed to categorize picture characteristics during the testing phase.

The classification procedure depends heavily on the description of training classes. To extract class descriptors in supervised classification, statistical procedures (i.e., based on an a priori knowledge of probability distribution functions) or distribution-free processes can be utilized. Clustering methods are used in unsupervised classification to automatically split the training data into prototype classes.

Convolutional Neural Network

A Convolution Neural Network also known as CNN is a deep learning architecture that has a little functionality difference when compared to a neural network. Mainly, it used in problems related to classification, recognition and processing to images or similar data. It also understands Natural Language Processing (NLP) and speech recognition. But most commonly it is used for image classification i.e., identification of details in an image, like finding a feature like eyes in an image of a person. A CNN is basically a method of applying a filter to the input data using convolutions.In simple words, if you want to recognize if the person is smiling or not in an image then you input several images of various people smiling, laughing, crying etc. and then using convolutions layers put filters to those images and retrieve information and train your model to create a system that will detect a smiling person if a person's photo is inputted to it. It can be built from scratch or we can use a pre-built CNN architecture that are tested and trained.

Many of the researchers proposed an image classification approach for detecting brain MRI anomalies. Y. Zhang, L. Wu, and others [1]. Principal component analysis (PCA) and kernel support vector machine were used to suggest a classification approach (KSVM) and Convolutional neural network classification model. There are four essential steps to this procedure.

These steps are consequently as follows:

i) Preparation (including feature extraction and feature reduction)

ii) Train the Kernel SVM and

iii) Submit new MRI brains for output to the learned kernel SVM

iv) Lastly CNN model is classify the output cancerus or non cancerus.

Feature extraction is done with two-dimensional discrete wavelet transformations, and feature reduction is done via principal component analysis.By introducing a feature extraction and feature selection based classification technique for MRI brain tumor detection, [5] The image quality and visual attractiveness are improved through pre-processing procedures. For the training and testing phases, important features from MRI images are extracted. The primary goal of an MRI image identification system is to find similarities between training and testing MRI image samples. The Spatial Gray Level Dependence Matrix (SGLDM) is a numerical system based on the construction of a Co-occurrence matrix to reflect the spatial spread of demanded gray intensities in the ROI. This method emphasized feature extraction, feature reduction, and feature selection for classification. The feature extraction is done with the PCA and SGLDM algorithms, and the optimum features are chosen with the genetic method and the joint entropy.

We discovered four fundamental steps for a classification model by studying important offered methods. The following are the basic steps in creating a categorization model:

i. Preprocessing

ii. Feature Extraction

iii.Detection and

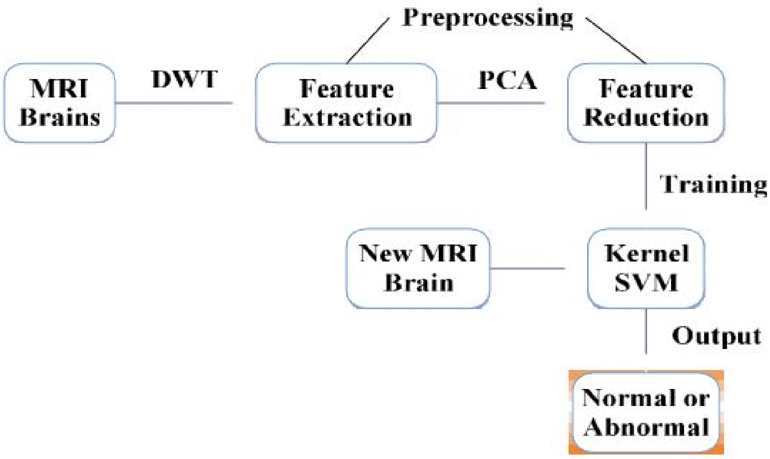


Figure 2.4 Algorithm for Classification Method [1]

iv.Classification

2.3.1 Preprocessing

Pre-processing is the most important and grueling task in computer- backed segmentation. Before applying any algorithm on the image it's necessary to perform thepre-processing for every image. Because the same towel types having in different scale of intensities. This noise degrades the delicacy of discovery ofabnormalities.Pre- processing is especially important in excrescence discovery since it ensures that the segmentation system works duly. As a result, image quality should be increased before to segmentation. It's vital to retain prints while reducing noise and vestiges without demeaning the original image. Resizing a picture is an important element ofpre-processing since it increases or decreases the total number of pixels, and remapping an image can be done by correcting or rotating it. Traditional image resizing followed by scaling andcropping.Warping, confluence figure, object figure, and multi driver are all part of the content apprehensive resizing system. A homogeneous chart between pixels of the original image and pixels of the target image defines the scaling. The interpolation of original image pixels is the most popular scalingmethod.From the original image, the cropping procedure excerpts a blockish window of the applicable size. As an affair resizing result, the standard cropping system simply crops a cropping cube from the image's center cite lin2014survey Under the constraints of topological relations and the global environment, the primary thing of image resizing is to save the most charming regions and applicable information, reduce visual deformation, achieve real- time resizing, and fulfill stoner preferences. Another significant tool for imagepre-processing is filtering. Filtering is a fashion for enhancing or changing an image to emphasize certain rudiments while removing others. Smoothing, stropping, and edge improvement are all exemplifications of imagefiltering.Convolution is the process of applying pollutants to a picture and is divided into two orders

i). Spatial sphere and ii). frequence sphere.

For noise junking and edge recognition from MRI images, common spatial sphere pollutants include the mean sludge, median sludge, Gaussian sludge, Laplacian sludge, grade sludge, and Mid-point sludge [13]. frequence sphere image filtering is a system of image improvement that differs from spatial sphere improvement and is used to ameliorate images for certain operations. For image improvement, frequence sphere pollutants similar as low pass, high pass, Fast Fourier metamorphosis, Ideal sludge, Butterworth sludge, and Gaussian sludge areused.Frequency sphere filtering is achieved by changing the Fourier transfigure of the picture of interest to produce frequence sphere filtering, and also recovering the spatial sphere image by taking the inverse Fourier transfigure of the filtered image [14]. The image quality and aesthetic appearance are bettered by preprocessing procedures. Preprocessing is critical when using MRI images for excrescence discovery and bracket since it improves the delicacy of the results. Preprocessing chores are associated with image processing, and noise junking can be fulfilled using pollutants. By altering the picture trait, image improvement improves image creation. Image noise was dropped using filtering ways, still numerous algorithms generated vestiges that hampered segmentation. Another important aspect of preprocessing is intensity normalization, which is used in the classification approach generated from segmentation [9].

2.3.2 Segmentation

The process of segmenting a picture into small parts based on qualities such as gray level, color, texture, brightness, and contrast is known as segmentation. The following are the goals of segmentation in medical pictures [15].

i) To Estimate ROI (Region of Interest).

ii) To investigate the anatomical structure of body parts.

iii) To calculate the size of the tumor.

iv) It also assists the radiologist in planning the amount of radiation prior to the radiation therapy.

The performance of various automatic tumor segmentation methods based on a variety of parameters, including [11]:

i) Partial volume effect.

ii) Intensity of homogeneity.

iii) Existence of artifact.

iv) Different soft tissue.

In the presence of non-sharp edges in a picture, removing artifacts using correct filtering will increase tumor segmentation performance in terms of accuracy, time, and number of iterations. A suitable restoration procedure can be used to remove the motion artifacts [16]. The gray level and texture-based methods are now the most often utilized segmentation algorithms.

We will discuss various segmentation techniques that are routinely used to detect and classify tumors from brain MRI data.

i) Intensity based segmentation.

ii) Threshold based segmentation.

iii) Cluster based segmentation.

iv) Histogram based segmentation

v) Region based segmentation.

vi) Edge based segmentation.

From Edge based segmentation, three edges are notably identified:

i) Horizontal edges.

ii) Vertical edges.

iii) Diagonal edges.

It's interesting to see that one solution does not work for every image [11]. Every approach is appropriate for particular types of photos. The texture features, for example, convey spatial information about an image.

2.3.2.1 Intensity based segmentation

The simplest basic segmentation approach, which classifies pixels/voxels based on intensity levels. The intensity-based strategy to identifying brain tissues such as white matter, gray matter, and cerebral spinal fluid is used in MRI brain tumor segmentation. The intensity of scalp tissue is the same as that of brain tissue. Because the intensity profiles of brain structures sometimes overlap, this method will not provide the whole intensity profile of a brain image. The overlapping of pixel intensities causes tissue types to be miss-classified.

2.3.2.2 Thresholding based segmentation

One of the most prevalent ways to image segmentation is thresholding. This method is particularly effective when dealing with photos of varying brightness. The image is separated into different parts depending on the intensity levels using this method [16].

2.3.2.3 Cluster based segmentation

Clustering is one of the most practical MRI segmentation algorithms, as it separates pixels into classes without prior knowledge or training. It assigns pixels to the same class with the highest likelihood. For the process of appropriate clustering, pixel characteristics with qualities of each class are used.

Here we discuss some familiar clustering procedure.

i) **K-Means Clustering:** The K-means clustering technique is the most basic unsupervised learning approach for clustering. The technique for classifying a batch of data into a specified number of clusters is extremely straightforward. K-means defines 'K' centers, one for each cluster. These groups must be separated by a large distance. The following step is to associate a point from a given data collection with the nearest center. The first stage is accomplished and early grouping is done when no points are outstanding. The second step is to recalculate 'k' new centroids as the bary centers of the clusters created in the first phase. After creating 'K' new centroids, a new binding between the identical data set points and the nearest new center must be created. There has been created a loop. As a result of this loop, the k centers gradually shift their location until they no longer move [17].

The K-means method is quick, reliable, and simple to grasp. It also produces better results when data sets are neatly segregated. However, k-means will not be able to distinguish between two clusters if the data is significantly overlapping.

ii) **Fuzzy C-Means (FCM) clustering:** FCM clustering is an unsupervised data analysis method. On the basis of the distance between the cluster center and the data point, this algorithm gives membership to each data point corresponding to each cluster center. The data point closest to the cluster center has a higher membership to that center. In general, the sum of each data point's membership should equal one [18].

The FCM algorithm produces the best results for overlapped data sets and outperforms the k-means technique. The data point can belong to multiple cluster centers in this case.

2.3.3 Feature Extraction

A large amount of knowledge is needed to portray a brain imaging, that takes up plenty of memory and time. The options of a picture square measure extracted to scale back the quantity of knowledge, memory, and time needed. The image's essential info is incorporated into the retrieved options. It may be fed into a classifier for classification and segmentation of brain pictures [16]. Within the space of nineteen interest (ROI) for brain imaging, the options take issue between traditional and pathological. The intensity of the growth website is usually on top of that of the encompassing traditional tissue. Contrast, entropy, homogeneity, and different textural characteristics are varied. Once these characteristics square measure won't to determine the growth from different traditional tissues, it's useful info [19]. The power to observe tumors from brain imaging pictures is powerfully passionate about feature extraction. 3 sorts of parameters square measure claimed to be extracted, taking under consideration the loss of data and correct feature extraction.These are:

i) the form feature parameters (area, disk shape, irregularity, and so on),

ii) The intensity feature parameters (mean, variance, variance, and so on), and

iii) the texture feature parameters (contrast, correlation, entropy etc.) [8] Image similarity, homogeneity, brightness, darkness, and heterogeneousness square measure all measured exploitation intensity-based parameters, that square measure closely connected with the deviations of brain imaging pictures. The feel feature divides the grey matter, substantiaalba, spinal fluid, and growth regions during a resonance image of the brain. Texture could be a feature of a picture that gives higher-order characterization and includes information on the abstraction distribution of tonal variations or grey tones. The homogeneity or similitude between elements of a picture is outlined by texture extraction [16]. Excessive options extend computation times and memory needs. What is more, they'll usually create classification tougher, that is understood because the spatiality curse. A reduction within the variety of options is needed. the simplest set for feature choice contains the fewest dimensions that contribute to high accuracy whereas discarding the opposite, unimportant dimensions. Essential feature extractions from imaging pictures square measure ready for the coaching and testing phases. The goal of the imaging image identification system is to seek out similarities between the coaching and testing imaging image samples [5]. Following the outline higher than, the mixture of feature extraction, feature reduction, and have choice for growth detection and classification from brain imaging pictures is sort of important.

2.3.3.1 Convolutional Neural Network

A convolutional neural network (CNN) could be asort of artificial neural network that's specifically supposed to method component input and is employed in image recognition and process.

CNNs square measure image process, computer science (AI) systems that use deep learning to try to to each generative and descriptive tasks, often times exploitation machine vision that has image and video recognition, recommender systems, and tongue process (NLP).

A neural network could be a hardware and/or software package sculptured when the mannerneurons within the human brain work. ancient neural networks are not designed for image process and should be fed pictures in smaller chunks. CNN's "neurons" square measure structured a lot of like those within the lobe, the realm in humans and different animals chargeable for process visual inputs. ancient neural networks' piecemeal image process problem is avoided by transcription the layers of neurons in such some way that they span the full field of vision.

A CNN employs a technology like a multilayer perceptron that's optimized for low process needs. AN input layer, AN output layer, and a hidden layer with many convolutional layers, pooling layers, totally connected layers, and normalizing layers structure a CNN's layers. The removal of constraints and enhancements in image process potency end in a system that's considerably more practical and easier to coach for image process and tongue process.

Supremacy of convolutional neural networks: The fundamental ascendence of CNN over its predecessors is that it discovers essential traits while not the requirement for human intervention. Given an oversized variety of photos of imaging pictures, it will learn characteristic options for every category on its own. Additionally, CNN is computationally economical.

Image classification: For image categorization, convolutional neural networks square measure oftentimes utilised. CNN will acknowledge distinct things on photos by recognizing valuable traits. This property makes them valuable in medical, like in imaging diagnoses. CNN may be utilised in agriculture also. pictures from satellites like as LSAT square measure received by the networks, which may then be wont to classify fields looking on their level of cultivation. As a result, this info may be utilised to form forecasts relating to the fertility of the grounds or to plan a method for creating the foremost use of farmland. one in allthe primary applications of CNN for laptop vision was the popularity of written digits.

Object detection: CNN is usually won't to acknowledge and mark things in self-driving cars, AI-powered police investigation systems, and good homes. CNN willacknowledge things in pictures and classify and name them in real time. This can be however a self-driving automobile navigates around differentvehicles and folks, and good homes acknowledgethe owner's face amid all the others

2.3.3.2 Discrete Wavelet Transform (DWT)

Wavelet transformation could be a helpful methodology for extracting options. DWT could be a riffle rework technique that uses a separate assortment of riffle scales and translation supported a specific precedent. The riffle rework converts a proof into a collection of wavelets that square measure reciprocally orthogonal, as opposition the continual riffle rework (CWT). DWT constant is employed in sure in style existing systems to extract the riffle constant from brain adult male pictures. The DWT-generated localized frequency info is adjusted and scaled from precise wavelets. The basic riffle formation is obtainable as follows:

if x(t) is a square integrating function, the continuous wavelet transformation of x(t) corresponding to a given wavelet ψ(t) is constructed as

$$W_{\psi}(a,b) = \int_{-\infty}^{\infty} x(t)\psi_{a,b}(t)dt \tag{2.1}$$

Then,

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi(\frac{t-a}{b}) \tag{2.2}$$

In the equation (2.6), 'a' is the dilation factor and 'b' the translation parameter (both real positive numbers).

The wavelet ψ_a, b(t) is determined from the original wavelet ψ (t) by translation and dilation.Equation (2.6) can be discretized by constraining 'a' and 'b' to a discrete lattice (a $= 2^b$ *and* $a > 0$) *to deliver the DWT, which can be presented*

$as\ follows:$

$$ca_{j,k}(n) = DS[\sum_{n} x(n) g_j^*(n - 2^j k] \tag{2.3}$$

$$cd_{j,k}(n) = DS[\sum_{n} x(n) h_j^*(n - 2^j k] \tag{2.4}$$

In most cases, DWT is used to compose a single level of a 2D image. At each scale, this calculation yields four sub-band pictures (LL, LH, HL, HH). The LL sub-band is used for the following 2D DWT as an approximation element of the image, whereas

The LH, HL, and HH sub-bands are the image's detailed features. Then, utilizing picture framework with a simple hierarchical structure Wavelet is a tool for interpreting images.

The wavelet transform divides the signal into low- and high-frequency components using filters, and then divides the low-frequency component into low- and high-frequency components once more.

Decomposition is the term for this process. Because the most important information is available on the low frequency component, this decomposition is conducted on that component. Consider the human voice: when the high frequency component is removed, it is still audible.However, when low frequency components are removed, the voice becomes inaudible. The two co-efficients formed during the decomposition process are known as the approximation and detail co-efficients. The approximation co-efficient reflects the signal's high-scale, low-frequency component, whereas the detailed co-efficient represents the signal's low-scale, high-frequency component.

2.3.3.3 Principal Component Analysis (PCA):

Principal Component Analysis (PCA) is a useful approach for extracting key features from brain MRI images, and it was employed in this thesis. The greatest eigenvalues of the covariance matrix of the original feature set correspond to the principal components, which are the projections of the original features onto the eigenvectors. The mean squared error is minimized using principle components, which provide a linear representation of the original data with the fewest amount of components [9]. It converts a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables termed principle components via an orthogonal transformation. PCA is a technique for reducing redundant characteristics from data that has a high dimensionality. PCA is also known as the Hotelling Transform, the discrete Karhunen-Loeve Transform(KLT), or Proper Orthogonal Decomposition (POD).

2.3.3.4 Independent Component Analysis (ICA):

Researchers have been interested in Independent Component Analysis, a computationally efficient blind statistical signal processing technique, for many practical applications in diverse disciplines of science and engineering. Independent Component Analysis is used to minimize the feature vector dimensions (ICA). ICA is an important unsupervised method for extracting independent characteristics from large-scale data. The primary goal of ICA is to extract independent data from an observation that is linearly dependent on another data. ICA detects data correlation and de-correlates the data by decreasing or enhancing the contrast information. It's been used in a variety of signal and picture applications. PCA decreased second-order statistics by treating image elements as random variables with a Gaussian distribution. Largest variances clearly do not correlate to PCA basis vectors for any non-Gaussian distribution. ICA seeks to determine the basis along which the data are statistically independent by minimizing both second-order and higher-order dependencies in the input data [20]. The data model for independent component analysis is estimated by minimizing or maximizing a function that is an indicator of independence in some way. A comparison function, cost function, or objective function is a common name for such a function. The estimation of the independent components is made possible by optimizing the contrast function. The ICA approach combines an optimization algorithm and the selection of an objective function. The statistical properties of the ICA technique, such as consistency, asymptotic variance, and robustness, are determined by the objective function chosen, while algorithmic properties, such as convergence speed, memory requirements, and numerical stability, are determined by the optimization algorithm. The contrast function in some way or the other is a measure of independence [21]. The basic foundation of independent component analysis is statistical independence (ICA). When there are two random variables, x and y, x is independent of the value of y if knowing the value of y provides no information about the value of x. Statistical independence is defined theoretically in terms of probability densities as x and y are independent random variables [21]. if and only if-

$$P_{x,y}(x, y) = P_x(x)P_y(y).....10 \tag{2.5}$$

Where,

The joint density of x and y is $P_{x,y}(x, y)$,

while the marginal probability densities of x and y are $P_x(x)$ *and* $P_y(y)$.

Marginal probability density function of x is defined as-

$$P_x(X) = \int P_{x,y}(x, y)dx......11 \tag{2.6}$$

In the same way as previous approaches, ICA has some drawbacks. To begin with, the sources' variances powers cannot be determined because multiplying a column of the matrix A by any scalar can always be cancelled by dividing the appropriate column by the same scalar α.

Another issue emerges as a result of permutation, which is an inherent property of matrix processing. As a result, determining the source sequence is impossible. Finally, it should be noted that ICA only works with sources that have a non-Gaussian distribution. Only one source with a Gaussian distribution is permitted [22].

2.3.4 Classification

The system for classifying input patterns into original classes is known as classification. Although there are colorful types of classification algorithms for detecting brain excrescences, the discovery rate is still not sufficient. Furthermore, accurate image partitioning into meaningful sections is critical to the success or failure of image categorization [16]. Selection of a suitable classifier requires consideration of numerous factors :

i) Classificaiton accuracy

ii) Algorithm performance

iii) Computational resouces

There are two introductory classification systems. Unsupervised classification and supervised classification are two types of classification. The discovery of natural groups, or structures, within multi-spectral data is known as unsupervised classification [23]. The ensuing characteristics apply to an unsupervised classification i) No expansive previous knowledge of the region is needed
ii) numerous of the detailed opinions needed for supervised classification aren't needed for unsupervised classification creating loweroccasion for the driver to make crimes
iii) Unsupervised classification allows unique classes to be honored as distinct units
Whereas supervised classification, on the other hand, is the process of classifying unknown identity samples using samples of known identity. The ensuing characteristics apply to a supervised classification i) Requires detailed knowledge of the area
ii) Input patterns are handed with the markers
iii) suitable to descry serious crimes by examining training data to determine whether they've been rightly classified
Independent element analysis(ICA) is seen as an extension of top element analysis(PCA) for the categorization of brain MRI images since it performs better on data that has preliminarily been preprocessed using PCA [20]. PCA uses second- order statistics to gather data, whereas ICA uses high- order statistics. PCA identifies the most representative protuberance vectors, icing that projected

samples save the most information about the original brain MRI data [15]. ICA takes second and advanced- order statistics and systems the input data onto as statistically independent base vectors as possible. As a result, the ICA result is allowed to be more applicable than the PCA result, and PCA is the primary system for point birth and reduction in brain MRI image processing [20]. The viscosity vector, on the other hand, is radially symmetric and meetly gauged before being paled(sphere), but this isn't always the case, because decolorizing is basically de-correlation followed by scaling, for which the PCA fashion can be used in the preprocessing step of a brain MRI image. Because the order of independent factors in ICA can not be known, the correlation between a physical signal and the prognosticated independent element for categorization of brain MRI images isn't one- to- one. This indeterminacy is especially problematic in numerous situations where relating the estimated factors is critical, and it makes permutation nebulosity a problem [21]. When the energy of the independent factors can not be linked, ICA shows scaling nebulosity, which is gauged in source estimate [21]. Thus PCA system is best suited for classification of brain excrescence from scale steady MRI image. Beside other limitations ICA doesn't reflect time detainments that do in the signal [22].

Support Vector Machine (SVM):

The Support Vector Machine (SVM) is a supervised classifier based on statistical theory that uses a correlated learning algorithm. It started out as a development of the generalized portrait algorithm. It is based on the statistical learning theory notion of structural risk reduction. The SVM seeks to reduce the bound on the generalization error rather than minimizing an objective function based on the training samples (such as mean square error) (i.e., the error made by the learning machine on the test data not used during training).As a result, when applied to data outside of the training set, an SVM tends to perform well. SVM gets this advantage by concentrating on the most difficult-to-classify training instances [15]. Support vectors are these "borderline" training examples.

The hyper plane is used in the SVM classifier to maximize the separation margin between the two classes. The basic SVM takes a set of input data and forecasts and determines which of two potential classes forms the output for each given input, resulting in a non-probabilistic binary linear classifier. SVMs may accurately classify data in addition to working linearly, use the kernel method to do a non-linear classification, essentially mapping their inputs into high-resolution feature spaces Its kernel is designed to optimize the margin between classes. Controlling the empirical risk and classification [24]. Kernel functions include linear, polynomial of degree, and radial basis functions, among others (RBF). A radial basis function outperforms the other kernel functions for MRI brain pictures. Training and testing are the two stages of SVM. SVM learns from features that are fed into its learning process. SVM selects the correct margins between two classes during training. The association with a certain class is used to label features. The complexity and computation required to solve the problem are axiomatically reduced using this approach. This method is said to be superior to rule-based systems, however it has a poor level of accuracy.

2.4 Literature Review of Classification Methods

The categorizing of photographs into one of a number of specified categories is referred to as image classification. Picture sensors, image pre-processing, object identification, object segmentation, feature extraction, and object classification are all part of the classification process. For picture categorization, a variety of techniques have been developed. We will discuss some image processing classification algorithms in this section. LDA is a well-known classification system for face recognition, picture retrieval, microarray data classification, and other applications. The data is projected onto a lower-dimensional vector space in a way that maximizes the ratio of between-class distances to within-class distances, resulting in maximum discrimination. Using the Eigen decomposition on the scatter matrices, the best projection (transformation) can be quickly determined. LDA and related terms Fisher's Linear Discriminant are statistical and pattern recognition approaches.

Using machine learning to identify a linear combination of information that distinguishes or distinguishes two or more classes of objects or occurrences. The resulting combination can be used as a linear classifier or, more often, to reduce dimensionality before classification [25].

A decision tree classifier is a decision tree that is built based on cases and is used in data mining, machine learning, and computer vision. A decision tree is a classification algorithm that is expressed as a recursive division of the instance space. The decision tree is made up of nodes that create a rooted tree, which is a directed tree with no incoming edges and a root node. Each of the other nodes has one incoming edge. Each internal node in a decision tree divides the instance

space into two or more sub-spaces based on a discrete function of the input attribute values. The selection of an attribute to test at each decision node in the tree is the estimation criterion in the decision tree method. The purpose is to find the most useful property for classifying samples. Information gain, a statistical feature that quantifies how well a particular attribute differentiates training instances according to their intended classification, is a reasonable quantitative indicator of an attribute's worth [26].
One of the most basic machine learning methods is the k-nearest neighbors algorithm. An object is classed by a majority vote of its neighbors, with the object being allocated to the class with the most members among its k closest neighbors, where k is a positive integer, usually small.If $k = 1$, the object is simply assigned to the nearest neighbor's class. It is preferable to use an odd integer for k in binary (two class) classification tasks to avoid deadlocked votes. The same method can be used for regression by simply assigning the object's property value to the average of its k nearest neighbors' values. It's possible to weight neighbor contributions so that closer neighbors contribute more to the average than farther away neighbors [27].

Nearest neighbor classifiers, unlike decision tree induction and back propagation, give each attribute identical weight. When there are a lot of unnecessary attributes in the data, this can be confusing.Nearest neighbor classifiers can also be used to predict, or return a real-valued prediction for an unknown sample. In this example, the classifier returns the average of the real values associated with the unknown sample's k nearest neighbors.The training samples have n-dimensional numeric properties that describe them. Each sample represents an n-dimensional point.All of the training samples are stored in an n-dimensional pattern space in this fashion.A k-nearest neighbor classifier searches the pattern space for the k training samples that are closest to the unknown sample when given an unknown sample. "Closeness" is defined in terms of Euclidean distance, which is the distance between two points measured in Euclidean space [26].

An artificial neural network (ANN), sometimes known as a "neural network" (NN), is a mathematical or computational model based on biological neural networks, or, to put it another way, a simulation of a biological brain system.It is made up of a network of artificial neurons that processes data using a connectionist approach to computation.During the learning phase, an ANN is typically an adaptable system that changes its structure based on external or internal information that flows through the network [26].

A Bayesian Network (BN) is a graphical model for predicting probabilities between a set of variables. The Bayesian network structure S is a directed acyclic graph (DAG), and its nodes correspond to the features X one-to-one.The arcs represent incidental interactions between features, whereas the lack of arcs in S denotes conditional independencies.The effort of learning a Bayesian network is typically separated into two parts: first, learning the network's DAG structure, and then determining its parameters. Probabilistic parameters are encoded as local conditional distributions of a variable given its parents in a collection of tables, one for each variable.The joint distribution can be recreated by simply multiplying these tables given the independences recorded in the network. There are two scenarios in the general framework of inducing Bayesian networks: Structures that are known and unknown [27].

2.5 Literature Review of Classification Methods for MRI

In this section we explain some classification method which is commonly used in brain MRI classification. SVM-based classification and PCA-oriented feature extraction for brain tumors in MRI images [4]. Preprocessing, feature extraction, feature reduction, training, database storage, and testing are all processes in this procedure. MRI images are first fed into the classifiers for training, then the features of new MRI images are sent in, and the trained classifiers classify it efficiently based on the training. however, there was a lack of consistency in the extraction of features and the separation of carcinogenic and non-cancerous tumors. With high dimensional characteristics and contradicting data, it outperforms other classification methods. The biggest downside of this technology is the high computing cost, which requires a lot of CPU and physical memory. By introducing a feature extraction and feature selection based classification technique for MRI brain tumor detection [5]. The image quality and visual attractiveness are improved through pre-processing procedures. For training and testing, feature extractions of the required features from MRI images are prepared. The main goal of an MRI image identification system is to find similarities between training and testing MRI image samples. SGLDM will be a numerical system based on constructing a Cooccurrence matrix to reflect the spatial spread of demanded gray intensities in a given region (ROI). This work focuses on feature extraction, detection, and classification of extracted features, as well as selecting acceptable features for classification [28]. Wavelet transformation is used to minimize the dimension of retrieved features. The K-fold stratified cross-validation approach was used to improve the generalization of KSVM. Proposed a hybrid support vector machine (SVM) classifier based on linear and multi SVM [29]. Gray level cooccurrence matrix (GLCM) and discrete wavelet transform (DWT) were employed for feature extraction, followed by PCA, and k-means segmentation was utilized to detect brain tumors in this method. The Linear-SVM kernel classifier was utilized to divide the input MRIs into normal and aberrant brain pictures with a tumor, which the multi-SVM then recognized. If a tumor is discovered in an image, Multi-SVM is utilized to determine the tumor type. Glioblastoma, sarcoma, and metastatic bronchogenic carcinoma are three types of malignant tumors that it can classify. However, only malignant types of brain tumors (glioblastoma, sarcoma, and metastatic bronchogenic carcinoma) may be distinguished using this method. The idea of a multiple kernel learning support vector machine (MKL-SVM) for EEG signal classification was proposed by [30]. Authors in [31] developed a brain tumor MRI image segmentation and detection approach based on k-means clustering. For segmentation and tumor detection from brain MRI images, the K-means clustering algorithm and morphological filtering are applied. The use of hyper spectral pictures and parallel K-Means clustering for brain cancer detection was proposed by [32]. K-Means segmentation as an unsupervised learning approach [17]. In this method, the distance between each pixel and the K-cluster center is determined using a simple Euclidean function. In an iterative process, our approach focuses on decreasing the variation between each pixel and the cluster center.The use of principal component analysis and K-means clustering along with super pixels to distinguish tumor and non-tumor from PET scan pictures was first introduced in [33]. DWT and Fuzzy C-Means based segmentation of brain MRI data [18]. One approach is used for level set segmentation using fuzzy c means with special features (SFCM), and another is used for brain

MRI image segmentation using DWT and principal component analysis (PCA), which is then classified using support vector machine (SVM).Mean square error, peak signal to noise ratio (PSNR), maximum difference, absolute mean error, and other metrics are used to assess performance. DWT use k-means clustering, whereas level set employs fuzzy c-means clustering. PCA is then used in conjunction with SVM to classify just T-2 weighted brain MRI images [15]. The feature extraction from the horizontal (LH) and vertical (HL) subbands of the 2D-DWT using GLCM and an SVM-polynomial classifier was proposed to classify the image as normal or abnormal.In this system, a four-level decomposition was generated using the Daubechies (db1) wavelet, with features retrieved from the LH and HL subbands. Filtering provides the signal a time-scale representation. The classifiers divide the image into normal and abnormal categories and use fuzzy clustering to find the tumor's location. The tumor's area is calculated.

The company offered a dual-tree complex wavelet transform and twin support vector machine-based automatic classification system for brain images in magnetic resonance imaging (MRI) [34]. A hybrid approach for classification method was introduced in [24] malignancy detection using brain MRI images For feature extraction and decreasing the amount of features, this hybrid technique uses DWT and Genetic algorithm, followed by SVM for brain tumor classification.However, this method only extracts the value of five feature parameters, which is insufficient for sensitive categorization such as brain tumors. Authors in [35] KSVM was used to develop a classification strategy for brain tumor MRIs. Image segmentation was integrated with Otsu binarization and K-means clustering in this method, with DWT for feature extraction and PCA for feature reduction. This model can detect brain tumors in MRI, however it is unable to determine the tumor's condition (cancerous or non-cancerous). An enhancement to the above techniques that allows them to work with rotation and scale invariant features in the field of brain MRI pictures was first introduced in [36]. The Log-Polar Transform (LPT) was used in their method to remove the rotation and scale change effects and produce row shifted log-polar pictures, which were then subjected to an adaptive row shift-invariant wavelet transform to remove the row shift effects. This approach works with normal photos, however it fails miserably with infected images.

2.6 Discussion

Despite the fact that many works on tumor detection and classification from MRI images based on Convolution neural Network have been established, no important work has been done that can cover a wide range of brain tumor classification.On different types of brain tumor classificaiton, the suggested approach works well.The definformation of original images are the key issues for rotation and scale invariant images. In order to better understand this topic, this thesis uses CNN classification model as well as different types of preprocessing method.Wavelet-based transformation (WBT) confirms the accuracy of feature extraction from brain MRI images, and the supervised classification (KSVM) model supports suitable classification for cancerus or non cancerus and classify the type of brain tumor which type of cancer are belongs to like as, no tumor, glioma,menlngloma and pituitary etc.

Chapter 3

CNN Based Classificaiton

3.1 Introduction

The use of MRI to detect a brain tumor is critical in saving lives. Due to their lack of competence in the field of tumor identification, doctors may miss the abnormality. From a brain MRI image, a well-defined technique and algorithm are required for tumor detection and categorization based on cancerous and non-cancerous states of tumor. This thesis proposes an improved classification strategy for detecting anomalies in brain MRI.

3.2 Proposed Method

The suggested brain tumor detection and improved classification using CNN approach includes of pre-processing, feature extraction, and classification procedure for the aim of detection classifying tumors as different types glioma, meningioma, pituitary, etc from brain MRI.Pre-processing is the initial step in the image anal-

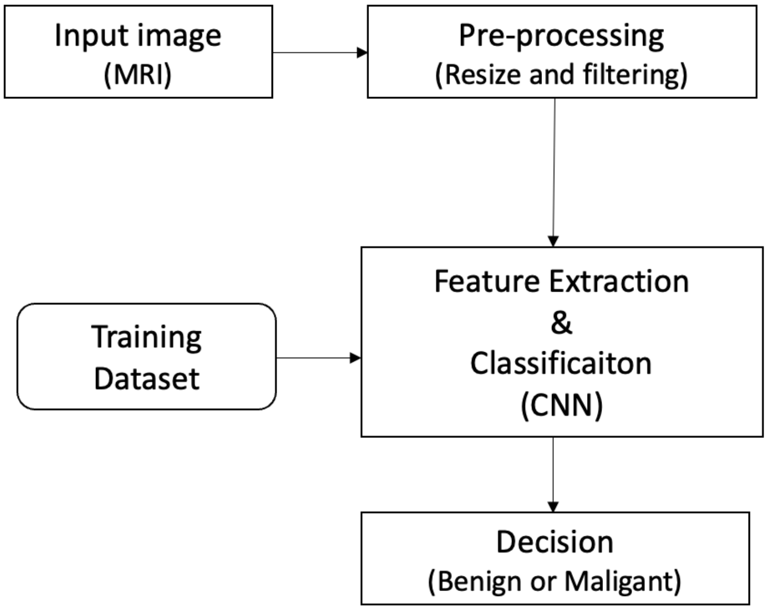


Figure 3.1 Block Diagram of proposed Method for tumor detection and classification.

ysis process, and it involves smoothing, sharpening, and decreasing input noise; The feature extraction approach collects features from brain tumors and the final phase in the image analysis approach is classification, which includes organizing feature data in an image into distinct classes.Once the interesting objects are isolated from the input,certain features are made,and these are used to classify the objects into particular classes. The working procedure of the proposed method shown in the figure 1.

3.2.1 Pre-processing

The first step in improving the quality of an image before processing it into an application is to employ an image pre-processing technique. The purpose of image pre-processing is to increase a model's accuracy, as well as reduce its complexity.

3.2.1.1 Image Resize

When you enlarge or distort an image from one pixel grid to another, you're using image interpolation. When you need to increase or decrease the total amount of pixels in an image, you'll need to resize it, whereas you'll need to remap it if you're correcting for lens distortion or rotating it. Without taking anything off, resizing allows you to make your image smaller or larger. Resizing an image changes its dimensions, which has an impact on file size and image quality. The most typical reason for resizing images is to make large files smaller so they may be emailed or shared online.

3.2.1.2 Image filtering

Image filtering is one of the most extensively used methods for removing noise from digital images. The image filtering tool is one of the most significant among all the tools present in image processing software. Image filtering is used in a variety of applications [37]. One of the most widely utilized approaches is to improve the quality of photos. Image quality is critical for human eyesight, and in image processing, images contain noise that is difficult to remove, lowering the image quality. That is why we employ picture filtering techniques. The mean filter is one of the most regularly used methods.

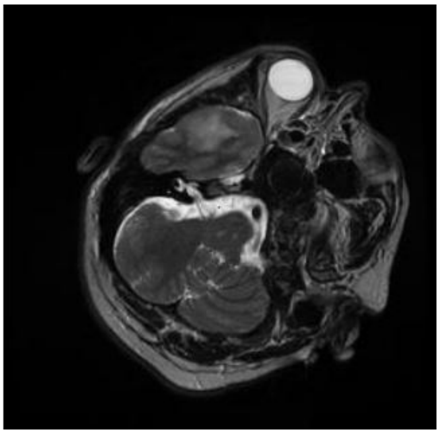
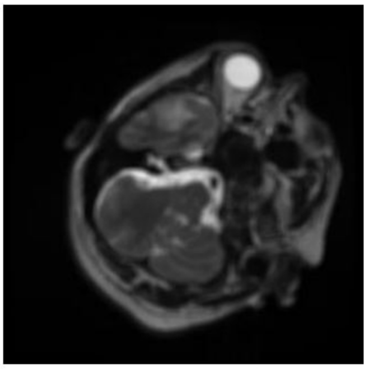


Figure 3.2 Original Image.



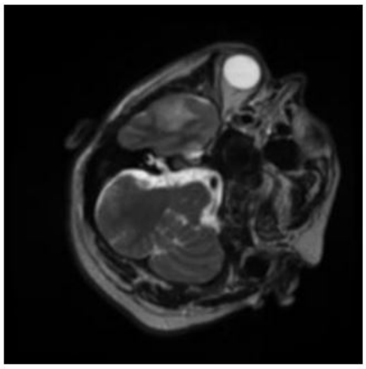


Figure 3.3 Mean Filter Image.

3.2.1.3 Mean filter

This filter is a linear filter that reduces the density variation across pixels. It is intrinsic and simple to use. The mean filter works by replacing each pixel's value on an image with an average value for both its neighbors and itself [12].

3.2.1.4 Gaussian filter

For many years, this filter has been widely used in image processing. This filter is known for being more organized than others in terms of keeping features and

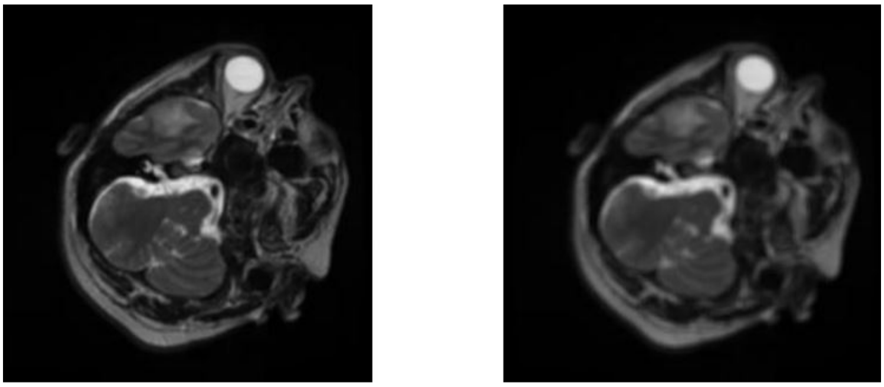


Figure 3.4 Gaussian Filter Image.

Figure 3.5 Laplacian Filter Image.

narrow borders. The Gaussian filter is ineffective at removing spontaneous (salt and pepper) noise, which necessitates the use of statistical method filters [38].

3.2.1.5 Laplacian filter

This filter is intended to be a replacement for existing edge-aware filters. It has been shown to produce high-quality outcomes in adjusting details map toning for a wide range of parameters when used. Despite this, the filter's performance is slow [39].

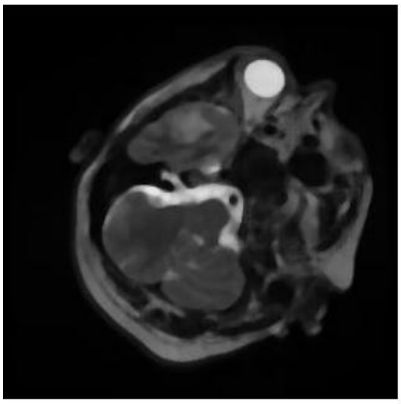


Figure 3.6 Median Filter Image.

3.2.1.6 Median filter

Nonlinear dynamic systems contain this filter as a component. It is not possible to apply median filters to a linear dynamic system that combines stability, impulse response, and the notion of superposition frequency analysis. This filter is rated based on its ability to modify the types of signals it affects.

3.2.1.7 Data Augmentation

When the dataset is small, data augmentation is a prominent technique in the field of CNN. This is used to increase the size of the training set and reduce overfitting [40]. Many academics now employ numerous augmentation strategies in data augmentation, such as introducing noise, rotation, flipping, and image improvement. Nonetheless, when some of these approaches are used, the pixel intensity of the original photos is altered. A non-intrusive preprocessing strategy is used to retain the real value of the image pixels and the associated ground truth values without modifying them. "Rotation at 900 (0,90,180,270) of the original image; Rotation at 900 (0,90,180,270) of the left-right flipped image.

3.2.2 Feature Extraction & Classification

The feature extraction approach collects features from brain tumors that have been segmented,For feature extraction, the CNN approach is chosen since it is currently the go to model for any image related problem.The main advantage of CNN compared to its predecessors is that it automatically detect the important features without any human supervision.It can also share parameters, allowing the CNN model to run on any device.Furthermore, this strategy takes less data for faster training and searches for features at their most fundamental level. It is made up of many completely connected layers that follow a series of specific convolutions with pooling operations.The basic architecture of feature extraction and classificaiton can be best describe by the figure2.
CNN technique accepts an

$$input\ image\ of\ size\ height \times width \times dimesion$$

Where the dimension determines whether the picture is RGB or grayscale, it should be processed according to particular categories. To identify an item with probabilistic values between 0 and 1, the CNN model's image input layer transfers the input data for training and testing through a sequence of convolution layers with filtering details, pooling, fully connected layers, and softmax function. The convolution layer extracts the features of an input image, using the convolution approach learning image features to preserve the relationship between pixels. Greater features can be discovered by increasing the number of filters in the convlolution layer, but this comes at the cost of more training time. The pooling layer reduces the number of parameters by subsampling operations

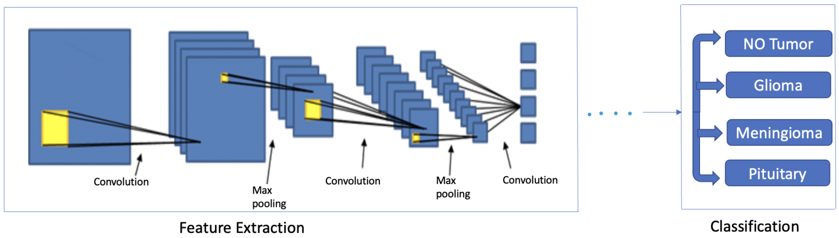


Figure 3.7 Feature Extraction and Classification using CNN.

retaining important information. The fully connected layers that is similar to a neural network converted the feature map matrix into a vector. The feature vectors are combined to form a model that is used to classify as the target object using softmax operations.

3.2.3 Convolutional Neural Network (CNN)

Convolutional neural networks are composed of neurons as well as weights and biases.These neurons receive input from the preceding layer. It is then followed by a calculation of a dor product in the middle of the input and weights, which is then voluntarily followed by a non-linearity [3]. The CNN architecture is mathematical in nature, consisting of a cluster of feed forward layers that include convolutional layers that include more than one convolutional layer with activation function ReLU and a pooling layer [12]. It is then followed by a fully connected layer [3].

The Convolution and pooling layers which are the first two layers carry out extraction of feature from the input image and the feature that has been extracted are mapped to final output and this is done by converting the 2D feature maps into the ID vector in classifying images through complete connected layer [12].

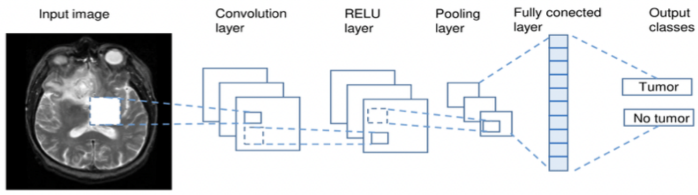


Figure 3.8 Architecture of CNN [2].

3.2.3.1 Convolution Layer

The convolution layer is the foundation of a CNN [41]. The elements of the input image are carefully connected to the next convolutional layer because attaching the next layer to all of the pixel image input would be mathematically complicated [3]. The feature from the input image of the pixels is kept in a 2D array using an optimizable extractor called convolving the kernel. The output feature map's depth is set to 3x3 or 5x5 times the kernel size. [12].

3.2.3.2 Padding

This is the merging of a zero layer outside of the input size so that the data about the borders isn't lost and the output percentage matches the input size. This equation is used to calculate the output size.

$$W_2 * H_2 * D_2$$

Where:

$$(W_2 = (W_1 - F + 2P)/S + 1)$$

$$(H_2 = (H_1 – F + 2P)/S + 1)$$

$$(D2 = K)$$

“[W1 * H1 * D1 is the size of the input image, F represents receptive field size, P for amount of padding and K is depth” [3].

3.2.3.3 Rectifier Activation Function ReLU

The feature map was given the ReLU (Non-linear activation function) treatment after sending the input volume through the convolution layer to offer the system non-linearity. The equation for ReLU [3]:

$$(f(X) = max(0, X))$$

The ReLU is preferred over other activation functions such as sigmoid and tanh because it is the most widely used and does not have a problem with speeding up training while maintaining a constant 0 that limits gradient flow and hence weight adaption. The use of a leaky rectifier linear unit (LReLU), which provides a little slope on the negative side of the function, overcomes this restriction. This is defined as [40] :

$$(\backslash f(X) = max(0, X) + min(0, X)\text{”})$$

3.2.3.4 Pooling Layer

After the convolution layer, this layer minimizes the feature map dimensions of the input image, as well as the computational overhead for the following layer and the capacity to regulate fitting. [12]. Max pooling, average pooling and mean pooling are the different types of pooling [3].

3.2.3.5 Fully Connected Layers

This layer's conversion of the feature maps' pooling layer into an ID vector is linked to one or more thick layers that map the networks' ultimate output [12].

This layer creates classified pictures as a result of the training dataset, therefore the end result will either be tumor images or normal brain images, which will be displayed [3].

3.2.3.6 Softmax

For multi-class classifications, the Softmax function is employed in many machine learning applications [3].

3.2.3.7 Adaptive Movement Estimation

This is used for deep neural network training; its goal is to calculate the single learning rate of distinct variables. The learning rate starts at 0.001 [3].

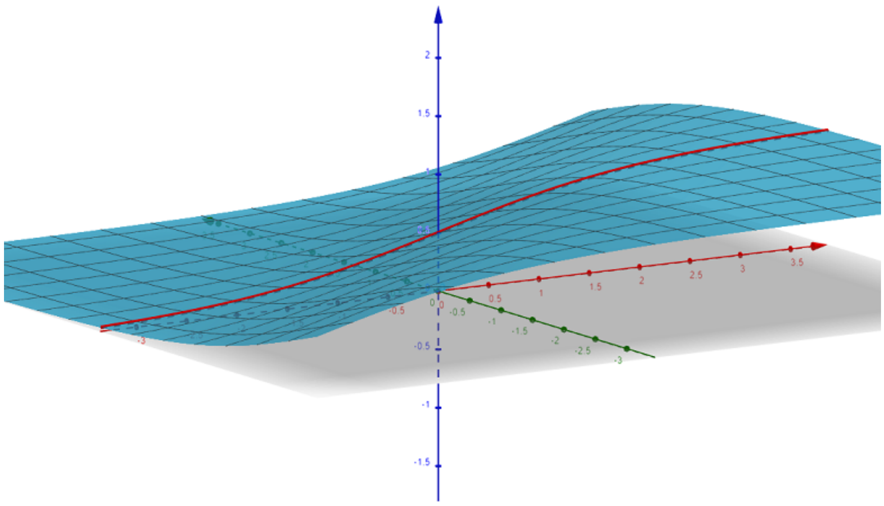


Figure 3.9 softmax Function [3].

3.2.3.8 Cross Entropy / Loss Function / Log Loss

During training, it is a function to be reduced [40]; it also calculates the performance of a model to be classified with an output value range between 0 and 1 [3].

3.2.3.9 Epochs

When a neural network propagates the complete dataset forward and backwards, this is referred to as forward and backward propagation. If it moves once, it is considered one epoch. [3].

3.2.3.10 Batch Size

"The full dataset for training is used for one iteration; if the dataset is large, a batch size of 25 or 32 with an epoch of roughly 100 is sufficient." [3].

3.2.3.11 Training Accuracy

The accuracy obtained when a model is applied to a training dataset. This is referred to as training accuracy [3].

3.2.3.12 Validation Accuracy

When the dataset is trained and then tested against the test dataset, it produces a validation accuracy [42].

3.3 Discussion

This thesis proposed an innovative method to detect and to classify three different tumors in MRIs of brain namely glioma,meningioma,puitary and also classify the image which is not affected to the tumor. This approach is effective in both feature extraction and classification. First, we use certain preprocessing techniques such as image resizing, followed by a gaussian filter, and finally an augmentation technique. Outstanding approach such as CNN can be used to extract features and classify tumor MRI images efficiently. The reasoning of the classifier is thoroughly taught by the given dataset, hence this method produces excellent accuracy. If the proposed method could be used for all types of MRI pictures, the performance of the method might be improved for diagnosis.

Chapter 4

Experimental setup & Result Analysis

In this Chapter analyze our proposed method with Brain Tumor with brain tumor classificaiton dataset. At first we disscuss about our experimental setup, dataset and then shown the different types of resultant values eg.performance matrix, accuracy, confusion matrix etc.

4.1 Experimental Setup

For our thesis purpose we use our own PC for implement the model.
System Configeration:
Processor: Apple silicon M1 8 core CPU & 8 core GPU clock rate:3.2GHZ
Installed memory (RAM): 8.00 GB
System type: 64-bit Operating System

During our thesis work,we mainly use ...

- Google Colab platform.
- Keras.
- Numpy
- Pandas.
- Matplotlib.
- open CV
- scikit learn and others neccessary library and method.

Finally we work on 2870 images from our dataset, where 2583 samples are used for train and 287 samples are used for validation.
We define the hyper parameters such as batch size, number of epochs for training, and number of samples to train.

- Batch_size = 20.
- Epochs =50.
- Learning rate = 0.001.
- Softmax activation function.

4.2 Dataset

This Dataset consist different types images from MRI. There are 3264 image data in our dataset. This dataset divided into two part one part is training data and another consists testing data.Each part of training and testing dataset are contains four types images 'No tumor','Glioma','Meningioma', and 'Pituitary'.

4.2.1 Training data

We used 2870 four types of brain tumor images as training data which are glioma, meningioma, pituitary, no tumor. The sample of training images data are showing below:

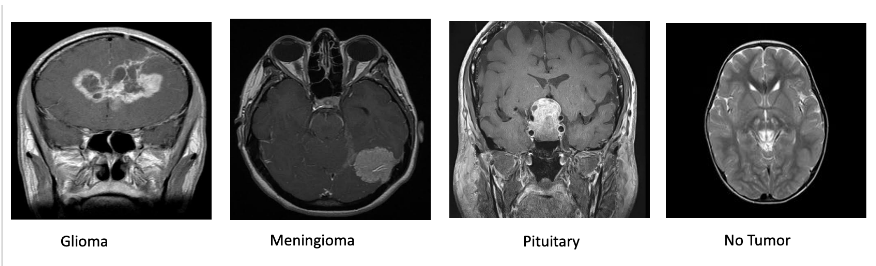


Figure 4.1 sample of training dataset.

4.2.2 Testing data

We used 394 four types of brain tumor images as testing data which are glioma, meningioma, pituitary, no tumor. The sample of testing images data are showing below:

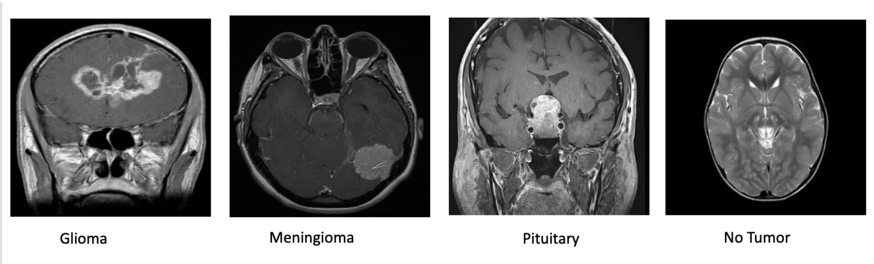


Figure 4.2 Sample of testing dataset.

4.3 CNN Architecture

Our proposed CNN Architecture is showing below:

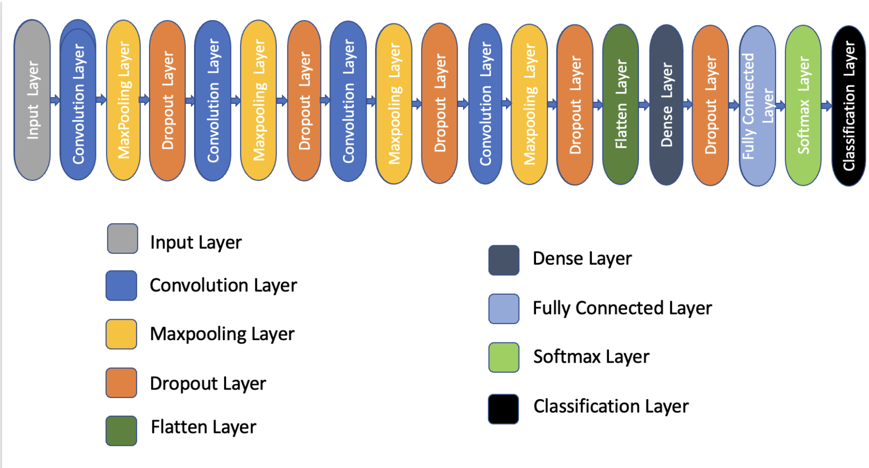


Figure 4.3 sample of training dataset..

4.4 Accuracy Measurement

The lower the loss, the more accurate the model (unless the model has over-fitted to the training data). The loss is calculated during training and validation, and its interperation represents how well the model performs for these two sets. Loss, unlike accuracy, is not a percentage. It is the sum of the errors made in training and validation sets for each sample. The loss value indicates how well or poorly a certain model performs after each optimization cycle. Ideally, loss should be reduced after each, or few, iterations.

The accuracy of a model is typically measured after the model parameters have been learned and fixed and no further learning has occurred. The test samples are then fed into the model, and the number of errors (zero-one loss) made by the model are recorded following comparison to the genuine targets. The percentage of missclassification is then computed. Validation loss is proportional to accuracy, which means that lower validation loss always leads to higher accuracy.

Epochs	Loss	Accuracy	Val_loss	Val_acc
1	1.1820	0.5148	0.9179	0.6318
2	0.7988	0.6761	0.7552	0.6822
3	0.667	0.7299	0.6692	0.7171
4	0.5649	0.7755	0.6035	0.7907
5	0.4746	0.8176	0.5589	0.8178
6	0.3839	0.8624	0.4831	0.8372
7	0.3140	0.8817	0.9566	0.8101
8	0.2750	0.9028	0.4732	0.8372
9	0.2632	0.9161	0.4082	0.8643
10	0.2304	0.9200	0.5070	0.8450
11	0.1924	0.9312	0.3747	0.8915
12	0.1642	0.9428	0.4407	0.8837
13	0.1724	0.9467	0.7557	0.8876
14	0.1737	0.9488	0.6372	0.8682

Table 4.1 Performance Matrix.

We have shown different types of accuracy in the curves given above. Figure 4.4 shows the curve between the loss and accuracy with respect to the epoch. The figure 4.5 show the curve between the loss and validation loss with respect to the epoch. And the figure show the curve of loss,validation loss,accuracy and the validation loss.

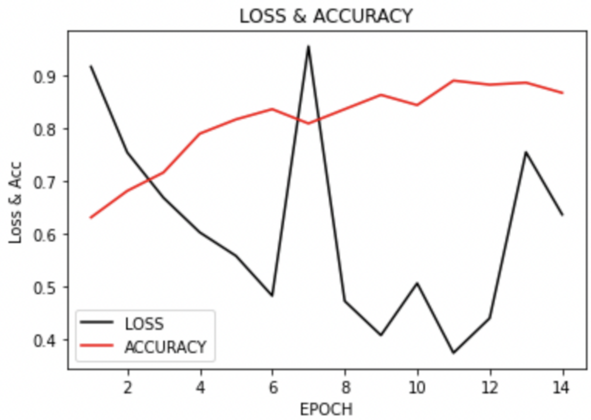


Figure 4.4 Curve between Loss & Accuracy.

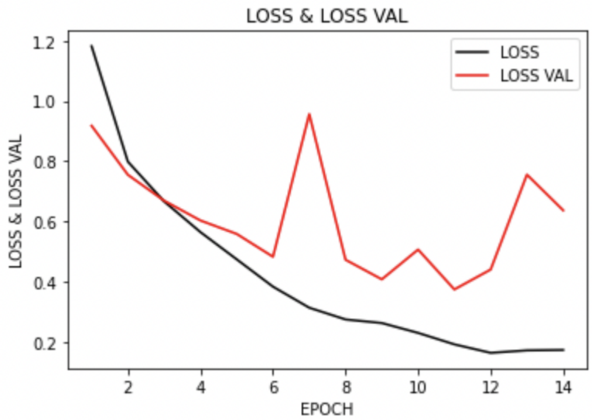


Figure 4.5 Curve between Loss & Validation Loss.

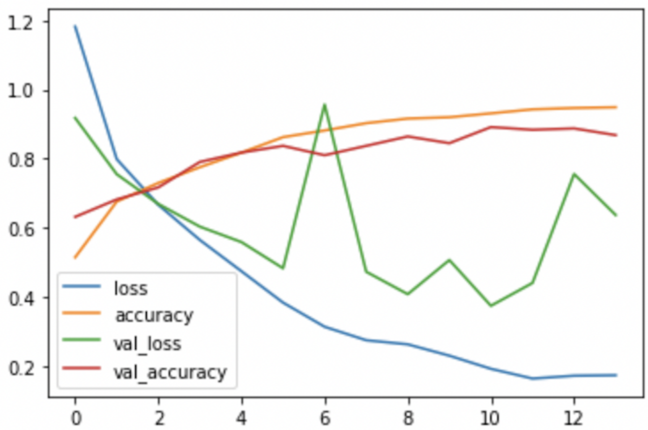


Figure 4.6 Curve of Loss_Accurary vs Validation Loss_Accuracy

4.5 Experimental Result

These are all about our proposed model predicted result. Our proposed method gives the 91% training accuracy whrere the loss accuracy is only 30%.

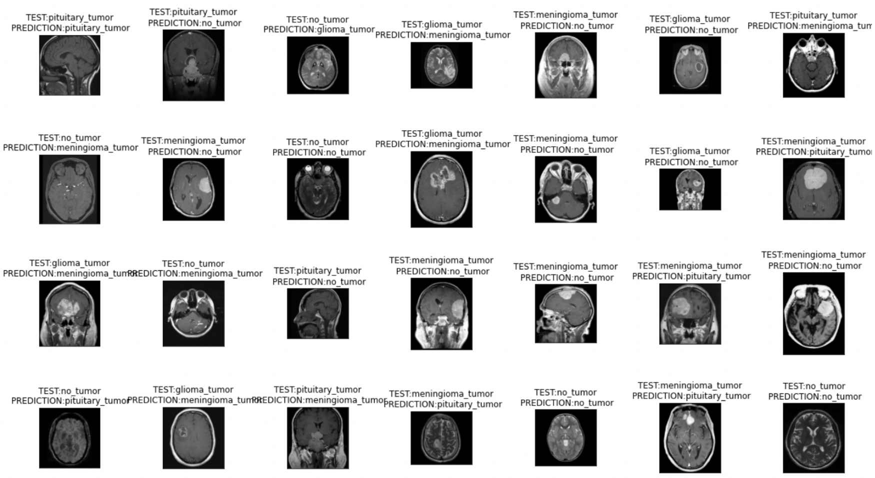


Figure 4.7 Our Model predicted output.

Accuracy of Other Existing Method:

Author's	Method	Accuracy
K'Salcin [43]	Faster R-CNN	91.66%
Sachdeva [44]	PCA ANN	85.23%
Our model	CNN	91.86%

Table 4.2 Comparision between Our model and other model .

4.6 Confusion Matrix & Classification Report

A n x n confusion matrix connected with a classifier illustrates the anticipated and actual classification, where n is the number of possible classes.It's a table that shows how well a classification model performs on a set of test data for which the true values are known. It makes it possible to see how an algorithm performs.The confusion matrix of our proposed method is shown table 4.3:

		Actual			
		Meningioma	Glioma	Pituitary	No-tumor
Predicted	Meningioma	90	10	1	5
	Glioma	4	85	0	3
	Pituitary	12	5	70	2
	No-tumor	10	0	4	96

Table 4.3 Confusion Matrix.

In this table 4.4 below, we shown the classifcaiton report . The extensive experimental result have demonstrated that the use of CNN with the proposed method results in a flexible and effective framework for Tumor detection and classification task. The proposed method classifies the Tumor appropiately that was validated by using the accuracy,precision and recall value.

	Accuracy	Precision	Recall	f1-score	support
Meningioma	0.908	0.77	0.84	0.80	116
Glioma	0.91	0.84	0.92	0.87	101
Pituitary	0.91	0.93	0.78	0.84	106
No tumor	0.91	0.90	0.87	0.88	75

Table 4.4 Classificaton report our proposed method.

4.7 Conclusions And Future Work

A feature extraction approach was created in this thesis work for detecting and classifying tumors from brain MRI images, and it was verified through a series of experimental evaluations utilizing a collection of brain MRI datasets. The results of the experiments demonstrated that our classification system can successfully distinguish between normal and abnormal brain MRI pictures. Finally, aberrant brain MRI pictures are used to classify distinct types of cancerous and non-cancerous tumors. It can identify and classify four forms of brain tumors, including glioma, meningioma, pituitary tumor, and no tumor. Guassian filtering method provides noiseless images and the CNN method extract the feature form brain MRI images. The softmax function categorize the different types of tumor. Our experiment's Accuracy measurement is perfected by applying modified Convolutional Neural Network (CNN) procedures. Our method is resilient and efficient due to the combined performance of feature extraction and classification by using a large dataset.

In the future, we work in brain blood flow related disease like vertebral stenosis and intracranial stenosis,vascular malformation etc. Our further analysis concentrate on combined method that is gabor wavelet transformation and convolutional neural network(CNN) which is called Gabor Convolutional Neural Network(GCNN). Our future focus will be on using Gabor Convolution Neural Network (GCNN) to classify a wider range of brain diseases, as well as reducing time consumption and raising success rates.

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