

INTELLIGENT BRAIN TUMOR DETECTION AND CLASSIFICATION TO  
ASSIST PHYSICIAN IN CLINICAL DIAGNOSTIC SYSTEM

AAMER ABDULHAMID ALKHATEEB

A project report submitted in fulfilment of the  
requirements for the award of the degree of  
Master of Engineering (Mechatronics and Automatic Control)

School of Electrical Engineering  
Faculty of Engineering  
Universiti Teknologi Malaysia

FEBRUARY 2021

## DEDICATION

This thesis is dedicated to my father, who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to my mother, who taught me that even the largest task can be accomplished if it is done one step at a time.

## **ACKNOWLEDGEMENT**

In preparing this thesis, I was in contact with many people, researchers, academicians, and practitioners. They have contributed towards my understanding and thoughts. In particular, I wish to express my sincere appreciation to my main thesis supervisor, Dr. Mohd Ariffanan Mohd Basri, for encouragement, guidance, critics and friendship. Without his continued support and interest, this thesis would not have been the same as presented here.

My fellow postgraduate student should also be recognised for their support. My sincere appreciation also extends to all my colleagues and others who have provided assistance at various occasions. Their views and tips are useful indeed. Unfortunately, it is not possible to list all of them in this limited space. I am grateful to all my family member.

## ABSTRACT

This project is an artificial intelligence model that classifies brain tumor MR images into three different classes, namely Glioma, Meningioma and Pituitary Tumors. The existing method of analysing MRIs is manual classification, which suffers from difficulties such as the long time it takes to classify and the accuracy that can vary based on the experience of the physicians. The researchers are working on classification of MRIs since years, and each of them are competing to get a higher accuracy and performance results. However, the competition in this field is widely focusing on getting higher accuracy and better performance and trying different datasets to get variety of all possible combinations. After doing a successful experiment on Alexnet network and reaching an accuracy better than the state of the art. After noticing that the research field is full of researches, but no real application is applied in the hospitals, it is the time to start thinking practically about moving the research one step toward practical side, which is the medical application of this problem. In this project, an application is developed for giving multiple opinions about MR image of a brain tumor of the three types, helping the physicians with not only 2<sup>nd</sup> opinion, but with 4 different opinions from four different AI entities, increasing the accuracy that can be obtained in deciding which tumor is in the image, in an easy to use environment with few clicks, making the numbers and technical aspect of the AI technology to us as engineers and the solution is simplified as possible in the hands of physicians. The pre-trained networks used in the project are Googlenet, Alexnet, Mobilenetv2, Resnet101, and the training accuracy obtained using the Figshare dataset on all of them are 100%, 97.66%, 100%, 100% respectively, and a validation accuracy of 92.27%, 86.87%, 94.34%, and 94.23% respectively.

## ABSTRAK

Projek ini adalah model kecerdasan buatan yang mengklasifikasikan gambar MR tumor otak menjadi tiga kelas yang berbeza, iaitu Glioma, Meningioma dan Tumor Pituitari. Kaedah yang ada untuk menganalisis MRI adalah klasifikasi manual, yang mengalami kesulitan seperti waktu yang lama untuk mengklasifikasikan dan ketepatan yang dapat berbeza-beza berdasarkan pengalaman doktor. Para penyelidik berusaha untuk mengklasifikasikan MRI sejak bertahun-tahun, dan masing-masing bersaing untuk mendapatkan hasil ketepatan dan prestasi yang lebih tinggi. Walau bagaimanapun, persaingan dalam bidang ini banyak difokuskan untuk mendapatkan ketepatan yang lebih tinggi dan prestasi yang lebih baik dan mencuba set data yang berbeza untuk mendapatkan pelbagai semua kemungkinan kombinasi. Setelah melakukan percubaan yang berjaya pada semester lalu di rangkaian Alexnet dan mencapai ketepatan yang lebih baik daripada yang terkini. Setelah menyedari bahawa bidang penyelidikan penuh dengan penyelidikan, tetapi tidak ada aplikasi nyata yang diterapkan di rumah sakit, inilah saatnya untuk mulai berfikir secara praktikal tentang memindahkan penyelidikan selangkah ke arah praktikal, yang merupakan aplikasi perubatan dari masalah ini. Dalam projek ini, sebuah aplikasi dikembangkan untuk memberikan banyak pendapat mengenai gambaran MR tumor otak dari tiga jenis tersebut, membantu doktor dengan tidak hanya pendapat ke-2, tetapi dengan 4 pendapat yang berbeza dari empat entiti AI yang berbeza, meningkatkan ketepatan yang dapat diperoleh dalam menentukan tumor mana yang sesuai dengan gambar, dalam lingkungan yang mudah digunakan dengan beberapa klik, menjadikan nombor dan aspek teknikal teknologi AI kepada kami sebagai jurutera dan penyelesaiannya dipermudah mungkin di tangan doktor. Jaringan pra-terlatih yang digunakan dalam projek ini adalah Googlenet, Alexnet, Mobilenetv2, Resnet101, dan ketepatan latihan yang diperoleh menggunakan set data Figshare pada semuanya adalah masing-masing 100%, 97.66%, 100%, 100%, dan ketepatan pengesahan 92.27%, 86.87%, 94,34%, 94.23%.

## TABLE OF CONTENTS

	TITLE	PAGE
	DECLARATION	ii
	DEDICATION	iii
	ACKNOWLEDGEMENT	iv
	ABSTRACT	v
	ABSTRAK	vi
	TABLE OF CONTENTS	vii
	LIST OF TABLES	x
	LIST OF FIGURES	xi
	LIST OF ABBREVIATIONS	xii
	LIST OF APPENDICES	xiii
<b>CHAPTER 1</b>	<b>INTRODUCTION</b>	<b>3</b>
1.1	Problem Background	3
1.1.1	Brain Tumor	3
1.1.2	MR Imaging	3
1.1.3	Manual Classification vs Automatic Classification	4
1.1.4	Deep Learning Algorithms for Classification	5
1.1.5	Second Opinion Concept	6
1.2	Problem Statement	6
1.3	Scope of the Project	7
1.3.1	Objectives	8
<b>CHAPTER 2</b>	<b>LITERATURE REVIEW</b>	<b>9</b>
2.1	Introduction	9
2.2	Machine Learning and Artificial Intelligence Algorithms	10
2.3	Deep Learning Algorithms	12

2.3.1	Deep Convolutional Neural Networks	13
2.3.1.1	Transfer Learning	13
2.4	Research Gap	14
<b>CHAPTER 3</b>	<b>RESEARCH METHODOLOGY</b>	<b>17</b>
3.1	Introduction	17
3.2	Networks Selected	18
3.2.1	AlexNet	18
3.2.2	GoogleNet	19
3.2.2.1	Global Average Pooling :	20
3.2.2.2	Inception Module:	20
3.2.2.3	Auxiliary Classifier for Training:	20
3.2.3	MobileNetV2	23
3.2.3.1	Residual Blocks:	23
3.2.3.2	Inverted Residual	23
3.2.3.3	Spatial Separable Convolutions:	24
3.2.3.4	Depthwise Separable Convolutions:	25
3.2.4	ResNet101	25
3.3	Proposed Method	27
3.3.1	Data Acquisition	27
3.3.2	Data Preprocessing	28
3.3.3	Feature Extraction	28
3.3.4	Classification	29
3.4	Re-Training	29
3.5	Tools and Platforms	30
3.5.1	Python	30
3.5.1.1	Jupyter	30
3.5.2	Matlab	30
3.5.2.1	Deep Learning Toolbox	30
3.6	Chapter Summary	31

<b>CHAPTER 4</b>	<b>RESULTS AND DISCUSSION</b>	<b>33</b>
4.1	Introduction	33
4.2	Parameters Measurements	33
4.3	Training Results and Confusion Matrices	34
4.3.1	AlexNet Results	34
4.3.1.1	Validation Accuracy vs Training Accuracy	37
4.3.1.2	Results Comparison	38
4.3.2	GoogleNet Results	38
4.3.3	Resnet101 Results	41
4.3.4	MobilenetV2 Results	43
4.4	Results Comparison	45
4.5	Developing the Second Opinion Application	47
4.5.1	Testing the program.	49
4.5.2	Limitations of the program	49
<b>CHAPTER 5</b>	<b>CONCLUSION</b>	<b>51</b>
4.6	Conclusion	51
4.7	Future Works	52
<b>REFERENCES</b>		<b>53</b>
4.8	Creating Layer Graph	55
4.9	Adding Layer Branches	55
4.10	Connect Layer Branches	61
4.11	Plotting Layers	63
<b>Appendices A - C</b>		<b>55-72</b>



## LIST OF TABLES

<b>TABLE NO.</b>	<b>TITLE</b>	<b>PAGE</b>
Table 1:	Literature Review Comparison Table	14
Table 2:	Summary of networks used	26
Table 3:	Training Settings for all networks	29
Table 4:	Confusion Matrix Table Example with its components	34
Table 5:	Training accuracy and Validation Accuracy for AlexNet	35
Table 6:	Training Data Confusion Matrix	35
Table 7:	Validation Data Confusion Matrix	36
Table 8 :	Performance metrics of the proposed model (Based on Validation Confusion Matrix)	36
Table 9:	Performance metrics of the proposed model (Based on Training Confusion Matrix)	37
Table 10:	Results Comparison	38
Table 11:	GoogleNet Training results	39
Table 12:	Confusion Matrix of GoogleNet Validaton Data	39
Table 13:	Confusion Matrix of GoogleNet Training Data	39
Table 14:	Performance Metrics for GoogleNet Validation Data	40
Table 15:	Performance Metrics for GoogleNet Training Data	40
Table 16:	Confusion Metrics of Resnet101 for Validation	41
Table 17:	Confusion Matrics of Resnet101 for Training	42
Table 18:	Performance Metrics for Resnet101 Validation Data	42
Table 19:	Performance Metrics for Resnet101 Training Data	42
Table 20:	Confusion Matrix of MobileNetV2 for Validation	43
Table 21:	Confusion Matrix of MobileNetV2 for Training	44
Table 22:	Performance Metrics for MobileNetV2 Validation Data	44
Table 23:	Performance Metrics for MobileNetV2 Training Data	44
Table 24:	Detailed Comparison Between Networks Performances (Red: highest percentages    Brown: Lowest Percentages)	45

## LIST OF FIGURES

<b>FIGURE NO.</b>	<b>TITLE</b>	<b>PAGE</b>
Figure 1:	(a) T1-weighted, (b) T2-weighted, (c) Flair	4
Figure 2:	a) General Brain MR Image, b) Gray Matter, c) White Matter d) Cerebrospinal Fluid [2]	5
Figure 3:	Literature Review tree funnel	9
Figure 4:	Literature Review Funnel - Project Area	10
Figure 5:	Flowcahrt of the classification algorithm for each selected netowrk	17
Figure 6:	Expanded Flowchart of selecting a network as seond opinion	18
Figure 7:	AlexNet structure	19
Figure 8:	Upper Part of GoogleNet network (read the picture in the next page first)	21
Figure 9:	part 2 of GoogleNet (read from bottom to top)	22
Figure 10:	Residual Block	23
Figure 11:	Residual Block vs Inverted residual block [20]	24
Figure 12:	Simple and Spatial Seperable Convolution	25
Figure 13:	Data sample from Figshare Dataset	28
Figure 14:	Infographic summary of Methodology	31
Figure 15:	Accuracy over Iterations	37
Figure 16:	Trining and Loss graph over Iterations for GoogleNet	41
Figure 17:	Training and Loss graph over Iterations for Resnet101	43
Figure 18:	Trining and Loss graph over Iterations for MobileNetV2	45
Figure 19:	Scan The QR Code to download the app source files with the guide	48
Figure 20:	Application Graphical User Interface (GUI)	48

## LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
CNN	-	Convolutional Neural Network
CM	-	Confusion Matrix
DNN	-	Deep Neural Network
DCNN	-	Deep Convolutional Neural Network
AI	-	Artificial Intelligence
UTM	-	Universiti Teknologi Malaysia
TL	-	Transfer Learning
KNN	-	K nearest neighbor
SVM	-	Support Vector Machine
PSO	-	Particle Swarm Optimizatio
TP	-	True Positive
FP	-	False Positive
TN	-	True Negative
FN	-	False Negative

## LIST OF APPENDICES

<b>APPENDIX</b>	<b>TITLE</b>	<b>PAGE</b>
Appendix A	Matlab Code	55
Appendix B	Gantt Chart	63
Appendix C	App Development Code	64

## CHAPTER 1

### INTRODUCTION

#### 1.1 Problem Background

##### 1.1.1 Brain Tumor

There has been an increase in the amount of work on brain tumors in recent years. A brain tumor is an irregular mass of tissue where only cells develop and uncontrollably grow, seemingly uncontrolled by the processes that regulate normal cells. There have been five brain tumor kinds which are Astrocytoma, Oligodendroglioma, Ependymoma, Gangliocytoma, and Medulloblastoma. More than 150 various brain tumors have been identified, however the primary and metastatic tumors are two major brain tumor classes [1]. The primary brain tumor is referred to as either benign or non-cancer. The brain tumor Metastatic originates from the other part of the body breast or lungs and has spread across the bloodstream to the brain. Which are considered malignant or cancerous [2]. Researchers created a separate Brain Tumor Identification component in [3] that is named the St Anne-Mayo classification system. In which tumors are classified determined by the presence or absence of four cellular characteristics: nuclear atypia, mitoses, proliferation of endothelial cells and necrosis. For instant, grade one brain tumors get none of the four cellular characteristics, grade two tumors have only one of the characteristics, grade three tumors have two characteristics and Grade IV tumors have three or four characteristics[4].

##### 1.1.2 MR Imaging

Due to its low radiation and high contrast characteristic, MR images are more efficient than Computer Tomography (CT) scans. MRIs can distinguish circulating blood and ambiguous vascular dysfunctions. Nervous illness may be observed there

have been no artefacts that harden beams. MR imaging is done with no ionizing radiation MRI 's critical phenomenon is to expose the body to a magnetic field and electrify the human body's hydrogen by emission radio frequency pulses, therefore the hydrogen nuclei absorb energy and transmit it as an electrical signal since stopping the radio signals The atoms emit energy and then return to their preceding stage. The Magnetic Resonance Imaging of the brain periods can be classified into three groups depending on rest and relaxation: Relaxation Time for longitudinal (T1), Transverse Relaxation Time for transverse (T2) and Fluid Attenuated Inversion Recovery (Flair) as seen in Figure 1, while T1 takes long period of time in Time to Echo and Repeat time. The time among echo and radio frequency remittance signal transmission called time to echo. The Repeat Time (RT) is the length of the two consecutive pulse sequences on the same slice of image [2].

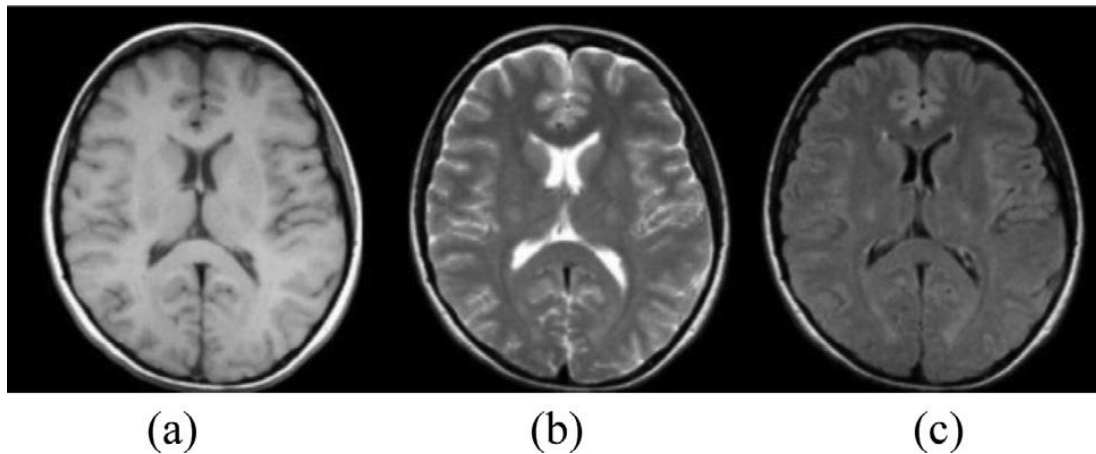


Figure 1: (a) T1-weighted, (b) T2-weighted, (c) Flair

### 1.1.3 Manual Classification vs Automatic Classification

Manually conducting the segmentation of brain MR images is a challenging task, as this entails many difficulties. Automatic detection is an important experiment which has given the best results. It helped researchers to face the challenges of classification of brain tumors. Artificial intelligence one of the most recognized techniques. AI is the study of computer systems able to do tasks that require human intelligence. AI has various methods. In this paper, a brain tumor was identified from MRI images by using deep learning algorithm. Performing the brain MR images segmentation manually is a difficult task as there are several challenges associated

with it. Radiologist and medical experts spend plenty of time for manually segmenting brain MR images, an automatic segmentation of brain MR images is needed to correctly segment White Matter (WM), Grey Matter (GM) and Cerebrospinal Fluid (CSF), tissues of brain (as seen in Figure 2) in a shorter span of time.

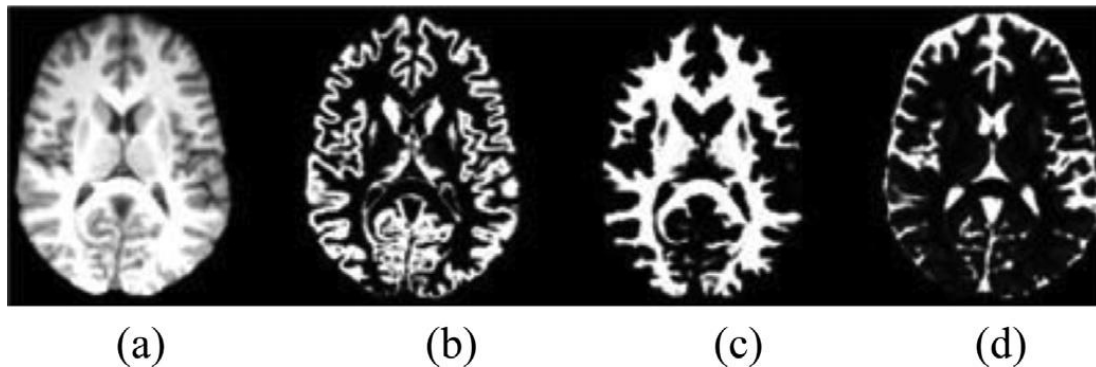


Figure 2: a) General Brain MR Image, b) Gray Matter, c) White Matter d) Cerebrospinal Fluid [2]

#### 1.1.4 Deep Learning Algorithms for Classification

Deep learning can be defined as a special type of artificial neural network that bear resemblance to human decision making process [5]. Deep learning (DL) models provided an interesting trend in machine learning because deep architecture can effectively reflect complicated relationships without the need for a large amount of nodes [6]. Deep learning methods can be used as they can help in feature selection, extraction and can also create new features [5]. Previously the focus was on region-based tumor segmentation, but these days by the assistance of machine learning advancements and deep learning, the paradigm shifted to be in feature extraction and classification. This approach is data starving one, and necessitates huge amount of data to get to the accuracy needed. In order to address this issue, transfer learning is used where the use of already trained network on hundreds of thousands of data samples become a practical solution, in which this network creates a knowledge in classification that can be fine-tuned to the problem in hand and modified in a way it classifies brain tumor i.e. the network is trained on an base dataset called a dataset,

and the learned information is transferred to a small dataset (in this case it is the brain MR images).

### **1.1.5 Second Opinion Concept**

According to National Cancer Institute (NCI), second opinion In medicine, is the opinion of a doctor other than the patient's current doctor. The second doctor reviews the patient's medical records and gives an opinion about the patient's health problem and how it should be treated. A second opinion may confirm or question the first doctor's diagnosis and treatment plan, give more information about the patient's disease or condition, and offer other treatment options. [7]

The main idea of this project is to provide multiple second opinions for an MR image, giving multiple sources of accurate diagnosis for patients, helping physicians to make their minds about the type of tumor in hand with high level of trust.

Doing that is to be done by training multiple high performance networks on brain tumor MRIs then classify images using all of them, and read the accuracy and percentage of the classification of each of them, and package all of that in an simple graphical user interface that is easy to use by doctors and physicians.

## **1.2 Problem Statement**

Medical diagnosing is one of the most important steps in any medical treatment. One of these diagnoses takes place by physicians to identify the type, size and shape of brain tumor by analysing the MR images scanned for the patient. However, these analysis is time consuming, and subjected to human error in diagnosing the tumor types and features due to different quality of images, types of tumors, and the situation of the physician during the process of diagnosing, i.e. the accuracy is another important factor as otherwise the wrong identification of disease can lead to severe consequences. For this reason, an accurate, rapid, and sophisticated solution should be available to assist as second opinion for doctors and physicians. Artificial Intelligence (AI) technology helped researchers identify many ways of classifying



tumors throughout the years via machine learning and neural networks algorithms, however, classifying the images of brain tumor was challenging due to the need of long string of pre-processing labour to be done as mentioned in the literature review. After the emerging of deep learning and Convolutional Neural Networks (CNNs), the pre-processing became very minimal and simple task to do, and the job of features extraction of the tumor is done by the algorithm itself. The matureness of the research in this field is coming to a decent level and results, and yet, there is no serious step in the way of using these knowledge in the medical field yet, that's why this project has a practical side to it, to get closer to have a strong link between engineers and doctors.

The aim of this project is to develop a multi-second opinion application that run an algorithm using deep learning techniques and transfer learning to classify brain tumor through MR Images. The networks used in the project are GoogleNet, AlexNet, MobileNetV2, ResNet101.

### **1.3 Scope of the Project**

1) The algorithm is data based, so the accuracy will be limited to the number of data samples and the quality of them, meaning that the quality of classification will be depending on the data mostly, so the knowledge created will be limited to the knowledge that can be extracted from these samples and not all the types or shapes of tumors.

2) Computer used is personal computer with Graphic Card: NVIDIA GTX1060 and CPU: i7-9750H @2.3GHz, so data processed is limited by computing power, leading to time limitation in order to process the data samples and train the algorithm.

3) The dataset used is Figshare dataset, which is free on the web, no purchased data used in this research.

4) The pre-trained networks are open source and used in the project as base of the work, so no network building from scratch is needed.

### **1.3.1 Objectives**

1. Reaching to accuracy above 90% in validation accuracy in all networks.
2. Design a 5<sup>th</sup> opinion application for classification of brain tumor using 4 different Deep Neural Network using Transfer Learning

## **4.7 Future Works**

While I have developed some aspects of my last semester project future works, I still have some future work to be done. First, the dataset used is not sufficient to move the application to real medical application because the dataset is not capable enough to make the networks real expert in the field due to low number of samples and biased nature of this dataset (Figshare); therefore a training on different and much more samples is required to achieve the required accuracy that can be trusted.

Second, the application can be made stand alone, or web application so it can be commercialized, while it is a MATLAB based app, it is difficult for medical staff to deal with it, so it could be a door of improvement.

Third, the number of networks can be increased as much as possible so it provides the maximum number of predictions possible, increasing the collective second opinion percentage by high percentage.

## REFERENCES

- [1] M. Talo, U. B. Baloglu, Ö. Yıldırım, and U. Rajendra Acharya, "Application of deep transfer learning for automated brain abnormality classification using MR images," *Cognitive Systems Research*, vol. 54, pp. 176-188, 2019/05/01/2019, doi: <https://doi.org/10.1016/j.cogsys.2018.12.007>.
- [2] A. Tiwari, S. Srivastava, and M. Pant, "Brain tumor segmentation and classification from magnetic resonance images: Review of selected methods from 2014 to 2019," *Pattern Recognition Letters*, Article vol. 131, pp. 244-260, 2020, doi: 10.1016/j.patrec.2019.11.020.
- [3] C. Daumas-Duport, B. Scheithauer, J. O'Fallon, and P. Kelly, "Grading of astrocytomas: A simple and reproducible method," *Cancer*, Article vol. 62, no. 10, pp. 2152-2165, 1988, doi: 10.1002/1097-0142(19881115)62:10<2152::AID-CNCR2820621015>3.0.CO;2-T.
- [4] N. D. Doolittle, "State of the science in brain tumor classification," *Seminars in Oncology Nursing*, Review vol. 20, no. 4, pp. 224-230, 2004, doi: 10.1016/S0749-2081(04)00086-5.
- [5] J. Jotheeswaran and S. Tanwar, "Survey on Deep Learning for Medical Imaging," vol. 5, pp. 1608-20, 12/01 2018.
- [6] H. Mohsen, E.-S. El-Dahshan, E.-S. El-Horbarty, and A.-B. M.Salem, "Classification using Deep Learning Neural Networks for Brain Tumors," *Future Computing and Informatics Journal*, vol. 3, 12/01 2017, doi: 10.1016/j.fcij.2017.12.001.
- [7] "Definition of second opinion - NCI Dictionary of Cancer Terms," ed, 2020.
- [8] S. Somasundaram and R. Gobinath, "Current Trends on Deep Learning Models for Brain Tumor Segmentation and Detection - A Review," in *Proceedings of the International Conference on Machine Learning, Big Data, Cloud and Parallel Computing: Trends, Perspectives and Prospects, COMITCon 2019*, 2019, pp. 217-221, doi: 10.1109/COMITCon.2019.8862209.
- [9] J. Amin, M. Sharif, M. Yasmin, and S. L. Fernandes, "A distinctive approach in brain tumor detection and classification using MRI," *Pattern Recognition Letters*, Article in Press 2017, doi: 10.1016/j.patrec.2017.10.036.
- [10] S. Damodharan and D. Raghavan, "Combining tissue segmentation and neural network for brain tumor detection," *International Arab Journal of Information Technology*, Article vol. 12, no. 1, pp. 42-52, 2015.
- [11] M. M. Thaha, K. P. M. Kumar, B. S. Murugan, S. Dhanasekaran, P. Vijayakarhick, and A. S. Selvi, "Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images," *Journal of Medical Systems*, vol. 43, no. 9, p. 294, 2019/07/24 2019, doi: 10.1007/s10916-019-1416-0.
- [12] M. Havaei *et al.*, "Brain tumor segmentation with Deep Neural Networks," *Medical Image Analysis*, vol. 35, pp. 18-31, 2017/01/01/ 2017, doi: <https://doi.org/10.1016/j.media.2016.05.004>.
- [13] I. Ahmad. "How Much Data Is Generated Every Minute? ." *SocialMediaToday*. <https://www.socialmediatoday.com/news/how-much->