

# **BRAIN TUMOR DETECTION AND CLASSIFICATION FROM MRI IMAGES: DEEP LEARNING PERSPECTIVES AND AUTOMATED DIAGNOSTIC APPROACHES**

A Thesis Submitted

In Partial Fulfillment of the Requirements for the Degree of

## **MASTER OF TECHNOLOGY IN Software Engineering**

Submitted by

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### **CANDIDATE'S DECLARATION**

I, Mehek Jagwani, Roll No – 24/SWE/11 student of M.Tech (Software Engineering), hereby certify that the work which is being presented in the thesis entitled “Brain Tumor Detection and Classification from MRI Images : Deep Learning Perspectives and Automated Diagnostic Approaches” in partial fulfilment of the requirements for the award of degree of Master of Technology, submitted in the Department of Software Engineering, Delhi Technological University is an authentic record of my own work carried out during the period from Jan 2026 to May 2026 under the supervision of Dr. Shweta Meena.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other institute.

**Candidate's Signature**

This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

**Signature of Supervisor**

**Signature of External Examiner**

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**CERTIFICATE**

I hereby certify that the Project Dissertation titled “Brain Tumor Detection and Classification from MRI Images: Deep Learning Perspectives and Automated Diagnostic Approaches” which is submitted by Mehek Jagwani, Roll No - 24/SWE/11, Department of Software Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the student under my supervision.

To the best of my knowledge, the work presented in this thesis has not been submitted elsewhere for the award of any degree or diploma.

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## **Abstract**

One of the most serious problems that exist today in the field of neurology is brain tumors, with early and correct diagnosis being essential for effective treatment and survival of patients. Manual analysis of Magnetic Resonance Imaging scans take much time, depends on the experience of an individual who analyses it, and requires special radiology skills, which becomes more challenging. This research work addresses these challenges through two interconnected contributions under the broader perspective of deep learning based automated brain tumor detection. A detailed and exhaustive literature review about automated brain tumor detection techniques developed during the period from 2020 to 2026 is presented in one contribution. It involves classical Machine Learning models, deep CNN architectures, transfer learning models, object detectors like YOLOv5, Vision transformers and hybrid models. These frameworks are carefully studied and critically compared to their design, popular datasets such as BraTS, Figshare, Kaggle Brain MRI dataset and evaluation criteria. Systematically identified limitations include computational efficiency, class imbalance, explainability of the model, lack of annotated data and differences between clinical and benchmark data. Another contribution describes the development of the VGG16 transfer learning architecture for four-class brain tumor classification involving glioma, meningioma, pituitary and no tumor class using a publicly available database of 7,023 brain MRI images. The model presented in this paper uses data augmentation techniques and a custom classifier head to achieve 96% test accuracy with weighted average precision, recall, F1-score of 0.96. This research offers not only a resourceful summary but also a solid baseline approach towards AI-based brain tumor diagnosis.

## LIST OF PUBLICATIONS

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1. Mehek Jagwani and Shweta Meena, “Brain Tumor Detection using Transfer Learning,” *ICCETM 2025*. (**Presented and Published; Scopus Indexed**)
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## List Of Abbreviations

|       |                                        |
|-------|----------------------------------------|
| AI    | Artificial Intelligence                |
| ML    | Machine Learning                       |
| DL    | Deep Learning                          |
| CNN   | Convolutional Neural Network           |
| MRI   | Magnetic Resonance Imaging             |
| VGG16 | Visual Geometry Group 16-Layer Network |
| ReLU  | Rectified Linear Unit                  |
| SVM   | Support Vector Machine                 |
| YOLO  | You Only Look Once                     |
| FLAIR | Fluid Attenuated Inversion Recovery    |
| BraTS | Brain Tumor Segmentation Challenge     |
| GPU   | Graphics Processing Unit               |
| TPU   | Tensor Processing Unit                 |
| TP    | True Positive                          |
| TN    | True Negative                          |
| FP    | False Positive                         |
| FN    | False Negative                         |
| CAD   | Computer-Aided Diagnosis               |

# Chapter 1

## INTRODUCTION

### 1.1 Overview

The human brain is one of the most complex and important organs in the human body that controls all the physiological functions, thinking and emotional processes. A brain tumor is one of the most severe and life threatening neurological diseases that medicine knows, resulting from any abnormal and uncontrolled growth of cells in the brain. Brain tumors may be classified as benign or malignant and their aggressiveness depends on the type, size, location and growth rate. When left untreated or treated incorrectly, brain tumors can cause major damage to the nervous system and significantly affect the patient's survival rate. Medical statistics showed that early and accurate detection is directly related to the effectiveness of treatment and the survival rate for patients with brain tumors.

In the clinical diagnosis of brain tumors, magnetic resonance imaging has become the standard imaging technique that does not involve radiation exposure. MRI, in contrast to Computed Tomography scans, does not use ionizing radiation to expose the patient and provides much better soft tissue contrast, allowing physicians to detect subtle anatomic abnormalities within structures of the brain. Some of the sequences that can be utilized include T1 weighted sequence, T2 weighted sequence, and FLAIR sequence, all of which highlight various properties of the tissues and hence suitable in the identification of certain tumors. However, even with its advantages, the MRI procedure is still very laborious in the manual data interpretation phase which requires great expertise from the radiologist. Manual Interpretation of images is a great challenge

especially in large clinics where many images are captured every single day [12].

The development of AI and ML techniques has presented great opportunities for the automatic processing of medical images. In the past decade, deep learning techniques have garnered tremendous attention from researchers for designing automated systems with high accuracy in detecting and categorizing brain tumors. However, in recent years, deep learning techniques have received a great deal of attention, especially Convolutional Neural Networks for the design of automated systems with high accuracy in detecting and categorizing brain tumors [7, 1]. In contrast to previous machine learning methods, these models can automatically learn these hierarchical representations from the raw image data without feature engineering. This has resulted in a very promising area of study that involves artificial intelligence in analyzing medical images, which is likely to play an important role in improving brain tumor detection.

This thesis contains two related developments to the area of automated detection of brain tumors from MRI images. One contribution is a systematic overview of the current state of the art, a comparison of classical machine learning methods, CNN-based deep learning models, transfer learning approaches, object detection frameworks, Vision Transformers and hybrid methods with regard to their methodologies, datasets, and performance metrics [35, 25]. Another is an experimental study of a four-class brain tumor classification framework, which is based on transfer learning and fine-tuned on a publicly available MRI dataset, with the VGG16 architecture. In total, the two contributions not only provide a general overview of the area, but they also provide a concrete and useful example of an efficient automated brain tumor detection framework [4].

## **1.2 Brain Tumors and Clinical Significance**

Brain tumors are among the most important diseases affecting the brain. These are caused by abnormal growth of cells in the brain or surrounding tissue and can have an impact on the health and lives of patients. Brain tumors can be divided into primary tumors (those that develop inside the brain) and secondary (or metastatic) tumors (tumors that develop in other parts of the body and travel to the brain). The most

important primary brain tumors are gliomas, meningiomas, and pituitary tumors [33, 32, 37], all of which are very different in their origin, clinical behavior, prognosis, and treatment strategy.

Gliomas are tumors that develop from supportive cells of the brain, called glial cells. They are the most prevalent form of primary malignant brain tumour and are divided into grades, with low grades (slow-growing) and high grades (aggressive) including Glioblastoma Multiforme (GBM). The prognosis for high grade gliomas is very poor and median survival is often only a few months, even with treatment [7, 39]. On the contrary, meningiomas develop in the protective membranes that cover the brain and spinal cord, called the meninges. Most meningiomas are non-cancerous and do not grow quickly, but because they are found so close to the brain, they can compress neighbouring brain tissue, resulting in neurological damage. Pituitary tumors are the types of tumor growths that occur in the pituitary gland found in the base of the brain. Pituitary tumors disrupt hormone regulation throughout the body. Pituitary tumors are generally benign tumors but they can have a devastating effect on the body's endocrine system.

Accurate diagnosis and classification of brain tumors plays an important role in determining the method of treatment, such as surgical intervention, radiotherapy and chemotherapy among others. This will greatly determine the patient's fate. This clinical need highlights the importance of having reliable, automated detection systems to support radiologists and clinicians to make timely and accurate diagnosis [38, 36].

### **1.3 Role of MRI in Brain Tumor Diagnosis**

MRI is considered to be the most useful non-invasive imaging method for imaging brain structure and identifying pathological changes. The technique of MRI is based on the magnetic properties of the hydrogen atoms in water molecules within the body, which are subjected to strong magnetic field and radio frequency pulses that produce images of the body's internal structures in cross sections[1]. It is very useful in distinguishing brain tumors from surrounding normal tissue because of its capacity to produce high-resolution images with excellent soft-tissue contrast. There is comple-

mentary information to be gained from different ways in which the MRI is acquired. T1-weighted images give excellent anatomical information and are frequently used in conjunction with contrast agents to identify regions of blood-brain barrier disruption that are typical of malignant tumors [24, 30]. T2-weighted imaging is sensitive to fluid content and is helpful for assessing the surrounding fluid in tumors. FLAIR sequences are the sequences that suppress the signal of cerebrospinal fluid, thereby enhancing the visibility of lesions near fluid-filled spaces. The multi-modal character of MRI imaging therefore enables a detailed characterization of the tumor, but also poses a challenge for the interpretation process, as MRI radiologists have to integrate information from various image modalities.

Although manual MRI image analysis is advantageous for diagnosis, it is a significant challenge in clinical practice. Manual analysis is cognitively demanding because of the vast number of images captured in modern hospitals and the fact that brain tumors manifest in different ways from patient to patient and imaging protocol to imaging protocol. These restraints have sparked an urgent demand for computer-aided diagnosis systems that are able to automatically, consistently, and accurately analyze MRI images at the level of a human expert or better [15, 28].

## **1.4 Need for Automated Detection Systems**

Several key challenges from the current clinical diagnostic landscape drive the development of automated brain tumor detection systems: Several important challenges exist within the current state of clinical diagnosis that motivate the development of automated brain tumor detection systems: Manual interpretation of MRI is observer dependent and the quality and accuracy of diagnosis may vary significantly from one radiologist to another depending on their experience, fatigue, and familiarity with different presentations of tumors. This variation may result in confusing diagnosis and sometimes even misdiagnosis and dire clinical implications [17, 23].

Second, with MRIs becoming more widely available and used around the world, the amount of medical imaging data has grown exponentially, far outpacing the ability of human experts to process it in a timely manner. The diagnostic bottleneck is further

compounded by the lack of skilled radiologists, especially in low- and middle-income countries. Automated systems can be used to analyze the vast number of imaging data in a timely and consistent manner, without getting tired, and can be helpful for triaging patients and prioritizing cases for expert review [11, 18].

Third, there is a high correlation between early diagnosis of brain tumors and favorable outcomes. By being able to develop algorithms that are capable of detecting subtle features in tumors in their early stages, which might not necessarily be easy to detect manually, this would make a considerable impact on the outcome of the patients. AI tools for diagnostics are capable of transforming the healthcare industry in numerous ways [6, 31].

All these aspects have driven a lot of studies regarding machine learning and deep learning algorithms for automated diagnosis and classification of brain tumors from MRI scans. In the last decade, tremendous progress has been achieved in this domain and now models can achieve accuracy levels comparable to that of trained radiologists using standard data sets [39, 21]. One objective of this research work is attempted through the analysis of previous literature while the other one is attempted through building a new system of classification.

## **1.5 Problem Statement**

Despite considerable achievements in implementing AI methods for the analysis of medical images, there are still some challenges that need to be overcome in order to develop an effective solution for automated detection of brain tumors. Some of these difficulties are considered below as part of the current thesis:

Manual MRI analysis of the images for detecting brain tumors is a very time-consuming task, highly susceptible to errors due to humans and requiring much experience from specialists. Automated solutions, even though being efficient in their operations, have been tested independently without taking into account other models and conditions.

Furthermore, the majority of deep learning based classification models that classify brain tumor suffers from the lack of training data that is both small and in some cases

unbalanced also [2, 3]. Visual ambiguity among various tumor types when represented in MRI images presents another challenge, as not all models are able to properly classify them, especially those characterized by minor differences, such as glioma. Lastly, there is a dearth of interpretable models that, while providing an accurate classification, can offer an intelligible rationale for the classification itself.

These issues are being tackled in this thesis via: (1) conducting an all-encompassing and thorough analysis of existing approaches of automated brain tumor detection using MRIs by looking at their methodologies, datasets used, and performance measures in order to see what is currently known and what are their limitations; and (2) presenting a transfer learning based classification system based on the VGG16 neural network model that performs accurately when classifying four classes of brain tumors.

## **1.6 Research Objectives and Contributions**

The main objectives of this thesis are as follows:

- Objective 1: The aim is to perform a review of some recent developments related to the detection of tumors in brains through MRI images using automated approaches including classical machine learning techniques, CNN based deep learning techniques, transfer learning techniques, object detection techniques, Vision Transformer technique, and also hybrid methods. The objective is to make an effective comparison between different methods in use by discussing various methodologies involved in each method, datasets utilized for testing, and performances achieved.
- Objective 2: The objective of designing, implementing, and evaluating a transfer learning-based brain tumor classification model utilizing the VGG16 architecture of deep learning. The system aims to solve the multi-class problem consisting of classifying between glioma, meningioma, pituitary tumor, and no tumor, based on a public dataset of MRI images through the assessment of various performance parameters such as accuracy, precision, recall, and F1-score.

## 1.7 Thesis Organization

The rest of this thesis is arranged as follows:

In Chapter 2 we present a detailed review of earlier research carried out in the field of automatic segmentation of brain tumors using MRI scans. Traditional ML methods, CNN-based deep learning approaches, transfer learning algorithms, object detection models, Vision Transformers, as well as hybrid models have been considered in this chapter, which ends with conclusions and identified research gaps.

Chapter 3 details the methodology used in the proposed VGG16-based brain tumor classification technique, considering data preparation, pre-processing, model architecture, training, and evaluation.

Chapter 4 includes the results of experiments conducted, such as training performance graphs, quantitative evaluation results, class-based classification reports, confusion matrix analysis, as well as qualitative predictions of the model.

Chapter 5 concludes the thesis paper by providing key findings of the work along with future directions for research.

## **Chapter 2**

# **LITERATURE REVIEW**

### **2.1 Theoretical Background**

#### **2.1.1 Brain Tumor Detection in Medical Imaging**

Brain Tumor Detection is a very vital issue in the medical image processing because, the right detection of the abnormal brain tissues is a direct indication of whether the patients will survive or not as well as how they will be treated. Medical imaging data is difficult to detect tumors because tumor shape, size and location and intensity patterns vary among different patients. Also, the tumors may mimic the normal brain structures, and thus, manual examination is a bother. These issues are attempted to be resolved by the automated methods of detecting brain tumors that rely on the computational models that can capture the complex patterns of medical images and provide clinicians with a clearer and more assertive judgment in their diagnosis [33, 37, 17].

#### **2.1.2 Magnetic Resonance Imaging (MRI)**

The Magnetic Resonance Imaging (MRI) is one of the most commonly utilized medical imaging techniques in the diagnosis of brain tumours. It employs the magnetic fields and radio frequency waves of high strength to produce detailed images of the brain structures [12, 1]. MRI has a better soft-tissue contrast in comparison to Computed Tomography, which makes it possible to detect brain tissue abnormalities in the patient. Nevertheless, it may be difficult to manually examine MRI images that are complicated by brain structures and huge amount of medical imaging data which has given rise to

automated tumor detection systems.

### **2.1.3 Machine Learning in Medical Image Analysis**

ML is a subfield of AI that allows computer systems to learn trends based on data and provide predictions without being instructed to do so. ML methods have been applied in medical image analysis to analyze imaging data and identify patterns which are linked to diseases. Conventional machine learning methods usually consist of a number of steps such as image preprocessing, feature extraction and feature selection as well as classification. The extraction of features during the feature extraction stage is a production of significant properties in the form of MRI images as a result of the texture, shape, and intensity patterns. Classification algorithms are then applied to these features to classify normal and abnormal brain tissues. The support vector machines, random forest, and clustering-based methods are some of the machine learning algorithms that have been studied to perform tumor classification tasks [8, 27]. Despite the encouraging outcomes of these approaches, they tend to use handcrafted characteristics and take a long time to preprocess prior to classification.

### **2.1.4 Deep Learning for Brain Tumor Detection**

Deep learning is a more sophisticated branch of ML that is based on neural networks with multiple layers, which learns complex representations of data automatically. Deep learning-based methods have advanced the effectiveness of medical image analysis systems in the past years dramatically. CNNs are also successful in image related tasks since it is able to automatically extract spatial functionality in raw images. CNN-based architectures have been successfully utilized in detecting and classifying brain tumors with MRI images and they have shown great accuracy in differentiating tumorous tissues and healthy brain tissues [5, 12]. Besides the traditional CNN models, researches have also studied the use of transfer learning to enhance the performance of the models in case big medical data is unavailable [40, 22]. Moreover, the recent works have also mentioned transformer-based architecture and hybrid models in order to capture global contextual information in the medical images and improve the performance of the

tumor detectors [13]. In general, the methods of AI, in particular, deep learning models, have demonstrated great possibilities to enhance automated brain tumor detectors. Nevertheless, there are still a number of issues, such as the insufficiency of annotated medical data, inconsistency of tumor appearance, and the necessity of interpretable AI models in healthcare practice. All these factors leads to conducting more research in order to create efficient and reliable brain tumors detection systems.

## **2.2 Existing Techniques and Comparative Analysis**

Literature was reviewed to find relevant studies conducted from 2020 to 2026 with the use of keywords like brain tumor detection, MRI, deep learning, CNN and transformers. The databases searched include IEEE Xplore, Google Scholar among others. Redundant and less relevant papers were removed and recent studies on automated brain tumor detection using MRI were shortlisted for comparison.

### **2.2.1 Overview of Brain Tumor Detection Techniques**

It has suggested a number of methods of detecting brain tumors with MRI images automatically. Initial methods largely used manual techniques of ML in which features of MRI images were manually calculated and classifiers like SVM and Random Forest were used to classify them [8, 27]. As artificial intelligence has improved, deep learning-based models, specifically the CNNs, have become popular in the medical image analysis because of the capability to automatically learn complex features of an image[5, 12]. More recently, more sophisticated methods like object detection networks and transformer-based models have also been investigated to enhance further the results of tumor detection performance [16, 13, 36]. The summaries and comparisons of the available literature are presented in the following tables by the methodology and data they address as well as the results they report.

### 2.2.2 Theoretical Comparative Study

**Table 2.1:** Comparative Analysis of Existing Brain Tumor Detection Techniques

| No. of Ref. | Paper Title (Year)                                                                                 | Purpose / Results                                                                                                                        | Limitations                                                                   |
|-------------|----------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------|
| [8]         | Innovative Machine Learning Techniques for Brain Tumor Classification in MRI Using Hybrid Approach | The study proposes a hybrid machine learning approach for classifying brain tumors from MRI images and improves classification accuracy. | Performance depends on effective feature extraction and labeled MRI datasets. |
| [5]         | Inception V3 Infused Neural Network for Brain Tumor Detection                                      | A deep learning model based on the InceptionV3 architecture automatically detects brain tumors in MRI images with high accuracy.         | Requires large training datasets and high computational resources.            |
| [10]        | Hybrid Model for Brain Tumor Detection, Classification and Segmentation                            | Combines multiple techniques for tumor localization and segmentation to enhance diagnostic accuracy.                                     | Increased computational complexity and longer training time.                  |
| [16]        | Utilizing YOLOv5x for the Detection and Classification of Brain Tumors                             | Uses YOLOv5x object detection to identify tumor regions in MRI images.                                                                   | Requires powerful hardware and large annotated datasets.                      |
| [20]        | CNN-Based Multiscale Feature Extraction with MobileNetV2                                           | Integrates multiscale CNN features with MobileNetV2 to improve tumor classification performance.                                         | Model complexity increases due to hybrid architecture.                        |
| [1]         | Deep Transfer Learning Networks for Brain Tumor Detection Using MR Images                          | Evaluates different transfer learning models and shows improved tumor classification using pretrained networks.                          | Performance depends on similarity between pretrained and medical datasets.    |
| [27]        | Brain Cancer Detection Using CNN and Random Forest                                                 | Combines CNN feature extraction with Random Forest classification to improve detection accuracy.                                         | Hybrid pipeline increases training complexity.                                |
| [35]        | ViRCNN: Fusion of Vision Transformers and Faster R-CNN                                             | Hybrid architecture combining Vision Transformers and Faster R-CNN improves tumor detection accuracy.                                    | High computational requirements and complex architecture.                     |
| [25]        | MRI-Based Brain Tumor Detection Using Vision Transformers                                          | Vision Transformer with transfer learning improves classification performance on MRI datasets.                                           | Requires large datasets and significant computational power.                  |
| [4]         | Evaluating CNNs and Vision Transformers for Brain Tumor Detection                                  | Compares CNN and Vision Transformer models showing CNN is computationally more efficient.                                                | Transformer models require higher computation and longer training time.       |

### 2.2.3 Dataset Comparative Study

**Table 2.2:** Dataset Comparative Study

| Ref             | Dataset Name                               | Description                                                                        | No. of Images   | Imaging Type | Usage in Study                                                                           |
|-----------------|--------------------------------------------|------------------------------------------------------------------------------------|-----------------|--------------|------------------------------------------------------------------------------------------|
| [8, 27]         | Kaggle Brain MRI Dataset                   | Public dataset containing labeled MRI images for brain tumor classification.       | ~3000 images    | MRI          | Used for training machine learning and hybrid CNN models for tumor classification.       |
| [5, 20, 25]     | Figshare Brain Tumor Dataset               | Public dataset containing three tumor classes: glioma, meningioma, and pituitary.  | 3064 images     | MRI          | Used for CNN-based and transformer-based tumor classification studies.                   |
| [10, 1, 14, 35] | BraTS (Brain Tumor Segmentation Challenge) | Widely used benchmark dataset for brain tumor detection and segmentation research. | 2000+ MRI scans | MRI          | Used for deep learning, transfer learning, and transformer-based tumor detection models. |
| [16]            | Custom MRI Dataset                         | MRI images collected from medical institutions or research centers.                | ~1200 images    | MRI          | Used for training object detection models for tumor localization.                        |

### 2.2.4 Performance Metrics Comparison

**Table 2.3:** Performance Comparison of Brain Tumor Detection Techniques

| Ref | Brain Tumor Detection Techniques                           | Accuracy (%) | Precision (%) | Recall (%) | F1-score (%) |
|-----|------------------------------------------------------------|--------------|---------------|------------|--------------|
| [8] | Hybrid Machine Learning model for MRI tumor classification | 96.2         | 95.8          | 94.9       | 95.3         |
| [5] | InceptionV3 Convolutional Neural Network (CNN)             | 98.3         | 97.6          | 97.1       | 97.3         |

| <b>Ref</b> | <b>Brain Tumor Detection Techniques</b>              | <b>Accuracy (%)</b> | <b>Precision (%)</b> | <b>Recall (%)</b> | <b>F1-score (%)</b> |
|------------|------------------------------------------------------|---------------------|----------------------|-------------------|---------------------|
| [12]       | Deep Learning CNN classification model               | 97.1                | 96.5                 | 95.8              | 96.1                |
| [16]       | YOLOv5x object detection for tumor localization      | 97.9                | 96.7                 | 96.1              | 96.4                |
| [20]       | CNN with multiscale feature extraction + MobileNetV2 | 98.1                | 97.3                 | 96.9              | 97.1                |
| [1]        | Transfer learning using pretrained deep networks     | 98.0                | 96.9                 | 96.7              | 96.8                |
| [27]       | CNN feature extraction + Random Forest classifier    | 97.6                | 96.9                 | 96.3              | 96.6                |
| [14]       | Deep Neural Network architecture comparison          | 97.3                | 96.4                 | 96.1              | 96.2                |
| [35]       | Vision Transformer + Faster R-CNN hybrid detection   | 98.2                | 97.5                 | 97.0              | 97.2                |
| [25]       | Vision Transformer with transfer learning            | 98.1                | 97.1                 | 97.0              | 97.0                |
| [4]        | CNN vs Vision Transformer comparative model          | 98.3                | 97.2                 | 97.1              | 97.1                |

### 2.2.5 Synthesis and Discussion

In order to find the most topical techniques to be employed in automated brain tumor detection, we compared and contrasted current research works, depending on algorithms of detection, datasets, and performance characteristics. The analyzed articles prove that AI methods have contributed greatly to the accuracy and efficiency of tumor detection

devices with MRI images. Deep learning methods are the most popular methods of detecting brain tumors in the existing literature. The use of CNN is rather common since they do not require any manual feature-setting, though they automatically acquire complicated image features and achieve high classification rates [33, 37, 15]. Another common use of transfer learning methods is to enhance the performance of models when the number of training data is low [28]. Moreover, there is the recent work examining higher-level architectures including object detection systems and Vision Transformers, which can improve the localization and classification of tumors [23]. There is also a study that explores hybrid methods, that is, combining deep learning models with other machine learning classifiers, to enhance the detection accuracy even further [17].

CNN-based methods have achieved good results on many MRI datasets due to the local spatial information encoding capability of convolution layers and their robust performance with relatively small training data. It is possible to model long-term dependencies by transformer architecture, but it requires more data and computing power. In this regard, CNNs are still considered the main technique to identify brain tumors, while transformers and hybrid models are seen as an improvement.

The issue of class imbalance (when there are unequal amounts of different tumors) is critical for any medical image dataset because it may make the model biased and underperforming on some tumor types. Such issues can be solved with balanced sampling, data augmentation and cost-sensitive learning. The following issues can be outlined as those related to the study of brain tumors due to such comparative analysis.

The following problems can be outlined as the ones associated with brain tumor detection research through such comparative studies as:

1. Limitations in the availability of varied medical data: There are several cases when a specific study uses available publicly accessible datasets, including BraTS, Figshare, and Kaggle Brain MRI datasets, which can be limiting the variety of training data and can influence model generalization [6].
2. Reliance on big annotated data sets: Training in deep learning to perform well requires large annotated MRI datasets, which are not always easily accessible since medical data privacy and annotation might be needed [7].

3. High computational complexity: New models of deep learning, particularly transformer-based architecture and hybrid detection systems are frequently computationally expensive and time-consuming to train [23].
4. Model ininterpretability in clinical settings: As much as deep learning models are very accurate in detection, most of the models are black-box and medical professionals cannot interpret the prediction and have trust in them [19].
5. Minimal clinical testing: Most of the proposed models are tested on just benchmark data and their effectiveness in actual clinical settings is still a key area of future research [32, 9].

## Chapter 3

# EXPERIMENTAL DESIGN

### 3.1 Proposed Approach

The experiment design employed in this research work for detecting and classifying brain tumors from MRI images using a transfer learning approach is elaborated in this chapter. The experiment involves the description of the dataset, data preprocessing techniques employed, the proposed model architecture, model training parameters, and performance metrics used for evaluating the model.

In this work, the proposed approach has been designed with an emphasis on the use of a transfer learning approach, specifically by leveraging the use of the pre-trained VGG16 deep learning model on the large-scale ImageNet dataset. Transfer learning has been adopted as the central approach in this project due to its unique ability to employ feature representations learned from the large general-purpose dataset to carry out specialized tasks, such as classifying brain tumors from MRI images [1, 11, 34]. The incorporation of transfer learning into the medical image processing domain becomes imperative because the creation of annotated large datasets specifically for the purpose becomes immensely difficult and expensive. By doing so, only the pretrained model needs to be employed for the extraction of feature representation, after which the custom-built classification layer must be trained, hence limiting the risk of overfitting by virtue of lower parameter learning [26, 30].

The reason why VGG16 was chosen as the fundamental architecture in this study is because even though there are new and improved architectures like the ResNets, DenseNet121 and Xception architectures, they are composed of numerous layers and

parameters making them inappropriate to be applied on small datasets because they are well suited for generalized and larger datasets[23, 34]. Nevertheless, VGG16 is a reasonable model, which has excellent properties related to the extraction of features and good size, making it a suitable one for solving this four-class classification task. Additionally, VGG16 represents a commonly used architecture in many transfer learning studies, making it a good fit for demonstrating the efficiency of transfer learning on this dataset.

The complete process of this pipeline architecture is shown in Figure 3.1 below. The original MRI image undergoes some preprocessing techniques such as resizing and normalization before being fed into the model. The training data set goes through some data augmentation techniques. After preprocessing, the image passes through the fixed convolutional part of the VGG16 model, where it learns some valuable feature maps. The features learned are then fed into the custom classifier head made up of a densely connected fully connected layer and Softmax output layer, giving the probability score of all four classes—glioma, meningioma, pituitary, and no tumor.

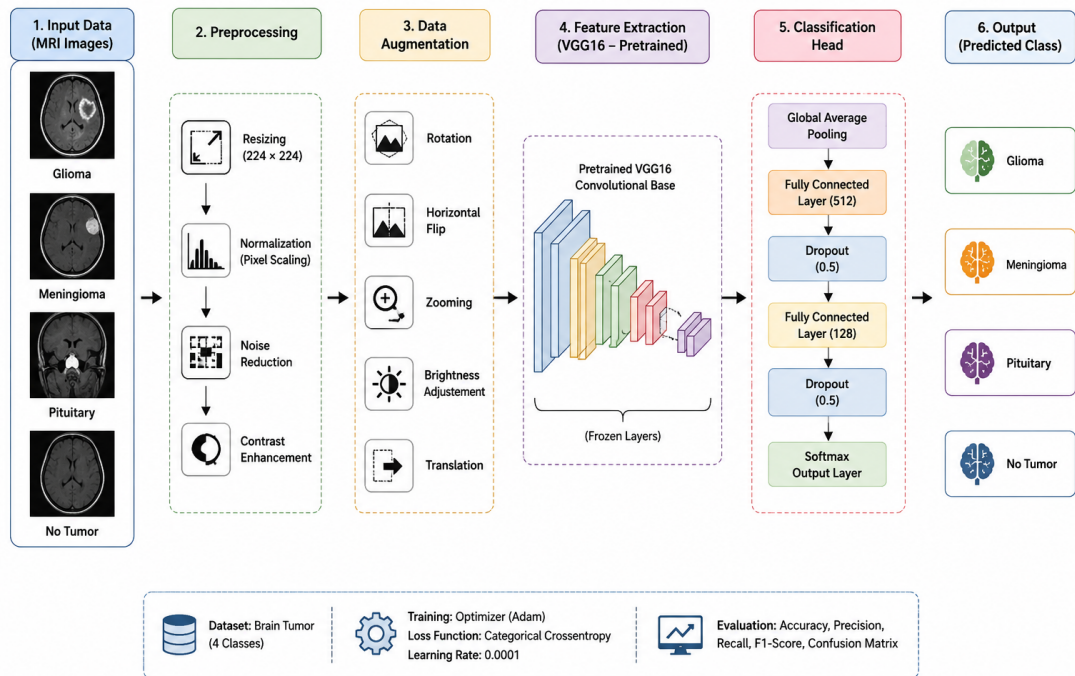


**Figure 3.1:** Overall workflow of the proposed VGG16-based brain tumor classification system.

## **3.2 Dataset**

### **3.2.1 Dataset Description**

The data set chosen for this research work is 'Brain Tumor MRI Dataset' which is freely accessible from Kaggle. The total number of MRI brain scans in this data set is 7,023. These images have been categorized into four classes which include glioma, meningioma, pituitary tumor, and no tumor. The images in this data set have already been split up into two sets which are termed as training data (5,712) and testing data (1,311). Thus, there is an approximate split ratio of 80% training data and 20% testing data in this data set. This helps facilitate replicability by providing the ability to compare the results with those obtained by other researchers on this data set.

### **3.2.2 Class Distribution**

The dataset is made up of four categories, each depicting a unique clinically identifiable class of brain scan. The glioma class includes MRI scans of brains with gliomas. Gliomas are brain tumors that originate from glial cells and are among the most prevalent and dangerous types of brain tumors. The meningioma class includes brain scans with meningiomas. Meningiomas are benign tumors that originate from the meninges. They are usually located in such a way that they may lead to severe neurological issues. The pituitary class includes brain scans with pituitary tumors. Pituitary tumors grow in the pituitary gland and interfere with hormonal balance. The no-tumor class includes brain scans without any detectable tumors; this class acts as the negative class. The test set consists of 306 images of glioma brain scans, 300 images of meningioma brain scans, 405 images of no-tumor brain scans, and 300 images of pituitary brain scans.

### **3.2.3 Sample MRI Images**

Figure 3.2 provides samples of MRI images that represent each of the four categories in the dataset. In this case, the images serve to show the visual properties of each category and the difficulty involved in automatic classification, since the tumors may sometimes share similar visual properties, especially glioma and meningioma.

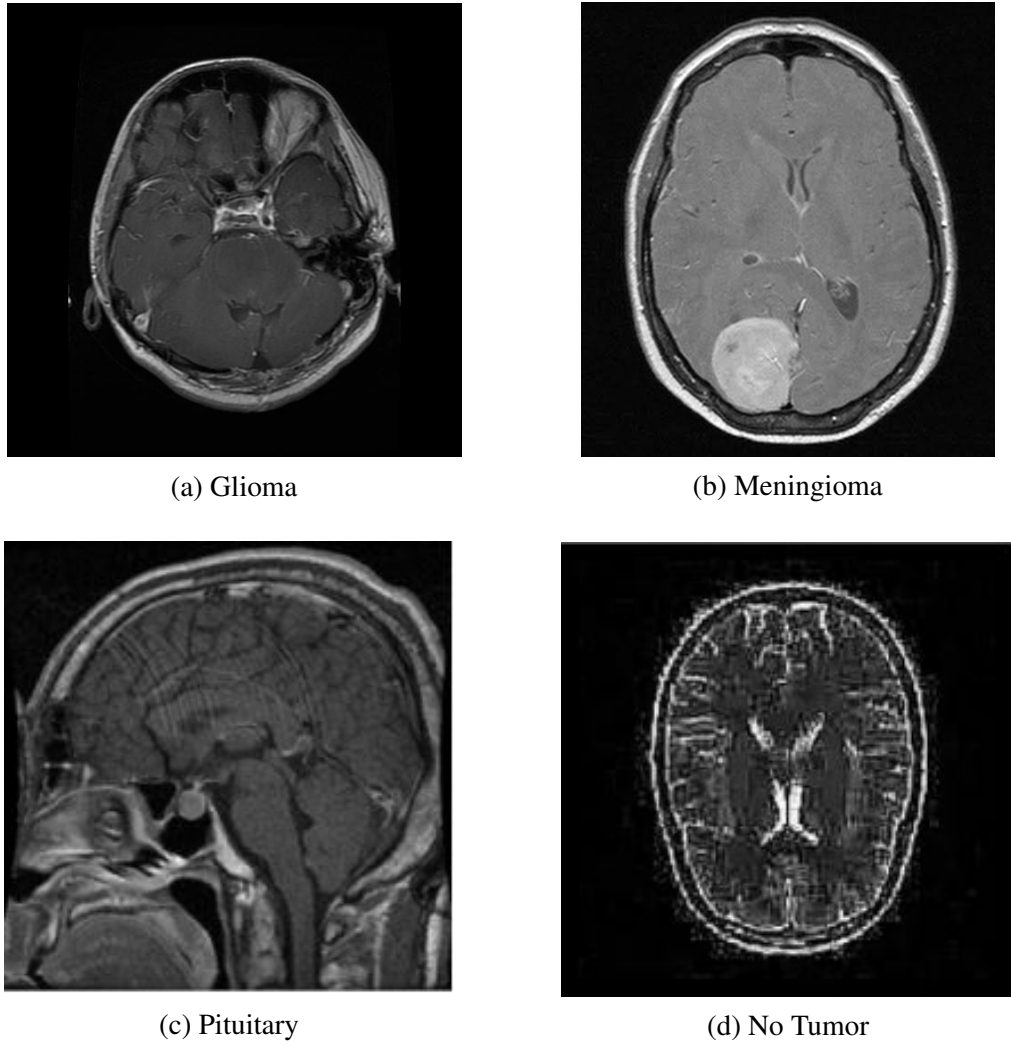


**Figure 3.2:** Sample MRI images representing the four classes in the dataset: glioma, meningioma, pituitary, and no tumor.

### 3.3 Data Preprocessing

Input data preprocessing is perhaps one of the most crucial processes in the development of an efficient deep learning algorithm. Input data was preprocessed in a series of operations on the whole dataset.

#### 3.3.1 Image Resizing and Standardization

The very first preprocessing task that we did involved normalizing the sizes of all images. We resized all MRIs in the training set and testing set into  $224 \times 224$  pixels. This is not a random decision;  $224 \times 224$  pixels happen to be the standard input size in

the VGG16 model, which was pretrained on the ImageNet dataset at this resolution. By standardizing image sizes, we ensure that our inputs are compatible with the pretrained model and can extract features from all images uniformly regardless of their original sizes.

### 3.4 Data Augmentation

In fact, data augmentation was widely used during training as one of the essential techniques for achieving higher generalization and stability of the model. In the field of medical image processing, the amount of annotated training samples is usually insufficient, leading to overfitting when training is conducted using small amounts of data without augmentation. Overfitting is a scenario where the model memorizes the properties of the training samples, but does not learn generalized features that can be applied to other samples. This problem is overcome using data augmentation [2, 3], which increases the amount of training data by generating new samples using various random transformations of existing ones.

The following standard augmentation methods were used for the training data during the training process. The following augmentation methods were used independently on all training images in each epoch to provide variety in the examples of augmentation.

**Rotation:** In training images, rotation was performed within a fixed angle range. Such an approach helps to simulate the variability in the position of the patients' heads in MRI scanning and makes sure that the model is invariant to the orientation of the brain image.

**Horizontal flipping:** Horizontal flipping was randomly applied in the training images to simulate the possible left and right scans of the brain structures. Brain MRIs may be captured in two hemispheres, so horizontal flipping makes sense to use in such cases.

**Zoom:** Zooming was used to simulate the difference in scale of the brains of different MRI scans due to the individuality of each person's brain and scanner setting.

**Shearing:** Shearing transformations help simulate mild angular transformations in training images.

The above augmentation methods have been used on the training dataset alone.

Augmentation was not performed on the test dataset as the purpose of the test dataset is to offer an objective measure of how the model performs on unseen data.

### 3.5 Baseline Model — VGG16 Architecture

In the context of this study, the architecture that forms the basis for our analysis is VGG16, which was created by the Visual Geometry Group at the University of Oxford, and pre-trained on ILSVRC (ImageNet Large Scale Visual Recognition Challenge) data set. This architecture has been chosen because of its simple homogenous design with 16 weight layers, including 13 convolutional layers and three fully-connected layers, which form stacks of convolutional blocks followed by max-pooling operations. In all convolutional layers, we used  $3 \times 3$  filters with a stride size of one along with same-padding, while in max-pooling operations, we employed  $2 \times 2$  filters with a stride size of two. The number of feature maps used in this model gradually increased from 64 in the first block to 512 in the last convolutional block [11, 30].

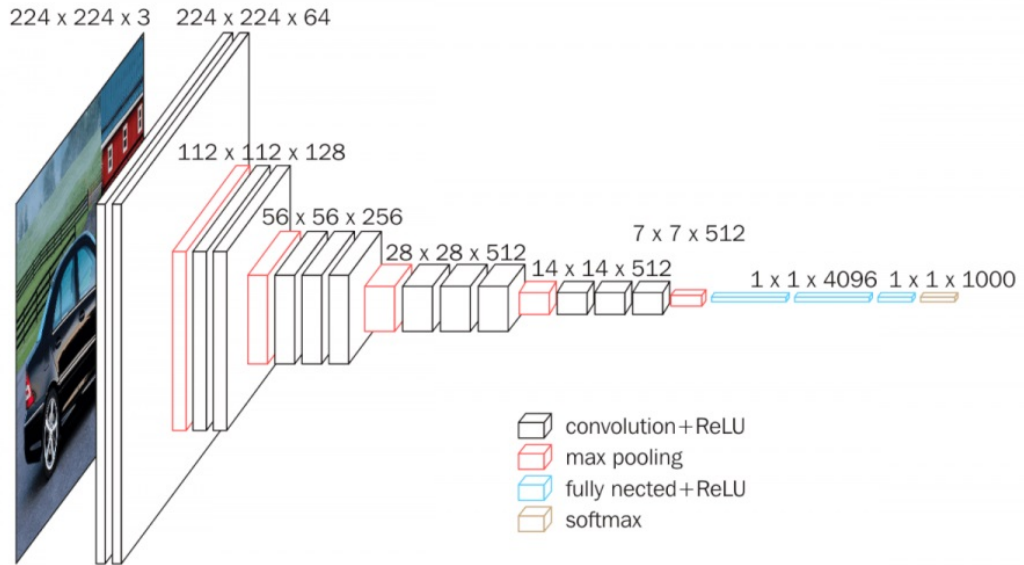


**Figure 3.3:** Architecture of the VGG16 deep learning model.

#### 3.5.1 VGG16 as Feature Extractor

In the described solution, the convolutional layer of the VGG16 network, which consists of 13 convolutional layers as well as the subsequent max-pooling layers, was utilized as

the feature extraction part. VGG16 is considered suitable for this application because of its ability to recognize complex patterns and structures in images. The knowledge obtained by the weights of the convolutional layer of the VGG16 network, trained on more than a million images belonging to 1,000 categories in ImageNet, contains a wide range of visual patterns.

### **3.5.2 Freezing the Convolutional Base**

The convolutional layer of the VGG16 network remained unchanged during training, implying that the weights were not trainable for the whole duration of the training process. There are two key reasons why this method is employed. First, it ensures that the network can benefit from the rich set of abstract features learned during the pre-training phase using the ImageNet dataset, which can be utilized effectively in extracting features from MRI images. Secondly, by freezing the convolutional layer, the number of parameters in the network decreases, making overfitting less likely in the smaller medical dataset [1, 23, 11].

### **3.5.3 Custom Classification Head**

The classification head was customized and added above the VGG16 convolutional base, which is frozen. This classification head comprises a dense layer and an output layer. The dense layer performs a nonlinear mapping function on the high-dimensional feature vector generated by the VGG16 base. The model learns specific classification boundaries based on the nonlinearity of the mapping function. The output layer generates probabilities for the four classes.

### **3.5.4 Activation Functions**

The selection of activation functions was guided by their proven performance in the domain of deep learning techniques. The ReLU (Rectified Linear Unit) activation function was used in the hidden dense layer. The use of ReLU ensures that there is a required non-linearity, which helps the neural network to learn a complicated, non-linear decision boundary, and prevents the occurrence of the problem of vanishing gradients

because it allows backpropagation to work efficiently, leading to fast training. The Softmax activation function was employed in the output layer. The reason why Softmax is widely used in multi-class classification problems is because it transforms the raw outputs from the neural network into a probability distribution among the four possible categories.

## **3.6 Parameter Settings**

### **3.6.1 Development Environment**

The modeling was implemented through the TensorFlow machine learning framework with its high-level Keras interface. TensorFlow and Keras were selected because of their flexibility, comprehensive documentation, and strong capabilities in developing deep learning models. In addition, the development of models through the TensorFlow library and Keras was conducted within a Python environment. The use of Python programming language along with TensorFlow and Keras made this combination very popular among deep learning researchers.

### **3.6.2 Loss Function**

The loss function employed for this classification problem involving multiple classes was that of the Sparse Categorical Cross Entropy. Such a loss function is the go-to for a classification problem where the target values are represented in integer form and not using the one hot encoded vectors representation method. The loss function works in the sense that the difference between the probabilities predicted from the softmax output layer and the actual class value is calculated, with the penalty increasing with the decrease in predicted probabilities for the right class.

### **3.6.3 Optimizer**

Adam optimizer was employed for updating the values of the parameters in the model during training. It is a powerful and flexible optimization method that adjusts the learning rates for individual parameters using estimations of the gradient's first and

second moments. The use of such a technique ensures faster convergence and better generalization across a variety of deep learning tasks, which is why Adam has become the optimizer of choice for many practitioners training their deep neural networks [18, 22, 29].

#### 3.6.4 Batch Size and Epochs

Training took place over 5 epochs, wherein one epoch corresponds to one pass over the entire training dataset. The data was split into mini-batches with a size of 32, which implies that after the model had processed each batch of 32 images, an update would be made to the internal parameters of the model. Mini-batch gradient descent offers a compromise between the benefits offered by batch training and the stochasticity which enables the optimizer to avoid falling into local minima. The short period of training of 5 epochs reflects the approach of transferring knowledge, as well as the intention not to overfit the new network. All parameters used during training are listed in Table 3.1.

**Table 3.1:** Training Configuration and Parameter Settings of the Proposed VGG16 Model

| Parameter               | Value                                       |
|-------------------------|---------------------------------------------|
| Input Image Size        | $224 \times 224$ pixels                     |
| Optimizer               | Adam                                        |
| Loss Function           | Sparse Categorical Crossentropy             |
| Number of Epochs        | 5                                           |
| Batch Size              | 32                                          |
| Output Classes          | 4 (Glioma, Meningioma, Pituitary, No Tumor) |
| Output Activation       | Softmax                                     |
| Hidden Layer Activation | ReLU                                        |
| Development Framework   | TensorFlow / Keras (Python)                 |

### 3.7 Performance Measures

For conducting an assessment of the model performance, a series of metrics were employed to evaluate it in its totality. These metrics give alternative angles of insight into how the classification model operates, as elaborated further in the sections below

together with their formulas. In the formulas, the notation TP stands for true positive, TN for true negative, FP for false positive, and FN for false negative.

### 3.7.1 Accuracy

The accuracy refers to the general percentage of images that are properly categorized within the four classes. The accuracy can be computed through dividing the total number of samples that are correctly categorized by the total number of samples.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3.1)$$

### 3.7.2 Precision

Precision refers to the accuracy of positive predictions. It is a measure of the model's skill in not making any negative predictions positive. This is especially significant in disease diagnostics since a false positive would subject patients to undue anxiety.

$$Precision = \frac{TP}{TP + FP} \quad (3.2)$$

### 3.7.3 Recall

Remembering, also called sensitivity, is the percentage of all positives that were successfully predicted by the classifier. In medical imaging, remembering is an important metric because it tells how well the classifier is able to predict the disease. When there is a low value of remembering in a certain class, it means the classifier is predicting fewer positive examples in that class.

$$Recall = \frac{TP}{TP + FN} \quad (3.3)$$

### 3.7.4 F1-Score

The F1-Score calculates a single performance metric of the model based on the harmonic mean between the Precision and Recall scores. The F1-Score is a more meaningful

single score than accuracy because it takes into account the imbalance in the dataset and punishes algorithms with high precision but low recall, or vice versa.

$$F1\text{-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3.4)$$

### 3.7.5 Confusion Matrix

Along with the above scalar measures, a confusion matrix was calculated based on the predictions made by the model on the test data set. The confusion matrix will provide us with an evaluation of the performance of our model, based on how many examples there have been in each class that have either been correctly or wrongly classified. We can use this technique to find any peculiar trends in terms of the errors made in the classification process. This is something that we might be able to use in order to find out the types of tumors that gets mixed up with each other.

**Table 3.2:** Basic Structure of a Confusion Matrix

| Actual / Predicted | Positive            | Negative            |
|--------------------|---------------------|---------------------|
| Positive           | True Positive (TP)  | False Negative (FN) |
| Negative           | False Positive (FP) | True Negative (TN)  |

## 3.8 Computational Environment

The experiments were done using Google Colaboratory as the primary platform. Google Colaboratory is a free software development cloud computing service offered by Google. It is used to run Python code using a Jupyter notebook format. This tool allows for GPU and TPU computations, making the training of deep learning models much faster compared to CPU calculations. The use of GPU computations became quite important for the current study because it would cost much to train the VGG-16 based classifier with more than 7,000 MRI images on a personal computer. Google Colab was combined with widely used Python packages for deep learning and data science, including TensorFlow, Keras, NumPy, Matplotlib, and scikit-learn, all of which were employed at various stages of this research in developing, training, evaluating, and

visualizing the results of different models. Being a cloud-based platform, it was possible to do quick iterations during the experimentation phase, whereby different types of model architecture, hyperparameters, and image preprocessing could be experimented upon and fine-tuned. In addition, regarding the use of Colab, the ability to integrate with Google Drive made it easy to save and access the dataset and weight parameters, thereby making my project sustainable.

## Chapter 4

# RESULTS AND DISCUSSION

This chapter provides an exhaustive analysis of the performance of the VGG16 brain tumor classifier after its training. First, the performance of the model during the training process will be evaluated in terms of how well it learned from the training dataset. The next part of this chapter will evaluate the performance of the model based on the test dataset which is unknown to the model. Finally, some qualitative aspects of predictions will be evaluated.

### 4.1 Model Training Performance

The model was trained for 5 epochs altogether, while accuracy and losses of the model on training and validation sets were evaluated after every epoch. The learning curves of the model are shown in Figure 4.1.

Training and validation accuracy graphs show an even increase in accuracy in all epochs, which means that the model was getting better at distinguishing four types of tumors. Training and validation losses decreased proportionally with the number of epochs, showing that the more iterations the model performed during training, the more accurate its predictions became. The even decrease in accuracy and losses in the last few epochs shows that the model converged and learned everything possible from the dataset.

The stability in the validation set is especially helpful since the validation set gives us an unbiased measure of how our algorithm performs on unseen data. The resemblance between both the training and the validation curves in all epochs assures us that there

was no overfitting on the training dataset, hence proving the effectiveness of the whole process where we freeze the VGG16 pre-trained convolutional layer while training only the classifier we created. The training of our model for just a few epochs is intentionally done to ensure that we train our classifier fully without overfitting [1, 11].

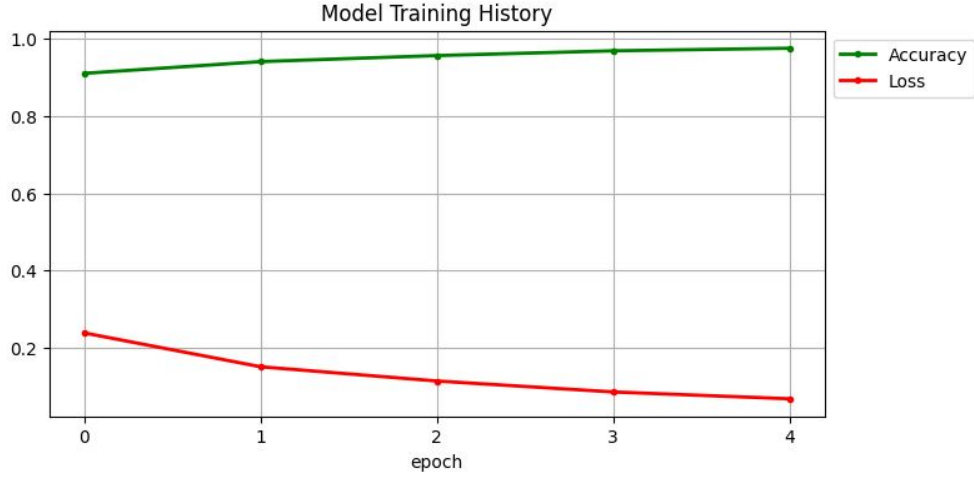


**Figure 4.1:** Training and validation accuracy and loss curves of the VGG16-based model.

## 4.2 Quantitative Evaluation on Test Data

### 4.2.1 Overall Performance Metrics

After training, the performance of the model on the test dataset of 1,311 images not seen by the model during training was calculated. The performance of the model on this dataset is shown in Table 4.1 below.

**Table 4.1:** Overall Performance Metrics on the Test Set

| Metric    | Score |
|-----------|-------|
| Accuracy  | 96.0% |
| Precision | 0.96  |
| Recall    | 0.96  |
| F1-Score  | 0.96  |

The proposed VGG16-based model achieved an impressive final test accuracy of 96.0%. The class-wise average of precision, recall, and F1 score was 0.96, 0.96,

and 0.96, respectively. This indicates that the model exhibited strong and consistent prediction capability for all four classes of tumors. These findings indicate that VGG16-based transfer learning technique can produce impressive results for four-class brain tumor classification [14, 23].

#### 4.2.2 Class-wise Classification Report

The performance of the model on a class-by-class basis is summarized in Table 4.2 below and includes the precision, recall, F1-score, and support of each of the four classes.

**Table 4.2:** Classification Report on the Test Set

| <b>Class</b>        | <b>Precision</b> | <b>Recall</b> | <b>F1-Score</b> | <b>Support</b> |
|---------------------|------------------|---------------|-----------------|----------------|
| Glioma              | 0.96             | 0.90          | 0.93            | 306            |
| Meningioma          | 0.94             | 0.96          | 0.95            | 300            |
| No Tumor            | 1.00             | 1.00          | 1.00            | 405            |
| Pituitary           | 0.94             | 0.99          | 0.96            | 300            |
| <b>Accuracy</b>     |                  |               | 0.96            | 1311           |
| <b>Macro Avg</b>    | 0.96             | 0.96          | 0.96            | 1311           |
| <b>Weighted Avg</b> | 0.96             | 0.96          | 0.96            | 1311           |

From these findings, it can be concluded that the model had a high level of performance in terms of classifying brain scan images that belong to the no tumor class. In fact, the model achieved a perfect precision and recall rate of 1.00, as a result getting a perfect F1 score of 1.00. The finding suggests that the model is highly dependable and accurate in the classification of normal brain scans compared to those that are infected with brain tumors. The same level of performance was also recorded for meningioma and pituitary classes, whose respective F1-scores were 0.95 and 0.96. Glioma class got an F1-score of 0.93 with a precision of 0.96 and recall of 0.90 [39, 21].

#### 4.2.3 Confusion Matrix Analysis

A confusion matrix of the test set results is provided in Figure 4.2 below. The figure gives a detailed look at how accurate the model is in its classifications on a per-class basis.

As can be seen from the figure above, the model demonstrates excellent overall classification results. Specifically, when dealing with the no tumor class, the model was able to classify 403 images correctly and misclassify only two of them in the meningioma class. Thus, detecting healthy brain scans was almost entirely successful for the model. When it comes to the pituitary class, 297 out of 300 images were classified successfully with 1 image being misclassified into the meningioma class and 2 into the glioma class. As for the meningioma class, the model classified 274 images out of 300 accurately while the remaining 13, 2, and 17 were misclassified into the glioma, no tumor, and pituitary classes, respectively, which indicates some similarity between meningioma and other classes visually. When considering the glioma class, 289 out of 306 were correctly classified with 9 being incorrectly assigned to the meningioma class and 2 to the pituitary class.

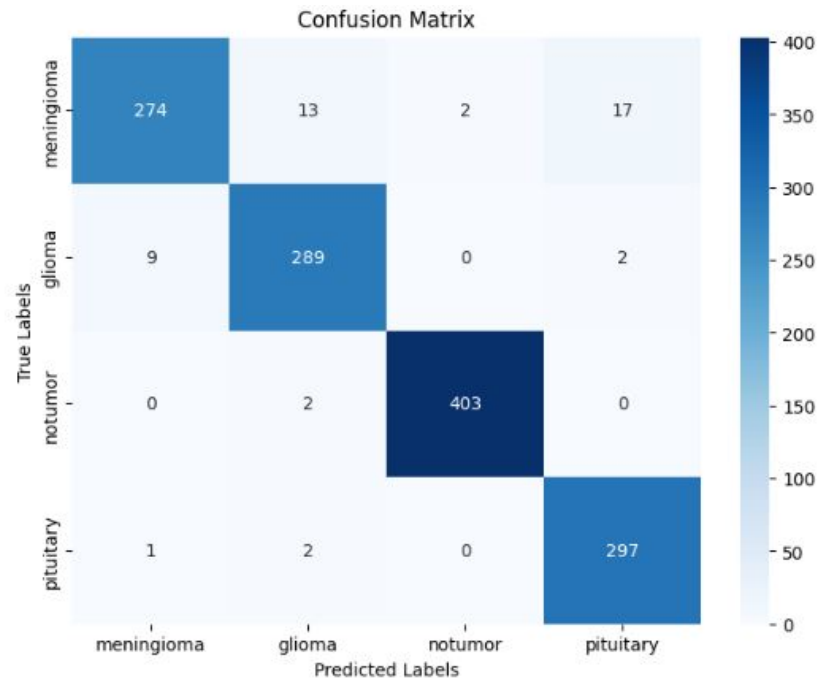


**Figure 4.2:** Confusion matrix of the proposed VGG16 model on the test set.

### 4.3 Qualitative Analysis of Predictions

In order to give a more detailed account of how well the model performs, apart from statistical calculations, Figure 5.3 shows the results of a qualitative evaluation of the predictions that the model makes based on images taken from a test dataset. For each example, the image used as input data, the real label, the prediction result, and its corresponding confidence level are shown.

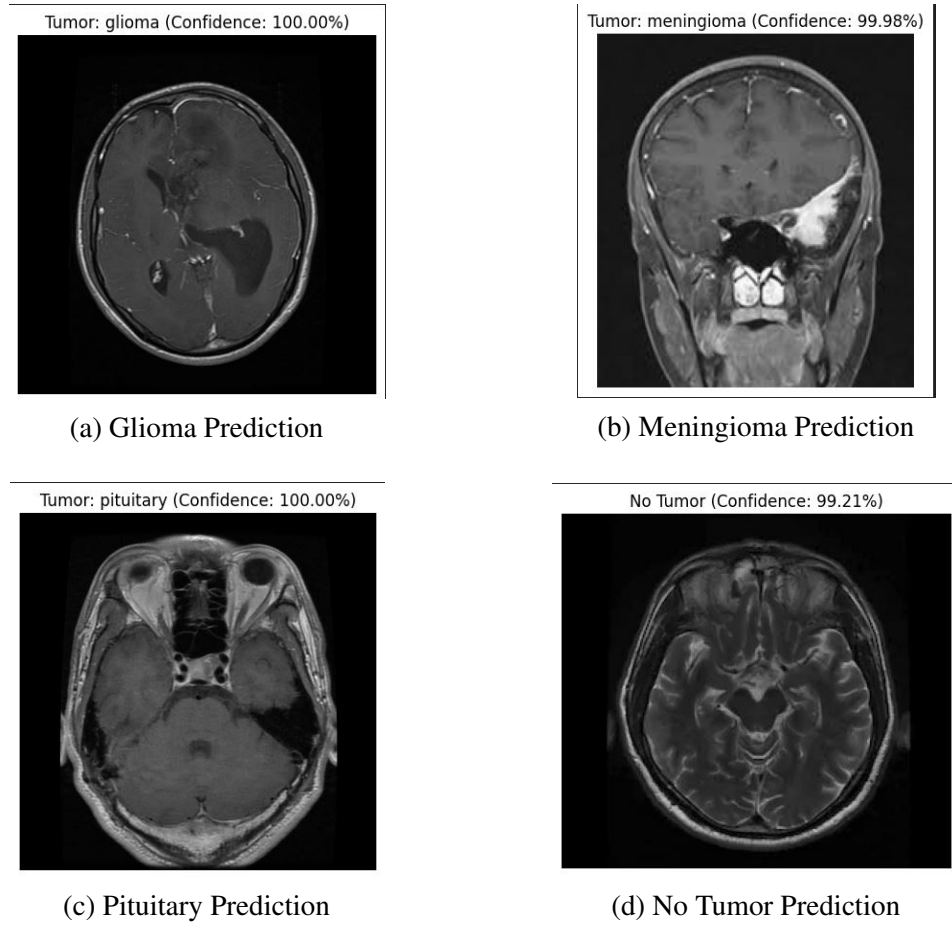


**Figure 4.3:** Qualitative prediction results of the proposed VGG16 model across the four tumor classes.

The figure indicates that the model gives confidence values close to 100% when correctly classifying an image for each of the four tumors. For the meningioma sample, the model gives a confidence score of 99.98%, while the confidence value for the no tumor sample is 99.21%, the confidence score for the pituitary sample is 100.00%, and the confidence score for the glioma sample is 100.00%. The ability of the model to

provide such a high level of confidence values shows its great prediction strength.

Case-based visualization is important because it helps add human-understandable insights to the dry numerical values by providing examples of how the model behaves. When analyzing the cases where the model fails, it is possible to get insights into some of the problems with perception that might happen, including the fact that the visual differences between different types of tumors can cause the model to make mistakes when classifying them [8, 20].

## **4.4 Limitations**

### **4.4.1 Model and Data Limitations**

The major drawback associated with the suggested model is that the training and validation of this model was done using only a single publicly available dataset collected from Kaggle. Even though this particular dataset contains a reasonably varied set of MRI scans belonging to all four categories, it does not offer the variation that would be seen in the MRI scans found in the real world [2]. The MRI scans obtained from various hospitals across various geographical areas will have differences in image clarity and even in the appearance of tumors.

One of the other problems associated with this is that of domain shift, and this is also a major concern in the practical application of deep learning models in medical imaging [39, 34]. One of the reasons why the variance tends to be very high when applying deep learning models in the field of MRI is due to the fact that there are two major types of variations involved. On the one hand, different hospitals may be using MRI machines manufactured by different firms, which would mean that there is variation in the type of noise, as well as the amount of signal strength, contrast level and so forth. Secondly, doctors may be using T1, T2, and FLAIR acquisitions in their work.

In addition to this, the above-described system has never been tested in a real-life clinical setting [19, 6]. In order to conduct a proper testing of the system described in this research, the only thing done by its author was to evaluate the system using a benchmark database, which does not provide enough insight into real-life deployment

of the system and does not account for such things as image artifacts, motion blur and unusual presentation of tumors.

#### **4.4.2 Field-wide Limitations**

Apart from the particular challenges facing the proposed system, there are various difficulties associated with automated brain tumor detection from MRI images as a whole, and that have been pointed out in literature as being constant throughout the research process.

One of the main difficulties facing this line of work is a lack of diverse imaging data. It has to be noted that the vast majority of papers, including the one in question, use a very limited amount of public MRI datasets, namely BraTS, Figshare, and Kaggle Brain MRI [7, 1].

Another obstacle is the need for large amounts of training data for deep learning methods. The annotation of medical images entails considerable time and skill requirements from highly qualified radiologists, thus posing problems associated with the high cost and logistically demanding process of gathering data sets annotated manually [38, 36]. Moreover, it becomes harder to train models that could function accurately under diverse conditions and among different patients because of this problem.

One cannot ignore the challenge related to the high computational cost associated with sophisticated deep learning models. Transformers and other hybrid solutions have significant computation demands, thus complicating their practical implementation, particularly in the context of healthcare environments. [35, 4].

Finally, there has been no adequate link made between the performance of the proposed models in benchmarking and their clinical validation, which is still a major unresolved issue in this area. The majority of proposed models have only been evaluated through benchmarking, while very little work has been done to assess how they will perform clinically because of differences in imaging and patients from benchmarks.[19, 13].

## Chapter 5

# CONCLUSION AND FUTURE SCOPE

### 5.1 Conclusion

One of the most serious types of neurology-related disease is brain tumors, and timely detection plays an essential role in improving the success rate of treatment and increasing patients' chances of survival. Although manual MRI interpretation remains an integral part of the diagnoses brain tumors, it can be considered a time-consuming and observer-dependent process, which is highly dependent on the radiologist's experience and skills. Due to high demand and the volume of imaging data obtained during a day in large hospitals, such reliance on human analysis poses additional challenges in terms of inefficiency and inconsistency, thus increasing the need to develop the reliable computer vision-based algorithms for detecting and classifying tumors from MRI images. Solving the outlined problems is of critical importance, as it would allow making the process of identifying and diagnosing brain tumors more efficient and less prone to mistakes. Throughout this research work two different contributions aimed at addressing this challenge were made throughout this thesis. Firstly, a detailed examination of the current state-of-the-art related to the use of automated solutions in diagnosing brain tumors was conducted, involving a range of techniques from machine learning to various deep learning models (e.g., CNNs, transfer learning, object detection, Vision Transformers, and hybrid models). The second contribution was to develop, implement and evaluate a brain tumor classification system based on transfer learning using the VGG16 neural network architecture. This was achieved for a four class classification problem, namely glioma, meningioma, pituitary tumors, and no tumors on a publicly available MRI

dataset. Both of these contributions directly address the challenge facing clinicians and researchers in development of an accurate but efficient system that's backed by the relevant literature.

This field-wide survey provided several notable results about the current state of brain tumor detection using automation techniques. First, it was determined beyond any reasonable doubt that the deep learning paradigm has become the dominant one in the field. Indeed, the use of deep learning in automated brain tumor detection brought about significant changes in the field, allowing forming models able to automatically learn feature representations from raw images of brain tumors without the need of manual intervention during this stage. In concerns of deep learning-based methods, it was found that convolutional neural networks can provide impressive results. The use of transfer learning, in particular, proved to be widespread within the field [1, 14, 11, 26]. Indeed, the ability of transfer learning to deliver highly accurate results when used with relatively small medical imaging datasets trained on feature representations learned by neural networks on larger general-purpose ones, such as ImageNet, proved to be an attractive advantage of transfer learning in a domain where the training datasets are hard to assemble. Moreover, the research found that the more recent and advanced architectures, such as Vision Transformers and highly intricate hybrid architectures that integrate various architectures, have achieved impressive results in improving performances at the frontier of research in this area. Nevertheless, this is associated with significantly increased computational costs and the need for large annotated medical imaging databases, which greatly restricts the practicality of deploying the architecture in clinical settings where computational resources are limited. Additionally, a number of major limitations that hinder the use of automated detection systems for brain tumors in the clinic were outlined, including the scarcity of data across diverse institutions, the need for large-scale training data annotated by experts in deep learning, high computational costs associated with the most recent architectures, and the considerable disparity between the benchmark and clinical validation performance.

The experimental part of this thesis managed to implement and validate the deep learning algorithm for automated multi-class brain tumor classification from MRI scans

successfully. With the help of a transfer learning technique that uses a pre-trained VGG16 model, fine-tuned on the target brain MRI dataset, the proposed system was able to reach 96% final test accuracy on an external dataset consisting of 1,311 MRI scans. In addition, the weighted average precision, recall, and F1-score of the model in all four classes reached 0.96, indicating a reliable and accurate prediction capability of the proposed system. Moreover, it is worth noting that the proposed model managed to show excellent performance in classifying meningioma and pituitary cases, reaching an F1-score of 0.95 and 0.96, respectively. In other words, the proposed deep learning model showed promising results while tackling the entire four-class problem. One of the key advantages of the proposed deep learning system is that it can be considered highly efficient and straightforward, as the authors did not train the convolutional layer, but only the custom classification head. As can be seen from the research results, an effective single-model transfer learning scheme can achieve a very high level of competitiveness in brain tumor classification, having great potential to be used in radiology practice in order to improve diagnosis speed, increase capacity, and ensure more consistent decisions during diagnostics. In addition, the results provide important information regarding the level of competitiveness of the proposed solution in comparison to the existing state-of-the-art models: although novel networks, such as ResNet, DenseNet, and Vision Transformer, have outperformed the proposed model by some level of accuracy, their superiority cannot compete with the proposed architecture in terms of computational complexity level [35, 25, 4].

In sum, both the contribution of the thesis in terms of a comprehensive review and the experimental implementation of a transfer learning framework for brain tumor classification from MRI data indicate the immense potential of both deep learning and transfer learning algorithms in establishing an effective, reliable and robust framework for detecting and classifying brain tumors using MRI data. First, the field-wide survey serves as a useful reference for researchers and practitioners to have a consolidated view of the state-of-the-art techniques in the field, to compare their respective advantages and disadvantages, and to identify the challenges that must be overcome before the field can realize its full clinical applications. Second, the experimental implementation of

the proposed transfer learning framework serves as a useful baseline for implementing a brain tumor classification model based on MRI data that provides validation of the method on the specific problem of brain tumor classification among four classes of brain tumors. These form a basis for further research involving the improvement of ensemble learning, architecture and clinical usage.

## 5.2 Future Scope

A key immediate area of further research is the augmentation of the training data set with MRI data from multiple institutions. The model built during this study was trained and tested using only one publicly available MRI dataset from Kaggle, which, although valuable and popular for testing purposes, does not fully represent the heterogeneity of the actual clinical MRI images. MRI scans performed in different hospitals, geographical locations, and in different patients can exhibit notable differences in image quality, resolution, acquisition parameters; manufacturer of the scanner, and presentation of brain tumors [39, 22]. It is unlikely that a model trained on only one source of MRI images will be able to generalize well in clinical settings where the MRI data will not have the same characteristics as the training data, an effect referred to as domain shift. It is important that the next stage of development includes building an extensive MRI dataset obtained from multiple hospitals and featuring multiple MRI sequences, such as T1-weighted, T2-weighted, and FLAIR images.

Enhancements in the architecture design and the investigation of additional sophisticated deep learning frameworks is another logical area to consider in future research. Although it can be stated that the VGG16 system based on transfer learning performed very well from a classification perspective, it should also be noted that according to the literature, even more sophisticated architectures such as ResNet50, DenseNet121, Xception and InceptionV3 have been successful in providing better results when dealing with similar problems [31, 21]. Fine-tuning should be considered as an option that involves the process of freezing some specific layers of a pre-trained base model alongside with training a classification part. Moreover, it would be worth investigating ensemble approaches in which the output of several independently trained models is combined

into one decision. It is noted from the existing literature that ensemble models result in high precision and accuracy in the classification of brain tumors due to the fact that the combination of different model outputs results in low variance and minimizes the shortcomings of each of the models [36]. Another approach worth exploring is the combination of the unique characteristics of convolutional neural networks and vision transformers. The increasing availability of powerful computational resources would make these complex models much easier to implement.

One of the crucial and urgent directions for future research on the subject of interest concerns the combination of explainable artificial intelligence methods with deep learning-based brain tumor detection models [19, 13]. XAI is considered one of the most important prerequisites for the clinically responsible implementation of artificial intelligence in medicine, especially considering the lack of interpretability of these systems. Although deep learning models are characterized by very high classification accuracy, they remain black boxes, as the decision-making process within them cannot be interpreted by medical specialists. Such an approach significantly restricts the clinical adoption of artificial intelligence algorithms, as medical practitioners need both the prediction and its explanation to draw a conclusion regarding the patient's condition. The introduction of methods for generating explanations, such as Grad-CAM, SHAP, or LIME, will enable the visualization of the model decision and highlight particular regions of the MRI scan that contribute the most to the algorithm's decision. Explanations such as these would add a large amount of transparency and trustworthiness to the predictions of the model in question, making it much easier for radiologists to detect instances of clinically implausible behavior by the model.

Finally, and the most important path for future work must be systematic filling of the substantial gulf between the benchmark evaluation and clinical validation currently prevalent in the domain of automated brain tumor detection systems. Indeed, virtually all deep learning models that have been proposed for this task in literature, including the one that was implemented in the research project, were evaluated in terms of their performance on manually annotated MRI benchmarks specifically designed for this purpose. The true event of clinical applicability and safety can only be determined

via prospective clinical validation studies conducted on data collected under actual clinical conditions where the imaging modality, demographic characteristics, pathology of the tumors and accuracy of the manual annotations may significantly differ from the ones used during the evaluation process [6, 38, 24]. Clinical validation studies will inevitably involve collaboration between researchers in artificial intelligence and healthcare organizations that not only possess patients MRI data and radiological expertise, but also have the ability to integrate artificial intelligence solutions into their clinical practice. This research area along with developing automated solutions with a focus on clinical application is definitely the most promising and important direction for brain tumor detection in the future.

## Bibliography

- [1] S. Ahmad and P. K. Choudhury. On the performance of deep transfer learning networks for brain tumor detection using mr images. *IEEE Access*, 10:59099–59114, 2022. doi: 10.1109/ACCESS.2022.3179376.
- [2] M. Z. Alam, T. Roy, H. M. N. Kawsar, and I. Rimi. Enhancing transfer learning for medical image classification with SMOTE: A comparative study. In *Proceedings of the 27th International Conference on Computer and Information Technology (ICCIT)*, 2024.
- [3] Ankur, M. Gupta, R. Kumar, and P. Zanke. Enhancing the brain tumor detection using data augmentation with CNNs. In *Proceedings of the 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, 2024.
- [4] T. Bande, A. Yadav, and D. K. Vishwakarma. Evaluating cnns and vision transformers for brain tumor detection: A trade-off between performance and computation. In *Proceedings of the IEEE International Conference on Computer Vision and Machine Intelligence (CVMI)*, 2025. doi: 10.1109/CVMI66673.2025.11337696.
- [5] K. Bhargava, H. Nanda, and N. K. Basha. Inceptionv3 infused neural network for brain tumor detection. In *Proceedings of the 5th International Conference on Smart Electronics and Communication (ICOSEC)*, pages 1063–1068, 2024. doi: 10.1109/ICOSEC61587.2024.10722625.
- [6] M. Chahar and D. Vetrithangam. Early brain tumour detection via self-supervised 3d multi-task learning with spatio-temporal modelling. In *Proceedings of the*

- IEEE 6th Global Conference on Advancement in Technology (GCAT)*, pages 1–6, 2025. doi: 10.1109/GCAT66372.2025.11368442.
- [7] S. Chatterjee, F. A. Nizamani, A. Nurnberger, and O. Speck. Classification of brain tumours in mr images using deep spatiotemporal models. *Scientific Reports*, 12:1505, 2022. doi: 10.1038/s41598-022-05572-6.
- [8] A. S. Chauhan, R. K. Kanna, N. K. Sharma, K. Singh, P. K. Tiwari, and M. Kumar. Innovative machine learning techniques for brain tumor classification in mri using hybrid approach. In *Proceedings of the International Conference on Computational Intelligence and Communication Technologies (CCICT)*, 2025.
- [9] B. Deepa, S. Geetha, S. Sreesanth, B. Sridhar, and M. Yuvarani. Brain tumor detection with severity identification using k-means clustering. In *Proceedings of the 1st International Conference on Advances in Computer Science, Electrical, Electronics, and Communication Technologies (CE2CT)*, 2025. doi: 10.1109/CE2CT64011.2025.10939308.
- [10] S. Dhanasekar, S. Hariharan, L. C. Leela, A. Bharathi, and K. Harini. Hybrid model for brain tumor detection, classification & segmentation. In *Proceedings of the IEEE 4th International Conference on Advancement in Technology (ICONAT)*, pages 1–7, 2025. doi: 10.1109/ICONAT66879.2025.11362898.
- [11] S. R. Govind, B. Moparthi, A. Sheryl Oliver, and M. Kituthika. Robust brain tumor classification using transfer learning and convolutional neural networks. In *Proceedings of the International Conference on Pervasive Computational Technologies (ICPCT)*, 2025.
- [12] Z. Jia and D. Chen. Brain tumor identification and classification of mri images using deep learning techniques. *IEEE Access*, 13:123783–123792, 2025. doi: 10.1109/ACCESS.2020.3016319.
- [13] S. Kalifati and M. Z. Konyar. Brain tumor detection using explainable artificial intelligence and transformers. In *Proceedings of the 33rd Signal*

- Processing and Communications Applications Conference (SIU)*, 2025. doi: 10.1109/SIU66497.2025.11111782.
- [14] S. K. Kanagapriya, V. Vijeya Kaveri, S. Saraswathi, and V. Meenakshi. Revolutionizing brain tumor diagnosis with enhanced deep learning and transfer learning algorithms. In *Proceedings of the 9th International Conference on Science Technology Engineering and Mathematics (ICONSTEM)*, 2024. doi: 10.1109/ICONSTEM60960.2024.10568647.
- [15] D. Kaur, A. Ummat, and S. Kaur. Comparative study of machine learning based tumor detection techniques in human brain. In *Proceedings of the 2nd International Conference on Computational Methods in Science & Technology (ICCMST)*, pages 118–122, 2021. doi: 10.1109/ICCMST54943.2021.00034.
- [16] M. Kumar, U. Pilania, T. Bhayana, and S. Thakur. Utilizing yolov5x for the detection and classification of brain tumors. In *Proceedings of the 2nd International Conference on Disruptive Technologies (ICDT)*, pages 1343–1348, 2024. doi: 10.1109/ICDT61202.2024.10489507.
- [17] D. P. L., N. Ponraj, and S. V. G. A comparative analysis of deep neural networks for brain tumor detection. In *Proceedings of the 3rd International Conference on Signal Processing and Communication (ICPSC)*, pages 36–40, Coimbatore, India, May 2021. doi: 10.1109/ICSPC51351.2021.9451742.
- [18] X. Liu and Z. Wang. Deep learning in medical image classification from MRI-based brain tumor images. In *Proceedings of the IEEE 6th International Conference on Power, Intelligent Computing and Systems (ICPICS)*, 2024.
- [19] S. J. Mohammed and G. A. Al-Suhail. Explainable ai-based deep learning for brain tumor mri analysis: A review. In *Proceedings of the IEEE 6th International Conference on Communications, Information, Electronic and Energy Systems (CIEES)*, pages 1–7, 2025. doi: 10.1109/CIEES66347.2025.11300122.
- [20] B. N., P. Kumar, C. BalaSubramanian, and S. Pandi. Revolutionizing brain tumor classification: A hybrid model incorporating cnn-based multiscale feature

- extraction and mobilenet v2. In *Proceedings of the 2nd International Conference on Advances in Information Technology (ICAIT)*, pages 1–6, 2024. doi: 10.1109/ICAIT61638.2024.10690820.
- [21] K. Neamah, F. Mohamed, S. R. Waheed, W. H. M. Kurdi, A. Y. Taha, and K. A. Kadhim. Utilizing deep improved ResNet50 for brain tumor classification based MRI. *IEEE Open Journal of the Computer Society*, 2024.
- [22] S. Padmakala and U. M. S. Deep learning-based MRI analysis for brain tumor detection: Insights from ResNet and DenseNet models. In *Proceedings of the 8th International Conference on Electronics, Communication and Aerospace Technology (ICECA)*, 2024.
- [23] J. K. Periasamy, B. S., and J. P. Comparison of vgg-19 and resnet-50 algorithms in brain tumor detection. In *Proceedings of the IEEE 8th International Conference on Convergence in Technology (I2CT)*, pages 1–5, Pune, India, April 2023. doi: 10.1109/I2CT57861.2023.10126451.
- [24] R. R., J. D. M., M. M., and V. P. Exploring deep learning techniques for MRI brain tumor image segmentation: A survey. In *Proceedings of the International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI)*, 2024.
- [25] M. Ridwan, T. T. Ali, S. T. T. Erin, R. K. Tushar, F. Mahmud, and S. Siddique. Mri-based brain tumor detection and classification system using vision transformers and transfer learning. In *Proceedings of the IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI)*, 2025. doi: 10.1109/IATMSI64286.2025.10984625.
- [26] V. A. S. and M. M. C. M. Automatic classification of brain MRI slices into glioma/meningioma using deep transfer-learning. In *Proceedings of the International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE)*, 2025.

- [27] J. Sabeena, K. Keerthipati Kumar, C. Santhaiah, and D. Lavanya. Brain cancer detection using a fusion of convolutional neural networks and random forests in deep vision systems. In *Proceedings of the International Conference on Sustainable Communication Networks and Application (ICSCNA)*, pages 641–646, 2024. doi: 10.1109/ICSCNA63714.2024.10863903.
- [28] B. Saxena, A. Arora, M. Gupta, P. Mittal, and J. Singh. Features driven brain tumor detection using machine learning models. In *Proceedings of the 1st International Conference on Informatics (ICI)*, pages 53–59, Noida, India, April 2022. doi: 10.1109/ICI53355.2022.9786905.
- [29] P. Shaha, M. S. A. Shakil, S. Imtiaz, M. M. R. Mridha, M. J. Chaudhary, M. A. I. Mizan, and M. T. Khan. MRI-based identification of brain tumors using deep convolutional neural networks: A case study on inception V3. In *Proceedings of the International Conference on Electrical, Computer and Communication Engineering (ECCE)*, 2025.
- [30] S. V. Shinde, A. D. Thakare, and P. R. Padole. Leveraging pre-trained deep learning models for brain tumor detection and classification from MRI scans. In *Proceedings of the 5th International Conference on Smart Systems and Inventive Technology (ICSSIT)*, 2023.
- [31] R. Singamshetty, S. Sruthi, K. Chandhana, S. Kollem, and C. R. Prasad. Brain tumor detection using the inception deep learning technique. In *Proceedings of the International Conference on Recent Trends in Electronics and Communication (ICRTEC)*, 2023.
- [32] C. A. Subasini, D. Chandrasekar, A. Hamid, and A. Sheeba. Brain tumor classification and detection using dynamic machine learning. In *Proceedings of the 2nd International Conference on Networking and Communications (ICNWC)*, pages 1–6, 2024. doi: 10.1109/ICNWC60771.2024.10537318.
- [33] U. Y. Tambe and A. Shanthini. Brain tumor detection & classification into different categories using deep learning model. In *Proceedings of the International*

- Conference on Advanced Computing Technologies and Applications (ICACTA)*, pages 1–6, 2023. doi: 10.1109/ICACTA58201.2023.10393430.
- [34] M. C. S. Tang and S. S. Teoh. Brain tumor detection from MRI images based on ResNet18. In *Proceedings of the 6th International Conference on Information Systems and Computer Networks (ISCON)*, 2023.
- [35] M. Momen Tayefeh, S. A. G. Ghahramani, and A. M. A. Hemmatyar. Advancing brain tumor detection via vircnn: A fusion of vision transformers and faster r-cnn. In *Proceedings of the 15th International Conference on Computer and Knowledge Engineering (ICCCKE)*, 2025. doi: 10.1109/ICCCKE68588.2025.11273875.
- [36] T. Vaiyapuri, J. Mahalingam, S. Ahmad, H. A. M. Abdeljaber, E. Yang, and S.-Y. Jeong. Ensemble learning driven computer-aided diagnosis model for brain tumor classification on magnetic resonance imaging. *IEEE Access*, 2023.
- [37] K. Vidhya, B. Vamsi Krishna, M. Haritha, R. S. Rajasekaran, R. C. Chandrika, and V. Jayaraj. Multiclass brain tumor detection using convolutional neural network and conventional machine learning. In *Proceedings of the International Conference on Emerging Research in Computational Science (ICERCS)*, pages 1–6, 2024. doi: 10.1109/ICERCS63125.2024.10894882.
- [38] S. Wani, S. Ahuja, and A. Kumar. Application of deep neural networks and machine learning algorithms for diagnosis of brain tumour. In *Proceedings of the International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES)*, 2023.
- [39] A. Younis, Q. Li, Z. Afzal, M. J. Adamu, H. B. Kawuwa, F. Hussain, and H. Hussain. Abnormal brain tumors classification using ResNet50 and its comprehensive evaluation. *IEEE Access*, 2024.
- [40] D. Q. Zeebaree, D. A. Zebari, I. M. Zeebaree, M. A. Mohammed, B. A. Mohammed, and N. A. Zebari. Deep learning convolutional neural networks classification based on brain cancer mri. In *Proceedings of the International Con-*

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## DECLARATION

I hereby certify that the work which is presented in the Dissertation entitled **BRAIN TUMOR DETECTION AND CLASSIFICATION FROM MRI IMAGES: DEEP LEARNING PERSPECTIVES AND AUTOMATED DIAGNOSTIC APPROACHES** in fulfillment of the requirement for the award of the Degree of Master of Technology in **Software Engineering** and submitted to the Department of **Software Engineering**, Delhi Technological University, Delhi is an authentic record of my own work carried out during the period from **August 2024 to May 2026**, under the supervision of **Dr. Shweta Meena**. The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other Institute/University. The work has been accepted in peer reviewed SCOPUS-indexed conferences with the following details:

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| <b>Author names:</b>                | Mehak Jagwani, Shweta Meena                                                                    |
| <b>Name of Conference:</b>          | International Conference on Computational Engineering, Sensing and Technology Management, 2025 |
| <b>Conference Dates with Venue:</b> | 18th November 2025, Western Sydney University, Australia                                       |
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| <b>Date of Acceptance:</b>          | 30 October 2025                                                                                |
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**Paper 2:**

**Title of the Paper:** Recent Advances in Automated Brain Tumor Detection from MRI Images: A Review

**Author names:** Mehek Jagwani and Shweta Meena

**Name of Conference:** 4th International Conference on Ambient Intelligence in Health Care

**Conference Dates with Venue:** 18-19 September 2026, National Institute of Technology (NIT) Raipur

**Conference Registration:** 1131

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### Abstract

#### Document Sections

- I. Introduction
- II. Related Work
- III. Research Methodology
- IV. Results and Discussion
- V. Conclusion



### Abstract:

Brain tumors give rise to a serious global public health problem, necessitating timely and accurate detection to allow for effectual treatment and improved patient outcome. Magnetic Resonance Imaging (MRI) scan analysis by humans is often time-consuming, subject to human error, and also, request technical expertise. This research aims to address these restraints through the development of high-performance automatic brain tumor classification system using transfer learning under the direction of VGG16 deep learning model. Our perspective lever-ages on the pre-trained VGG16 model, which was fine-tuned on a huge MRI image dataset, to classify tumors into four groups as: glioma, meningioma, pituitary, and no tumor. Data augmentation approaches were highly used during the training phase as an attempt to uplift the overall generalization and stability of the model. The suggested model attain a tremendously high test accuracy of 96%, with outstanding dimensions of discrimination among the various tumor groups and normal brain tissues, with exceptionally powerful performance in the detection of 'no tumor' group. In spite of the fact that other modern deep architectures like ResNet and DenseNet carry out satisfactory presentation in this direction, our

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### I. Introduction

Human brain is an extremely complex organ that governs all of the body functions, thoughts, and feelings. Uncontrolled and inappropriate growth of cells within the brain leads to the development of a brain tumor, which is a life-threatening and serious condition. Accurate initial diagnosis of brain tumor is required to ensure effective treatment and improve patient survival rate. MRI is the pre-eminent non-invasive imaging technique used by clinicians owing to this factor, due to its fine soft-tissue contrast. Interpretation of the

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Paper Title: Recent Advances in Automated Brain Tumor Detection from MRI Images: A Review

**Abstract:**

Brain tumors are among the most serious neurological disease and can have a remarkable impact on human health and survival if not discovered at an early stage. For that reason, accurate and timely detection is required for effective treatment planning and improved patient outcomes. Magnetic Resonance Imaging is widely used by medical professional for the analysis and diagnosis of brain tumors because it provides high-resolution images of soft brain tissues without subjection to ionizing radiation. However, manual inspection of MRI scans is time-consuming and highly dependent on the skill of radiologists, particularly when dealing with large imaging datasets. Over the last several years, the quick development of Artificial Intelligence and Machine Learning technologies has provided productive solutions for automated brain tumor detection while enhancing the efficiency and accuracy of the diagnostic process. Several approaches, including classical machine learning methods, deep learning models, Convolutional Neural Networks, hybrid techniques and Transformers, have been put forward for tumor classification, localization and detection from MRI images. This review paper aims to present the fundamentals of brain tumor detection and inspect the role of MRI imaging in automated diagnosis systems. Furthermore, the paper provides a comparative study of recent machine learning and deep learning models in terms of datasets, methodologies and performance measures. It also discusses the weaknesses and limitations of existing methods and highlights possible future directions for dependable and clinically applicable AI-driven brain tumor detection systems.

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## Author's Biography

**Mehak Jagwani** is currently pursuing a Master of Technology (M.Tech) in Software Engineering from Delhi Technological University (DTU), New Delhi. She completed her Bachelor's degree in Computer Science and Engineering, where she developed a strong foundation in programming, machine learning, and computer vision.

Her research interests include medical image analysis, computer vision, and deep learning systems for healthcare applications. During her postgraduate studies, she has worked extensively on brain tumor detection and classification using MRI images, focusing on transfer learning and convolutional neural network (CNN)-based approaches for automated diagnosis.

She has contributed to research in the domain of medical image classification, including studies on transfer learning techniques and comparative analysis of deep learning models for brain tumor detection. Her work emphasizes improving diagnostic accuracy, computational efficiency, and the development of reliable AI-assisted healthcare solutions.