



BRAIN TUMOR DETECTION MODEL USING DIGITAL IMAGE
PROCESSING AND TRANSFER LEARNING

A Thesis Presented

By

Nazreth Tikher

To

The Faculty of Informatics

Of

St. Mary's University

In Partial Fulfillment of the Requirements

For the Degree of Master of Science

in

Computer Science

June, 2023.

ACCEPTANCE

BRAIN TUMOR DETECTION MODEL USING DIGITAL IMAGE
PROCESSING AND TRANSFER LEARNING

By

Nazreth Tikher

Accepted by the Faculty of Informatics, St. Mary's University, in partial fulfillment of the
requirements for the degree of Master of Science in Computer Science

Thesis Examination Committee:

Internal Examiner

External Examiner

Dean, Faculty of Informatics

June, 2023.

DECLARATION

I, the undersigned, declare that this thesis work is my original work, has not been presented for a degree in this or any other university, and all sources of materials used for the thesis work have been duly acknowledged.

Nazreth Tikher

Signature

Addis Ababa

Ethiopia

This thesis has been submitted for examination with my approval as an advisor.

Million Meshesha (PhD)

Advisor

Signature

Addis Ababa, Ethiopia

June, 2023.

ACKNOWLEDGMENT

Foremost, I would like to express my deepest and sincere gratitude to my advisor Dr. Million Meshesha for the continuous support of my M.Sc. thesis, and for his patience, motivation, enthusiasm, and immense knowledge. His guidance helped me a lot in all parts of the thesis. In addition to my adviser, I want to thank everyone who has helped me over the past two years in any way they can. These people include Dr. Edome, the head of the brain tumor section at Korea Hospital, Drs. Adugaa, Ruth, Frehune, and Daniel, the radiologists and director of medicine at Korea Hospital, as well as Ato Mesfine, the ICT head at Korea Hospital. Last but not least, without the encouragement and support of my dear family, especially my mother, nothing is impossible.

TABLE OF CONTENTS

ACKNOWLEDGMENT.....	iii
LIST OF FIGURES	vii
LIST OF TABLES	viii
LIST OF ACRONYMS	ix
ABSTRACT.....	x
CHAPTER ONE: INTRODUCTION.....	1
1.1 BACKGROUND	1
1.2. MOTIVATION	2
1.3. STATEMENT OF THE PROBLEM.....	3
1.4 RESEARCH QUESTIONS.....	5
1.5. OBJECTIVE OF THE STUDY	5
1.5.1. GENERAL OBJECTIVE.....	5
1.5.2. SPECIFIC OBJECTIVES	5
1.6. SIGNIFICANCE OF THE STUDY.....	5
1.7. SCOPE AND LIMITATION.....	6
1.8. METHODOLOGY OF THE STUDY	6
1.8.1. RESEARCH DESIGN	6
1.8.2. DATA PREPARATION	6
1.8.3. IMPLEMENTATION TOOLS	7
1.8.4. EVALUATION METHODS	8
1.9. ORGANIZATION OF THE THESIS.....	9
CHAPTER 2: LITERATURE REVIEW AND RELATED WORKS.....	10
2.1. BRAIN TUMOR OVERVIEW	10
2.1.1 TYPE OF BRAIN TUMORS	11
2.1.2 TUMOR GRADE	12
2.1.3 MAGNETIC RESONANCE IMAGE (MRI)	12

2.2. INTRODUCING IMAGE PROCESSING	12
2.2.1. DIGITAL IMAGE PROCESSING.....	13
2.3. IMAGE PROCESSING STEPS.....	13
2.3.1 IMAGE ACQUISITION.....	14
2.3.2 IMAGE PREPROCESSING	15
2.3.3 IMAGE SEGMENTATION	16
2.3.4. FEATURE EXTRACTION	17
2.4. DEEP LEARNING	17
2.4.1. Comparing CNN vs. Classical Classification methods.....	19
2.5. TRANSFER LEARNING METHODS.....	22
2.6. RELATED WORKS	24
2.7 RESEARCH GAP.....	26
CHAPTER 3: METHODS AND APPROACHES	27
3.1. OVERVIEW	27
3.2. THE PROPOSED ARCHITECTURE.....	27
3.3. IMAGE DATA PREPARATION	28
3.3.1. IMAGE PREPROCESSING.....	28
3.3.2. Adding More Data (Data Augmentation)	29
3.3.3. PROPOSED MODEL COMPONENTS.....	30
3.4. HYPER-PARAMETER TUNING.....	32
3.5. EVALUATION METHODS	35
CHAPTER 4: EXPERIMENTATION AND DISCUSSION	37
4.1. IMAGE DATASET	37
4.2. EXPERIMENTAL SETUP.....	37
4.3. CNN FEATURES	38
4.4. PARAMETERS USED FOR AUGUMENTATION.....	38
4.5 EXPERIMENTAL RESULT.....	39
4.5.1 BRAIN TUMOR DETECTION USING A MODEL.....	39

4.5.2 Experiment Result of VGG16.....	41
4.5.3. Experiment Result of InceptionV3	42
4.6. COMPARISON OF RESULTS	44
4.7. DISCUSSION OF RESULT	46
CHAPTER 5: CONCLUSION AND FUTURE WORK	47
5.1. CONCLUSION	47
5.2. FUTURE WORK.....	48
REFERENCES.....	49

LIST OF FIGURES

Figure 1 The brain and nearby structure [10]	10
Figure 2 image processing steps [22].....	14
Figure 3 Deep Learning architecture [21].....	18
Figure 4 CNN Layers [29]	20
Figure 5 the proposed Architecture for Brain tumor Model	28
Figure 6 CNN model.....	31
Figure 7 Hyperparameter's Model.....	34
Figure 8 augmentation parameters	38
Figure 9 graph of train and loss dataset. 1	40
Figure 10 Chart representation for Scratch Model.....	40
Figure 11 VGG 16 model.....	41
Figure 12 VGG16 model Training accuracy and loss.....	42
Figure 13 VGG16 model Accuracy and loss	42
Figure 14 Inception V3 Model.....	43
Figure 15 InceptionV3 model Training and Loss representation	43
Figure 16 comparison of the three algorithms	44
Figure 17 Model Comparison	45
Figure 18 Classification Report	46

LIST OF TABLES

Table 1: description of the Tools and Python Packages Used During the Implementation [8].--	7
Table 2 Method of over fitting [19]-----	22
Table 3: Image dataset -----	37
Table 4:hyper-parameter setting for pre-trained models. -----	38
Table 5:Summary of experimental results -----	39
Table 6 scratch model accuracy and loss-----	40
Table 7 VGG16 model result -----	41
Table 8 VGG16 Model representation Accuracy and loss-----	41
Table 9 InceptionV3 Model output -----	43
Table 10 three Models Comparison-----	44

LIST OF ACRONYMS

MRI	Magnetic Resonance Imaging
VGG 16	Visual Geometric Group
CNN	Convolutional Neural Network
DL	Deep Learning
IPCV	Image Processing Computer Vision
ROI	Region Of Interest
DIP	Digital Image Processing
TL	Transfer Learning
RELU	Rectified Linear Unit
FCM	Fuzzy C Means
DNN	Deep Neural Network
ResNET	Residual Network
RGB	Read Green Blue
FCL	Fully Connected Layer
ADAM	Adaptive Moment Estimation
CCE	Categorical Cross Entropy
MSE	Mean Squared Error
BCE	Binary Cross Entropy

ABSTRACT

MRI images are the first input used in the detection of brain tumors. The healthcare system would greatly benefit from the development of autonomous detection systems. Due to technological advancements, MRIs are now digital and can be analyzed utilizing image processing methods to automate classification methods. preprocessing steps help to improve the accuracy of brain tumor detection using digital image processing techniques. It typically includes image acquisition and normalization, image enhancement, feature extraction and feature selection.

This study has looked into a technique for classifying brain MRI images using transfer learning and convolution neural networks. This study's primary objective was to develop a model for the identification of brain tumors using transfer learning techniques and techniques for processing and classifying MRI images. This study is confined to categorizing 2800 brain MRI images from Korea hospital in Ethiopia either a tumor or healthy based on their size, shape, and pattern.

The suggested detection system uses a pre-trained model like VGG16 or Inception V3 and combines deep learning with transfer learning. Accuracy measurement like precision, recall and f-1 score metrics were used to illustrate the model's performance and results. The model's accuracy was increased by using a variety of model optimization strategies. The model properly classified images into classes of healthy or tumors 93.10% of the maximum Accuracy. incorporating more fully connected layers with appropriate NNs. Data augmentation is used to avoid over fitting hence the collected data is small in number for this study'. Standard datasets for in-depth experimentation were advised as tasks for the future because machine learning and deep learning algorithms need large size datasets for better performance and generalization.

Keywords: MRI images, brain tumor, CNN, transfer learning, deep learning

CHAPTER ONE: INTRODUCTION

1.1 BACKGROUND

A brain tumor is an abnormal, uncontrolled cell growth that develops within the brain and can reduce the brain's responsiveness [1]. A neurologic examination provides the foundation for a neurologist's or neurosurgeon's diagnosis of a brain tumor. Medical imaging techniques, such as magnetic resonance imaging (MRI), are frequently used to visualize the inside organs of a human body [1].

MRI images are utilized as an input for the detection and classification of brain tumors using a number of criteria, including shape, size, location, and intensity level of the images [2]. Therefore, the development of autonomous detection systems would be extremely beneficial for the healthcare system. MRIs are now digital due to technology improvements, and they can be analyzed utilizing image processing techniques to automate segmentation techniques. picture segmentation is the process of labelling each pixel in a picture so that pixels with the same labels share comparable visual characteristics [3].

The brain stem, thalamus, hippocampus, and other components can all be seen utilizing image processing techniques. Techniques for image processing and computer vision (IPCV) assist in the diagnosis of brain illnesses [4]. Images from MRI scans, which provide a high-resolution scan of different brain tissues, greatly simplify the identification of brain tumors thanks to deep learning [4]. Early detection and accurate categorization are thus made possible by the development of image processing technologies.

The technique of classifying an image or a portion of an image based on information retrieved during image processing [5] is known as image classification. Different categorization methods exist; the most advanced method in computer vision is convolution neural networks [5]. The most common neural network model for image classification problems is convolution neural networks (CNNs). In order to achieve high identification accuracy, CNNs may automatically extract multi-scale picture features using convolution kernels of varying sizes. The ability of CNNs to classify images using patterns rather than manually extracting features makes them particularly effective for identifying objects, faces, and scenes in photos. CNNs learn directly from image data. Training a deep

Convolution Neural Networks require a large number of training data sets; however, medical image data is very limited that could result in over-fitting problem in the training process. Transfer learning (TL) is a research problem in Deep learning (DL) that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem. In this study an attempt has been made to apply a brain MRI image classification algorithm combined with transfer learning and Convolution Neural Networks (CNNs).

1.2. MOTIVATION

After a cancerous brain tumor, the life expectancy is relatively poor [6]. Research is necessary to create brain tumor detection and classification systems, which fall within the category of medical image analysis, in light of new statistics on the death rate caused by brain tumors. Radiologists qualitatively evaluate the brain abnormalities based on the visual confirmation of the brain tumor's presence in the brain MRI. MRI is currently frequently used in hospitals and clinics for medical diagnostics, notably in brain tissue imaging, because it is non-radioactive, painless, and has the advantage of soft contrast. This study suggests using an MRI image classification algorithm along with transfer learning and traditional neural networks to eliminate manual effort, cut down on the amount of time needed to identify a brain tumor, and reduce human error. Automatic segmentation and classification on MRI images are needed to address this problem. Medical image processing's main goal is to accurately and meaningfully extract information from images with the fewest possible errors.

Image processing is one of the technologies that is currently expanding quickly. Within the fields of computer science and engineering, it is a core research area. Digital image processing aids in object identification, confirmation, and detection to streamline problem-solving and hasten decision-making. Brain and other nervous system cancer is the tenth leading cause of death for both men and women, according to data from the most recent ten years [7]. In light of these findings, a study is being carried out to develop the field of medical image analysis using digital image processing and analysis.

Developed nations now have access to automated medical picture analysis. Yet in poor nations like Ethiopia, it hasn't yet been universally accepted. Therefore, the objective of this work is to develop a model for brain tumor detection and diagnosis that is useful and efficient from Ethiopia's perspective.

1.3. STATEMENT OF THE PROBLEM

For the early detection and diagnosis of brain tumors as well as for reducing the mortality rate, magnetic resonance imaging (MRI) is crucial [8]. One of the most important applications of magnetic resonance imaging is the detection of brain tumors. However, as there is presently no technique that can fully automatically detect brain tumors, MRIs are assessed by human professionals. This requires time and focus, which increases the likelihood of human error. Increases in the number of magnetic resonance imaging (MRI) tests in particular increase tiredness and reduce professional performance.

It is quite challenging to diagnose brain tumors because of the variations in tumor location, shape, and size. MRI is the most effective and widely used technique for locating brain tumors. The majority of radiologists today classify and diagnose MRI images using manual labelling techniques, but these techniques are ineffective since they add time and expense to the process, which increases the chance of false positives and poses substantial issues for the patient. The objective of computer vision and image processing approaches is to give medical picture diagnoses that are more rapid and precise than manual methods for identifying brain tumors.

Accuracy is essential in the classification of medical images. It is necessary to use a computer-based strategy that can ultimately assist radiologists in making decisions. As a result, the identification of brain tumors is made simpler and easier when an image processing technology is combined with a deep learning algorithm. The diagnosis of brain tumors can frequently be made with conventional MRI, but it shouldn't be relied upon too heavily, especially for specific tumor types. Neurosurgeons are urged to confer with the reporting neuro-radiologists in cases of discrepancy in order to achieve the best preoperative diagnoses. The radiologist may interpret them wrongly for a variety of

reasons, as MRI scans and other radiological exams illustrate. A false negative diagnosis could mislead the patient's referring doctor and delay required treatment.

The most common reason why brain tumors are misdiagnosed is because a doctor neglected to order extra testing in response to a patient's symptoms. Since brain tumor symptoms commonly match those of other prevalent conditions, a doctor may diagnose and suggest treatment for another ailment instead. The use of artificial intelligence techniques for early brain tumor diagnosis can increase the likelihood that a patient would recover from their ailment following therapy. There aren't enough physicians, oncologists, or pathologists in Ethiopia to quickly and accurately identify, locate, and categorize brain tumors. According to reports, [2] there is one doctor for every 57,876 people nationwide, however [3], [4] between 200,000 and 300,000 people are served by one doctor in southwest and west central Ethiopia. Early diagnosis and treatment support patients in receiving proper care, which lowers the risk of brain tumor morbidity. Research shows that machine learning approaches can identify cancer with 91 percent accuracy, compared to most experienced doctors' 79 percent accuracy. Because of this, utilizing various Deep Learning and machine learning approaches can be quite helpful in identifying and categorizing brain tumors. Many internet datasets are available for use in creating deep learning models. The dataset in this study uses medical images gathered from Ethiopian hospitals to get around this issue. in order to use the most recent deep learning-based models for brain tumor detection. It is necessary to design a model for detecting brain tumor disease in order to address this issue and support specialists. Many people are interested in using deep learning to solve medical imaging issues as a result of its quick development as a family of machine learning techniques. This study uses a local imaging data set to investigate and construct a deep learning algorithm-based brain tumor detection model. The primary objectives of this study are to apply digital image processing and Transfer learning algorithms for brain tumor detection utilizing MRI scans and to evaluate the patient's state (i.e., normal or tumor).

1.4 RESEARCH QUESTIONS

To assess the aforementioned problem, this study will look at and address the following research questions:

- What characteristics are more critical to the description and representation of images of brain tumor?
- Which deep learning technique is better suited for detecting brain tumor?
- To what extent is the model useful for identifying and categorizing brain tumor?

1.5. OBJECTIVE OF THE STUDY

1.5.1. GENERAL OBJECTIVE

The overall objective of this research is to develop brain tumor detection model by utilizing transfer learning and Digital image processing classification techniques.

1.5.2. SPECIFIC OBJECTIVES

The following specific objectives are attempted to be completed in order to meet the study's overall goal.

- To review relevant material to find approaches and procedures that work.
- To gather and prepare dataset for experimentation's training and testing.
- To choose efficient feature extraction, segmentation, and image filtering algorithms.
- To assess the prototype's performance

1.6. SIGNIFICANCE OF THE STUDY

Because brain tumors are becoming more common, radiologists must diagnose an alarmingly greater number of MRI pictures. Patients had substantial challenges as a result of a shortage of skilled staff and high examination prices. This idea might considerably improve the way that brain tumors are now diagnosed in the medical field. It combines an algorithm for identifying MRI images using transfer learning, CNN architecture, and other techniques. In this situation, automating brain tumor identification could benefit radiologists, patients, and researchers in a variety of ways. It allows for quicker picture analysis than the present methods in a screening environment. It also minimizes the burden for radiologists, which brings down hospital expenses. This work might help other

researchers to carry out additional investigations that advance the development of automatic brain tumor identification and classification.

1.7. SCOPE AND LIMITATION

Since brain images produced by an MRI scan may be normal or abnormal, this study takes into consideration both normal and pathological (tumor) instances. Based on their size, shape, and color, brain images from an MRI scan will be classified in this study as either a tumor or a normal structure. However, after determining its irregularity and detecting a tumor, the study does not account for classifications of tumor types. The study uses the CNN algorithm with transfer learning techniques such feature extraction, fine tuning, and data augmentation to improve accuracy and learning rate. The suggested model would be developed using data that was compiled from images taken at the Korea hospital in Ethiopia between 2020 and 2023. The research has only been unable to cover X-ray and colposcopy images. Additionally, data that lacks category 1 and category 2 information is uneven.

1.8. METHODOLOGY OF THE STUDY

1.8.1. RESEARCH DESIGN

The goals of the thesis are met in this study through the use of an experimental research design. Experimental research is a term used to describe a study that uses a scientific research methodology. The primary steps conducted in this study were gathering the data, doing the experiment, and analyzing the outcomes. The parts that follow provide more information on the techniques used to finish the jobs.

1.8.2. DATA PREPARATION

We must first gather the data needed to train the neural network model in order to use deep learning or neural networks in our research. The main input for the model in this thesis is information from MRI imaging of brain tumor. However, we are unable to obtain and use enough publicly accessible databases that contain thousands of images of brain tumor in order to train the algorithm. As a result, with the assistance of doctors and other healthcare

professionals, I was able to receive MRI scans of brain tumor from Korea Hospital in Ethiopia. A strong magnetic field and radio waves are used in the MRI (Magnetic Resonance Imaging) process to provide precise images of the inside of the body. Korea hospital is well recognized as a high quality and standardized hospital in Ethiopia.

1.8.3. IMPLEMENTATION TOOLS

The suggested solution for brain tumor identification is put into practice by the study using a variety of implementation tools and packages. From data preprocessing to model building and evaluation of the implemented and suggested classifier models, Python is utilized in this study's implementation and experimentation with each suggested solution. Python will be utilized in this study since it is a popular choice among developers, academics, and data scientists who must work with machine learning models.

The list of implementation tools and Python packages utilized in this study is shown in Table 1 below, together with information about each package's version and description.

Table 1: description of the Tools and Python Packages Used During the Implementation [8].

NO	Tool	Description
1	anaconda Navigator (anaconda3)	a collection of various programming languages for scientific computing that include deployment and package management. The distribution provides software for machine learning and data science that are compatible with operating systems. Additionally, it permits the establishment of development applications.
2	Jupyter Notebooks	An open-source web application that enables the creation and sharing of documents including text, live code, equations, and visuals. It was utilized for machine learning, statistical modelling, data visualization, and data cleaning and transformation.
3	Python 3.9.0	A build environment for the powerful, simple-to-learn programming language Python is required to create a machine learning application.

4	Microsoft Excel	used data preparation procedures to clean, filter, sort, and get rid of duplicate data from the collected data utilized to control the annotation task as well.
5	Scikit-learn	a collection of data mining and machine learning modules for Python. It is utilized in this work for model training and testing as well as feature extraction. Sklearn is the name of the package.
6	TensorFlow	Google created the open-source TensorFlow library for machine learning and artificial intelligence. A versatile and effective platform for creating and refining machine learning models, especially deep neural networks, is what it's there to do.
7	Keras	A high-level interface for creating and training neural networks is provided by the open-source deep learning library known as Keras. To enable researchers and developers quickly prototype and deploy deep learning models, it aims to create a user-friendly and intuitive platform for deep learning.
8	Pandas	data structures and tools for data analysis that are fast and simple to use. It is used in this study to read, manipulate, write, and handle the data frame.

1.8.4. EVALUATION METHODS

Performance evaluation One of the primary objectives in the development of deep learning is performance evaluation of the model. The process of evaluating a model's predictive ability is called model evaluation. Test datasets should be used during the evaluation phase to gauge the effectiveness of the model.

One of the evaluation criteria used for the study is the confusion matrix. A good evaluation metric for deep learning and the machine learning classification problem of brain tumor identification is the confusion matrix performance measurement. Confusion matrices help us determine how accurately a model predicts certain specific classes as well as errors. The confusion matrix includes measurements for accuracy, precision, recall, and F1-score.

1.9. ORGANIZATION OF THE THESIS

There are six chapters in this thesis. An overview of images and image processing, steps in image processing, picture reprocessing, image analysis (segmentation and feature extraction), deep learning techniques, and a review of related literature are all covered in Chapter 2. The architecture and techniques for putting the brain tumor detection and classification prototype into practice are covered in chapter three. Additionally, it is committed to comprehending the data and pre-processing it to provide high-quality datasets for the classification task. The experiment of the research is described in Chapter 4. The models are trained, built, and then validated. The experiment's findings were also examined and explained. The study's conclusions and potential future directions are presented in chapter five.

CHAPTER 2: LITERATURE REVIEW AND RELATED WORKS

In order to identify a research gap and provide an explanation for earlier researchers' work, this chapter looks at literature reviews and related publications. The description of a brain tumor is explained in Section 2.1, followed by explanations of the different types of brain tumor diseases in Section 2.1.1, the use of digital image processing for brain tumor detection in Section 2.2, the description of brain disease detection using a convolutional neural network in Section 2.3, a some more related common works in Section 2.4, and a summary of the literature review also included.

2.1. BRAIN TUMOR OVERVIEW

The brain is a mushy, spongy mass of tissue that has a very complicated structure and is regarded as a core component of the body. It is shielded by the skull's bony structure, three delicate tissue layers called meninges, and the cerebrospinal fluid that circulates within the brain's ventricles and between the meninges [8] [9].

Tumor is a condition that inhibits cells from responding to common stimuli. Uncontrollable growth and division of aberrant cells can result in tumors [10]. An invasive tumor is one that has progressed past the site of its initial appearance and is now encroaching on neighboring normal tissues. In Ethiopia, brain tumors are the most prevalent illness category [10]. Many imaging modalities can be used to provide medical images, but they can all be categorized into those that display bodily anatomy and those that reveal metabolic activity or function. The goal of magnetic resonance imaging (or MRI), which is one type of anatomical imaging, is to find brain cancers.

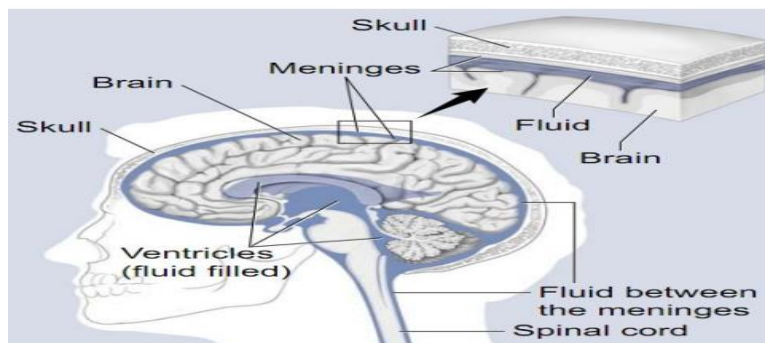


Figure 1 The brain and nearby structure [10]

The most typical signs are abnormal limb movement, numbness, abnormalities in vision or speech, or mental problems. Several types of seizures are one group of symptoms brought on by localized inflammation of the brain tissue. A group of symptoms known as the "syndrome of elevated intracranial pressure" primarily includes headache, nausea, and vision abnormalities.

2.1.1 TYPE OF BRAIN TUMORS

More than a hundred different forms of brain and spinal cord cancers exist (also called central nervous system or CNS tumors). There are two major types of brain cancers: primary brain tumors and metastatic brain tumors. They are typically termed by the cell type they began in [11].

2.1.1.1 PRIMARY BRAIN TUMOR

Primary brain tumors start, and tend to stay, in the brain; there are several types of primary tumor described below [10]:

A. Malignant Tumor

Malignant tumors typically spread across the brain and spinal cord and grow quickly. It is also possible for malignant brain tumors to prove fatal. Around 40% of tumors in the brain and spinal cord are cancerous [11].

B. Benign Tumor

Benign tumors frequently stay with the epithelium or have an outside surface made of fibrous connective tissue [12]. The majority of benign tumors has distinct borders (margins), slow-growing cells, and rarely spread. They may, however, be present in crucial brain regions that regulate key bodily processes, making them potentially fatal. Some benign brain tumors can transform into a malignant tumor that grows quickly [13]. The term "malignant transformation" refers to this process.

2.1.2 TUMOR GRADE

The tumor's grade is determined by how the cells appear under a microscope [14]:

- The tissue is grade I benign. The slow-growing cells seem like regular brain cells.
- Cancerous tissue, Grade II. The cells here look less like normal cells than the cells in a Level 1 tumour.
- Grade III: The malignant tissue contains cells that seem very different from normal cells. Cells that are actively undergoing aberrant development are said to be anaplastic.
- Grade IV: The malignant tissue contains the most atypical-looking cells and a propensity for quick development.

2.1.3 MAGNETIC RESONANCE IMAGE (MRI)

The outcomes of an MRI scan can be utilized to identify issues, formulate treatment plans, and assess the success of earlier interventions [15]. In order to provide precise images of the inside of the body, magnetic resonance imaging (MRI) scans use strong magnetic fields and radio waves.

2.2. INTRODUCING IMAGE PROCESSING

A two-dimensional object or scene that has been photographed and saved in a digital format is represented visually in a digital image. It is produced by utilizing a digital camera or scanner to turn an analogue picture, such as a painting or photograph, into a digital file. Pixels, the little dots that make up an image in digital form, are used to store and alter the images. The color value that is assigned to each pixel influences how it will appear in the final image. "Image processing," also referred to as "image manipulation," is the process of making various changes to photographs in order to improve their quality and extract information that may be used to describe them. In order to make an image more appealing to human viewers and to make it ready for measurement of the features and structures it includes, image processing is used. image acquisition, image augmentation, and image segmentation are examples of photo processing techniques [16].

2.2.1. DIGITAL IMAGE PROCESSING

To extract information, evaluate digital images, and most importantly, to fully utilize the processing of images, the procedure is divided into three levels, namely low, mid, and the highest-level processes. [17].

Processing at a Low Level: A few of the fundamental procedures required to remove and reduce noise from images are sharpening, improving the contrast, scaling of images, and preprocessing images. The ultimate aim of this fundamental process is to alter the character of the image so that it displays information more accurately. The low-level processing's input and output constitute separate images. [19], [20].

Processing at a Low Level: Sharpening, contrast improvement, resizing of and preprocessing images are just a few of the fundamental processes required to remove and eliminate noise from images. The final result of this fundamental process is to alter the character of the image so that it conveys information more accurately. The low-level processing takes the image as input, and generates results. [20].

High-level processing entails intricate image processing operations that interpret a collection of recognized objects. Computer vision is typically linked to this process. In these stages of processing, attributes are used as the input, and information is extracted from them to produce an understanding of the digital image [17] [20].

2.3. IMAGE PROCESSING STEPS

The bulk of studies have shown that the following crucial steps must be followed in order to create a successful application using digital image processing. There are many different substages and strategies for each fundamental stage. The main processes are shown in Figure 2, and the several sub stages—all of which are covered below—are where the work is really done. Similar to how an input step links to its successor phases, each phase's drop-down steps do the same [22].

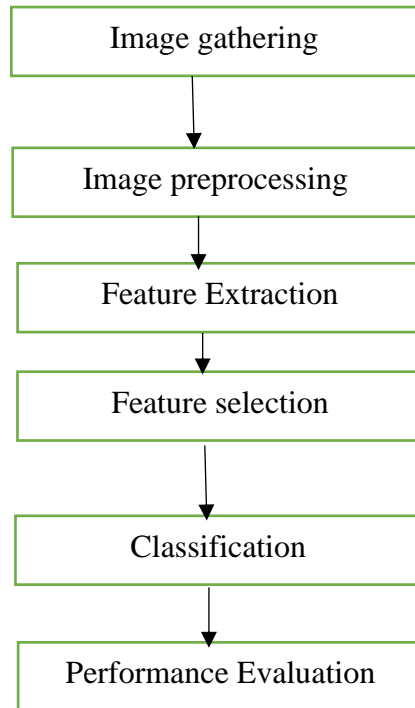


Figure 2 image processing steps [22]

2.3.1 IMAGE ACQUISITION

Every digital image processing task begins with obtaining a unique input image from the source that provided it (where an image may be discovered) [21]. There are actually numerous methods to utilize image gathering. When thinking about this step, the only thing that comes to mind is capturing a photo of the actual surroundings, however it is also feasible to obtain an existing image file from any electronic source using any gathering approach. When viewed from the side of the intended image processing project, the acquired image remains completely unprocessed. Having a consistent starting point can be quite important in several industries. It was created using the same hardware that created the original image.

Most environmental scene analysis applications, like face recognition, item or animal identification, plant disease detection, and environmental scene analysis, can be performed on raw images of environmental sceneries taken with an electronic camera, cell phone camera, or webcam. Different sources are utilized to retrieve raw photographs depending on the requirement or type of operation. Diagnostic imaging apparatus, such as a CT and

MRI machines, are devices that can be used to obtain images for diagnostic purposes, such as the detection of tumor and cancer. Satellites can also supply images for the administration of geographic data and related applications [22]. Magnetic resonance imaging was used to collect the data for the investigation.

2.3.2 IMAGE PREPROCESSING

A picture may be preprocessed using filters, formatting, removing artefacts, and shade correction, among other processes, to improve image data before computing processing. The purpose of filtering is to enhance the stability of the image's features by lowering a small amount noise in the surroundings, adjusting the intensity of each particle image, reducing reflections, and concealing portions of the images. [23].

Images can be scaled to make a smaller, more compact version of the initial image in order for easier processing [24], but this is only advised if the resulting image retains all of the original's meaning and appearance after scaling. Although it is physically conceivable, processing of digital images is the most used method. A few of the tasks involved in image preparation are described below.

Image conversion: This is a part of preprocessing, which may entail changing an image's format or color space in order to accelerate computation [25]. For instance, because they are simpler to analyses than those with wider color gamut, such as RGB or other sorts, colorful picture graphs are routinely turned into colorless or black and white images. image transformation is not often essential, nevertheless; it could potentially be omitted in circumstances when the results might change how an image is interpreted. In this case, compared to graphs composed of monochrome pictures, colored graphics offer more detailed information. Maintaining the color image in its original state or converting it back to color is essential for the aim of detecting brain cancer illnesses.

Image augmentation: A phase in the editing process where a number of approaches are used to give an image a further, more significant meaning. Contrast adjustment is the most widely used method for enhancing photographs. Improving the visual impact of an image is the major aim of the picture rehabilitation sub-step [26]. In contrast to picture augmentation, which is subjective, picture restoration is objective. This is due to the fact

that methods for photo restoration usually incorporate probabilistic or mathematical models of image deterioration.

Image enhancement:

Image enhancement is the technique of enhancing an image's visual appeal. Before photos are fed into a neural network in deep learning, they are first preprocessed using image enhancing methods. By lowering noise, boosting contrast, and enhancing the visual quality of the input image, image enhancement in deep learning aims to increase the accuracy and robustness of the neural network [27].

Image restoration:

Image restoration is a process of recovering the original quality of a degraded or corrupted image. In deep learning, image restoration techniques are used to preprocess images before they are fed into a neural network. The purpose of image restoration in deep learning is to improve the quality of the input image, which can improve the accuracy and robustness of the neural network. The purpose of image restoration in deep learning is to improve the quality of the input data and make it easier for the neural network to detect and classify features in the image. This can lead to more accurate and robust models that perform better on real-world data [28].

2.3.3 IMAGE SEGMENTATION

In the context of digital image processing, image segmentation refers to any method that splits or arranges an image into distinct pertinent chunks or segments [26]. Typically, these regions coincide with the regions of the image where people can quickly identify various items. A variety of data are used to construct the picture segmentation approach. This can be a portion of a picture, color data, or border data. The reliability of extraction of features and the accuracy of identification are closely related to the quality of the segmentation result. The fields of image processing and computer vision today use a range of image segmentation methods based on the difficulty or image that needs to be segmented [26]. There are benefits and drawbacks to each strategy. The two primary strategies for segmentation are region-based and edge-based. A picture is separated into portions for area-based approaches to segmentation based on how similar the pixel values are inside a

region, for as in terms of color, texture, or intensity. Edge-based approaches divide a picture into portions based on pixel value shifts or discontinuities, such as edges or division lines.

2.3.4. FEATURE EXTRACTION

Feature extraction is a process of extracting meaningful features from raw input data, such as images, audio, or text that can be used as inputs to a machine learning model. In deep learning, feature extraction involves using a pre-trained neural network to extract high-level features from the input data, which can then be used as inputs to a new neural network. For analysis utilizing a convolution tool, pooling, or stride, feature extraction is the process of extracting and noticing various elements of an image, such as lines, shapes, and margins. According to the aforementioned literature analysis and related studies, most brain MRI classification tasks that are carried out using deep learning approaches use GLCM and GLRLM algorithms to extract texture characteristics. Although CNN was used to divide the data into normal and pathological categories, transfer learning and CNN techniques were linked [29][31].

The main argument in favors of utilizing CNN in deep learning is the employment of several extraction of features processes, which can produce a representation of data autonomously from input data. Due to variables including the availability of a lot of data and improvements in hardware technology, CNN's research has expanded. A variety of innovative CNN designs have also been described recently. These structures, among other things, made use of diverse activation and loss functions, parameter optimization, and new architectural techniques [30].

2.4. DEEP LEARNING

Extraction of various features from dispersed representations is the aim of the "deep learning" subclass of machine learning techniques [27]. The distribution of data can be found using computational models with several processing layers and different degrees of description. Additionally, it is solving issues that the artificial intelligence sector encounters with considerable success [27]. Since it has delivered outstanding results in

professions requiring a complex operation with a sizable amount of data, such as speech recognition, image recognition, and other tasks, this field is groundbreaking [28].

As seen in figure 3, deep learning has input, output, and several hidden layers. Each layer in deep learning receives its output as an input before moving on to the next layer. When it originally arose a few years ago, the machine learning area of research was successful in comparison to some other areas of study, but it wasn't further investigated to address the problem in our community [28].

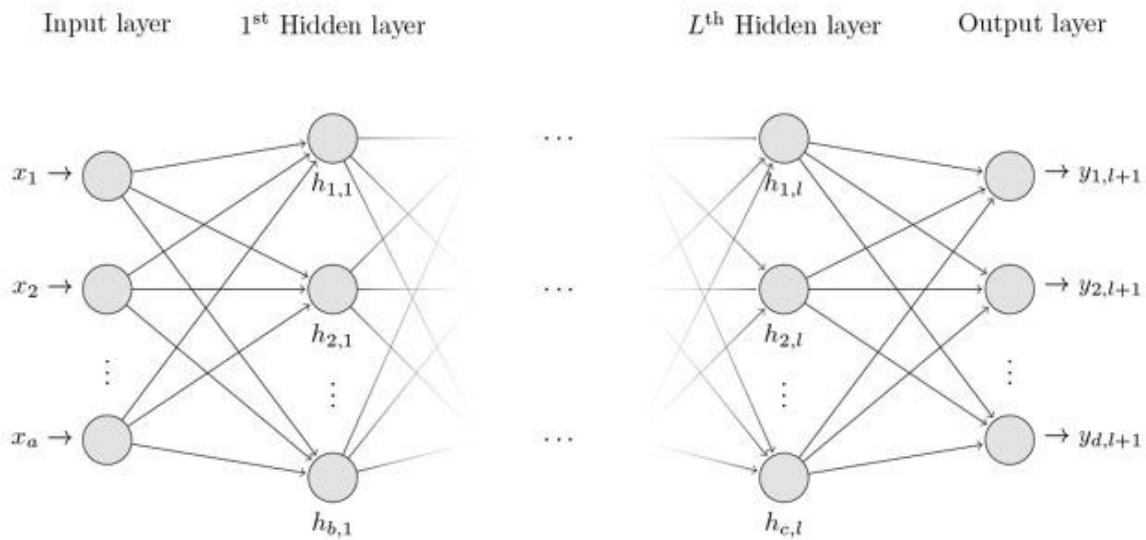


Figure 3 Deep Learning architecture [21]

According to Christopher Thomas [22], deep CNN has demonstrated outstanding performance in computer vision and deep learning problems. But architectural innovation was the main factor in CNN's development. The learning process is represented by deep learning. The most useful approach to represent data is found through optimization through learning representation model algorithms. Because the features are automatically learnt by the model as it is being trained.

2.4.1. Comparing CNN vs. Classical Classification methods

Compared to other traditional classification techniques, CNN is unique. The majority of randomized experiments, according to Khan [29], utilised support vector algorithms and random forest modelling as manual extraction of features methods, correspondingly, shortly after texture processing. On the other hand, the CNN design combines feature extraction and classification, with CNN automatically extracting invariant traits for effective categorization.

The following are the differences between CNN and conventional categorization methods [29].

- Neither expert-based feature extraction nor feature segmentation by human specialists are required by the CNN architecture.
- Due to the millions of learnable parameters, a model must be trained using a lot of data, which is more computationally intensive and necessitates the usage of GPU (Graphical Processing Unit) technology.

Convolutional neural networks (ConvNets) are a popular type of neural network that are employed to address problems such as identifying images, identifying objects, recognition of faces, and image categorization. Applications for the convolutional neural network include bioinformatics, recognition of speech, spoken language being processed, processing images, and picture rehabilitation. CNN can easily separate a feature with several layers and conduct in-depth research because it doesn't require as much preprocessing to identify and classify objects [30]. The four layers that make up CNN are the convolutional layer, the pooling layer, the RELU activation function, and the fully

connected

layer.

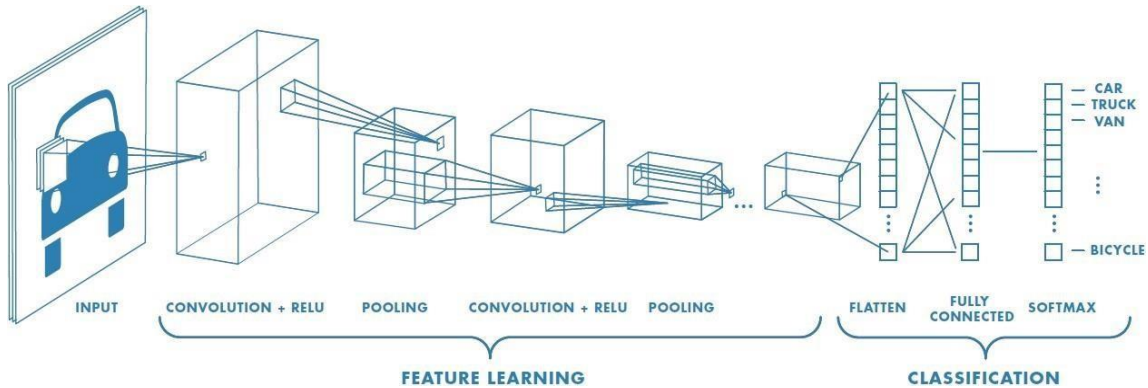


Figure 4 CNN Layers [29]

Convolutional Layer: The CNN algorithm was modelled after the convolutional layer. This layer applies several mathematical processes, such as a matrix operation, to the input image to extract a feature map [27]. Starting at the upper left corner of the image, the filter is initially slowly moved. The image data are multiplied by the filter (kernel) values at each step to get the weighted sum of the convolutional feature.

Pooling Layer: The pooling layer is used as the following layer after the convolutional layer procedure. The pooling layer introduces translation invariance to a minor shift and distortion, lowers the in-plane dimensionality of feature maps, and reduces the number of subsequently learnable parameters. [37], offers the typical down sampling approach. A map of features is produced as an output following the completion of a convolution layer operation. The pooling layer compresses the characteristic mapping output from the Conv layer. The pooling layer uses a range of filter sizes, but most frequently a 2 by 2 size filter. The layer for pooling utilizes a number of pooling procedures, including sum, average, and max pooling.

Max Pooling: With max pooling, the highest value is chosen from each pooling window, and all other values are discarded. As a result, the input's spatial dimensions are decreased yet the most crucial features are retained in a down-sampled feature map. For tasks involving object identification and classification, CNNs frequently adopt max pooling.

Average Pooling: Average pooling calculates the average value from each pooling window and discards the other values. This results in a down-sampled feature map that retains the general structure of the input and reduces the spatial dimensions of the input. Average pooling is commonly used in CNNs for tasks such as image segmentation and depth estimation.

Sum Pooling: Sum pooling calculates the sum of values from each pooling window and discards the other values. This results in a down-sampled feature map that retains the overall structure of the input and reduces the spatial dimensions of the input. Sum pooling is less commonly used than max and average pooling, but can be useful in some applications such as saliency detection and texture analysis.

Non-Linear Activation Function: A non-linear activation function is used in conjunction with the neural network in deep learning to solve a variety of challenging issues, including image categorization, object recognition, object detection, and others. This is one of the CNN design's criteria. Using the weighted sum and bias, the function's task is to decide whether or not to terminate a function. Selecting the appropriate activation function will improve the model's learning process. Examples of these activation function types are the rectified linear unit (RELU), Sigmoid function, Hyperbolic tangent (Tanh), SoftMax, and others. An alternative difficult problem, like image detection, is solved by a neural network's activation function.

Dense layer: This layer is crucial for CNN to correctly recognize and classify a picture using computer vision. After the convolution and pooling layers, the input image is separated into a set of features and given an independent analysis. In order to classify a picture, the FC layer flattens the output of the pooling layer.

Underfitting: When the model is either too simple or not complex enough to reflect the underlying patterns in the data, underfitting occurs. This could lead to a model that is overly generalized and underperforms on both the training data and fresh, untainted data. High training error and high validation error are indicators of underfitting.[19]

Over fitting: When a statistical model learns from the data and begins to recognize noisy and erroneous data inputs, it is said to be over fitted. As a result of the over fitted model's inability to generalize fresh data while being tested, over fitting is a significant difficulty in deep learning [19]. The set of tests dataset is necessary in order to assess a deep learning model's effectiveness. Table 2 provides a summary of various techniques that have been suggested to reduce over fitting.

Table 2 Method of over fitting [19]

How to avoid becoming too tight	
1	training datasets
2	Adding more datasets
3	Regularization is performed.
4	Batch size Normalization
5	Make architecture simpler

2.5. TRANSFER LEARNING METHODS

Transfer learning, a method of learning which involves training a network of neurons with data for one task and then applying the knowledge acquired to another, is one of the most helpful concepts in artificial intelligence [27]. Training a deep learning model may take a few hours or several weeks, depending on the difficulty of the task and the amount of the dataset. One approach to address this problem is to reuse the model weight from a pre-trained model that was built for popular machine learning benchmark datasets, such as Image Net image recognition tasks. Top-performing models can be downloaded and used, depending on the problem. On a problem resembling the one at hand, a neural network model is developed using the deep learning method of transfer learning. Then, one or more of the layers of the training model will be placed on top of one or more of the layers of the new model. The use of models that have been trained like InceptionV3, VGG16, ResNet, it was and others is one benefit of transfer learning [28]. These models were produced using a powerful computational system, numerous images, and thousands of classes. Transfer

learning, which uses less computer resources and training time, is used to address the issue of having less data. The following part provides a description of a few of the pre-trained models employed in this study, such as VGG16, and InceptionV3 [29].

Alex Net

Convolutional neural network architect Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton created AlexNet. It was the entry that was chosen as the winner of the 2012 ImageNet Large Scale Visual Recognition Challenge (ILSVRC). A major development in computer vision was AlexNet, which showed that deep neural networks could perform better than conventional machine learning algorithms at picture categorization tasks. Its architecture includes methods like local response normalization and dropout to enhance generalization. It consists of five convolutional layers, followed by three fully connected layers. The creation of more sophisticated deep neural network architectures, many of which are still in use today, was made possible by AlexNet's success. [30].

VGG16

The Visual Geometry Group (VGG) at the University of Oxford created the convolutional neural network architecture known as VGG16. When it was first used in 2014, it excelled in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). The design has 16 layers, including three fully linked layers and 13 convolutional layers. With its tiny filters (3x3), consistent padding across all convolutional layers, and usage of max pooling layers to condense the spatial dimensions of the feature maps, VGG16 is renowned for its simplicity and uniformity. The network can learn more complicated characteristics thanks to the usage of tiny filters with numerous layers, and the architecture's uniformity helps to minimize overfitting.

Google Net

The pre-trained model Google Net, sometimes referred to as InceptionV3, won the 2014 ILSVRC competition. The Google Net architecture tries to reduce computational costs, and the network's width and depth have increased while its computing cost has reduced [32].

2.6. RELATED WORKS

Seetha et al. [30] proposed classifying brain tumors using the CNN classifier. This technique involves the separation of the brain tumor using the FCM algorithm, the extraction of the features using the GLCM approach, and the classification of the features using the SVM and Deep Neural Network algorithms. In this work, normal and tumorous brain MRI classification based on CNN was used. The Image Nets retrained model is used to reduce training time. The training accuracy using this strategy was 97.5%. The suggested approach was assessed using a dataset of MR images of brain tumors, and the findings revealed that the CNN classifier had a high level of accuracy in classifying brain tumors. The study showed the potential for classifying brain tumors using deep learning techniques, which can increase diagnosis speed and accuracy and support the creation of individualized treatment programs.

Deepak et al. [31] advocated the application of transfer learning for feature extraction from brain MRI. The authors extracted elements from brain MRI and utilized them to classify brain tumors into several groups using a pre-trained convolutional neural network (CNN). The process involves feature extraction using the pre-trained model after fine-tuning a pre-trained CNN model on a small dataset of brain MRI images. In order to classify brain tumors according to their histological characteristics, a classifier was trained using the collected features. The suggested strategy was tested using a collection of brain MRI images, and the findings revealed that the transfer learning-based method classified brain tumors with a high degree of accuracy. The study showed the potential of using transfer learning to brain MRI feature extraction, which can enhance diagnosis speed and accuracy and support the creation of individualized treatment regimens.

Muhammad Sajjad et al.'s method for categorizing multi-grade brain tumors [32] made use of deep learning. This approach first uses the CNN model to segment the brain tumor, then adds various parameters to the segmented data to boost the training samples, before training the model with the appropriate VGG-19 CNN model. The accuracy of this system grew from its initial 87.38% to 90.67% with the additional data.

A technique for automating the diagnosis of brain tumors using magnetic resonance imaging (MRI) scans was put out by Kumar and Ganesh Kumar [10]. The suggested procedure required preprocessing the MRI images and then utilizing a level set method to separate the regions of the brain and tumor. A texture-based feature extraction method was used to analyze the segmented images, extracting properties including energy, entropy, and homogeneity. A support vector machine (SVM) classifier was trained to distinguish between normal brain tissue and tumor tissue using the collected features. The proposed method was evaluated on a dataset of MRI scans of brain tumors, and the results showed that the SVM-based classifier achieved high accuracy in the detection of brain tumors. The study demonstrated the potential of using texture-based feature extraction and SVM-based classification for automating the detection of brain tumors, which can help in the early diagnosis and treatment of the disease.

Magdi et al. [11] proposed an intelligent model for automatic brain tumor identification based on MRI scans. The proposed method involved preprocessing of the MRI images, followed by feature extraction using a combination of texture analysis, wavelet transformation, and morphological operations. The extracted features were then used to train a machine learning model, specifically a multilayer perceptron (MLP) neural network, to classify the MR images into four categories: normal, edema, malignant, or neutral. The proposed method was evaluated on a dataset of MRI scans of brain tumors, and the results showed that the MLP-based classifier achieved high accuracy in the identification of brain tumors. The study demonstrated the potential of using machine learning and image processing techniques for automating the identification of brain tumors, which can improve the accuracy and speed of diagnosis and help in the development of personalized treatment plans.

Javaria Amin et al. [33] proposed a method for image fusion of brain MRI and CT scans using a combination of wavelet transform and nonsubsampling contourlet transform (NSCT). The proposed method involved preprocessing of the MRI and CT images, followed by decomposition of the images using wavelet and NSCT transforms. The decomposed images were then fused using a weighted averaging method, followed by

reconstruction of the fused image using inverse wavelet and NSCT transforms. The fused image was then analyzed using a region growing algorithm to segment the brain and tumor regions. The proposed method was evaluated on a dataset of brain MRI and CT scans, and the results showed that the proposed method achieved high accuracy in the fusion of the images and segmentation of brain and tumor regions. The study demonstrated the potential of using image fusion techniques for improving the accuracy of brain tumor diagnosis and treatment.

2.7 RESEARCH GAP

A research gap refers to a topic or area within a field of study that lacks sufficient research or has not been adequately addressed by previous research. Identifying research gaps is important as it helps to highlight areas where further research is needed and can guide researchers in designing new studies. In the context of brain tumor detection using CNNs, some potential research gaps include:

- Limited datasets: There is a need for larger and more diverse datasets to train and test CNN models for brain tumor detection.
- Interpretability of CNNs: CNNs are often considered black boxes, making it difficult to interpret their outputs and understand how they make decisions.
- Integration into clinical practice: There is a need to integrate CNN-based methods into clinical practice, which requires addressing issues related to regulatory approval, validation, and clinical adoption.
- Generalization across different populations: CNN models trained on one population may not generalize well to other populations, highlighting the need for studies that evaluate the performance of CNNs across different populations.

By addressing these research gaps, this research can improve the accuracy and speed of brain tumor detection using CNNs, which can ultimately lead to improved diagnosis and treatment for patients in Ethiopia.

CHAPTER 3: METHODS AND APPROACHES

3.1. OVERVIEW

The experimental setup and design of the proposed model are the main topics of this chapter. The building of the recommended model, the gathering of its descriptions and attributes, the detection procedure, and the usage of other pre-trained models are all quickly explained using the so-called transfer learning approach.

3.2. THE PROPOSED ARCHITECTURE

It first collected and categorized the MRI pictures before processing the raw data that had undergone data preparation. The system is set up in this way. At this stage, data normalization, image cropping, and disease classification labelling are done to prepare the images. The preprocessed images with dimensions of $228*228*3$ clearly show the area of interest. From the CNN stacked layers, the salient features of each image are extracted, and detection is then carried out utilizing the retrieved feature to create a model. During training, features from the brain model were retrieved, and the classifier used these features to distinguish between patterns in healthy and tumor brains. The model's performance is assessed during training using a validation sample; as an alternative, the validation set is used to evaluate the model's effectiveness after training. The best performing model is chosen via model evaluation after the highest performing model has been created entirely from scratch and has undergone thorough testing using pre-trained models. The most effective model is assessed using unlabeled, unseen data at the conclusion of the testing session. Class prediction, the model's final output (in our case, the classes are healthy and tumor), shows the likelihood that a picture will fall into one of the predefined classes after training.

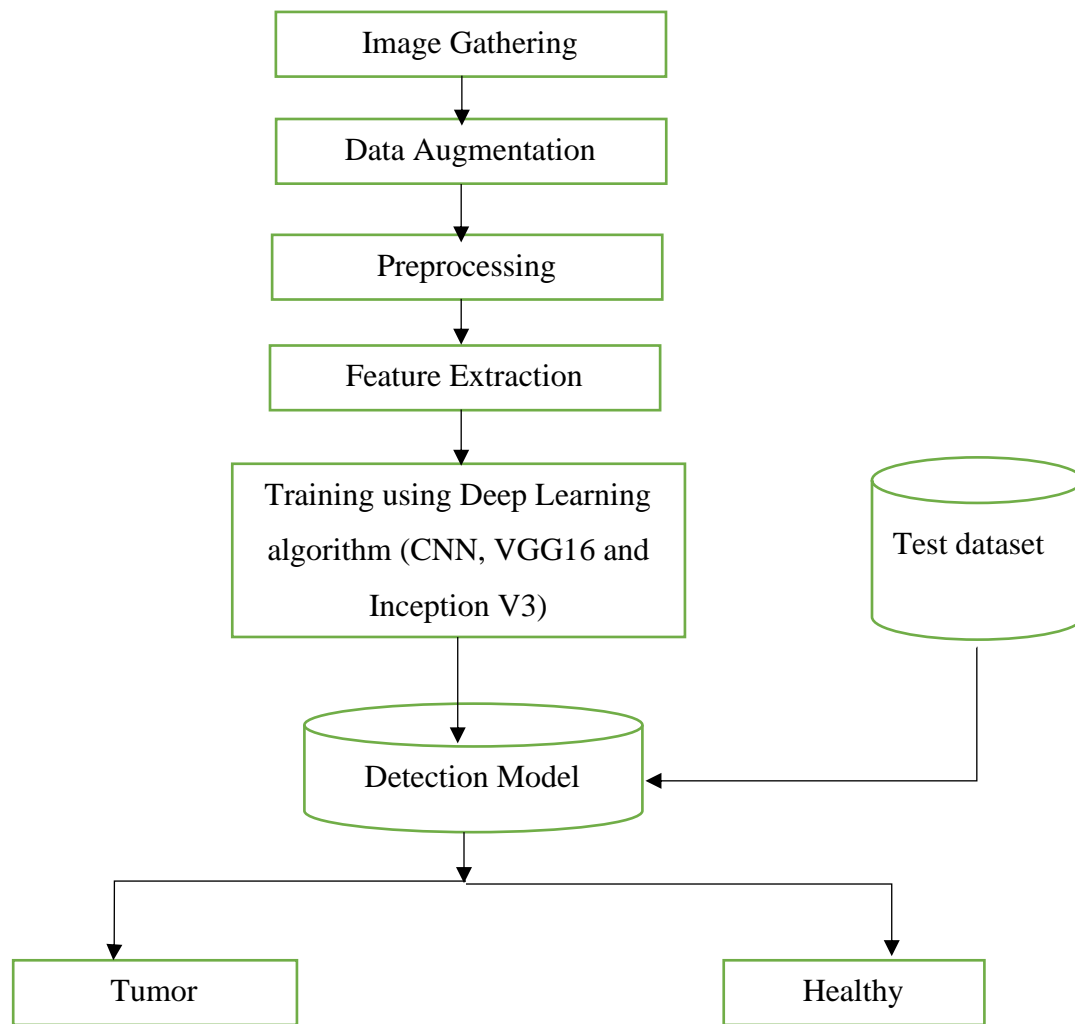


Figure 5 the proposed Architecture for Brain tumor Model

3.3. IMAGE DATA PREPARATION

3.3.1. IMAGE PREPROCESSING

Preparing medical pictures, such as MRI and CT scans, for analysis and interpretation is referred to as image preprocessing. In the context of finding tumors in the brain, image preprocessing methods have been used to improve the images' quality, eliminate noise and artefacts, and restore the image intensity. The obtained photos are standardized to a size of 228*228 using a Python resize function.

Using the Label Image tool, the enlarged photos are labelled or classified due to the proper tumor phase categories. The type of file used when annotating an image is jpg. Software programs used to annotate or label medical pictures, such as MRI and CT scans, for the purpose of spotting brain tumors include (3D slicer, Mango, and Brain suite). Using these instruments, the brain and tumor regions in the pictures are manually segmented or labelled so that machine learning models for brain tumor identification can be trained and validated.

3.3.2. Adding More Data (Data Augmentation)

After the annotated data has been transferred to the Rob Stream workspace, a variety of augmentation techniques can be carried out automatically. The workspace offers the option to enhance the data that has been annotated. The original image has been 90 degrees rotated, mirrored, and made confusing. While creating additional training examples that are vertically mirrored replicas of the original photos, vertical flips can be helpful. The creation of new training examples that are horizontally mirrored counterparts of the original images can be accomplished with the help of horizontal flips. Since CNN includes a lot of parameters, a sizable amount of data is needed to create a useful model. An issue brought on by insufficient data is overfitting. Augmentation [33] is a method to increase the amount of image data that might aid in addressing the problem of model overfitting.

Dataset Division

To avoid overfitting, the data was divided using the train-test split approach. The train dataset was used to build the model, and the dataset for testing was used to evaluate the model. The dataset used in this thesis has a training, testing and validation ratio of 80%, 10% and 10%. To reduce over fitting, the data set for validation has to be used. This means that 80% of the training dataset was used for training, while 10% of it was used for validating. Ultimately, training took up 80% of the dataset, followed by validation at 10% and testing at 10%. Because it offers enough data for training, validation, and testing while still leaving enough data for each subgroup to be statistically significant, the 80:10:10 split is a popular option. When the dataset is small, a larger training set might be required, whereas if the model requires a lot of computing to evaluate, a smaller test set would be required. The 80:10:10 dataset splitting is a popular and effective machine learning

technique because it makes it possible to train, validate, and test machine learning models in a statistically sound manner.

3.3.3. PROPOSED MODEL COMPONENTS

The final classification of the images is then carried out applying the results of the convolutional and combined layers by a layer or layers that are completely connected [32]. Pre-trained models like VGG, ResNet, and Inception are honed using datasets for the identification of brain tumors after being trained on massive picture classification projects like ImageNet. Using the previously constructed models as an initial base, transfer learning entails training the model on a smaller dataset with the explicit goal of identifying brain tumor. This technique can enhance the performance of the model when the dataset is small or the task is similar to the original task for which the pre-trained model was created. For instance, a pre-trained model like VGG or ResNet can be utilized as the base model in brain tumor detection utilizing transfer learning, and the final few layers can be retrained on a brain tumor detection dataset. Only the weights of the last few layers are changed during training in order to learn the features unique to the goal of detecting brain tumors. The weights of the earlier levels are frozen. Brain tumor identification can be accomplished with success using pre-trained models like VGG, ResNet, and Inception together with deep learning techniques like CNNs. Transfer learning can also be used to improve the performance of the models by using models with previous training that have been trained on broad image classification tasks [34].

The output layer of the scratch model contained three convolution layers, three pooling layers, two fully linked layers, and a sigmoid activation function. The RELU non-linear activation function is used for all estimations of the first dense layer, Conv2d, Conv2d_1, and Conv2d_2. To address our numerous image categorization issues, the framework was built from the ground up applying the various hyper-parameters listed below. The hyper-parameter values were tested in different circumstances.

Layer one: Our CNN model will accept RGB images with a size of 128 by 128 by 3 and input from two different classes (class1 and class2). This layer is not performing any calculations; it only serves as a source of data to the initial convolution layer. As therefore,

this layer lacks parameters and features that are able to be learned. Convolutional layer: The scratch model is composed of three convolution layers: Conv2d, Conv2d _1, and Conv2d _2. Images of the following dimensions are accepted by the input layer: (None, 417, 417, 3). In order to produce the output (None, 417, 417, 16), Conv2d uses (None, 417, 417, 3) as the input layer.

```
# Build the CNN model
cnn_model = Sequential()
cnn_model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(img_width, img_height, 3)))
cnn_model.add(MaxPooling2D((2, 2)))
cnn_model.add(Conv2D(64, (3, 3), activation='relu'))
cnn_model.add(MaxPooling2D((2, 2)))
cnn_model.add(Conv2D(128, (3, 3), activation='relu'))
cnn_model.add(MaxPooling2D((2, 2)))
cnn_model.add(Flatten())
cnn_model.add(Dense(128, activation='relu'))
cnn_model.add(Dropout(0.5))
cnn_model.add(Dense(1, activation='sigmoid'))

# Compile the CNN model
cnn_model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```

Figure 6 CNN model

Figure 6 illustrates the Conv2d layer's default settings, which are as follows: dilation rate=1, stride, kernel size=3x3, and filter=16. (Image Height - Kernel Height + Stride, Image Width - Kernel Width + Stride, Filtering) is the algorithm used to figure out the output shape. The output shape is (128-3/2+1, 417-3/2+1, 16) when all of the formula's parameters are employed, and the number of a parameter in this layer is computed by (KernelHeight * KernelWidth * InputChanal * OutputChanal + OutputChanal) if bias used. There are 448 (3*3*3*16+16) parameters after applying the calculation. The max-pooling layer (None, 417, 417, 16) receives its input from the output of the Conv2d layer.

The suggested model consists of three max-pooling layers: the first max-pooling layer reduces the output of the first convolutional layer using a filter of size 3*3, the second max-pooling layer pools the provide information using a filter of size 2*2, and the result of the first layer of convolution is merely reduced by the third max-pooling layer using a filter of size 2*2 and stride 2.

Completely Connected (CC) layer: The proposed paradigm has three levels, including the output layer, that are entirely interconnected. The first two completely linked layers of the model have 64 neurons each, however the final layer of the output layer has just one neuron.

The first FC layer accepts the output of the fifth Conv layer after flattening the 3D input volume into a vector value. In this layer, the class score and the total amount of neurons that were specified for the layer during model construction are computed. It is a typical convolutional neural network because, as the name suggests, each of the neurons in this layer has a connection to every single integer in the layer that lies in front of it. One neuron with a Sigmoid activation function is present in the final output layer of the model, the third FC layer. The model uses a number of categorizations because its goal is to distinguish between two groups.

3.4. HYPER-PARAMETER TUNING

Before training, hyper-parameter values are decided upon, and they are not dependent on the deep learning approach. There is no one right technique to choose the optimum hyper-parameters for a given problem. To select the hyper-parameters, numerous tests are carried out. The next paragraphs provide explanations of the additional parameters that have been selected for the model.

By selecting an appropriate optimization technique during neural network training, a model can learn more quickly and perform better. The back propagation error of the method is used to update and calculate the weights. One important optimization strategies, the Adam method, have been tested with learning rates of 0.001 and 0.002, respectively, in an attempt to reduce the error rate. Gradient descent is the most well-liked and frequently applied optimization method in deep learning research. At the same time, Keras and other gradient descent optimization techniques (used in this thesis) are used by every modern deep learning package. In order to reduce the loss function, it adjusts the model weights and value of the parameters. The gradient descent is improved via the Adaptive Moment Estimation (Adam) optimizer. For each parameter, Adam determines the adaptive learning rate and scales it with the gradient's moving average and squared gradients. The learning rate is defined as the amount of weight that is updated all over training. It is a hyper parameter that can be customized and is used to train neural networks. The value usually varies from 0 to 1.0. It's the most crucial hyper parameter since it decides how quickly a model replies to a specific problem. The training epoch changes often when the learning

rate is high, but several training epochs and weight updates are required when the learning rate is low. One of the challenges in creating a neural network model is choosing a learning rate that is neither excessive nor inadequate. Based on several experiments, the learning rate is between 0.001 and 0.002.

Loss function: The loss function we use and the function of activation we use in the output layer of the model are strongly associated with whether we are trying to solve a classification or regression problem. The final entirely linked layer of the proposed model uses the sigmoid activation function. The greater part of our classification concern is a binary classification. The Binary Cross-Entropy (BCE) loss is the loss function for our model. Although there are alternative loss functions which evaluate the gap between the desired and actual outcome, such as Categorical Cross-Entropy (CCE) and Mean Squared Error (MSE), they perform better for models that output probabilities. The experiment used both BCE loss and CCE loss. The work employs two distinct activation functions: RELU in the hidden layer and Sigmoid in the proposed model. The Sigmoid activation function, which is the perfect response to the multiple categorization issue, because is used in the layer of outputs.

Epoch: The rate at which training data is presented to the neural network. 100 epochs were used as a baseline number throughout testing. The accuracy validation graph analysis revealed that epochs of 30 were employed for a suggested model and 65 for other pre-trained models. The size of a batch affects how many subsamples are sent to the network and how frequently the parameters are changed. The batch size's default values are 32, 64, 128 and so forth. After numerous testing, a batch size of 32 produced the greatest results.

Model-based learning

Use the input data

$$\begin{bmatrix} x_{1,0} & x_{1,1} & \dots & x_{1,n} \\ x_{2,0} & x_{2,1} & \dots & x_{2,n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m,0} & x_{m,1} & \dots & x_{m,n} \end{bmatrix} \text{ and } \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_m \end{bmatrix}$$



To learn a set of parameters

$$\begin{bmatrix} \theta_0 & \theta_1 & \dots & \theta_n \end{bmatrix}$$



Which yield a **generalized** function

$$f(x; \theta) = \theta_0 x_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_n x_n$$



Capable of predicting values or classes on new input data

$$f(x_i; \theta) = 39$$

$$f(x_j; \theta) = 1$$

Figure 7 Hyperparameter's Model

The hyperparameters provide the actual structure of our model, whilst the model parameters specify how to translate the input data into the desired output. Unfortunately, there isn't a mechanism to calculate "which way should I update my hyperparameter to reduce the loss?" (i.e., gradients) to find the ideal model architecture; as a result, we typically rely on experimenting to determine what works.

3.5. EVALUATION METHODS

It is crucial to study a model in order to assess how useful and effective it is. In computational issues like classification and detection, the instance's class membership is determined using evaluation metrics like accuracy, precision, recall, and F1-score. These measurements were computed using the detection metrics. The detection metrics give details on a model's effectiveness for each class. The confusion matrix value was used to construct all of the metrics given below:

Where:

TP: The instance's expected and actual classes are both positive.

TN: The instance has a projected class of negative, which also happens to be its actual class.

FP: The instance actually has a negative class, although the expected class is positive.

FN: Despite predictions that it would be negative, the instance's true class is positive.

The following evaluation measures are developed using the condensed data from the confusion matrix.

Accuracy is defined as the complete correct the categorization instances to their sense of belonging. The question of how frequently the model correctly foresees the class, i.e., normal MRI image and tumor MRI picture, is responded to by the below description. It is determined using this formula [38].

$$A = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision: reveals the probability that a positive value prediction will materialize. For instance: Estimating the probability that a disease will be present in an image. It is calculated using the formula below [38].

$$P = \frac{TP}{TP+FP}$$

Sensitivity: Also known as Recall, this word implies how recall a classifier is to identifying good samples. This is how the computation appears [38].

$$R = \frac{TP}{TP+FN}$$

F1score: The lowest F1score number is 0, meaning that one of the metrics has a value of 0. F1-score is the harmonic mean of precision and recall. It means utmost precision or memory. This is how the computation appears [38].

$$F1\text{-score} = \frac{2 * Recall * Precision}{Recall + Precision}$$

Specificity: The chance of a negative outcome in the event that the person is free of the disease is calculated using the formula below [38].

$$\text{Specificity} = \frac{TN}{FN+TN} * 100.$$

CHAPTER 4: EXPERIMENTATION AND DISCUSSION

This chapter demonstrates how to use a CNN and transfer learning method to detect brain tumors. The specifics of the investigations are described using a number of scenarios, and the hyper parameter used in the trials is also explained.

4.1. IMAGE DATASET

The key input for the model in this thesis is imaging data for brain cancer. The MRI imaging data came from the Korea Hospital in the Ethiopian city of Addis Ababa, and some of the data was increased by means of data augment. Because Ethiopia has a less developed culture of data handling, gathering such MRI images is a more difficult task. Additionally, the expertise and equipment needed to use this efficient approach of tumor detection are lacking. Nevertheless, we create a 2800 image collection to identify and categorize brain tumors into two groups (healthy and unhealthy).

Table 3: Image dataset

	Total image dataset	Gathered images	Augmented Images
Total	2800	2000	800
Normal	1400	1000	400
Tumor	1400	1000	400

4.2. EXPERIMENTAL SETUP

Three scenarios are included in the experimental design of the study to effectively diagnose and categories brain tumor sickness. The transferable models are used in the additional testing. As a consequence, the InceptionV3, which structure is employed in the following study, and the VGG16 model is used in the third trial.

4.3. CNN FEATURES

Using filter 32, the size of the filter 3*3, and stride 2 to add the RGB image to the model, which is demonstrated with the input 417*417*3. The convolutional layer is then applied to the image, with a maximum pooled output of 415*415*16. In addition, an additional max pooling layer is used to max pool the 208*208*16 inputs that are used to create the subsequent layer (206*206*16). The output supplied into the final convolutional layer is max pooled. To choose and display one of the classes, the SIGMOID activation function utilizes the full linked layer.

4.4. PARAMETERS USED FOR AUGUMENTATION

Figure 8 below displays the experiment's augmentation component. In order to help the model acquire more features, the number of photos was raised via data augmentation from 2,000 of all of the class images in the set used for training to 2,800 images.

```
rescale=1./255,  
rotation_range=40,  
width_shift_range=0.2,  
height_shift_range=0.2,  
shear_range=0.2,  
zoom_range=0.2,  
horizontal_flip=true,  
fill_mode='nearest'
```

Figure 8 augmentation parameters

Table 4:hyper-parameter setting for pre-trained models.

Parameter	Epoch	Batch Size	Activation Function	Optimization Algorithm	Learning rate
Value	90	32	RELU	Adam	0.001
	30	64	RELU		0.002
	65	128	Sigmoid		

4.5 EXPERIMENTAL RESULT

4.5.1 BRAIN TUMOR DETECTION USING A MODEL

The experiment began by developing a CNN model from the ground up and comparing it to other models that had already been trained before employing the pre-trained model. Although it outperforms previously trained models like VGG16 and InceptionV3 when missing data is present, it still has good training and validation accuracy. The model is only learning a tiny part of an image's attributes, so starting from scratch with a small dataset is not advised because testing on untrained data might not produce adequate results. In general, many scenarios were used to experiment with the models.

We can test scenario 1 by utilizing a 224x224x3 picture, a learning rate of 0.0002, and an activation function that combines SoftMax and RELU. Scenario 2: Testing utilizing images with a resolution of 224x224x3, a learning rate of 0.0001, using the SoftMax and RELU activation functions. Test scenario 3: using RELU and SOFTMAX, with a 300x300x3-pixel picture, a learning rate of 0.0002, and an activation function. Testing Adam's optimization method with settings including a learning rate of 0.0001 and an image size of 300x300x3. The model that was created from scratch and evaluated in all four scenarios performed the best. It had an image dimension of 300x300x3, a learning rate of 0.001, and final layer activation of the RELU and RMSprop optimization strategy.

Table 5: Summary of experimental results

Experiment	Accuracy	Recall	Precision
Scenario 1	86	81	82
Scenario 2	87	83	84
Scenario 3	88.2	86	86.5
Scenario 4	88.6	86.8	87

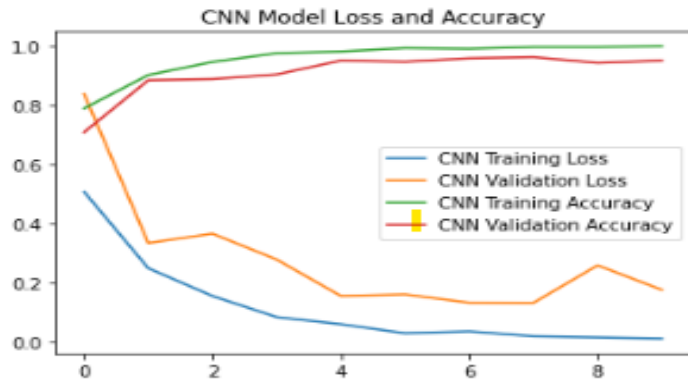


Figure 9 graph of train and loss dataset. 1

Table 6 scratch model accuracy and loss

Metrics	Scratch model Accuracy			Scratch Model Loss		
	Training	Validation	Testing	Training	Validation	Testing
Value	88%	89%	86%	5.01%	5.6%	14%

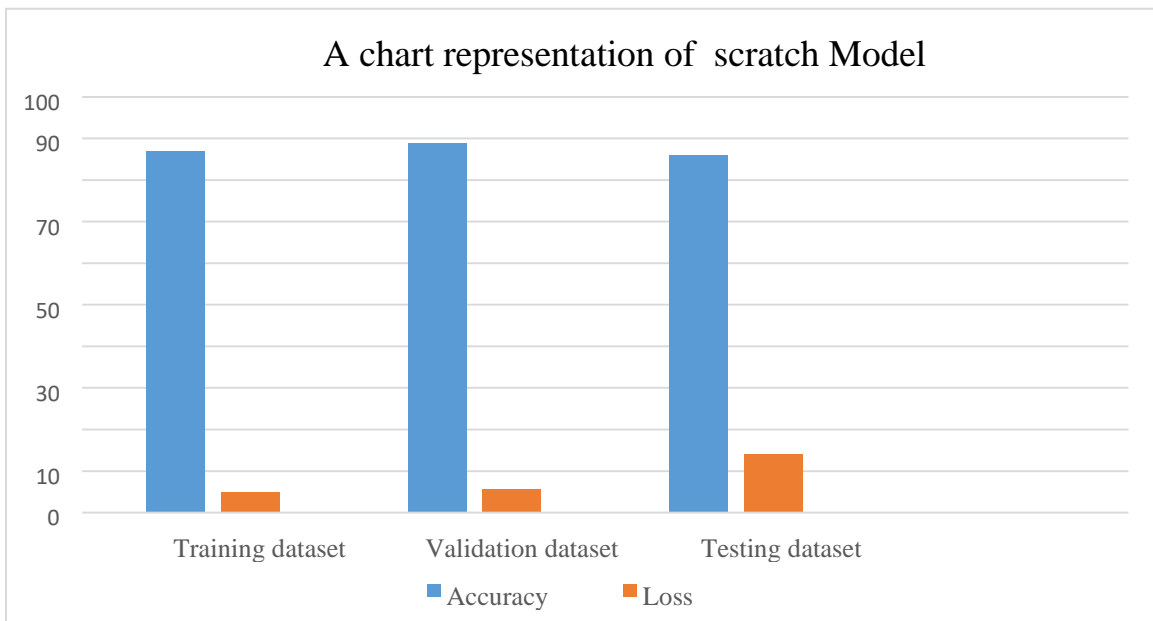


Figure 10 Chart representation for Scratch Model

4.5.2 Experiment Result of VGG16

The VGG16 experiment makes use of all implementation data and hyper-parameters from the underlying papers. To initialize the kernel with the Adam optimizer, the initial fifteen epochs were trained using Image Net weight. The architecture has been altered significantly. To compute dropout rates, learning rates of 0.001, 0.002, and 0.2 are employed.

```
# Build the VGG16 model
vgg16_model = VGG16(weights='imagenet', include_top=False, input_shape=(img_width, img_height, 3))
vgg16_model.trainable = False

vgg_model = Sequential()
vgg_model.add(vgg16_model)
vgg_model.add(Flatten())
vgg_model.add(Dense(128, activation='relu'))
vgg_model.add(Dropout(0.5))
vgg_model.add(Dense(1, activation='sigmoid'))

# Compile the VGG16 model
vgg_model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```

Figure 11 VGG 16 model

Table 7 VGG16 model result

	Learning rate	Accuracy	Sensitivity	Precision
Image Net weight	0.001	89	86	85
	0.002	87	85.2	84.6

The experiment findings of VGG16 on the dataset for identifying brain tumors are shown in Table 7 according to evaluation metrics.

Table 8 VGG16 Model representation Accuracy and loss

Metrics	VGG16Model Accuracy in percent			VGG16 Model Loss in percent		
	Training	Validation	Testing	Training	Validation	Testing
Value	89.8	88.4	86	5.0	5.70	12.5

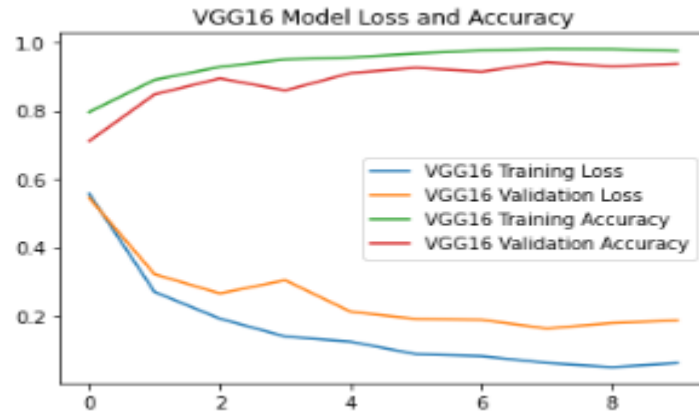


Figure 12 VGG16 model Training accuracy and loss

The graph illustrates how the model's capacity for learning and its capacity for loss both decrease over time. Additionally, Adam optimizers change the performance of the model.

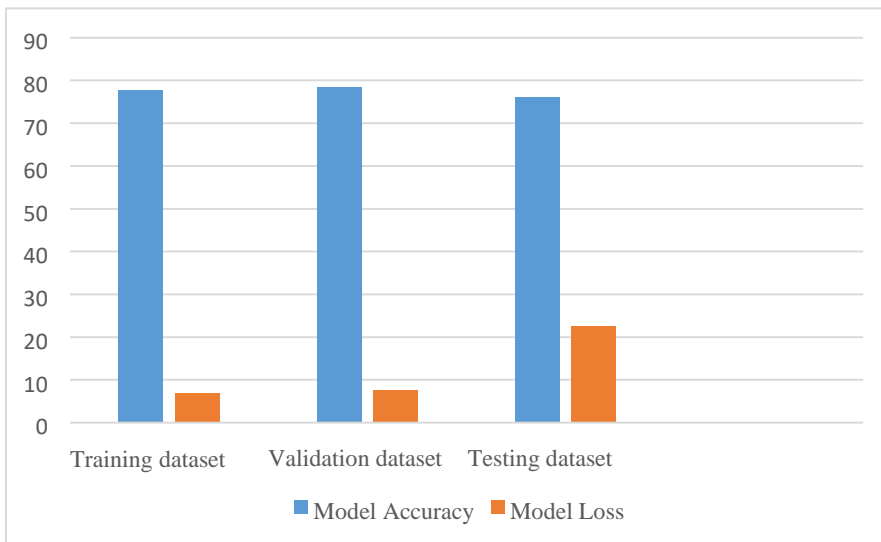


Figure 13 VGG16 model Accuracy and loss

4.5.3. Experiment Result of InceptionV3

The performance of the model during neural network training directly depends on the hyper-parameter configuration. It uses InceptionV3 and trains over 90 epochs with an average proficiency rate of 10 to 4 and a value of failures.

```
# Build the Inception V3 model
inception_model = InceptionV3(weights='imagenet', include_top=False, input_shape=(img_width, img_height, 3))
inception_model.trainable = False

inception_model = Sequential()
inception_model.add(inception_model)
inception_model.add(Flatten())
inception_model.add(Dense(128, activation='relu'))
inception_model.add(Dropout(0.5))
inception_model.add(Dense(1, activation='sigmoid'))

# Compile the Inception V3 model
inception_model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```

Figure 14 Inception V3 Model

The classification of brain tumor outcomes from the InceptionV3 experiment is shown in Table 9.

Table 9 InceptionV3 Model output

	Learning rate	Accuracy	sensitivity	Precision
Image Net weight	0.001	93.1	92	90
	0.002	90	89	88

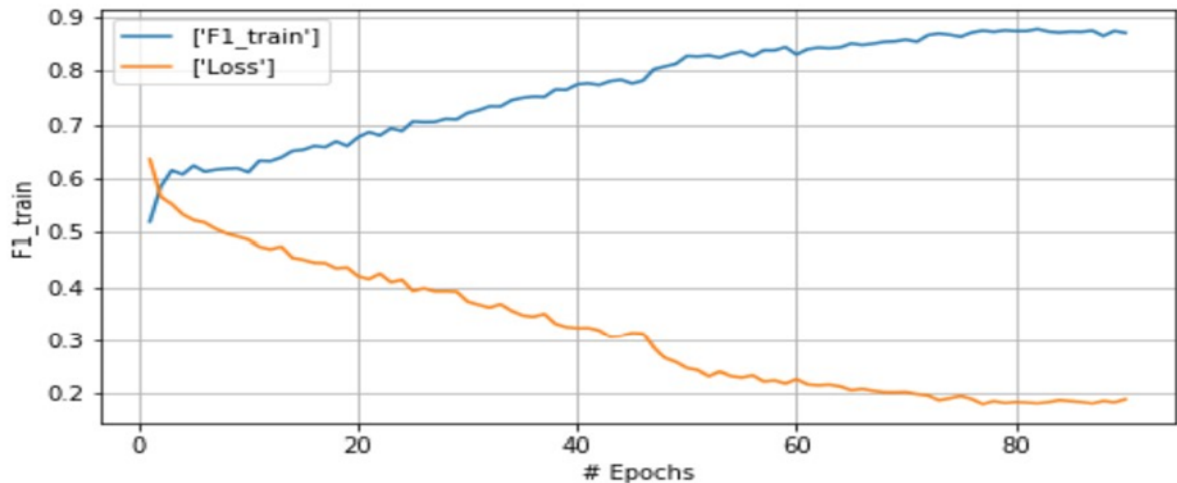


Figure 15 InceptionV3 model Training and Loss representation

On training and testing, the InceptionV3 performs well. The model's learning capacity increases with increasing epoch, as seen in figure 15, and Adam optimizer is used to optimize the created model.

4.6. COMPARISON OF RESULTS

The study's ultimate objective was to create a model for classifying brain tumour illnesses. To do this, a wide range of literary works were evaluated and tests were carried out. CNN was the algorithm that was utilised to identify and categorise the brain tumour condition. Building a model from scratch and applying transfer learning to an existing model allowed for a thorough evaluation of the methodology. The disadvantage of creating a model from scratch is that it requires a lot of data, and the performance of the model depends on the quantity of data. Even though the model was created from scratch, it performed well during training and validation but poorly during tests using fictitious data. As a result, the pre-trained model fixed the issue with the model that was created from scratch. Variable hyper parameter settings were tested by the pre-trained model (VGG16).

```
# Compare the performance of the three models
print('CNN Test Accuracy:', scores_cnn[1])
print('VGG16 Test Accuracy:', scores_vgg[1])
print('Inception V3 Test Accuracy:', scores_inception[1])

# Select the best model based on the test accuracy
best_model = None
if scores_cnn[1] > scores_vgg[1] and scores_cnn[1] > scores_inception[1]:
    best_model = cnn_model
    print('CNN model selected')
elif scores_vgg[1] > scores_cnn[1] and scores_vgg[1] > scores_inception[1]:
    best_model = vgg_model
    print('VGG16 model selected')
else:
    best_model = inception_model
    print('Inception V3 model selected')
```

Figure 16 comparison of the three algorithms

Table 10 three Models Comparison

List Of Model	Model Accuracy	Model Loss
Scratch model	87.5	13
VGG16 Model	89	9
Inception V3 Model	93.1	5

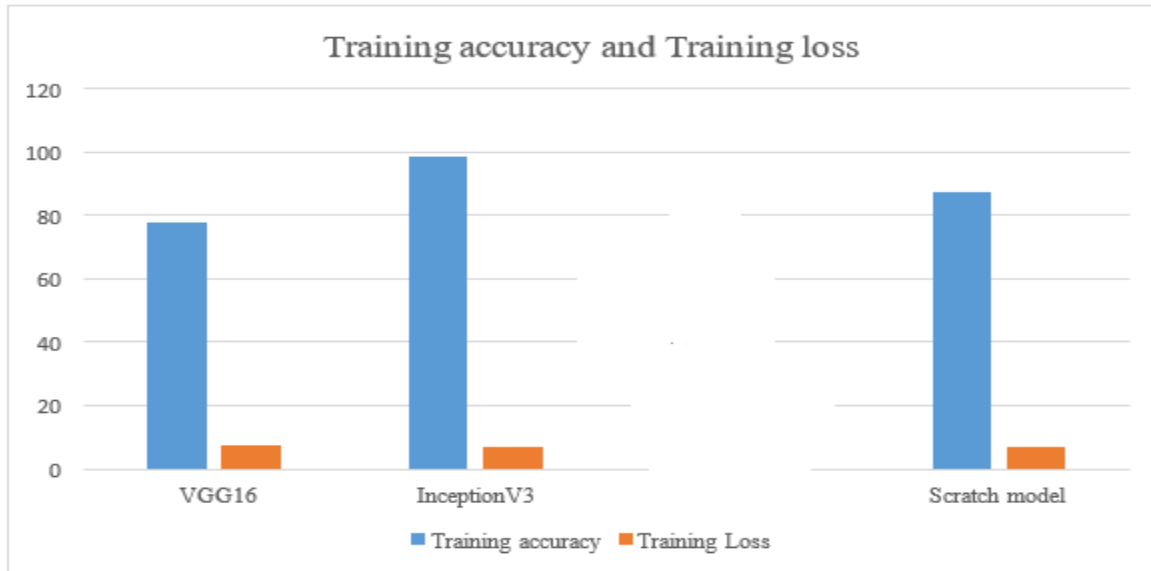


Figure 17 Model Comparison

VGG16 has decent accuracy on the practice set. Based on the evaluation metrics and testing set, it has the smallest value, though. The regularization process reduces over fitting, which has been experimentally shown to be a problem with the small dataset used. This is due to over fitting, which occurred as a result of the high parameters that were estimated using a small sample size. The suggested CNN model, VGG16, and inception V3 has a mean training accuracy of 86.6, 89, and 93.1, as seen in the ensuing graphs. On the training dataset, they demonstrate that the models produce precise results. The VGG16 and inception models had mean validation accuracy percentages of 89 and 93.1, respectively. When we calculate the difference between mean training accuracy and mean validation accuracy for each of the three experiments, the suggested model almost has the same mean training accuracy and mean validation accuracy. They show that the models are not overfitted, and we can conclude that the suggested model is fairly generalizable as a result. The mean training loss, a metric that measures the difference between the value predicted and the actual value, was 14, 9, and 5 for the three trials: VGG16, inception, and suggested model. The mean validation loss, which is relatively comparable to the mean training loss, is calculated as the difference between mean training loss and mean validation loss, and it is 13, 11, and 6.9. The models were put to the test using confusing data, and the results are promising. The suggested model's accuracy on the VGG16 test and on the inception, test

is 89% and 93.1%, respectively. The experiment's outcomes indicate that, when applied to categorise the provided image as either healthy or unwell, the recommended model outperforms the trained inception models.

	precision	recall	f1-score	support
Healthy	0.86	0.89	0.87	280
Tumour	0.89	0.85	0.87	280
accuracy			0.87	560
macro avg	0.87	0.87	0.87	560
weighted avg	0.87	0.87	0.87	560

sensitivity: 0.8893
 specificity: 0.8536

Figure 18 Classification Report

4.7. DISCUSSION OF RESULT

Using the Inception model, we were successful in this study in detecting brain tumours with a 93% accuracy rate. The simplicity with which humans can classify the photos in the dataset we used to train the recommended model is one of the key reasons influencing its improved performance. The second crucial part of our recommended strategy is the inclusion of smaller-sized filters to the convolution layer. There is very little risk of losing a significant feature because smaller-sized convolution is utilised to identify relatively tiny characteristics that are used to differentiate between the input image and the output image. The majority of deep learning techniques train their models using a sizable quantity of data (in the millions of photos), tens of millions of parameters, and high-performance computing equipment with faster GPUs, notably those using computer vision for image classification issues. Smaller networks, fewer parameters, less hardware, and less data, on the other hand, could be easier to train and produce better outcomes with. If the dataset's photographs were taken under consistent environmental conditions, such as constant object distance from the camera, suitable lighting, and precise focus, better results were produced. By preprocessing the images to reduce noise and unwanted characteristics, the model's accuracy is also increased.

CHAPTER 5: CONCLUSION AND FUTURE WORK

5.1. CONCLUSION

Due to their success in the identification and categorization of different diseases, convolutional neural networks have gained enormous recognition in the medical community. Particularly, infections, skin conditions, and tumors have been used to recognize and categorize a variety of illnesses. In this study, brain tumor infections are identified using transfer learning and convolutional neural networks. Brain cancer is one of the most severe conditions that can destroy the brain, the computer that controls the entire body. There are two types of brain tumors: benign and malignant. The method of determining the type of tumor is quite challenging and necessitates extensive knowledge of cancer disorders. The implementation of computer-based decision support systems is important to help medical doctors in their decisions.

The use of various technologies in the detection of brain cancer is a research area of interest. Convolutional neural networks were introduced and investigated for the identification and classification of brain tumors in numerous publications. They have proven to be quite accurate and successful in identifying a variety of brain tumors. In this study, the use of the CNN and Transfer Learning algorithms for imaging-based brain tumor detection was reported. 2800 magnetic resonance brain pictures were used in this experiment. There were 1400 photos of tumors and 1400 photographs of health in all. The database photos were all improved using a combination of binary segmentation, CNN, and Transfer Learning to find common areas of interest. Numerous image processing techniques were also used in this study to improve how the photos were implemented using ANN. These techniques comprised averaging algorithms for picture reduction, normalization techniques for pixel normalization, and matrix vectorization prior to feeding data to CNNs.

Multiple stages of the transfer learning algorithm were applied to the treated images to explore the effects of each image processing technique on the system performance. The results show both how convolutional neural networks perform well at detecting tasks and how picture processing influences this performance. The neural network implementation

yielded an 82% detection efficiency using the original grey scale MRI data. This efficiency was increased to 98% when multiple image processing stages were used. The findings obtained have shown how the neural network's functionality and processing performance are impacted by image segmentation and filtering. The requirement for a lot of data is the main flaw. Large datasets are necessary for deep learning algorithms to learn from, but sometimes their availability is constrained. Accurate model development may be difficult for populations with underrepresented data or for rare forms of brain tumors due to this.

5.2. FUTURE WORK

The goal of research is to determine the best solution to a present problem and offer direction for the future. More layers with compatible fully connected NNs should be added to the feature extractor as it would improve accuracy and reduce the number of parameters that need to be calculated. A system that provides diagnosis and therapy must be designed and developed after the model has been optimized. Future iterations of this work will also incorporate more MRI datasets and other types of brain tumor datasets. Since only a Rectangle box was utilized in this thesis to identify the region of interest, segmentation used before CNN can increase the model's performance. In order to do extensive experimentation and create a model that is more reliable and consistent, a standard dataset is also necessary.

Finally, in order to address more difficulties with brain cancer, this research must be expanded in the future. In addition to determining whether the person is healthy or not, delivering treatment completes our task.

REFERENCES

- [1] Sara Hosseinzadeh Kassani , Peyman Hosseinzadeh Kassani, Michal J. Wesolowski,, "Brain Cancer Diagnosis with Transfer Learning and global pooling,," in *ICTC*, 2019.
- [2] Sunita M. Kulkarni, G. Sundar, "Brain Tumor Classification using deep learning algorithm," *international journal of* vol 5,.No.,pp.23-35, 2020.
- [3] Neethu Ouseph C1, Asst. Prof. Mrs.Shruti K2, "A Reliable Method for Brain Tumor Detection Using Cnn Technique," *IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)*, vol. 4, pp. 64-68, YEAR.
- [4] S. Saini and K. Arora,, "A Study Analysis on the Different Image Segmentation Techniques," *International Journal of Information and Computation Technology*, vol. 4, pp. 1445-1452, 2014.
- [5] K. K. Hiran, Ruchi Doshi,, "An Artificial Neural Network Approach for Brain Tumor Detection Using Digital Image Segmentation," *International Journal of Emerging Trends & Technology in Computer Science (IJETTCS)*, vol. 2, No. 5, No.p 224-45 September – October 2013.
- [6] P. S. Kumar and P. Ganesh Kumar, "Performance Analysis of Brain Tumor Diagnosis Based on Soft Computing Techniques," *American Journal of Applied Sciences* , vol. 2, pp. 329-336, 2014.
- [7] Magdi B.M Amien, Ahmed Abd-elrehman and Walla Ibrahim, "An Intelligent Model for Automatic Brain Tumor Diagnosis Based on MRI Images," *International Journal of Computer Applications(0975-8887)*, vol. 72, pp. 21-24, June 2013.
- [8] S. E. Umbaugh, *Computer Imaging: Digital Image Analysis and Processing*, Taylor andFrancic Group, 2005.
- [9] Olga Miljkovic,, "Image pre-processing tool, Kragujevac J. Math," NAME OF JOURNAL, vol. 32, pp. 97-107, 2009.

- [10] T. Gevers and H. Stokman, "Classifying color edges in video into shadow-geometry, highlight, or material transitions, *IEEE Trans. Multimedia*," vol. 2, pp. 237-243, 2003.
- [11] Zhang, M. Z.; Livingston, A. R.; Asari, V. K. , "A High Performance Architecture for Implementation of 2-D Convolution with Quadrant Symmetric Kernels," *International Journal of Computers and Applications*, vol. 4, pp. 298-308, 2008.
- [12] S. Saini and K. Arora, , "A Study Analysis on the Different Image Segmentation Techniques," , *International Journal of Information and Computation Technology*, vol. 4, pp. 1445-1452, 2014.
- [13]] Mark S. Nixon and Alberto S. Aguado, "Feature Extraction and Image Processing, Second edition, Elsevier Ltd.," 2008.
- [14] Sara Isabel Moreira Francisco, "Recognition of Cancer using Random Forests as a Bag-of-Words Approach for Gastroenterology, MSc Thesis," Porto University, Portugal, june, 2015.
- [15] Bo Li, Wei Li, and Dazhe Zhao, "Global and Local Features Based Medical Image Classification,," *J. Med. Imaging Health Inf.*, p. 748–754, 2015.
- [16] M. Nishibori, "Problems and solutions in medical color imaging, Proc. Int. Symp. Multi-Spectral Imaging and High Accurate Color Reproduction," pp. 9-17, 2000.
- [17] Isabelle G. and Andre E., "An Introduction to Variable and Feature Selection," *Journal of Machine Learning Research*, vol. 3, pp. 1157-1182, 2003.
- [18] Pooja Kamavisdar, Sonam Saluja, Sonu Agrawal, "A Survey on Image Classification Approaches and Techniques," *IJARCCCE*, vol. 2, pp. 1005-1009, 2013.
- [19] Sérgio Pereira, Adriano Pinto, Victor Alves and Carlos A. Silva, "Brain Tumor Segmentation using Convolutional Neural Networks in MRI Images," 2006.
- [20] G. Urban et al., "Multi-modal brain tumor segmentation using deep convolutional neural networks," in *MICCAI Multimodal Brain Tumor Segmentation Challenge (BraTS)*, 2014, pp. 1-5.

- [21] D. Ciresan et al., "Deep neural networks segment neuronal membranes in electron microscopy images," in *Advances in neural information processing systems*, 2012, p. 2843–2851.
- [22] J Seetha,, "Brain Tumor Classification Using Convolutional Neural Networks," *Biomed Pharmacol J*, vol. 11, 2018.
- [23] Deepak, "Brain tumor classification using deep CNN features via transfer learning," *Journal of Computers in Biology and Medicine*, vol. 111, pp. 1-7, 2019.
- [24] N. C., "Brain Tumors," [Online]. Available: <http://www.cancer.gov/publications>.
- [25] K. M. Michal Kvet, "Brain Tumor Detection," *Journal of Biomedical*, 2013.
- [26] K. Varshini, R. K. Sethuramamoorthy et al., "Breast cancer prediction using machine learning techniques,," *Int. J. Adv. Sci.*, vol. 29, pp. 2026-2032, 2020.
- [27] Y. Cheng and B. Li, "Image segmentation technology and its application in digital," *Proc. IEEE Asia-Pacific Conf. Image Process. Electron.*, vol. 3, pp. 1174-1177, 2021.
- [28] S. Minaee, "Image Segmentation Using Deep Learning: A Survey,," vol. 10, pp. 1-22, 2021.
- [29] K. Singh, A. Seth, H. S. Sandhu, and K. Samdani, "A comprehensive review of," in *2019 IEEE, ICSCAN*, 2019.
- [30] T. A. Korzhebin and A. D. Egorov, "Comparison of Combinations of Data," in *IEEE, ElConRus*, 2021.
- [31] A. Titoriya and S. Sachdeva,, "Breast Cancer Histopathology Image Classification," *Int. Conf. Inf. Syst. Comput. Networks*, vol. 3, pp. 708-712, 2019.
- [32] R. Watanabe, N. Soga, and H. Noji, "Novel nano-device to measure voltage-driven," *IEEE Trans. Nanotechnol*, vol. 15, pp. 70-73, 2016.
- [33] S. M. Badawy, "Classification of Breast Ultrasound Images Based on," *Int. Telecommun.*, vol. 4, pp. 7-12, 2021.

- [34] M. A. Anupama, V. Sowmya, and K. P. Soman, , "Brain cancer classification using," *Proc. 2019 IEEE Int. Conf.*, vol. 1, p. 143–147, 2019.
- [35] Hao-Chun Lu , El-Wui Loh ,Shih-Chen Huang,, "The Classification of Mammogram," *in IEEE*, 2019..
- [36] K. Nguyen, C. Fookes, and S. Sridharan,, "IMPROVING DEEP," *Int. Conf. Image Process*, vol. 4, pp. 2-6, 2015.
- [37] Anupama M A , Sowmya V , Soman K P,, "Brain Cancer Classification using," *in IEEE*, 2019.
- [38] H. Dalianis,, "Evaluation Metrics and Evaluation,," *Clin. Text Min*, vol. 1967, p. 45–53, 2018.
- [39] N. Arya and S. Saha,, "Multi-modal classification for human brain cancer prognosis," *IEEE*, 2020.
- [40] H. C. Lu, E. W. Loh, and S. C. Huang,, "The Classification of Mammogram Using," *2019 2nd International Conference on Artificial Intelligence and Big*, vol. 1, pp. 9–12, 2019.
- [41] M. Z. Islam, M. M. Islam, and A. Asraf,, "A combined deep CNN-LSTM network for the detection of novel coronavirus (COVID-19) using X-ray images,," *Informatics Med. Unlocked*, vol. 20, pp. 100-412, 2020.
- [42] F. Ertam,, "Data classification with deep learning using tensorflow,," *Comput. Sci. Eng. UBMK 2017, 2nd Int. Conf.*, p. 755–758, 2017.
- [43] "Big data deep learning framework using keras: A case study of pneumonia prediction,," *2018 4th Int. Conf. Comput. Commun. Autom. ICCCA 2018*, vol. 6, p. 1–5, 2018.
- [44] R. Watanabe, N. Soga, and H. Noji,, "Novel nano-device to measure voltage-driven membrane transporter activity,," *IEEE Trans. Nanotechnol.*, vol. 15, pp. 70-73, 2016.
- [45] T. A. Korzhebin and A. D. Egorov,, "Comparison of Combinations of Data Augmentation Methods and Transfer Learning Strategies in Image Classification

Used in Convolution Deep Neural Networks," *Proceedings of the 2021 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering*, vol. 3, pp. 479-482, 2021.