**BRAIN TUMOR IDENTIFICATION USING**

**IMAGE PROCESSING TECHNIQUES**

A thesis presented in partial fulfilment of the

requirements for the degree of

Bachelor of Science Honors

in

Information Technology and Management

at IT Unit 2, Faculty of Science, University of Colombo

Sri Lanka.

M.H.D. Maduraarachchi

2016/2017

**Declaration**

**Abstract**

A brain tumor is a mass or proliferation of uncontrollable abnormal cells in the brain tissues. It is one of the most harmful and hazardous causes of cancer death in both men and women worldwide. Tumors do not all turn into malignancies; nevertheless, some do. MRI or CT scan images are used by doctors to manually identify brain malignancies. As a result, analysis reports differ depending on the doctors' expertise, experience, and perspective. For these reasons, standardizing and automating the operation would be a superior option. This paper proposes a methodology that can identify brain tumors automatically using image processing techniques. The proposed solution consists of three basic steps. The first phase is the preprocessing stage, which will improve the image's quality by eliminating noise and increasing the contrast. Next, we propose creating a neural network that can detect brain tumors and determine whether a patient has one. We also have a parallel approach, a model that uses a set of image processing techniques to detect the tumor location. The proposed methodology will be described in depth in this study.

**Acknowledgement**

**Table of Contents**

[Chapter 01 – Introduction 8](#_Toc99202254)

[1.1 Introduction 8](#_Toc99202255)

[1.2 Problem in Brief 9](#_Toc99202256)

[1.3 Significance 10](#_Toc99202257)

[1.4 Scope and Objectives 11](#_Toc99202258)

[Chapter 02 – Literature Review 12](#_Toc99202259)

[2.1 Introduction 12](#_Toc99202260)

[2.2 Brain Tumor Detection using Image Processing Techniques 12](#_Toc99202261)

[2.2.1 Pre-processing 13](#_Toc99202262)

[2.3 Deep Learning Techniques 15](#_Toc99202263)

[2.4 Image Processing Techniques 18](#_Toc99202264)

[Chapter 03 – Adopted Technologies 21](#_Toc99202265)

[3.1 Introduction 21](#_Toc99202266)

[3.2 Programming Languages 21](#_Toc99202267)

[3.3 Libraries 21](#_Toc99202268)

[3.3.1 OpenCV 21](#_Toc99202269)

[3.3.2 Keras 22](#_Toc99202270)

[3.3.3 Tensorflow 22](#_Toc99202271)

[3.3.3 Scikit-learn 22](#_Toc99202272)

[3.3.4. Matplotlib 22](#_Toc99202273)

[Chapter 04 – Methodology 22](#_Toc99202274)

[4.1 Introduction 23](#_Toc99202275)

[4.2 Architecture of overall system 23](#_Toc99202276)

[4.2.1 Pre-processing 23](#_Toc99202277)

[4.2.2 CNN Segmentation Model 25](#_Toc99202278)

[4.2.3 Image Processing Model 27](#_Toc99202279)

[Chapter 05 – Implementation 31](#_Toc99202280)

[5.1 Introduction 31](#_Toc99202281)

[5.2 Preprocessing 31](#_Toc99202282)

[5.2.1. Artifact Removal 31](#_Toc99202283)

[5.3 CNN Model 33](#_Toc99202284)

[5.3.1 Data Augmentation 33](#_Toc99202285)

[5.3.2 Data Preparation 35](#_Toc99202286)

[5.3.3 Split Dataset 37](#_Toc99202287)

[5.3.4 Model Building 37](#_Toc99202288)

[5.3.5 Model Training 38](#_Toc99202289)

[5.3.6 Checking the Model Results 38](#_Toc99202290)

[5.4 Image Processing 39](#_Toc99202291)

[5.4.1 Bilateral Filtering 39](#_Toc99202292)

[5.4.2 Enhancement 39](#_Toc99202293)

[5.4.3 Thresholding 40](#_Toc99202294)

[5.4.4 Morphological operations 40](#_Toc99202295)

[5.4.5 Contour Identification 42](#_Toc99202296)

[Chapter 06 – Results and Discussion 43](#_Toc99202297)

[6.1 CNN Model 43](#_Toc99202298)

[References 44](#_Toc99202299)

**List of Figures**

[Figure 1: Curved edges on wave let vs curve let 14](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202397)

[Figure 2: Image with artifacts 14](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202398)

[Figure 3: Different view of Brain MRI 16](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202399)

[Figure 4: Proposed method by Ali Ari and Davut Hanbay 17](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202400)

[Figure 5: CNN architecture of the model by Malathi and Sinthia 18](#_Toc99202401)

[Figure 6: The proposed system by Vipin Y. Borole et al 19](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202402)

[Figure 7: Proposed system by Sravanthi et al 19](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202403)

[Figure 8: Proposed system by P.D.Yadav and Y.M.Patil 20](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202404)

[Figure 9: Output of the system by P.D.Yadav and Y.M.Patil 21](#_Toc99202405)

[Figure 10: Process of the System 23](#_Toc99202406)

[Figure 11: Pre-processing Architecture 24](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202407)

[Figure 12: Acquired Image 24](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202408)

[Figure 13: Architecture of CNN model 25](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202409)

[Figure 14: Structure of a Convolutional Neural Network 25](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202410)

[Figure 15: Image Processing Model 27](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202411)

[Figure 16: MRI and the relevant Image histogram 29](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202412)

[Figure 17: Visual representation of an input image and Dilated image 30](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202413)

[Figure 18: Python code 01 31](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202414)

[Figure 19: Python code 02 32](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202415)

[Figure 20: Different thresholding options 33](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202416)

[Figure 21: Importing libraries 34](#_Toc99202417)

[Figure 22: Data augmentation function 34](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202418)

[Figure 23: Determine the number of augment images 35](#_Toc99202419)

[Figure 24: Cropping of MRI 35](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202420)

[Figure 25: Brain MRI after cropping process 36](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202421)

[Figure 26: Loading Data 36](#_Toc99202422)

[Figure 27: Splitting Dataset 37](#_Toc99202423)

[Figure 28: Model Summary 37](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202424)

[Figure 29: Fitting the model 38](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202425)

[Figure 30: Predictions 38](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202426)

[Figure 31: Code snippet to apply bilateral filtering 39](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202427)

[Figure 32: After applying bilateral filtering 39](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202428)

[Figure 33: Applying pixel transformation 39](#_Toc99202429)

[Figure 34: After the enhancement 40](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202430)

[Figure 35: Code snippet for thresholding 40](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202431)

[Figure 36: After applying thresholding 40](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202432)

[Figure 37: Applying erosion 41](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202433)

[Figure 38: Applying dilation 41](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202434)

[Figure 39: Contour Identification and Final output 42](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202435)

[Figure 40: Confusion Matrix of model 43](file:///D:\Acedemics-UOC\Level%204\Research\Thesis_s14089.docx#_Toc99202436)

# Chapter 01 – Introduction

## Introduction

A brain tumor is a lump or growth formed by uncontrollable aberrant cells in the brain tissues. It is one of the most harmful and hazardous causes of cancer death in both men and women all over the world. Tumors do not all turn into malignancies; nevertheless, some do. Tumors are divided into two categories. Such as malignant and benign tumors. Cancerous tumors are malignant tumors, and non-cancerous tumors are benign tumors [1]. As a result, they are accurately identifying a tumor as malignant is critical for patients' subsequent treatments.

Headache, seizures, vision problems, vomiting, mental changes, and difficulty walking, speak in sensation are some symptoms in brain tumors [2]. Inherited genetic disorders from parents are the most common cause of brain tumors, albeit they may not always be genetically inherited. As a result, clinicians cannot accurately forecast physical behaviors that may lead to the development of a brain tumor—for example, drinking alcohol, smoking, and so on. There are numerous advanced medical tests available to detect brain tumors, and these tests should be used as the first step when a patient presents with an irregular headache to determine if it is a brain tumor or not.

There are three main steps within this proposed solution. The first step is the preprocessing stage which will enhance the quality of the image by reducing noise and increasing the contrast level of the image. Next, a neural network is developed to identify brain tumor and output whether the patient has a tumor or not. And an image processing-based approach to identify the tumor region.

Since obtaining medical-related sensitive data from government hospitals is strict, pre-collected medical datasets can be obtained from Kaggle (www.kaggle.com).

## 1.2 Problem in Brief

Brain tumor occurrence is increasing rapidly all over the world. The American Cancer Society estimates for brain and spinal cord tumors in the United States for 2021 include adults and children. About 24,530 malignant tumors of the brain or spinal cord (13,840 in males and 10,690 in females) will be diagnosed. These numbers would be much higher if benign (non-cancer) tumors were also included. About 18,600 people (10,500 males and 8,100 females) will die from brain and spinal cord tumors [3]. The leading cause of brain tumor misdiagnosis is observer error on MRI and CT (Computed Tomography) scan images. The observer error causes decision-making errors, scan and recognition errors, and a decrease in search satisfaction. Pre-processing is required before making conclusions based on an MRI scan image because it aids in magnifying inaccuracies caused by changes in the position of the relevant tumor. Manual processing of CT scan and MRI scan images takes a long time, and because the eyes are less sensitive, it leads to cancers being missed in scanned images.

## Significance

When a brain tumor grows, other organs near it may become pushed, causing most of the symptoms, and the tumor may also expand to other neighboring organs in the brain. As a result, detecting a brain tumor at an early stage is more beneficial to the patient without causing additional health complications. The major benefit is prevention of expose to drugs with bad side effects and massive surgeries.

With the advancement of technology, CNNs and image processing techniques may now be utilized to detect brain tumors using MR images, which is a significant benefit. Furthermore, with less human engagement, these types of brain tumor detection devices reliably detect the tumor. As a result, it will assist in the reduction of errors caused by the human analytical process. On the other hand, because it uses a common standard approach to evaluate digital photos, this proposed solution produces an unbiased analysis result. As a result, the goal is to offer a systematic approach that uses new methodologies to improve brain tumor diagnosis in the future, with the goal of reducing brain tumor fatalities.

## Scope and Objectives

Deep learning methods have accounted for the tremendous acceleration of artificial intelligence research in medical image analysis, interpretation, and segmentation, with several potential applications across a variety of medical subdisciplines. However, only a small number of studies that investigate various application scenarios are used in the medical context to evaluate the actual need and the practical challenges of model deployment. With the advancement of technology, CNN (Convolutional Neural Network) and image processing techniques may now be utilized to detect brain tumors using MR images, which is a significant benefit. Furthermore, these types of brain tumor detection devices are more accurate and require less human engagement to detect the tumor. Gathering up different inputs, computing the some of their weights, forward output to operate functions reply with the expected output are few steps which follows in the CNN. According to the CNN classification, the important features of MR Image are line, edge, object etc. In additionally, CNN can automatically recognize complex features with more accuracy.

Main aim of this research is to implement an application to optimize brain tumor detection using MR images. Furthermore, the objectives of the research are as follows.

• Study about the brain, the impact of brain tumors.

• Study about the types of brain tumors and the traditional ways of detecting them.

• Learn about preprocessing techniques.

• Study about the features based on MR images

• Implement an optimized solution for brain tumor detection

# Chapter 02 – Literature Review

## 2.1 Introduction

This chapter discusses the related parallel research work being conducted on similar and

related fields to evaluate, establish, compare, and contrast the necessary technologies, methodologies, strategies, and techniques which would be adopted in the research. Most of the systems consists with three main modules and these modules are widely discussed under this section.

## 2.2 Brain Tumor Detection using Image Processing Techniques

The research paper published in IEEE International Conference proposes a novel system for Brain tumor detection through (MRI) Magnetic Resonance Imaging. In this proposed technique, it used Optimized Kernel Probabilistic C-Means Algorithm to pre-process MR Images. Then Adaptive DW-MTM Filter is used to enhance the MRI quality. Finally, the enhanced image is segmented by using Regression Neural Network. Segmentation method is used to separate the tumor area from background. This segmented image is used for the diagnosis of brain tumor in prior stage [4].

Another study presents an automatic brain tumor identification technique that uses a convolutional neural network (CNN) to train the brain tumor detection model and Python to implement it. As 3D photos can be fed into this system, 3D images will be produced. The conventional brain tumor classification is performed by using Fuzzy C Means (FCM) based segmentation, texture, and shape feature extraction and SVM (Support Vector Machine) and DNN (Deep Neural Network) based classification are carried out [5].

Sourabh Hanwat and Chandra Jayaraman has proposed research work, where three different classification algorithms used for brain tumor classification as a benign, malignant, and normal MRI images. Proposed method used Dilate and Bwareafilt method for skull removing. The median filter is used to remove noise of the image. Binary threshold with morphological segmentation helped for highlight the tumor in MRI images. The classification is performed with the help of CNN, RF (Random Forest), and KNN (K-Nearest Neighbor) algorithms. According to this research paper, CNN is achieved maximum accuracy of 98% with cross-entropy is 0.097 and validation accuracy of 71%. Random Forests achieved 80% of accuracy and K-Nearest Neighbors achieved 74% of accuracy which is lesser than CNN. The analysis of research work, results proved that Convolutional Neural Network image classification method is better compares to other machine leaning classification methods [6].

There is another proposed method, which remove noise and sharp edges. Gaussian, median filters are used to remove noise in pre-processing phase. This process enhances the quality of the image. Sharping edges will help to clearly segment MR images. Extract the 18 important features from the segmented image and train the model using that features during the process phase. Final phase of post-processing of this method is done using Threshold Segmentation, Watershed Segmentation and Morphological Operators [7].

### 2.2.1 Pre-processing

#### 2.2.1.1 Noise Removal

In every image pre-processing phase, the main and the important part is to remove the unwanted noise of an image and enhancing it to make sure that it is ready to extract the focused features.

A. Lakshmi M.E et al proposed a pre-processing method for MRIs using the curve let transform method which is enable of reducing the noise and smooth the image for further processing. The curve let transform is better than the wave let transform perceptually. This technique provides more sharp edges as well as sharp images.

• Curve let transform

This is a technique which can enhance the curves of the images. The basic way of the technique is based on dividing the whole image into smaller parts of overlapping rectangles and applying the ridge let transform on each rectangle.

Diagram

Description automatically generated

**Figure 1: Curved edges on wave let vs curve let**

In the above image you can see the curved edges of curve let is sharper than the wave let transform. And the problem of discontinuity of the edges are addressed by curve let transform rather than the wave let transform [8].

#### 2.1.1.2 Artifact Removal

A close-up of a human skull

Description automatically generated with medium confidenceIn an MRI, an artifact is something that causes a disturbance but does not appear in the original image. Because of hardware issues, software issues, and the printed details of the patients, artifacts appear in an image.

**Figure 2: Image with artifacts**

Sudipta Roy et al has proposed a method to remove these artifacts. First the image will be converted to binary image. Then the standard deviation of the image will be calculated and decide the threshold value, so that the background and the foreground of the image will be separated. So, the total intensity is calculated by,

T =

I [m, n] – binary image

h- Intensity of each pixel of gray image

So, the average intensity is calculated by,

*Iavg =*

And the standard deviation or the threshold value is also calculated.

Next each pixel will be categorized to 0 or 1 based on the calculated threshold value.

Then in the second stage the different connected components will be identified and

arranged based on their areas, 1st, and 2nd. Then the 2nd component will be identified as the artifacts [9].

## 2.3 Deep Learning Techniques

There are several Deep learning-based systems for automatically detecting brain tumors and their location without the need for human intervention. Deep learning techniques are being used to detect brain tumors and identify regions in the clinical process in this type of research. There are currently just a handful solutions in use as a solution for the issue.

Ali Ari and Davut Hanbay have proposed a method in the Turkish Journal of Electrical

Engineering & Computer Sciences 2018 named “Deep learning-based brain tumor

classification and detection system”. DICOM (Digital Imagine and Communication in

Medicine) images are used for this project. These dataset contains both benign and

malignant tumor images which are belongs to each axial, coronal and sagittal plane.

A picture containing text

Description automatically generated

**Figure 3: Different view of Brain MRI**

There are three main stages as pre-processing stage, image classification stage and extraction of tumor region based on image processing techniques. Brain tumors were classified as benign or malignant using ELM-LRF (Extreme Learning Machines) within the classification stage. Applied convolution and pooling operation to the dataset in the input layer. Convolution filter size r, convolution filter number K, pooling size, and regulation coefficient C. Values were selected for r, K, and pooling size and select the most suitable value for C with the minimum fault. This CNN was implemented with six layers. Input layer is the first one, second one is the convolution layer after the input layer, six convolution filters are used in this layer. Pooling layer is the third layer, which was built after first convolutional layer. There is another convolution layer with 12 convolution filters as the fourth layer. Again, there is a pooling layer after second convolution layer as the fifth layer. Fully connected layer is the last layer. This CNN model used sigmoid activation function as the activation function. Performance of the proposed ELM-LRF method is compared with the few other approaches. Such as CNN, Statistical features, and Gabor-wavelet features. Comparatively to the other method this method is quite simple, useful, need very short time to train because of no iteration and randomly generated input weights [10].

Diagram

Description automatically generated with medium confidence

**Figure 4: Proposed method by Ali Ari and Davut Hanbay**

Another solution, called "Brain Tumor Segmentation Using Convolutional Neural Network with Tensor Flow," was proposed by M. Malathi and P. Sinthia. The dataset for this study includes MRI scans, and the segmentation approaches are tensor flow. Because of the code's compatibility and clarity, as well as the availability of more graphic packages, the research was conducted in Python. The proposed system's segmentation was built using CNN with small 3x3 kernels, which helps to generate deep architecture with a limited number of weights in the network. The CNN that was used in this case is made of four layers. These are the input and convolution layers, respectively. The picture patches for the remaining half of the CNN are generated by the input payer. The purpose of picture patching is to save computing time and memory space by calculating linear and non-linear relationships between each voxel of a big 3D input image. It was also beneficial to look for a relationship inside a specific region rather than the entire image. Multiple convolution layers were used for extracting law-level features like borders and corners. Feature maps are the output of the convolution layer. The activation function for this project was ReLU (Rectified Linear Units). Keras is used to build training model [11].

A screenshot of a computer

Description automatically generated with medium confidence

**Figure 5: CNN architecture of the model by Malathi and Sinthia**

## 2.4 Image Processing Techniques

Research that done by Vipin Y. Borole, Sunil S. Nimbhore and Dr. Seema S. Kawthekar has proposed a system which can identify the tumor region by the MR image. First, they have used the median filter for noise removal. It replaces the value of the center cell with the median value of the intensity values of the neighbourhood cells. The image that removes salt and paper noise also called as impulse noise is send to the next phase. In the next phase this system enhances the input image by improving the contrast of the MR image. Edge detection can be easily done after this enhancement. This system has used various methods to find the edge. Canny edge detection method has given the most accurate output as they found. This technique finds boundaries of objects within the image. It detects discontinuities in brightness of each pixel.

In this system the thresholding has done by manually according to the input image. After thresholding this system uses morphological operations to maximize the accuracy of the output [12].

Diagram

Description automatically generated

**Figure 6: The proposed system by Vipin Y. Borole et al**

Diagram

Description automatically generatedN. Sravanthi et al proposed a tunor identification system using Image processing techniques. The proposed method for detecting a brain tumor includes three diagnostic tasks which are pre-processing, segmentation, and feature extraction. At a later stage, they calculated and classified the area based on this. As mentioned above, the obtained CT image is pre-processed. The pre-processed image is segmented and later they extract features from the segmented image [13]

**Figure 7: Proposed system by Sravanthi et al**

Diagram

Description automatically generatedP.D.Yadav and Y.M.Patil of Electronics Engineering, Department KIT (India) proposed a tumor identification system by using k-means, fuzzy c means and watershed segmentation. Pre-processing and picture segmentation are the two steps of the proposed system. A tracking method and a median filter are used for pre-processing. K-means and Fuzzy c methods are used to do classification.

**Figure 8: Proposed system by P.D.Yadav and Y.M.Patil**

* Fuzzy c means method

The goal of Fuzzy c method is to find the centers of the cluster, also called as centroid to minimize the dissimilarity functions. As the beginning step, the algorithm selects the initial cluster centroid. After several iterations of the algorithm, the final output converges to actual centroid. Therefore, a high-quality set of initial clusters should be achieved, and it is very important on FCM algorithm. If a right set of initial cluster centroids are chosen, the algorithm does not need many iterations to give the optimal result. The Fuzzy C-Means algorithm is an algorithm which iterates multiple times to find clusters in data which uses the fuzzy membership concepts.

A picture containing text, screen, set, screenshot

Description automatically generated

**Figure 9: Output of the system by P.D.Yadav and Y.M.Patil**

# Chapter 03 – Adopted Technologies

## 3.1 Introduction

This chapter includes a brief description of the technologies used in the system's implementation. It also contains reasons for using such technologies, such as the technology's performance and applicability to the issue domain.

## 3.2 Programming Languages

Python will be used as the core programming language in implementing the system. Python's flexibility of use allows programmers to create reliable systems. It can input photos (as well as transformations, meshes, and point sets) and view and analyse them using a user-friendly graphical interface. It is well-known for its functionality and adaptability.

## 3.3 Libraries

### 3.3.1 OpenCV

This project is mainly focused on the image processing techniques. So, the OpenCV library has used for this. It is an open-source computer vision library that can be used in many different platforms. OpenCV aids the research in performing various processing activities. It has a good performance compared to the other libraries available.

### 3.3.2 Keras

Keras is a free open-source Python framework for developing and evaluating deep learning models that is both powerful and simple to use. It covers Theano and TensorFlow, two efficient numerical computation frameworks, and allows to create and train neural network models with just a few lines of code. It has features like activation function, optimizers, layers, tools, and objectives to write deep neural network codes.

### 3.3.3 Tensorflow

Tensorflow is an open-source Machine Learning Framework made by Google facilitates efficient performance in machine learning and complex computational tasks. In Tensorflow nodes represent mathematical operations and the edges represent the data arrays (tensors) use to communication between them.

### 3.3.3 Scikit-learn

Scikit-learn is a key machine learning toolkit for the Python programming language. Scikit-learn is a set of machine learning tools that includes mathematical, statistical, and general-purpose algorithms that serve as the foundation for a variety of machine learning technologies.

### 3.3.4. Matplotlib

Matplotlib is a Python package that allows you to create static, animated, and interactive visualizations. It is basically a plotting library for python programming language. It provides an object-oriented API for embedding charts into applications utilizing GUI toolkits such as Tkinter, wxPython, Qt, or GTK.

# Chapter 04 – Methodology

## 4.1 Introduction

This chapter discusses the design of the system that is proposed for the problem addresses in the research. It contains the proposed system's top-level architecture as well as the conceptual designs for each of the system's modules. It explains what each module does and how the modules relate to one another.

## 4.2 Architecture of overall system

This is a system which can identify the brain tumors automatically using image processing techniques. There are three main steps in the proposed solution. The first step is the pre-processing stage which will enhance the quality of the image, cropping and obtaining the desired part of the brain. Next, we propose to develop a convolutional neural network to identify brain tumor and output whether the patient having a tumor or not. Along with that we propose to implement a module to identify the tumor region with image processing techniques.

A picture containing arrow

Description automatically generated

**Figure 10: Process of the System**

### 4.2.1 Pre-processing

To increase the accuracy of the CNN and the classification, pre-processing must be done before it. The pre-processing part is required because of main two reasons:

1. The presence of artifacts could impact on result.

2. Enhance the quality of image.

##### 

**Figure 11: Pre-processing Architecture**

#### 4.2.1.2 Dataset Acquisition

Medical image dataset acquisition is much more difficult as those data are very confident. Obtaining a high-quality dataset which is preferred for image processing and model training is also a challenge.

For this research the MRI scanned images were acquired from online available web site, [www.kaggle.com](http://www.kaggle.com).

The dataset acquired from kaggle.com contained 253 images with 155 images with

“yes” or tumorous Brain MRIs and 98 images with “no” or non-tumorous brain MRIs.

This is a clear and labelled dataset which can be directly used for pre-processing.



**Figure 12: Acquired Image**

#### 4.2.1.2 Removing artifacts

Different artifacts, as well as the patient's name, id, and other information, can be found in MRI or CT scan images. Before moving on to the processing stage, these artifacts should be removed. To do this, a threshold mechanism can be used. The major component, the skull, as well as the entire brain, will be extracted after this operation.

### 4.2.2 CNN Segmentation Model

Magnetic Resonance Images are feed into Convolutional Neural network as test data and those test data includes both tumors and non-tumor MR Images.



**Figure 13: Architecture of CNN model**

#### 4.2.2.1 Convolutional Neural Network Classifier

Diagram

Description automatically generatedThe Convolutional Neural Network (CNN) is a deep neural network used largely in image classification and computer vision applications. A simple neural network consists of an input layer, a hidden layer, and an output layer. Two or more hidden layers can be found in a deep neural network. Convolution layers are followed by a fully connected neural network in a convolutional neural network. According to the CNN classification, the important features of MR Image are line, edge, object etc. In additionally, CNN can automatically recognize complex features with more accuracy.

**Figure 14: Structure of a Convolutional Neural Network**

#### 4.2.2.2 Activation Function

The Rectified Linear Unit (ReLU) activation function is used to overcome the vanishing

gradient problem letting models to learn faster and perform better in the neural network

with more layers like CNN. There are two more activation functions, such as Sigmoid and Tanh Activation Functions. But these activation function cannot overcome the vanishing gradient problem in the neural network which consists with more layers.

#### 4.2.2.3 Pooling

It combines contiguous nearby features in the feature maps. This integration of possibly redundant features builds the representation more tightly packed and invariant to small image changes, such as insignificant details; it also reduces the computational load of the next stages. Max-pooling or average-pooling is commonly used approach to join features.

#### 4.2.2.4 Regularization

Regularization is a technique that regulates the model complexity. Deep learning neural networks like CNN quickly overfit a training dataset with few outlined examples. This helps to make less risk of overfitting while enhancing the generalization of convolutional neural networks. Dropout will be used as regularization method in fully connected layer. Make large number of different network architectures with use of single model by indiscriminately dropping out the nodes within the training period and all nodes are involved to execute this process. This method called as dropout.

#### 4.2.2.5 Loss Function

This will calculate the gap between predicated value and real value. The calculation is done during model optimization process. Simply, the loss is used to calculate the gradients.

#### 4.2.2.6 Dataset

The dataset for this project consists of only 253 brain MRI images, and the model used to train these images is a Convolutional Neural Network (CNN), which is the best neural network for training image datasets. However, this amount of data is insufficient for those types of models, as the model's accuracy might be low. Hence, the size of the dataset proposed to increase, and there are tumorous images more than non-tumorous images. That means this is not a balanced dataset. Therefore, dataset have to be converted to the balanced dataset while increasing its size, before feed the Neural Network. Data augmentation is to be done to minimize that issue.

### 4.2.3 Image Processing Model

The goal of the model is to identify the tumor region accurately based on the

results obtained by the CNN module. Morphological operations such as Erosion,

Dilation and feature extraction technics will be used for this process.

Graphical user interface, text, application, chat or text message

Description automatically generated

**Figure 15: Image Processing Model**

#### 4.2.3.1 Smoothing

A bilateral filter is a non-linear image smoothing filter that preserves edges while reducing noise. It uses a weighted average of intensity data from surrounding pixels to replace the intensity of each pixel. A Gaussian distribution can be used to calculate this weight.

#### 4.2.3.2 Enhancement

Image enhancement is the technique of highlighting key aspects of an image while weakening or deleting any extraneous information based on the demands of the user. Eliminating noise, uncovering blurred details, and altering levels to highlight parts of an image are just a few examples.

Text

Description automatically generatedPoint operators which called as pixel transformations and neighborhood operation are also called as area-based operators which are the prominent approaches that can use in image processing. Considering the intensity distribution of an average brain MR image, here used the pixel transformation approach to improve the correctness of brightness and contrast. Here ‘α’ and ‘β’ are the parameters that use with the transformation equation, and they are representing contrast and brightness respectively. Here used the value of alpha as 1.3 (gain factor) and the value of beta as .8 (bias factor).

Pixel Transformation Equation

#### 4.2.3.3 Thresholding

After the enhancement binary thresholding method is used to identify separate

components of the MR image. In binary thresholding the pixel values which are below

the threshold level will be assigned 0 and the pixel values which are above the threshold

will assigned 255. The enhanced image should be converted to the gray scale prior to

the binarization to reduce the three RGB channels to a single channel.

A histogram-based algorithm has used here to find the threshold value from each

image.

A picture containing text

Description automatically generatedChart, histogram

Description automatically generated

**Figure 16: MRI and the relevant Image histogram**

#### 4.2.3.4 Morphological Operations

Morphological image processing is a set of non-linear processes that deal with the shape or morphology of image features. These operations are used to determine an object's shape and boundary. Morphological operations depend only on the relative ordering of pixel values, not on their absolute numerical value. There for these methods suit properly with binary images.

The purpose of using morphological operators here is to display the classified brain tumor area to the user. In this section mainly the Erosion and Dilation methods are used.

* Erosion

Erosion separates objects in a binary image by increasing black pixels and decreasing white pixels according to the structuring element. This technic is used for shrinking process of an image. Objects with connected edges in an image can be separated by using this technic. In this system, we have used the 3x3 kernel to do erosion.

* Dilation

Dilation works as a grow up process of the image. It increases the white pixels and

decrease the black pixels according to the structural element.

A picture containing text, crossword puzzle

Description automatically generated

**Figure 17: Visual representation of an input image and Dilated image**

#### 4.2.3.5 Contour

Contour is a hypothetical curve that connects all the continuous boundary points in each component of the binarized image. This method identifies pixels which have same intensity level. Therefor we can use this method to identify separate components of a binarized image. Contour finding methods mainly works according to the square tracing algorithm.

# Chapter 05 – Implementation

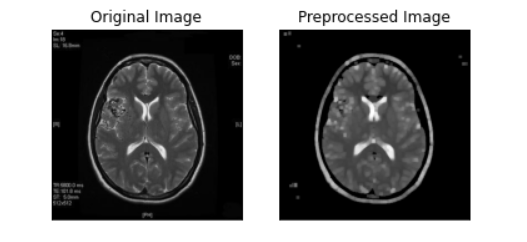
## 5.1 Introduction

The experiments carried out in implementing the system is illustrated in this chapter. It gives a description about the current status of the implementation process of the system.

## 5.2 Preprocessing

### 5.2.1. Artifact Removal

In order to identify the tumor region of a MR image first the artifacts should be removed. It is important since it improve the accuracy of tumor identification. There can be many approaches to obtain artifact removal. But in this study, Image processing techniques were used.



As the implementation, first the required libraries were imported. Then, the targeted image was loaded and checked the color levels and converted to a gray image.

It is easy to handle a gray image than any other color image since it has only 256 color

levels. Even the dataset is MRI images, there can be differences in the color levels. Hence it is a good practice to convert all the MRI images to gray color format.

**Figure 18: Python code 01**

Graphical user interface, text, application, chat or text message

Description automatically generated

Next a histogram was plotted based on the intensities of the gray scale image. Image

histogram is one of the main methods to enhance the images.

Text, table

Description automatically generated

Chart, histogram

Description automatically generated

**Figure 19: Python code 02**

By looking at the histogram, we can roughly decide the nearest threshold value that can be used to make the digital image binary. There are many methods to threshold an image.

Graphical user interface

Description automatically generated

**Figure 20: Different thresholding options**

An optimum method of thresholding is Otsu’s method. Comparing with the above methods, Otsu’s method is identified as the best method to threshold the MRIs. So finally, the Otsu’s method was used to make the image binary. By this the artifacts have been removed.

## 5.3 CNN Model

### 5.3.1 Data Augmentation

This will help to synthetically make grater in amount of training dataset and decrease the overfitting. Increase the size of training dataset by generating new versions of selected dataset. Large size of training dataset will increase the accuracy of the CNN. Augmentation technique create verity of images and this process improve the ability of the fit models to generalize what they have learned to new images.

The used dataset includes 253 brain MRI images. Those images were separated in to two categories such as “yes” and “no”. “yes” folder contains 155 brain MRI images with the tumors and “no” folder Implementation contains 98 brain MRI images without tumor. This dataset has not enough data to train a convolutional neural network. Hence, increment of the dataset is done using data augmentation techniques.

TensorFlow, OpenCV, Matplot are used for the data augmentation.

Graphical user interface, text, application

Description automatically generated

**Figure 21: Importing libraries**

Text

Description automatically generated

**Figure 22: Data augmentation function**

From the above code segmentation, image loading from original location was done and

additional images were generated by reshaping original images using techniques like rotate, shift, and flip. After, the generated images were stored.

Text

Description automatically generated

**Figure 23: Determine the number of augment images**

There are 61% of tumorous brain MRI images and 39% non-tumorous brain MRI images in the dataset which was used for the research project. Create nine new images for each image in “no” set and six images for each image in “yes” set, to generate balance dataset by solving this problem. The newly created augmented dataset contains 2065 total number of brain MRI images which has 1085 “yes” images (positive images) and 980 “no” images (negative images). As a percentage, dataset includes with 52.5% “yes” and 47.5% “no” images.

### 5.3.2 Data Preparation

Text

Description automatically generatedUnnecessary background of the images was removed with use of cropping techniques by finding extreme left, right, top, bottom points of the pre-processed input brain MRI. Code segment which used to crop images is given below.

**Figure 24: Cropping of MRI**

A picture containing graphical user interface

Description automatically generatedThe image is slightly blurred and covered in grayscale in the above code snippet. Then, to reduce minor noise in the photos, run a process of erosion and dilation. Then, to grab the largest image, detect the contours of the thresholded images. Finally, locate the brain MRI’s extreme data point and crop the original image to create a new brain MRI.

**Figure 25: Brain MRI after cropping process**

Resize all the images to same size. Because data set contains different size of images and need same size data to feed the convolutional neural network. After resizing, the image size is 240, 240, 5 (image width, image height and number of channels). Normalize the data because need to range scaled pixel value between 0-1.

Graphical user interface, text, application

Description automatically generated

**Figure 26: Loading Data**

### 5.3.3 Split Dataset

Graphical user interface, text, application

Description automatically generated

**Figure 27: Splitting Dataset**

### 5.3.4 Model Building

Text

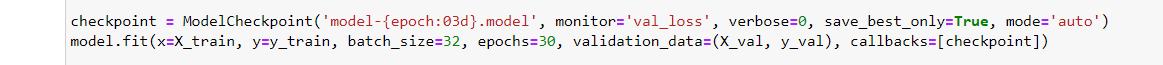
Description automatically generated

Graphical user interface, text

Description automatically generated

**Figure 28: Model Summary**

### 5.3.5 Model Training



**Figure 29: Fitting the model**

### 5.3.6 Checking the Model Results

After selecting the model with the highest accuracy as the best model, it was used to predict new MRI image of the brain is tumorous or not. Following figures show the result for images.

Graphical user interface

Description automatically generated with low confidence

**Figure 30: Predictions**

## 5.4 Image Processing

### 5.4.1 Bilateral Filtering

Here Bilateral Filtering method has used to refine edges. The OpenCV library provides Bilateral Filter method which comprises of four arguments such that the input file, the diameter of each pixel neighbourhood, Sigma Colour and Sigma Space respectively.

**Figure 31: Code snippet to apply bilateral filtering**

Graphical user interface, text, application

Description automatically generated

A picture containing text, invertebrate, arthropod

Description automatically generated

**Figure 32: After applying bilateral filtering**

### 5.4.2 Enhancement

For the easiness of contour finding, the smoothed image is enhanced by using pixel

transformation function.



**Figure 33: Applying pixel transformation**

A picture containing text, invertebrate

Description automatically generated

**Figure 34: After the enhancement**

### 5.4.3 Thresholding

Graphical user interface

Description automatically generated with low confidenceBinary thresholding has used to find the separated objects by considering the intensity of the input image.

**Figure 35: Code snippet for thresholding**

A picture containing text, invertebrate

Description automatically generated

**Figure 36: After applying thresholding**

### 5.4.4 Morphological operations

**Erosion**

Erosion is used to shrinking process of an image. Objects with connected edges in an image can be separated by using this technique.

Graphical user interface

Description automatically generated

**Figure 37: Applying erosion**

**Dilation**

**Graphical user interface, application

Description automatically generated**Pixels in a picture are enlarged via dilation. It increases the white pixels and decrease the black pixels according to the structural element.

**Figure 38: Applying dilation**

### 5.4.5 Contour Identification

Contours are the separate objects where the number of pixels connected each other. This method returns an array of contours with its area. Hence, the maximum value gives the contour we need which is the tumor.

Graphical user interface, text, application, email

Description automatically generated

**Figure 39: Contour Identification and Final output**

# Chapter 06 – Results and Discussion

## 6.1 CNN Model

**Confusion Matrix**

A confusion matrix is a method of summarizing a classification algorithm's performance. Calculating a confusion matrix can help to figure out what the classification model is getting right and where it's going wrong.

In this research two CNN sequential models were developed to classification of brain tumor. Among these two, the best model is chosen for further use. The respective confusion matrices for each model are depicted below.

Chart

Description automatically generated

**Figure 40: Confusion Matrix for model 01**

Chart

Description automatically generated

**Figure 41: Confusion matrix for model 02**

**Classification Report**

It's one of the metrics used to evaluate the success of a classification-based machine learning model. It shows the precision, recall, F1 score, and support of the model. It allows to gain a better understanding of trained model's overall performance.

Chart

Description automatically generated with medium confidenceChart

Description automatically generated

**Figure 42: Model 01**

**Figure 43: Model 02**

**Accuracy and the Loss of the Model**

In machine learning, learning curves are a common diagnostic tool for algorithms that learn progressively from a training dataset. After each update during training, the model can be tested on the training dataset and a holdout validation dataset, and graphs of the measured performance can be produced to display learning curves.

Chart, line chart, histogram

Description automatically generated

**Figure 44: Learning curves of Model 01**

Chart, line chart

Description automatically generatedChart

Description automatically generated

**Figure 45: Learning curves of Model 02**

Considering the above curves and reports, model 01 has high accuracy, high f1 score as well as precise confusion matrix than model 02. Hence, model 01 is used for classification of brain tumors.

## 6.2 Discussion

The aim of this project is to implement a methodology to optimize the brain tumor detection using MR images. The proposed methodology is based on a core assumption that even if the doctors' experience varies, the manual brain tumor identification technique will remain the same. When investigating the manual procedure of brain tumor detection, it is convinced that final judgment differed slightly depending on the doctors and their experience. But this methodology could be feed into mechanism parallel to MRI scanning to give predictions to radiologists as well as doctors to aid their decisions.

There were several limitations faced within the project. It is precise that if this kind of CNN can train using at least 20,000 MRI images. It is difficult to find such an amount as those are confidential data and the PCs are not that enough for training a large model.

Other than the proposed methodology, this can be more optimized using several enhancements.

* Develop a parallel model to identify tumor severity.
* Use 3D images for analyzing
* Execute a parallel model to confirm the classification of brain tumor done by current model.

.

# References

1. Shivakumarswamy G.M., Akshay Patil.V., Chethan T.A., Prajwal B.H., Sagar.V.Hande, "Brain tumour detection using Image processing and sending tumour information over GSM," International Journal of Advanced Research in Computer and Communication Engineering, vol. 5, no. 5, 2016.
2. American Society of Clinical Oncology (ASCO), https://www.cancer.net/
3. American Cancer Society, <https://www.cancer.org/cancer/brain-spinal-cord-tumors-adults/about/key-statistics.html>
4. D. M. K. N. Nandha Gopal, Diagnose Brain Tumor Through MRI Using Image Processing Clustering Algorithms Such as Fuzzy C Means Along with Intelligent Optimization Techniques, 2010
5. P. Gamage, "Identification of Brain Tumor using Image Processing Techniques," ResearchGate, 2017
6. Sourabh Hanwat, Chandra Jayaraman, "Convolutional Neural Network for Brain Tumor Analysis Using MRI Images," International Journal of Engineering and Technology, vol. 11, 2019
7. J. Seetha, S. Selvakumar Raja, "Brain Tumor Classification Using Convolutional Neural Networks," Biomedical & Pharmacology Journal, vol. 11, p. 4, 2018.
8. T. A. R. V. A.Lakshmi, "Noise and skull removal of brain magnetic resonance image using curvelet transform and mathematical morphology" in 2014. International Conference on Electronics and Communication Systems (ICECS), 2014
9. K. C. I. K. M. P. S. K. B. Sudipta Roy, "Artefact Removal from MRI of Brain Image," in International Refereed Journal of Engineering and Science (IRJES), March 2013
10. Ali Ari, Davut Hanbay, "Deep learning-based brain tumor classification and detection system," Turkish Journal of Electrical Engineering & Computer Sciences, p. 12, 2018
11. M Malathi, P Sinthia, "Brain Tumour Segmentation Using Convolutional Neural Network with Tesnsor Flow," Asian Pacific Journal of Cancer Prevention
12. S. S. N. S. S. K. Vipin Y. Borole, "Image Processing Techniques for Brain Tumor Detection: A Review," International Journal of Emerging Trends & Technology in Computer Science (IJETTCS), vol. Volume 4, no. Issue 5(2), October 2015
13. N. Sravanthi et al “Brain Tumor detection using Image Processing”,

International Journal of Scientific Research in Computer Science, Engineering and Information Technology, May 2021