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Empowering Healthcare: A Platform for Innovative Brain Tumor classification

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Dédicace

Thanks to Allah first-then the efforts of my loved ones who helped me a lot with their advice and efforts when we were going to offer this job.
Dedicate this work to my dear mother,
To my Father.
To my all brothers and sisters
To all my best friends
To my Supervisors Dr. Bilal Attallah and Dr. Oussama Bouguerra
To all my colleagues.
Lamri Islam

Abstract

Brain tumors pose a significant challenge to human health, demanding accurate and timely diagnosis for effective treatment. Artificial intelligence (AI), particularly deep learning, has emerged as a promising tool for medical image analysis, offering the potential to improve diagnostic accuracy and efficiency. This work investigates the impact of data balancing on brain tumor detection from Magnetic Resonance Imaging (MRI) scans using pre-trained EfficientNet models (B0, B3, and B5). We trained the models ona combined dataset of 7023 brain MRI images, categorized into four classes: Glioma, Meningioma, No Tumor, and Pituitary. A key aspect of our study was the comparison of performance between a balanced training set and the original imbalanced dataset. To optimize model performance, we incorporated Batch Normalization, Dropout, and Dense layers, while adjusting the number of epochs and batch size. The resulting models were evaluated based on Accuracy, F1-Score, Recall, and Precision metrics. Our results reveal a significant improvement in model performance when using a balanced training set. For example, on the imbalanced dataset, the EfficientNet B5 model achieved an accuracy of 98.85%, F1-Score of 98.88%, Recall of 98.92%, and Precision of 98.84%. However, after balancing the training data, the same model achieved an accuracy of 99.69%, F1-Score of 99.69%, Recall of 99.69%, and Precision of 99.70%. This high-lights the crucial role of data balancing in optimizing deep learning models for brain tumor detection, contributing to the advancement of AI-driven medical imaging and potentially leading to improved patient care and outcomes.

keywords :Medical image analysis, EfficientNet models, Data balancing, Convolution Neural Network, Brain tumors.

Résumé

Les tumeurs cérébrales représentent un défi important pour la santé humaine, exigeant un diagnostic précis et rapide pour un traitement efficace. L'intelligence artificielle (IA), en particulier l'apprentissage profond, est apparue comme un outil prometteur pour l'analyse des images médicales, offrant la possibilité d'améliorer la précision et l'efficacité du diagnostic. Ce travail étudie l'impact de l'équilibrage des données sur la détection des tumeurs cérébrales à partir d'examens d'imagerie par résonance magnétique (IRM) en utilisant des modèles EfficientNet pré-entraînés (B0, B3 et B5). Nous avons entraîné les modèles sur un ensemble de données combinées de 7023 images IRM du cerveau, réparties en quatre classes : gliome, méningiome, pas de tumeur et hypophyse. Un aspect clé de notre étude était la comparaison des performances entre un ensemble de formation équilibré et l'ensemble de données original déséquilibré. Pour optimiser les performances du modèle, nous avons incorporé la normalisation par lots, l'abandon et les couches denses, tout en ajustant le nombre d'époques et la taille des lots. Les modèles résultants ont été évalués sur la base des métriques Accuracy, F1-Score, Recall et Precision. Nos résultats révèlent une amélioration significative des performances des modèles lors de l'utilisation d'un ensemble de formation équilibré. Par exemple, sur l'ensemble de données déséquilibré, le modèle EfficientNet B5 a obtenu une précision de 98,85 %, un score F1 de 98,88 %, un rappel de 98,92 % et une précision de 98,84 %. Cependant, après avoir équilibré les données d'entraînement, le même modèle a atteint une précision de 99,69 %, un score F1 de 99,69 %, un rappel de 99,69 % et une précision de 99,70 %. Cette étude met en lumière le rôle crucial de l'équilibrage des données dans l'optimisation des modèles d'apprentissage profond pour la détection des tumeurs cérébrales, contribuant ainsi à l'avancement de l'imagerie médicale pilotée par l'IA et conduisant potentiellement à l'amélioration des soins et des résultats pour les patients.

Mots clés : Analyse d'images médicales, Modèles EfficientNet, Équilibrage des données, Réseau de neurones à convolution, Tumeurs cérébrales.

الملخص

تشكل أورام الدماغ تحديًا كبيرًا لصحة الإنسان، وتتطلب تشخيصًا دقيقًا وفي الوقت المناسب من أجل العلاج الفعال. وقد برز الذكاء الاصطناعي، ولا سيما التعلّم العميق، كأداة واعدة لتحليل الصور الطبية، مما يوفر إمكانية تحسين دقة التشخيص وكفاءته. يبحث هذا العمل في تأثير موازنة البيانات على اكتشاف أورام الدماغ من فحوصات التصوير بالرنين المغناطيسي (MRI)باستخدام نماذج EfficientNet المدربة مسبقًا (B0و B3وB5) .قمنا بتدريب النماذج على مجموعة بيانات مجمعة من 7023 صورة تصوير بالرنين المغناطيسي للدماغ، مصنفة إلى أربع فئات: الورم الدبقي، والورم السحائي، والورم السحائي، وعدم وجود ورم، والغدة النخامية. كان أحد الجوانب الرئيسية لدراستنا هو مقارنة الأداء بين مجموعة التدريب المتوازنة ومجموعة البيانات الأصلية غير المتوازنة. ولتحسين أداء النموذج، قمنا بدمج تطبيع الدُفعات والتسرب والطبقات الكثيفة، مع تعديل عدد الحلقات وحجم الدُفعات. تم تقييم النماذج الناتجة استنادًا إلى مقاييس الدقة ودرجة F1 والتذكر والدقة. تكشف نتائجنا عن تحسن كبير في أداء النموذج عند استخدام مجموعة تدريب متوازنة. فعلى سبيل المثال، في مجموعة البيانات غير المتوازنة، حقق نموذج EfficientNet B5 دقة بنسبة 98.85%، ودرجة F1- Score بنسبة 98.88%، واسترجاع بنسبة 98.92%، ودقة بنسبة 98.84%. ومع ذلك، بعد موازنة بيانات التدريب، حقق النموذج نفسه دقة بنسبة 99.69%، ودرجة F1 بنسبة 99.69%، واسترجاع بنسبة 99.69%، ودقة بنسبة يسلط هذا البحث الضوء على الدور الحاسم لموازنة البيانات في تحسين نماذج التعلم العميق للكشف عن أورام الدماغ، مما يساهم في تطوير التصوير الطبي القائم على الذكاء الاصطناعي وربما يؤدي إلى تحسين رعاية المرضى ونتائجهم.

الكلمات المفتاحية: تحليل الصور الطبية، نماذج EfficientNet، موازنة البيانات، الشبكة العصبية التلافيفية، أورام الدماغ.

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List of Abbreviations

AI Artificial Intelligence

CNN Convolutional Neural Networks

CT Computed Tomography

DL Deep Learning

DNN Deep Neural Networks

FC Fully Connected

FN False Negative

FP False Positive

ML Machine Learning

MRI Magnetic Resonance Imaging

MRS Magnetic Resonance Spectroscopy

PET Positron Emission Tomography

Relu Rectified Linear Unit

RNN Recurrent Neural Networks

SPECT Single-Photon Emission Computed Tomography

TN True Negative

TP True Positive

Contents

General Introduction

Brain tumors represent a significant health concern, posing a substantial challenge for both diagnosis and treatment. The complex nature of these tumors, their diverse sub-types, and their often-subtle presentation on imaging make accurate and timely detection crucial for effective management and improved patient outcomes. Early diagnosis allows for more targeted treatment options, potentially increasing survival rates and improving long-term quality of life. Traditional methods for brain tumor diagnosis rely heavily on manual interpretation of medical images, primarily magnetic resonance imaging (MRI). MRI provides detailed anatomical and structural information, allowing medical professionals to visualize the tumor's size, location, and characteristics. However, manual interpretation of MRI scans can be a time-consuming and labor-intensive process. It requires specialized expertise, and the accuracy of interpretation can be influenced by human error, fatigue, and inter-observer variability. Furthermore, the increasing volume of medical images generated by modern imaging techniques places a significant burden on healthcare systems, highlighting the need for more efficient and reliable diagnostic tools. The advent of artificial intelligence (AI), particularly deep learning,has ushered in a new era of medical image analysis. Deep learning algorithms, trained on massive datasets of medical images, can learn complex patterns and features, enabling them to automatically detect, segment, and classify abnormalities with remarkable accuracy. This has the potential to revolutionize medical imaging, providing faster and more reliable diagnostic insights, potentially leading to earlier detection, more precise treatment planning, and improved patient care. This thesis focuses on investigating the application of deep learning techniques, specifically EfficientNet models, for brain tumor classification. The study addresses the critical challenge of class imbalance, a common problem in medical image datasets, where different tumor types are represented unevenly. This imbalance can bias model training, leading to inaccurate predictions, especially for minority classes. The research compares the performance of EfficientNet models trained on both balanced and imbalanced datasets to evaluate the impact of class imbalance on model accuracy and reliability. The first chapter covers the medical aspect of this study, beginning with brain tumors and studying their basic causes, common symptoms, and other types, as well as how they are treated and how they affect people's lives around the world. We will also discuss the use of machine learning, deep learning, and various architectures. In the second chapter, we discussed the most recent results in the field of brain tumors during the previous few years before introducing our brain tumor system and its components. We offered a full description of each aspect of our system, giving readers a sense of the methodologies and strategies used in this work. In the last chapter, we provided a brief overview of the datasets used and some evaluation metrics for measuring the performance of the produced CNN models. Finally, we presented the findings of our research on the usefulness of several deep learning models for brain tumor classification.

Chapitre 1

Introduction to Brain Tumors and AI

1 Introduction

The prospect of being diagnosed with a brain tumor can be both frightening and life-changing. If your doctor discovers a brain tumor, you should consult with a specialist who specializes in detecting and treating brain tumors. The brain is a complicated and essential organ, and therapy frequently produces long-term changes. Brain tumor treatment research is continuous, Consequently, it is essential to have current medical information about available treatments for the particular type of brain tumor you have., as well as the opinions of professionals about your treatment strategy [1].This chapter's goal is to increase our understanding of brain tumors through the research of their basic causes that show the common symptoms and other types and the way they are treated, and how they affect the lives of people around the world, Medical Imaging Overview and we will talk about the use of machine learning, deep learning, and different architectures.

2 Brain Tumor Overview

A brain tumor is an abnormal growth of tissue that can affect brain function and is located in the brain or central spine. Tumors are classified as either malignant (cancerous) or benign (not cancerous). Left untreated, brain tumors can cause harm to normal brain tissue, perhaps leading to disability or death. Everyone's experience with brain and spinal cord tumors is unique. They arise in various regions, from distinct cell types, and may require different treatments [2]. Brain tumors can be classified as either benign or malignant.

2.1 Brain Tumor Type:

There are around 120 unique varieties of brain tumors, lesions, and cysts, which are classified by where they occur and what types of cells they contain. Certain forms of tumors are normally benign (noncancerous), whereas others are usually malignant (can-

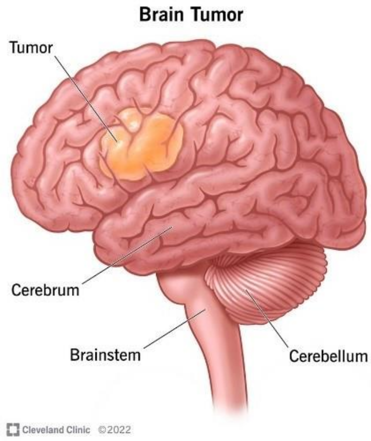

FIG 1.1 – *Brain tumor.*

cerous). Others may have a 50-50 probability of being malignant[3].

Glioma:

Glioma is a common kind of brain tumor that is also observable. The spinal cord. Gliomas account for around 33% of all brain tumors. These tumors develop from glial cells, which surround and support neurons. There are different Different types of glial cells, hence there are several forms of gliomas [3].

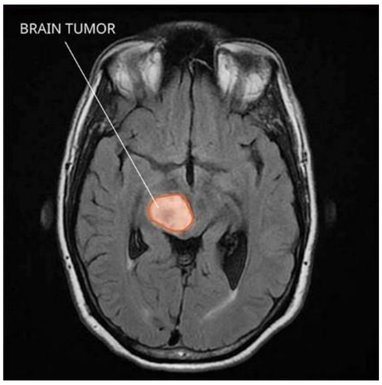

FIG 1.2 – *Glioma tumor.*

Meningioma:

Meningioma is the most common primary brain tumor, comprising al-most 30% of all brain cancers. Meningiomas arise within the meninges, which are thethree external layers of tissue that envelop and safeguard the brain directly underneaththe skull. Meningiomas have a higher prevalence in females compared to males. Approximately 85% of meningiomas are benign, indolent neoplasms. The vast majority ofmeningiomas are benign, however a few may persist and return after treatment[3].

Pituitary:

The most prevalent sort of pituitary tumor is adenoma, which originates ingland tissues. Pituitary adenomas come from the pituitary gland and normally develop slowly. Adenomas account for roughly 10% of all primary brain tumors. They may cause vision and endocrinological issues. Fortunately, adenomas are benign and treatable with surgery and/or therapy[3].

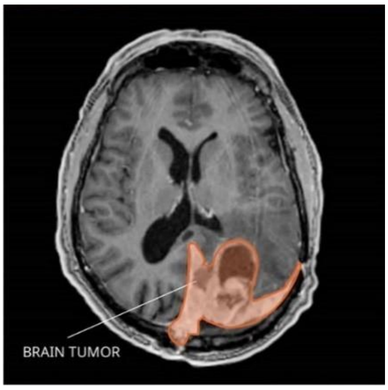

FIG 1.3 – *Meningioma tumor.*

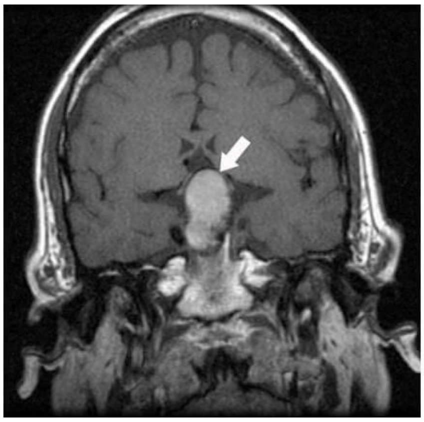

FIG 1.4 – *Pituitary tumor.*

2.2 Brain Tumor Symptoms:

According to the medical profession, there are a number of symptoms that are determined by distinct terms such as the type, size, and form, rate of growth, and location of the tumors. The first and apparent indicator is headaches, which are a frequent indicationof a brain tumor. are worse in the morning when waking up

- Occur when you're sleeping.
- Are exacerbated by coughing, sneezing, or activity [4].
- Nausea or vomiting without any explanation.
- Common visual issues include blurred vision, double vision, and loss of peripheral vision.
- Persistent loss of sensation or mobility in an arm or leg.
- Balance issues.
- Difficulty with speech.
- Difficulty following simple commands[5].

2.3 Brain Tumor Causes

The specific etiology of primary brain tumors remains uncertain. Most brain tumors are considered to originate when aberrant cells in the brain grow and replicate uncontrolled, generating a mass or growth[6]. There are various environmental and genetic variables that may raise your chance of getting brain tumors. These include: Exposure to large amounts of ionizing radiation, such as radiotherapy used to treat another cancer,or nuclear fallout. Increasing age, especially for individuals above 65 years old. Gender. Men are typically more prone than women to get brain tumors. Ethnicity. Caucasiansare at increased risk as compared to other races. Family history. About 5 - 10% of brain tumors are linked to hereditary disorders, such as neurofibromatosis. compromised im- munity system Diseases of the immune system, including acquired immunodeficiency syndrome (AIDS), could raise a person's risk of brain and spinal cord lymphomas[6].

2.4 Treatments for brain tumors

Different therapies are advised for brain tumors. Tumor size, kind, location, growth rate, and patient health all impact the outcome.

- Surgery is typically the initial step in treating tumors, removing as much as possible without injuring adjacent tissues.
- Radiation therapy: It employs x-rays, gamma rays, and radiation. Tronium, protons, and other sources to destroy cancer cells and decrease tumors Damage their DNA.
- Chemotherapy, often known as anti-cancer medications, is the use of chemical substances to halt or destroy rapidly dividing cells. It is indicated when surgery and/or radiation treatment are not required. Moore [7].
- Targeted biological therapy, also known as biologic therapy or immunotherapy. The therapy focuses on tumor-specific genes, proteins, or tissues. The therapytargets cancer cells, causing less harm to normal cells [8].

3 Medical Imaging Overview

Medical imaging involves capturing images of the body's inside for clinical assessment, intervention, and visualization purposes. Doctors and radiologists use it to inspect the body and identify medical disorders and illnesses. Medical imaging techniques give particular information about bodily parts, including illness, damage, and therapy efficacy. Currently in use are:

- Computed Tomography (CT).
- Positron Emission Tomography (PET).

– Single-photon Emission Computed Tomography (SPECT).
– Magnetic Resonance Imaging (MRI).
– Magnetic Resonance Spectroscopy (MRS)

3.1 Methodology of MRI

The most common technique is magnetic resonance imaging (MRI). widely used andsuccessful technology. In 2016, about 36,000 MRI machines were projected to be in operation by the statistics portal[2]. Figure 1.5 shows an MRI machine [9]. Our research

FIG 1.5 – *MRI Imaging machine.*

focuses on Magnetic resonance imaging (MRI), a non-invasive three-dimensional medical technology that employs radiation waves to capture pictures of the body's architecture and functions. MRI scanners create pictures using strong magnetic fields and computer-generated radiation waves. Radio waves account for the majority of the signal (9). A high magnetic field generates acoustic signals from water molecules in the body, while a transmitter/receiver in the equipment broadcasts and receives radio wavesto produce CT MRI pictures. Figure 1.6 depicts an MRI of a Brain tumor.

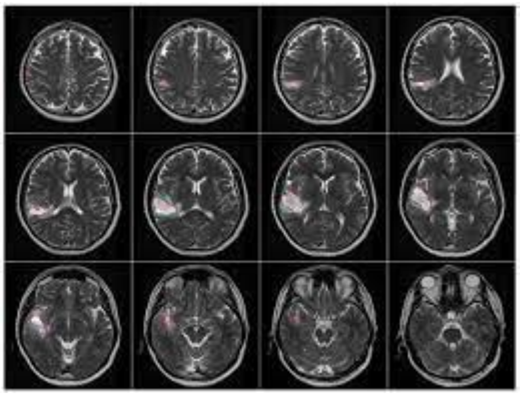

FIG 1.6 – *Brain tumor MRI scans.*

4 Artificial Intelligence (AI)

4.1 Definition of Artificial Intelligence (AI)

Artificial intelligence (AI) is a branch of computer science that allows computers to mimic human behavior in order to improve people's performance in science and technology. The particular aims of AI include replicating human intellect, solving knowledge intensive problems, constructing computers capable of doing jobs that need human intelligence, and developing a system that can learn on its own. Machine learning anddeep learning are two subsets of artificial intelligence that tackle problems with high- performance algorithms and multilayer neural networks, respectively. Structured data, such as genetic data, electrophysical data, and imaging data, are thoroughly studied in medical diagnosis using machine learning. AI enables sophisticated equipment, advanced drug design procedures, Tele-treatment and physician-patient contact via Chatbots, and intelligent robots for determining the cause and likelihood of emergence any illness in field of healthcare [10] .

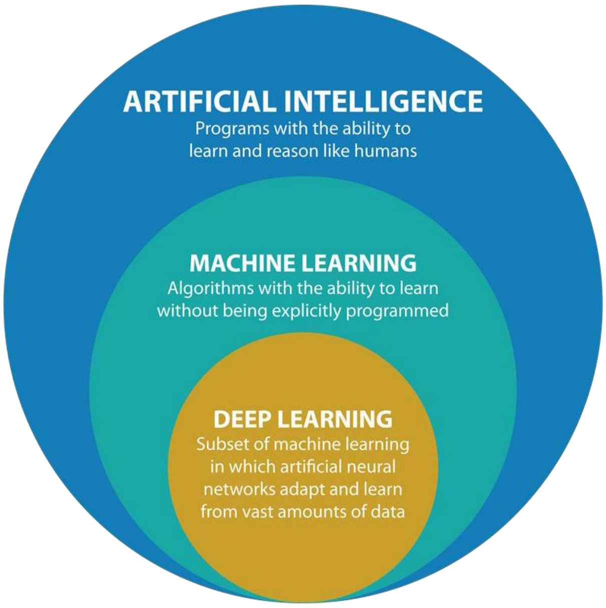

FIG 1.7 – *Artificial intelligence (AI).*

4.2 The importance of artificial intelligence in medical imaging

AI has caused a major transformation in the area of radiology, altering old workflowsand enhancing the radiologist's position. In the field of image acquisition, AI enhances scanning techniques, improves picture integrity, and promotes complex image reconstruction across MRI, CT, and PET. The most significant of these breakthroughs is deep learning, which speeds MRI scanning while balancing efficiency and quality, with com- parable progress in CT and PET image reconstruction [11].

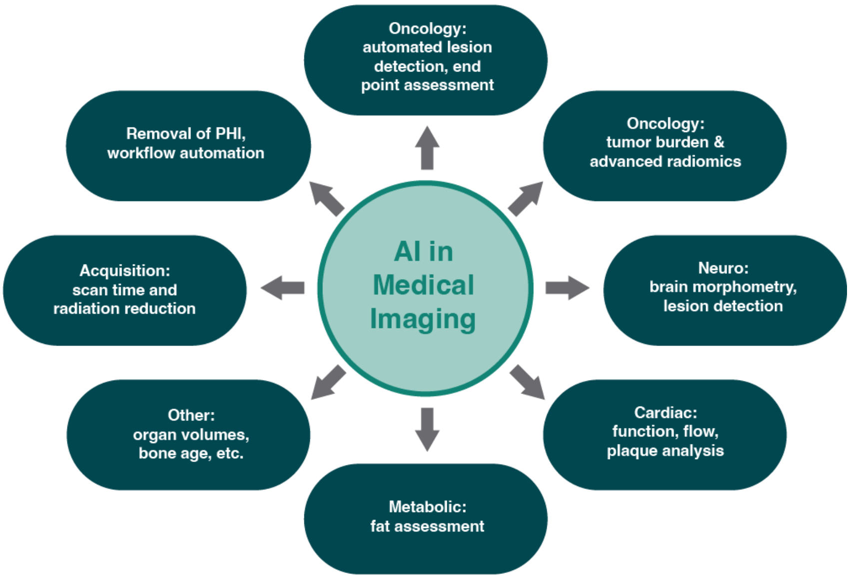

FIG 1.8 – *Applications of AI in medical imaging.*

5 Machine Learning (MI)

Machine learning applies statistics and computer science ideas to develop statistical models for tasks such as prediction and inference. Models represent mathematical connections between inputs and outputs of a specific system. The learning approach involves predicting the model's parameters to fulfill the specified objective [12].

5.1 Types of machine learning Algorithms

There are several variants in how to describe the sorts of Machine Learning Algorithms, but typically they may be grouped into groups based on their function[12], and themain categories are the following :

- Supervised learning.
- Unsupervised Learning.
- Semi-supervised Learning.
- Reinforcement Learning.

5.1.1 Supervised learning

Semi-supervised learning bridges the gap between supervised and unsupervised learning approaches by leveraging both labeled and unlabeled data. This hybrid approach proves particularly valuable in scenarios where unlabeled data is abundant but labeling it is time-consuming or expensive. In such cases, semi-supervised learning algorithms can effectively utilize the unlabeled data to enhance the model's performance, leadingto improved prediction or classification accuracy [13].

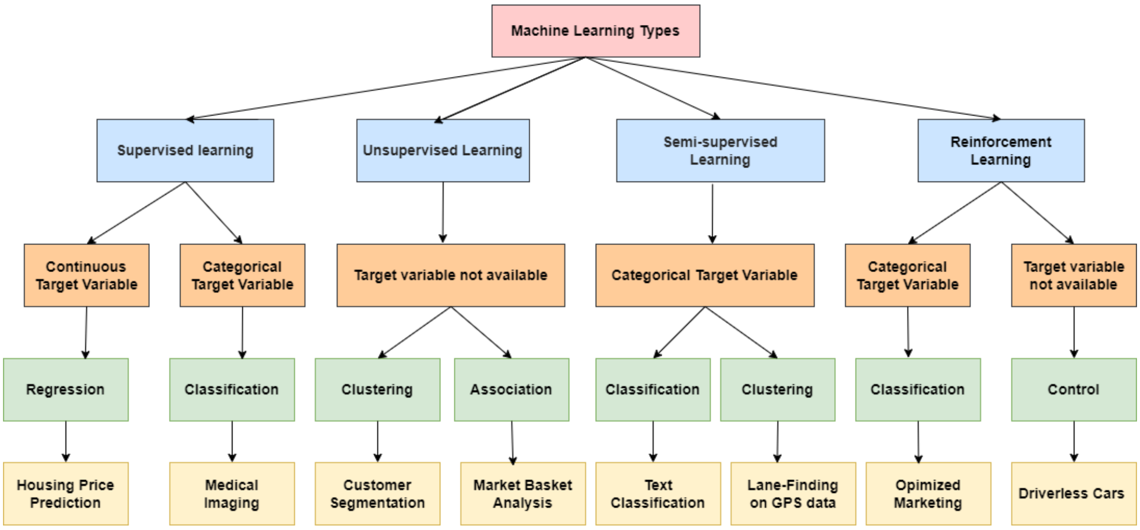

FIG 1.9 – *Types of Machine Learning.*

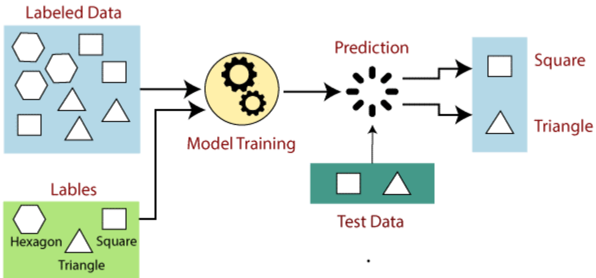

FIG 1.10 – *Supervised Machine Learning.*

5.1.2 Unsupervised Learning

Unsupervised learning is a machine learning approach that deals with unlabeled data. Unlike supervised learning, where the data is pre-classified and labeled, unsupervised learning algorithms seek to discover hidden patterns and structures within the data without explicit guidance. These algorithms are particularly useful for tasks such as clustering and dimensionality reduction [13].

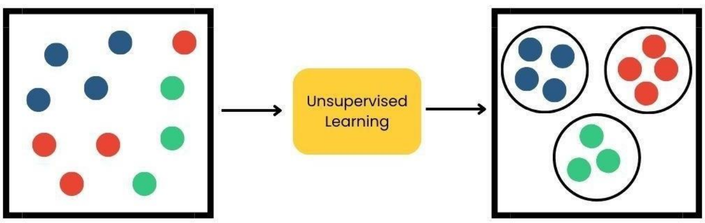

FIG 1.11 – *Unsupervised Learning.*

5.1.3 Semi-supervised Learning

Semi-supervised learning methods combine the advantages of supervised and unsupervised learning. It can be beneficial in fields like machine learning and data mining if unlabeled data already exists and categorizing the data is a tedious task [13] .

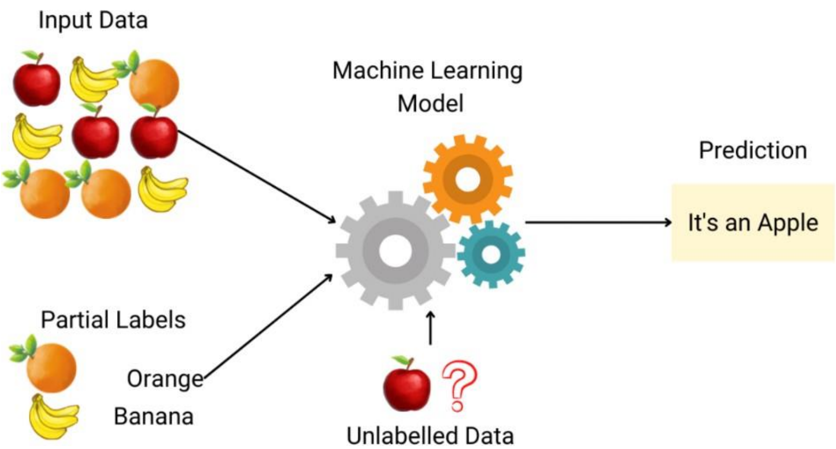

FIG 1.12 – *Semi-supervised Learning.*

5.1.4 Reinforcement Learning

Reinforcement learning is a type of learning in which decisions are made about which actions to take to obtain a more desirable outcome. Until confronted with a situation, the learner has no notion what measures to take. The learner's behaviors may have an impact on future situations and actions. Reinforcement learning is totally dependent on two criteria : trial-and-error search and delayed results [13] .

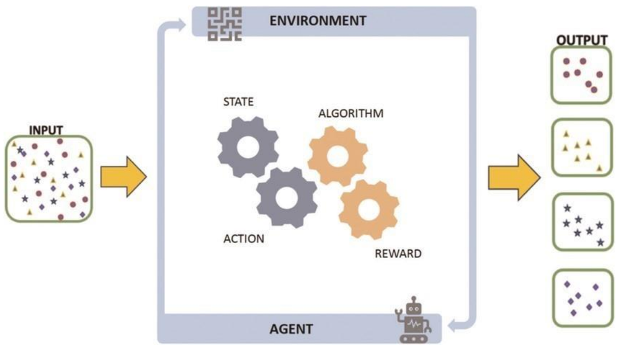

FIG 1.13 – *Reinforcement Learning.*

5.2 The challenges faced during the machine learning process

Difficulties in training a machine learning system might emerge from either the dataset or the system itself. The potential challenges might include:

Under fitting of Training Data: Under fitting in machine learning refers to a model that cannot adequately learn the issue and performs badly on both training and holdout

datasets. However, underfitting is a good counterpoint to overfitting [14].
Over fitting of Training Data: Over fitting is a typical problem in machine learning in which a model performs well on training data but suffers on fresh data owing to pattern memorization. This can cause poor model performance [14] .

6 Deep Learning (DL)

Deep learning (DL) is an area of ML and AI. Artificial Intelligence (AI) uses brain- inspired algorithms to evaluate, acquire, and interpret knowledge. The networks may perform supervised learning on both labeled and unlabeled data. Deep learning is a key component of data science, allowing for quicker and more efficient data processing and pattern creation for decision-making. Quickly [15] [16]. There are mainly three types of deep learning architectures, each architecture has its own field of use and its characteristics.

6.1 Deep Neural Networks

Artificial neural networks are very sophisticated brain-inspired computer models. These individuals have contributed to several fields, including medical, economics, engineering, and computers[17]. An artificial neural network is built on the principles of optimization theory. This computational model is based on how the human brain functions. The neural network is made up of artificial neurons that communicate with one another based on their weights. Neural Network refers to the interaction of neurons in multiple layers of a system. Weights indicate how neurons interact with one another [17]. Deep neural networks (DNN) are ANNs with numerous layers for input and output. DNNs come in several kinds but have common components: neurons, synapses, weights, biases, and functions.

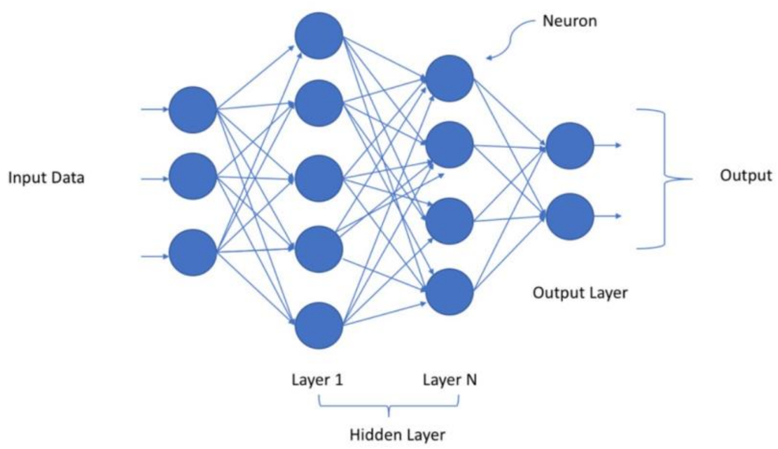

FIG 1.14 – *Architecture diagram DNN*

6.2 Convolutional Neural Networks

Convolutional neural networks (CNNs or ConvNets) are a common form of deep neural networks that use network-style deep learning processes A deep neural network model does not need feature extraction or picture segmentation. The system gathers abstract characteristics from player-suggested inputs, revealing simpler patterns initially and then more complex ones [18].

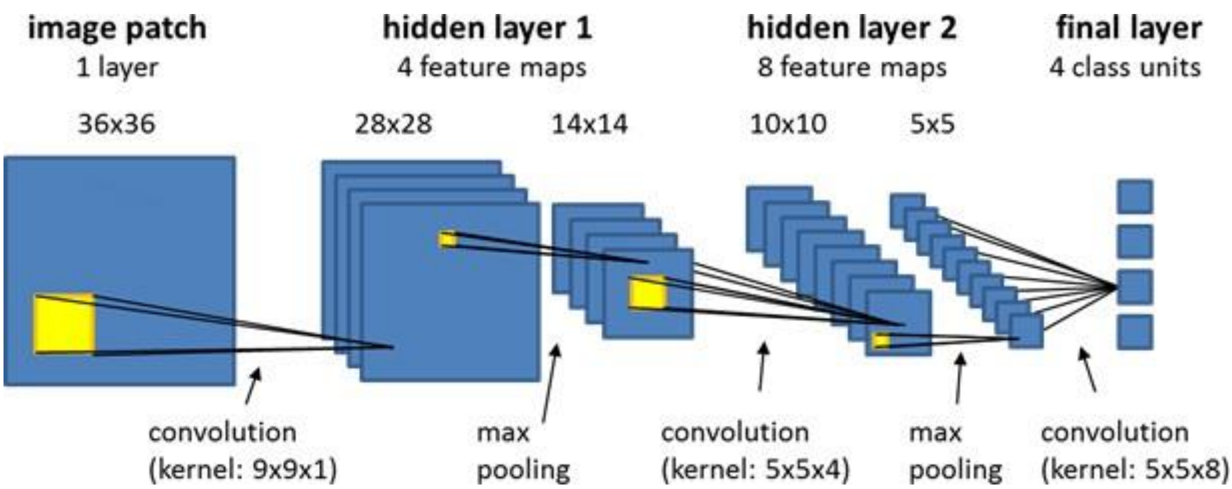

FIG 1.15 – *Architecture diagram CNN*

6.3 Recurrent neural networks

An RNN, a type of artificial neural network, extends the capabilities of a feedforward neural network by adding loops. An RNN may process numerous inputs by adopting a recurrent hidden state with activation at each step is determined by the activation at the previous step [19] .

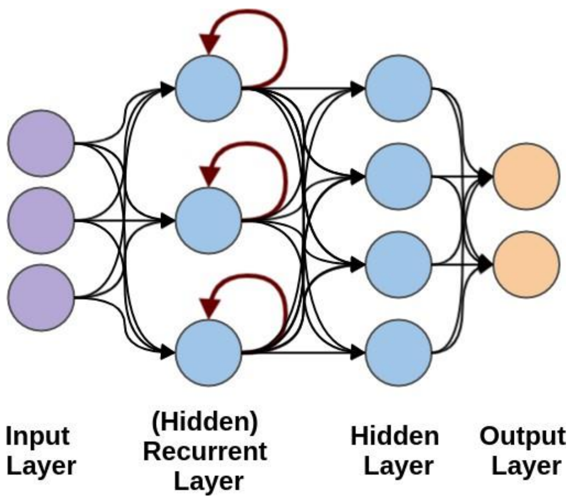

FIG 1.16 – *Architecture diagram RNN*

7 Conclusion

In this chapter, we talked about brain tumors by examining their underlying causes, common symptoms and types, how they affect the lives of people around the world, and discussed the use of machine learning, deep learning and different architectures.

PROPOSED SYSTEM AND METHODOLOGY FOR BRAIN TUMOR DETECTION

1 Introduction

This chapter provides an overview of brain tumors and introduces our novel system designed for specific purpose of your system related to brain tumors. We will begin by exploring recent advancements in brain tumor research. Subsequently, we will delve into the components and functionalities of our system, offering a detailed explanation of the techniques and strategies it utilizes. By the chapter's conclusion, readers will gain a comprehensive understanding of brain tumors and the innovative approach implemented within our system.

2 A literature survey on brain tumor classification techniques

This study investigates brain tumor classification using deep convolutional neural networks (CNNs) and transfer learning. The researchers employed a dataset of 3064 MRI images obtained from Figshare. Their proposed method leverages a pre-trained GoogleNet architecture for feature extraction from the brain MRIs. Subsequently, established classification models are integrated to categorize these extracted features. To assess the model's performance, a five-fold cross-validation approach was implemented at the patient level. The proposed approach achieved an average classification accuracy of 98% [20]. Building upon existing research in deep learning for medical image analysis, this study proposes a novel approach for multi-class brain tumor classification. The model leverages a ResNet-50 architecture combined with global average pooling to address challenges like vanishing gradients and overfitting. The proposed model's effectiveness was evaluated on a brain magnetic resonance imaging dataset containing 3064 images for three tumor types. Notably, the model achieved high accuracy, reaching 97.08%and 97.48% with and without data augmentation, respectively [21]. Researchers investigated a fully automated system for brain tumor segmentation and classification. Their approach leveraged a Deep Convolutional Neural Network (DCNN) incorporting a multiscale strategy. The system utilized a publicly available dataset containing

3064 MRI image slices. The authors implemented a novel approach where images were processed at three distinct spatial scales using various techniques. This method draws inspiration from the fundamental workings of the human visual system. Their model achieved an impressive tumor classification accuracy of 97.3% [22].

This study investigates brain tumor classification using a Dense EfficientNet architecture. The researchers employed a dataset of 3064 T1-weighted contrast-enhanced brain MRI scans obtained from Figshare. Their approach leverages a convolutional neuralnetwork (CNN) with Dense EfficientNet and min-max normalization for classifying the images into four categories : glioma, meningioma, pituitary tumor, and healthy controls. To enhance tumor cell distinction, the authors implemented data augmentation along- side min-max normalization. Their experiments yielded promising results, achieving an accuracy of 98.78% [23].

This study proposes a novel deep learning model, BTC-fCNN, for efficient multi-class brain tumor classification. BTC-fCNN aims to discriminate between various types of brain tumors from different image perspectives. To evaluate the model's performance, researchers employed a dataset containing 3064 contrast-enhanced T1-weighted MR images. The proposed model achieved high accuracy, reaching 98.63% using fivefold cross-validation with transfer learning and even exceeding that at 98.86% with a retraining approach within the cross-validation folds (internal transfer learning) [24].

This study evaluates the performance of seven deep convolutional neural network (CNN) architectures for brain tumor classification. We implemented a generic CNN model and investigated the effectiveness of six pre-trained CNN models on the task. The dataset employed in this research incorporates MRI images from Fighshare, SARTAJ,and Br35H collections, totaling 7023 samples. The CNN models under evaluation include a generic CNN, along with ResNet50, InceptionV3, InceptionResNetV2, Xception, MobileNetV2, and EfficientNetB0. Our analysis revealed that InceptionV3 achieved the highest average accuracy (97.12%) among all evaluated CNN models [25].

In a study comparing transfer learning techniques for brain tumor classification using magnetic resonance imaging (MRI) scans, researchers investigated a dataset of 7,023 MRI scans obtained from Fighshare, SARTAJ, and Br35H repositories. The authors employed pre-trained convolutional neural network (CNN) architectures, namely VGG- 16, Inception v3, and ResNet-50, to classify brain tumors. Their analysis revealed that ResNet-50 achieved the highest accuracy (99.93%) and validation accuracy (97.86%), outperforming both VGG-16 and Inception v3[26]. A paper proposes a NeuroNet19: an explainable deep neural network model for the categorization of brain cancers using magnetic resonance imaging data. To researchers utilized a dataset from MRI scans (7023) from Fighshare, SARTAJ, and Br35H datasets. NeuroNet19 obtains the maxi-mum accuracy at 99.3%, with precision, recall, and F1 scores at 99.2% and a Cohen Kappa coefficient (CKC) of 99%. by the iPPM collects multi-scale feature maps, ensue-

TABLEAU 2.1 – *Literature Survey.*

Authors, Year	**Dataset**	**Technique and Model**	**Accuracy**
Deepak et al [20]	MRI images (3064) from figshare dataset	Deep CNN features via transfer learning	98%.
Kumar et al[21]	3064 MRI images	Deep network model that uses ResNet-50 with and without data augmentation	97.08% 97.48% respectively
D´ıaz-Pernas et al [22]	MRI image dataset of 3064 slices	Deep Convolutional Neural Network	97.3%
Nayak et al [23]	MRI images (3064) from figshare dataset	CNN-based dense EfficientNet	98.78%
Abd El-Wahab et al [24]	3064 MRI images	Fast Convolution Neural Network (BTC-f CNN)	98.63%
Gómez-Guzmán et al [25]	Fighshare, SARTAJ, and Br35H datasets, 7023 MRI images	Generic CNN With, ResNet50, InceptionV3, InceptionResNetV2, Xception, MobileNetV2, and EfficientNetB0	InceptionV3, 97.12% .
Haque et al [27]	Fighshare, SARTAJ, and Br35H datasets, 7023 MRI images	NeuroNet19 : Deep neural network model	99.3%

ring the extraction of both local and global image contexts. This strengthens the feature maps created by the backbone, regardless of the geographical placement or size of the tumors. It should be mentioned that the conclusions of the study NeuroNet19 is trained on four classes of BTs : glioma, meningioma, no tumor, and pituitary tumors [27].

3 Techniques for training neural networks

Training a neural network entails an iterative process of modifying its parameters to minimize a certain loss function. This step is critical for the network's ability to generalize well to new inputs and perform successfully on a variety of tasks [28].

3.1 Loss function

A loss function is sometimes called a cost function, assesses the likelihood or uncertaintyof a forecast depending on how much it deviates from the true value. This provides usa more thorough view of how effectively the model is operating [28].

3.2 Dropout

Dropout is a regularization approach for deep learning models that prevents overfitting. It functions by randomly deleting (setting to zero) some of the neurons in the neural network during training. This encourages the network to learn more robust characteristics while preventing it from leaning too much on any particular attribute [28].

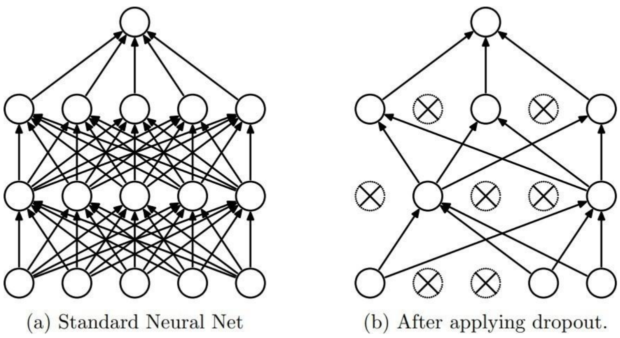

FIG 2.1 – *Dropout Regularization.*

3.3 Batch normalization

Batch normalization is a technique for normalizing the inputs to each layer. It enhances training stability and speed by minimizing internal covariate shift, which refers to changes in the distribution of the network's activations throughout training [28].

3.4 Hyperparameters

Hyperparameters are configuration settings that are specified prior to training a ma chine learning model. These parameters regulate many parts of the training process and have a substantial influence The model's performance and behavior [28].

3.4.1 Batch Size

Batch size refers to the number of training samples utilized in a single iteration of the model's training. It regulates how many samples are processed before to update the model's weights. A greater batch size may result in speedier training but demand more memory, whereas a smaller batch size may result in slower training but maybe better convergence.

3.4.2 Optimizer

During training, the optimizer updates the model's weights using the computed gradients. It describes the technique for updating the weights in order to minimize the model's loss function. The most common optimizers include Adam, Stochastic Gradient Descent (SGD), and RMSprop.

3.4.3 Learning Rate

The learning rate defines the step size at which the optimizer adjusts the model's weights during training. It sets the rate at which the model learns and converges. A greater learning rate might result in faster initial learning, but it can also lead to over- shooting or instability. In contrast, a lower learning rate may result in delayed convergence but more accurate outcomes.

3.4.4 Epochs

An epoch is a complete sweep of the whole training dataset during model training. It represents the number of times the model has observed and learnt from all of the training examples. Training over many epochs helps the model to refine and improve.

Its performance. However, training for an excessive number of epochs can lead to over-fitting, which occurs when the model becomes overly specialized to the training data and performs poorly with fresh data. These hyperparameters play an important role in influencing the efficacy and efficiency of the model training process, therefore careful selection and tweaking of these values is required for best performance.

3.5 Nonlinear Activation Function

An activation function is an important component of artificial neural networks since it decides whether a neuron should be engaged or not based on its input. This function is critical for neural networks to learn complicated patterns in input since it determines which neurons are engaged and impact the next layer. The activation function, similar to how neurons in the human brain activate one another, translates the output of one neuron into an input for the next. Its fundamental role is to inject nonlinearity into the neural network ; without an activation function, the neural network would only function as a linear regression model [28]. To activate a neuron, apply an activation function to the weighted sum of its inputs, including the bias factor, as follows :

$$A = G(W_1X_1 + W_2X_2 + W_3X_3 + \cdots + W_nX_n + B) \tag{2.1}$$

- **A:** Output of a neuron.
- **G:** Activation Function.

— **W :** Weights.

— **Xi:** Features.

— **B:** Bias.

The choice of activation function influences the neural network's performance and training process; prominent examples include sigmoid, tanh, and ReLU, each with unique qualities and applications.

3.6 SoftMax Function for Multiclass Classification

SoftMax is a sigmoid-based generalization for multi-class classification problems. It applies a SoftMax operation to normalize the input vector into a probability vector, with each value representing the confidence score or probability of the related class. The projected class is obtained by choosing the class with the highest confidence level. It is frequently used as the last activation function in neural networks, particularly at the last layer [28].

4 Methods in classification of brain tumors

4.1 An Overview on Convolutional Neural Networks

Convolutional neural networks (CNN or ConvNet) are a prominent form of deep neural networks. Deep learning is used to process data having a grid pattern, such as images. The CNN model does not require a hand-crafted feature extraction or Image Segmentation. When input is directed towards deep layers, abstract characteristics are obtained and organized to recognize simpler patterns initially, followed by more complex patterns [29]. There are five different layers in CNN :

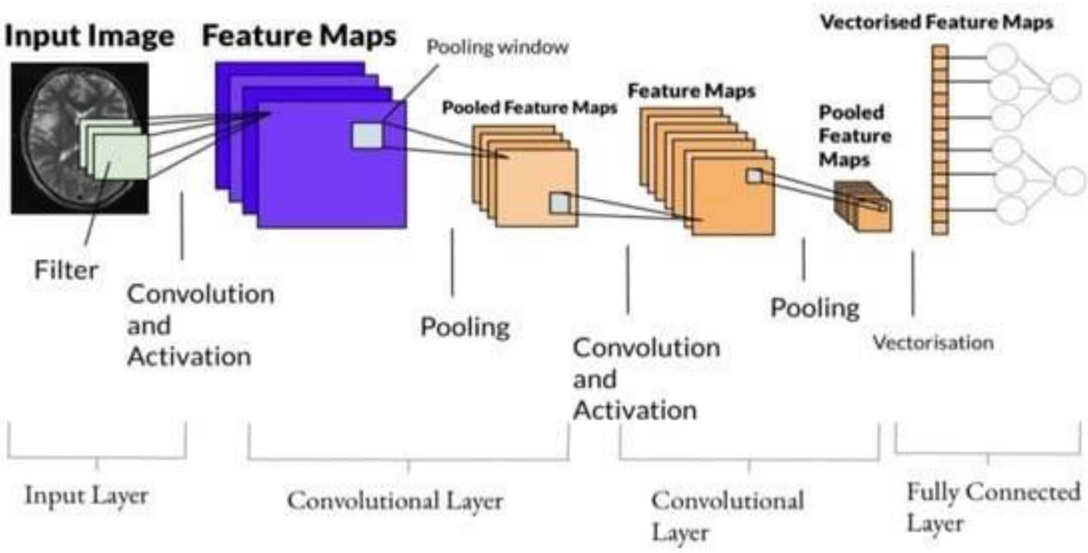

FIG 2.2 – *Convolutional neural network layers.*

- Input layer.
- Conv layer (Convo+ReLU).
- Pooling layer.
- Fully connected (FC) layer.
- Output layer (soft-max).

4.1.1 Input layer

It comprises picture data with the following dimensions: [width, height, and depth]. Itis a matrix containing pixel values.

4.1.2 Convolution layer

A convolutional layer consists of filters (kernels) that slide across input data. - Each kernel extracts characteristics from input data by using width, height, and width x height weights. - During the training stage, the kernel's weights start with random values, and learn from the training set. - Filters in the convolutional layer represent features [30]. Kernel size : also known as the convolution matrix, is a matrix that is dragged across a picture and multiplied by the input to increase the desired result. Stride: The stride defines the kernel's step size as it slides through the picture. Padding : is a phrase used in convolutional neural networks to represent the number of pixels added to an image during processing by the kernel.

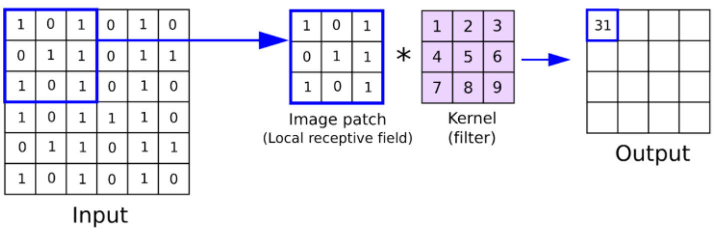

FIG 2.3 – *Convolutional layer operation.*

Relu Activation Function

In this layer, every negative value from the filtered picture is eliminated and replaced with zero [30].

4.1.3 Pooling layer

The pooling layer, sometimes called the down- sampling layer, reduces the dimensionality of feature maps while keeping critical information. The pooling layer filters input data and executes pooling operations like maximum, minimum, or average. The literature suggests that max pooling is the preferred choice [30].

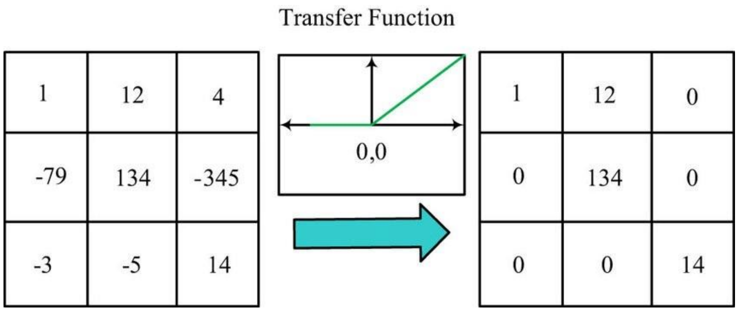

FIG 2.4 – *Relu operation.*

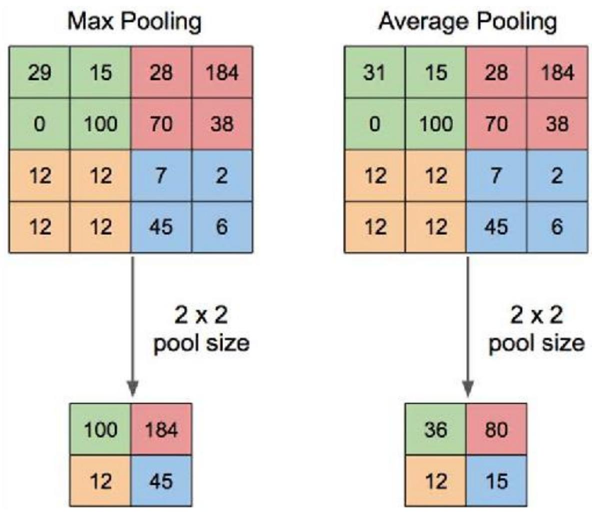

FIG 2.5 – *Max-pooling and Average-pooling layers.*

4.1.4 Fully-Connected Layer

The fully-connected layer performs categorization using characteristics derived from previous layers and filters. This layer links all neurons from the preceding layer to those in the current layer, forming A thick network of links. The fully-connected layer uses the collected characteristics to predict or classify input data. The final classification task takes into account information gained from previous levels [31].

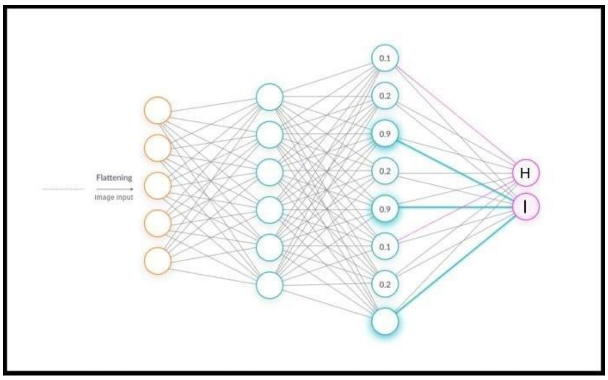

FIG 2.6 – *fully connected layer.*

4.1.5 Output layer

The output layer in neural networks is the ultimate layer of neurons responsible for generating the network's final output based on a particular input. The quantity of neurons in the output layer is contingent upon the intended function of the network.

4.2 Transfer Learning

In machine learning, transfer learning capitalizes on pre-trained models to address new challenges. It's not a specific algorithm, but a technique for leveraging existing knowledge. Essentially, transferable knowledge gained from prior training tasks aids in tackling new, related problems. This approach often involves significant model generalization to handle unseen data effectively.

Transfer learning eliminates the need to train models from scratch for every new task. By reusing pre-trained models, it saves significant time and resources. Large datasets, crucial for machine learning training, can be very time-consuming to label accurately. Since most organizational data remains unlabeled, particularly for large datasets, transfer learning allows training on existing labeled data and subsequent application to similar tasks that might have unlabeled data [32].

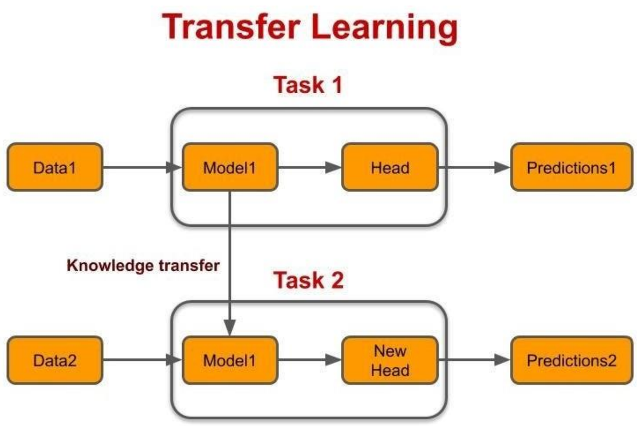

FIG 2.7 – *Transfer Learning.*

Advantages:

— Transfer learning provides for the effective adaption of pre-trained models to new datasets, lowering the quantity of data and resources necessary for training.

Disadvantages:

— Transfer learning can result in overfitting to the pre-training dataset, requiring careful tuning of the network to achieve optimal performance on new datasets.

5 Proposed Brain Tumor Classification System

This research proposes a deep learning system for brain tumor detection using MRI scans, addressing the challenge of class imbalance in medical datasets. The system incorporates pre-trained EfficientNet models, which are fine-tuned with additional layers, and trained on a balanced dataset. The trained model then classifies unseen MRI images into four tumor categories: no tumor, pituitary, meningioma, and glioma. Performance is evaluated using metrics like accuracy, F1-score, precision, and recall. By balancing the training data and leveraging powerful EfficientNet models, this system aims to improve the accuracy and reliability of brain tumor diagnosis, potentially leading to better patient outcomes.

5.1 Preprocessing

Preprocessing is an essential step in Brain Tumor detect systems The aim of preprocessing is to optimize the quality of MRI images. Therefore, several image preprocessing techniques have been used to optimize MRI images. Then:

Cropping: crop the image to place the brain in the center.

Resizing: For pre-trained models, dataset images are 270×230×3.

Data Splitting: The dataset is divided into training, testing, and validation:

— **Training data:** was utilized to fit the model, Number of images 4569.

— **Validation data:** Test and adjust the model, Number of images 1144.

— **Testing data:** are small data samples used to evaluate a final model, Number of images 1311.

Balanced Dataset Balancing a dataset simplifies model training by preventing the model from becoming biased toward one class. In other words, the model will no longerprefer the majority class simply because it has more data [33]. Here are some examples**Data Augmentation** Data augmentation is the process of expanding the quantity of data available for training the model. In Deep Learning, data augmentation refers toways for augmenting the quantity of data by adding slightly altered copies of currentdata or synthesizing new synthetic data from previously existing data. In This Work, We Apply Image Augmentation by Rotating, Shifting, And Flipping Horizontally.

5.2 Understanding EfficientNet Architecture

The researchers used neural architecture search to create a baseline network. This approach automates neural network creation. It enhances accuracy and efficiency based onFLOPS. basis. This design utilizes mobile inverted bottleneck convolution (MBConv).The researchers then built up this baseline network to produce a series of deep. Learning models known as Efficient Nets. The architecture is shown in Figure 24. The authors compared Efficient Net's performance to other sophisticated transfer learning

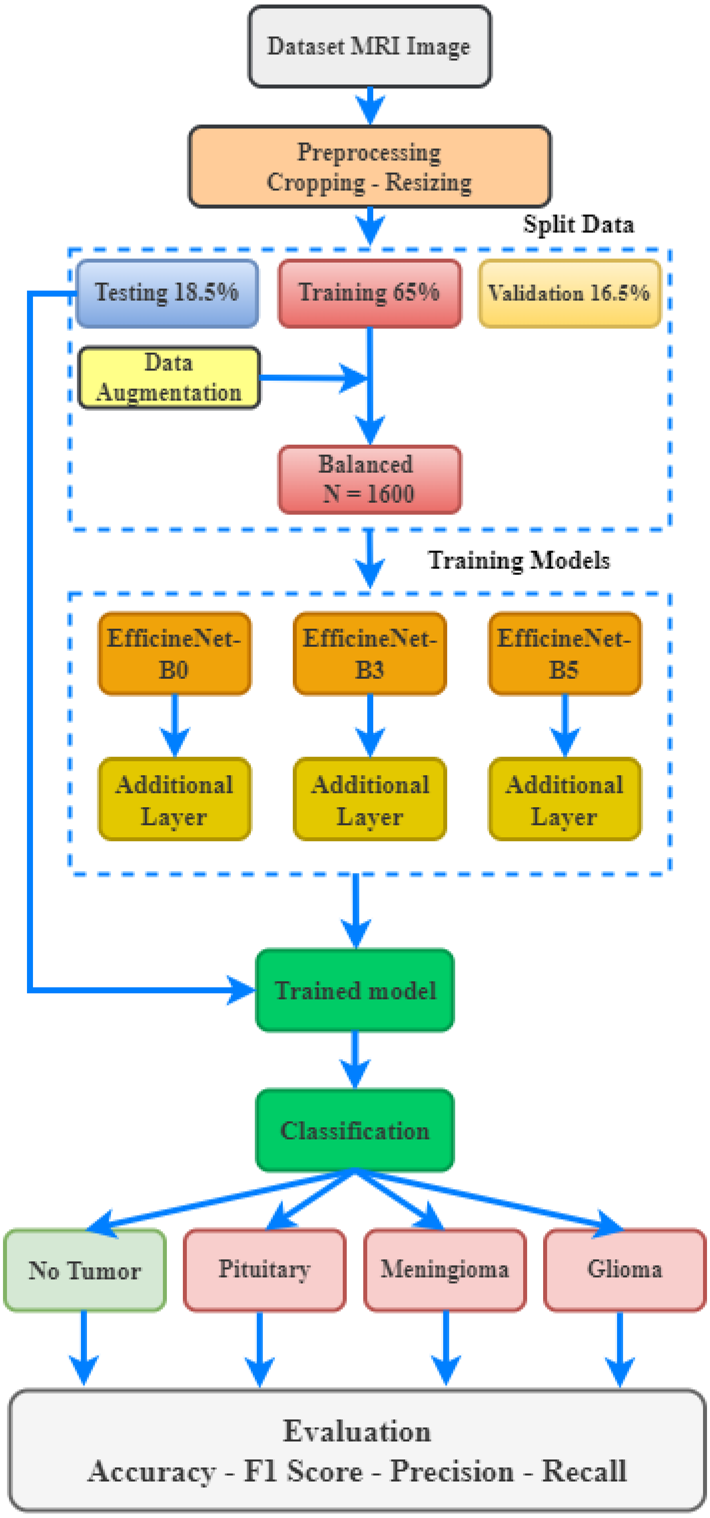

FIG 2.8 – *shows the suggested Brain Tumor Classification system.*

models on the ImageNet dataset. Figure 18 shows that the current version of EfficientNet, EfficientNet-B7, has the best accuracy and requires less parameters. AutoML MNAS created the baseline network, EfficientNet-B0, which is then scaled up to produce EfficientNet-B1 to B7. EfficientNet-B7 outperforms the best available CNN, achieving 84.4% top-1 and 97.1% top-5 accuracy despite being 8.4 times smaller [34].

FIG 2.9 – *Glioma Balanced.*

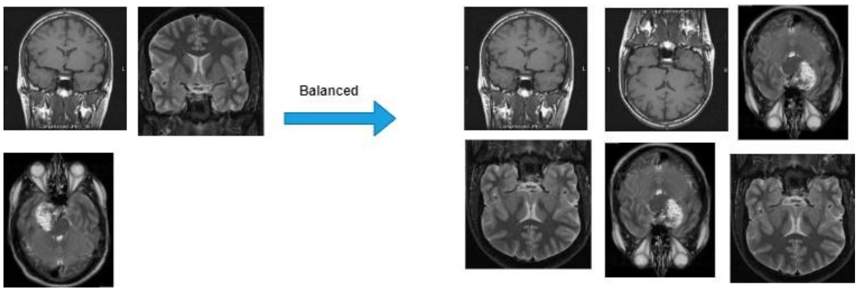

FIG 2.10 – *Pituitary Balanced.*

FIG 2.11 – *Meningioma Balanced.*

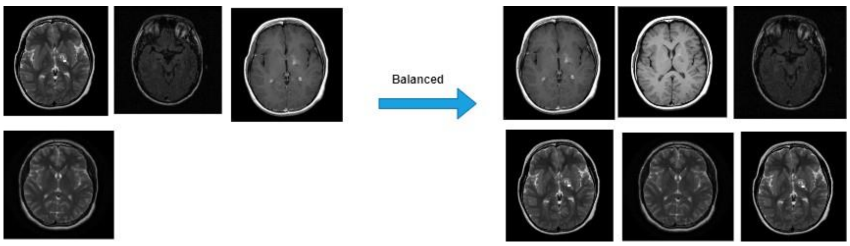

FIG 2.12 – *No Tumor Balanced.*

FIG 2.13 – *EfficientNet architecture.*

5.2.1 EfficientNet different models

EfficientNet includes seven models with increasing depth, breadth, and resolution. Hereare the details for each level :[35]

EfficientNet-B0: is the most compact and fast model in the EfficientNet family. The

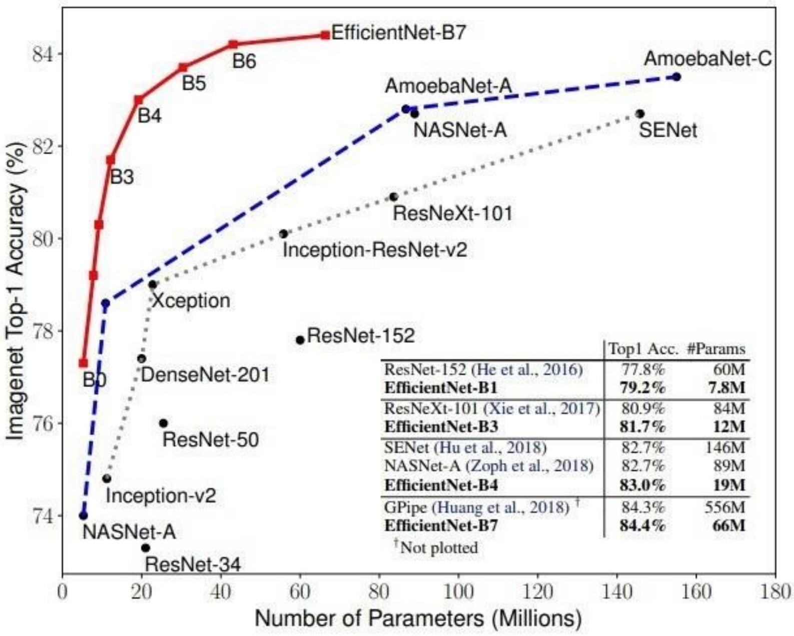

FIG 2.14 – *Model Size vs. Accuracy Comparison.*

model includes 5.3 million parameters and achieves 76.3% accuracy on ImageNet. shows that the input size is 224x224x3, with 16 convolutional layers [35]**EfficientNet-B1 :** EfficientNet-B1 has 7.8 million parameters and achieves 78.8% accuracy on ImageNet, surpassing B0's. The multipliers for depth and breadth are 1.1 and1.2, respectively. The input size is the same as B0, consisting of 16. depictsconvolutional layers[35].

EfficientNet-B2: EfficientNet-B2 has 9.2 million parameters and achieves 79.8% accuracy on ImageNet, outperforming B1. The multipliers for depth and breadth are 1.2 and 1.3, respectively. The input size is the same as B0 and B1, consisting of 16 Convolutional layers.

The design of this model is similar to that of the previous one, with the only variation being the number of feature maps (channels) used to increase parameter count [35].

EfficientNet-B3: It has 12 million parameters and achieves an accuracy of 81.1% on ImageNet, surpassing B2. It features a 1.4 multiplier for both depth and breadth. shows that the input size is 300x300x3, with 24 convolution layers [35].

EfficientNet-B4: EfficientNet-B4 has 19 million parameters and achieves 82.6% accuracy on ImageNet, outperforming B3. It has 1.8 multipliers for both depth and breadth.The input size is 380x380x3, and it is composed of 28 convolution layers.[35].

EfficientNet-B5: EfficientNet-B5 has 30 million parameters and achieves 83.3% accuracy on ImageNet, outperforming B4. The multiplier values are 2.2 for depth and 2.0for width. The input size is 456x456x3, and it is composed of 40 convolution layers. [35].

TABLEAU 2.2 – *Comparison between 7 EfficientNet models*

EfficnentNet Model	Parameters (ImageNet) (Million	Accuracy	Depth Multiplier	Width Multiplier	Input Size
B0	5.3	76.3%	1.0	1.0	224x224x3
B1	7.8	78.8%	1.1	1.0	240x240x3
B2	9.2	79.8%	1.2	1.1	260x260x3
B3	12	81.1%	1.4	1.2	300x300x3
B4	19	82.6%	1.8	1.4	380x380x3
B5	30	83.3%	2.2	1.6	456x456x3
B6	43	84.0%	2.6	2.0	528x528x3
B7	66	84.4%	3.1	2.0	600x600x3

EfficientNet-B6: With 43 million parameters, EfficientNet-B6 achieves an accuracy of 84.0% on ImageNet. It has a multiplier of 2.6 for depth and 2.0 for width.

shows that the input size is 528x528x3, with 53 convolution layers [35].

EfficientNet-B7: EfficientNet-B7 is the most advanced model in the EfficientNet series. The model includes 66 million parameters and achieves an impressive accuracy of88.4% on ImageNet. It has a multiplier of 3.1 for depth and 2.0 for breadth. shows that the input size is 600x600x3, with 66 convolution layers [35].

5.3 Architecture of the transfer learning models used in our work

In this proposed system, we used three models (EfficineNet-B0, EfficineNet-B3 and EfficineNet-B5). We will demonstrate the tools and technology utilized to create our system. EfficineNet-B0, EfficineNet-B3 and EfficineNet-B5 Model Models are made up of several layers:

— **Batch normalization:** Helps improve model training speed, performance, and stability.

— **Dense (256):** A completely linked layer with 256 units with ReLU activation.

— **Dropout:** Regularizes the model to prevent overfitting., Dropout(rate=.4)" means that 40% of the neurons in the layer will be randomly dropped out du- ring each training iteration.

— **Output Layer:** Another dense layer with 4 units and SoftMax activation to pro- duce probabilities for each class.

Model Compilation: Creates a model object by connecting the base model's input to the output layer and compiles it with:

— **Optimizer:** Adamax with the specified learning rate.

— **Loss Function :** categorical crossentropy for multi-class classification.

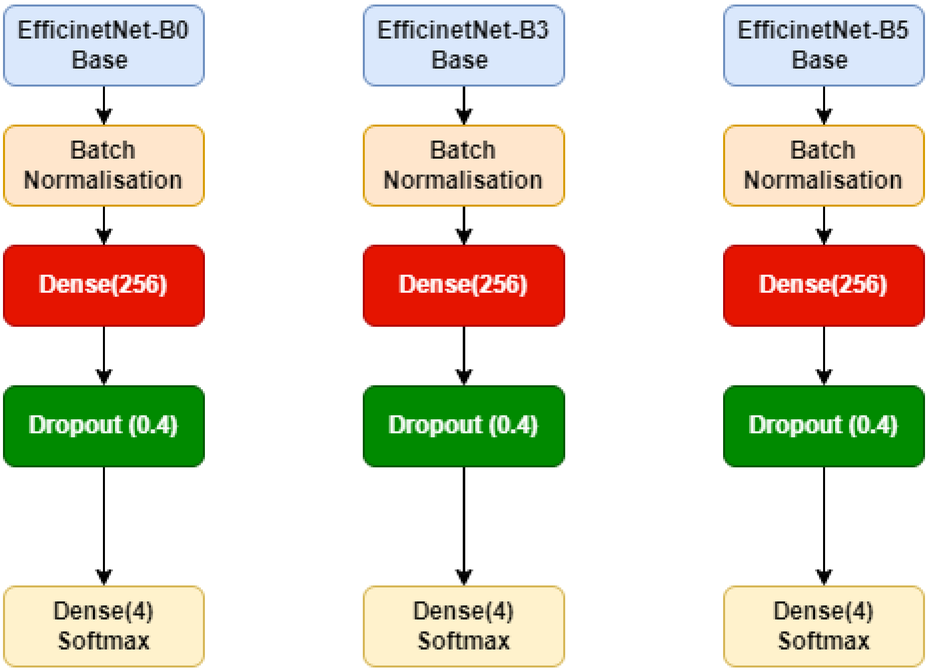

FIG 2.15 – *Architecture of the transfer learning models used in our work.*

6 Conclusion

This chapter provides an overview of brain tumors, methods for classifying brain tumors, and neural network training approaches. We also look at how our database is preprocessed and the various models we utilize. In the next chapter, we describe our findings through quantitative and qualitative discussions that emphasize our system's strengths and flaws.

RESULTS AND DISCUSSIONS

1 Introduction

This chapter contains a full overview of the database utilized in our research. We also explain the assessment measures and provide our findings, which include both quantitative and qualitative conversations to highlight our system's strengths and limitations. In addition, we undertake comparison research to further evaluate the effectiveness of our system.

2 Dataset Description

2.1 Original dataset

This dataset combines the following three datasets : Figshare [36], SARTAJ dataset [37], Br35H [38] : This dataset comprises 7023 pictures of human brain MRI imaging divided into four categories : glioma, meningioma, no tumor, and pituitary. No tumor class pictures were extracted from the Br35H dataset. I believe the SARTAJ dataset has a fault in that the glioma class photos are not accurately classified; I discovered this from the results of other people's work as well as the multiple models I trained; therefore,I removed the photographs in this folder and utilized the images on the Figshare site instead.

TABLEAU 3.1 – *Description of The Brain Tumor Dataset.*

Dataset	Class	Total Images
Figshare	Glioma	1621
Figshare ,Sartaj	Meningioma	1654
Figshare ,Sartaj	Pituitary	1757
BR35H	No tumor	2000

2.2 Balanced Dataset

We balanced the data in the training set only, keeping unbalanced data in the Testingand validation.

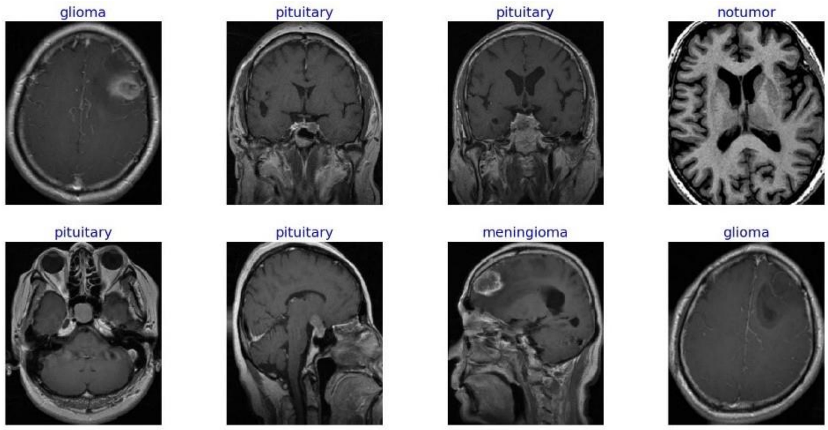

FIG 3.1 – *Samples from the dataset.*

TABLEAU 3.2 – *Training set Balanced.*

Class	Image initial	Image augment	Image total
glioma	1057	543	1600
Meningioma	1071	529	1600
No tumor	1276	324	1600
Pituitary	1165	435	1600
Total	**4569**	**1831**	**6400**

TABLEAU 3.3 – *Testing set Balanced.*

Class	Image initial	Image augment	Image total
glioma	300	-	300
Meningioma	306	-	306
No tumor	405	-	405
Pituitary	300	-	300
Total	**1311**	**-**	**1311**

TABLEAU 3.4 – *Validation set Balanced.*

Class	Image initial	Image augment	Image total
glioma	264	-	264
Meningioma	268	-	268
No tumor	319	-	319
Pituitary	292	-	292
Total	**1144**	-	**1144**

3 Evaluation Metrics

The confusion matrix is an intuitive statistic for determining model accuracy. This method is commonly used for classifying problems with several output kinds. CM is a table having two dimensions (" Predicted" and" Actual") with many" classes" in each dimension. Our predicted classes are rows, while the actual classifications are columns. Although the Confusion Matrix (CM) is not a performance measure, it serves as a foundation for many other measures [39].

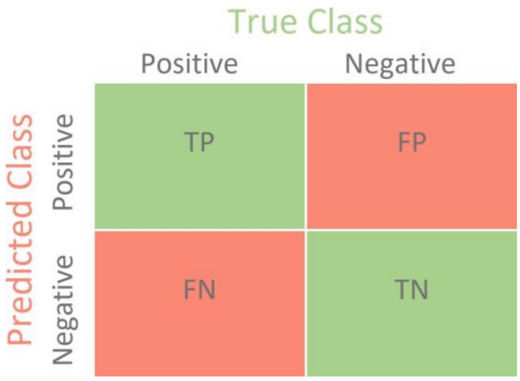

FIG 3.2 – *Confusion matrix.*

TP: The instance's expected and actual classes are both positive.
TN: The instance has a projected class of negative, which also happens to be its actual class.
FP: The instance actually has a negative class, although the expected class is positive.
FN : Despite predictions that it would be negative, the instance's true class is positive.
The following evaluation measures are developed using the condensed data from the confusion matrix.

3.1 Accuracy

Accuracy is the number of correct classifications out of all classifications made.

$$\text{Accuracy (Acc)} = \frac{(TP + TN)}{(TP + TN + FP + FN)} * 100 \tag{3.1}$$

3.2 Precision

Precision is the ratio of true positives to the sum of true and false positives.

$$\text{Precision (Pre)} = \frac{TP}{(TP + FP)} * 100\% \tag{3.2}$$

3.3 Recall

Recall is the ratio of true positives to the sum of true positives and false negatives.

$$\text{Recall} = \frac{TP}{(TP + FN)} * 100\% \tag{3.3}$$

3.4 F1-Score

The F1 is the weighted harmonic mean of precision and recall. The closer the value of the F1 score is to 1.0, the better the expected performance of the model.

$$\text{F1} - \text{score} = \frac{2 * \text{Precision} * \text{Recall}}{(\text{Precision} + \text{Recall})} * 100\% \tag{3.4}$$

4 Tools and Technology

4.1 Python

Python is a free, easy-to-learn programming language that can be used for many different tasks. It allows programmers to write clear and concise code using indentation and provides a variety of tools and libraries to tackle various problems. Originally developed by Guido van Rossum in 1991, Python has become a widely used language in many fields [40].

4.2 TensorFlow

TensorFlow is a widely used open-source framework for machine learning. It offersa comprehensive set of tools, libraries, and a supportive community. This empowers researchers to push the boundaries of machine learning, while also allowing developers to build and deploy real-world ML applications with ease.

4.3 Keras

Keras, a user-friendly Python library, simplifies building and deploying artificial neural networks. It acts as a high-level interface for TensorFlow 2, offering a productive environment for tackling machine learning challenges, particularly in the realm of deep learning. By providing essential building blocks, Keras allows for rapid development and deployment of machine learning solutions. This empowers engineers and researchers to harness the scalability and versatility of TensorFlow 2. Keras models can be executed on powerful hardware like TPUs and GPU clusters, and even exported for deployment on web platforms or mobile devices.

4.4 Google Colab

Google Colab, abbreviated as Colab, is a cloud environment for writing and running Python code. Developed by Google Research, this platform provides free access to powerful computing resources like GPUs and TPUs, making it ideal for tasks involving machine learning, data analysis, and education.

5 Results and Discussion

This section displays the findings of our investigation into the effectiveness of different deep- learning models for classifying brain tumors, focusing on the impact of data balancing on model performance. We evaluated three state-of-the-art EfficientNet architectures – EfficientNet B0, B3, and B5 – on a dataset of 7023 MRI images representing four tumor types. To assess the impact of data balancing, we conducted experiments using both a balanced dataset, where each class had an equal number of samples, andan imbalanced dataset, reflecting the original class distribution.

5.1 Results for Balanced Dataset

Table 3.5 presents the performance metrics of the three EfficientNet models (B0, B3,and B5) trained on the balanced dataset. The table shows the accuracy, precision, recall, and F1-score for each class (Glioma, Meningioma, No tumor, Pituitary) as well as the overall model performance. All three EfficientNet models (B0, B3, and B5) achieved impressive performance across different input image resolutions (20, 30, and 40) in terms of accuracy, F1-score, recall, and precision. The scores are consistently above99% for all metrics, indicating excellent performance in brain tumor classification on the balanced dataset.

TABLEAU 3.5 – *Performance of EfficientNet Models on the Balanced Dataset*

Learning rate	Epochs	Batch size	Models	Testing Evaluation			
				Accuracy	F1-Score	Recall	Precision
0.001	20	16	EfficientNet B0	99.54	99.54	99.54	99.55
			EfficientNet B3	**99.69**	**99.69**	**99.69**	**99.70**
			EfficientNet B5	99.62	99.62	99.62	99.62
	30	16	**EfficientNet B0**	**99.69**	**99.69**	**99.69**	**99.70**
			EfficientNet B3	99.54	99.54	99.54	99.55
			EfficientNet B5	99.54	99.54	99.54	99.55
	40	32	EfficientNet B0	99.69	99.69	99.69	99.70
			EfficientNet B3	99.69	99.69	99.69	99.70
			EfficientNet B5	**99.69**	**99.69**	**99.69**	**99.70**

5.1.1 EfficientNet B3 (Epochs=20, Batch Size=16)

The EfficientNet B3 model, trained over 20 epochs with a batch size of 16, exhibits outstanding brain tumor classification performance. It converges rapidly, with training and validation loss decreasing steeply in the initial epochs. Notably, the validation accuracy peaks around epoch 9, suggesting optimal generalization is achieved at this point. Beyond epoch 9, the validation accuracy remains relatively stable, indicating no significant overfitting to the training data. The model achieves remarkable 99.69% accuracy and an F1-score of 0.9969. Its precision (0.9970) and recall (0.9969) are also very high, highlighting its ability to correctly identify true positives while minimizing false positives and false negatives. The confusion matrix confirms the model's accuracy with very few misclassifications.

FIG 3.7 – *Balanced EfficientNet B3 - Training and Validation Loss and Accuracy (Epochs=20, Batch Size=16).*

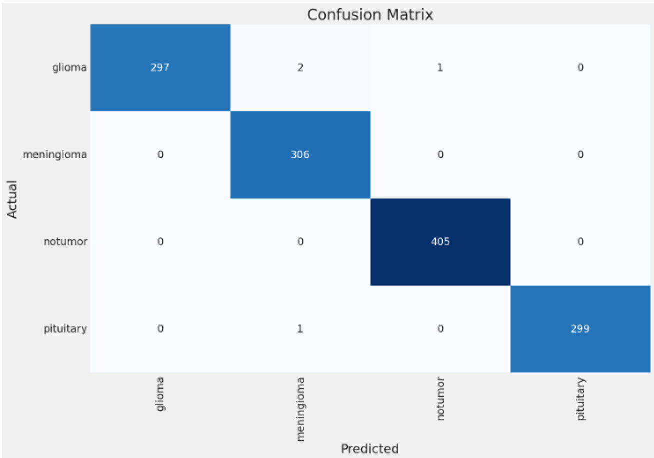

FIG 3.8 – *Balanced EfficientNet B3 - Confusion Matrix (Epochs=20, Batch Size=16).*

```
Classification Report:
______________________
              precision    recall  f1-score   support

      glioma     1.0000    0.9900    0.9950       300
  meningioma     0.9903    1.0000    0.9951       306
     notumor     0.9975    1.0000    0.9988       405
   pituitary     1.0000    0.9967    0.9983       300

    accuracy                         0.9969      1311
   macro avg     0.9970    0.9967    0.9968      1311
weighted avg     0.9970    0.9969    0.9969      1311
```

FIG 3.9 – *Balanced EfficientNet B3 - Classification Report (Epochs=20, Batch Size=16).*

5.1.2 EfficientNet B0 (Epochs=30, Batch Size=16)

When trained for 30 epochs with a batch size of 16, EfficientNet B0 exhibits a Similar performance pattern as with 20 epochs. It demonstrates rapid convergence, with training and validation loss decreasing sharply in the initial epochs, indicating efficient learning. The validation accuracy curve peaks around epoch 13 and then stabilizes, suggesting optimal generalization is achieved. at this point. The model attains an impressive 99.69% accuracy along with a high 0.9969 F1 -score. Its precision (0.9970) and recall (0.9969) are also excellent, highlighting its ability to correctly identify true positives while minimizing false positives and negatives. The confusion matrix confirms high accuracy with very few misclassifications.

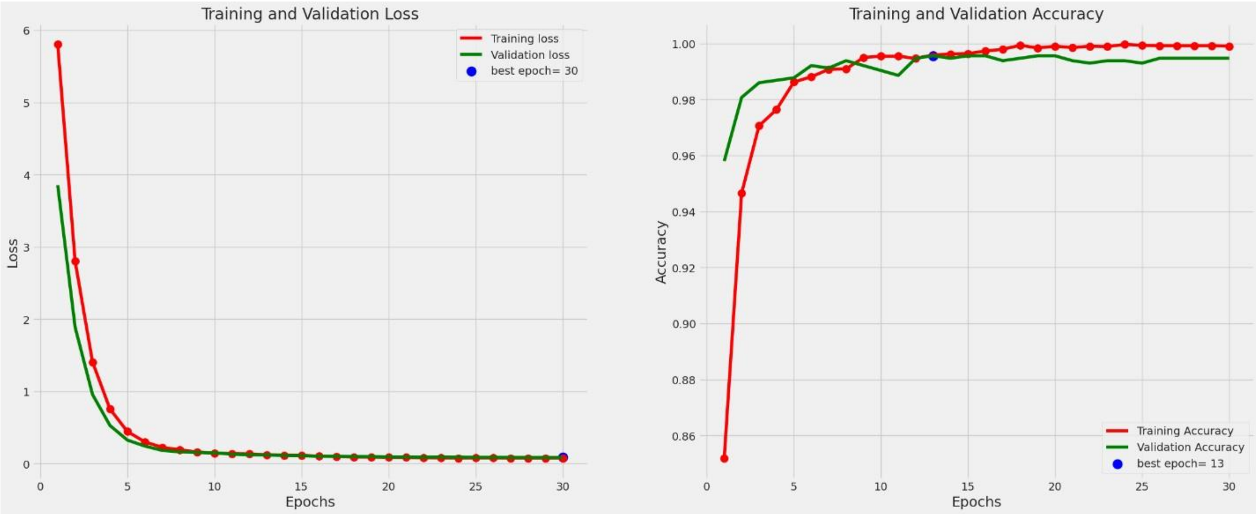

FIG 3.10 – *Balanced EfficientNet B0 - Training and Validation Loss and Accuracy (Epochs=30, Batch Size=16).*

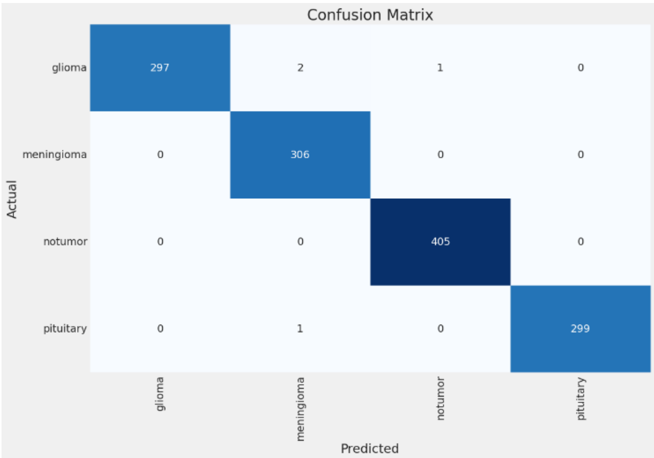

FIG 3.11 – *Balanced EfficientNet B0 - Confusion Matrix (Epochs=30, Batch Size=16).*

5.1.3 EfficientNet B5 (Epochs=40, Batch Size=32)

When trained over 40 epochs with a batch size of 32, EfficientNet B5 exhibits a similar performance pattern as with 30 epochs and a batch size of 16. It demonstrates rapid convergence, with training and validation loss decreasing sharply in the initial epochs, indicating efficient learning. The validation accuracy curve peaks around epoch 10 and then stabilizes, suggesting optimal generalization is achieved at this point. The model attains an impressive 99.62% accuracy along with a high 0.9962 F1-score. Its precision

Classification Report:

	precision	recall	f1-score	support
glioma	1.0000	0.9900	0.9950	300
meningioma	0.9903	1.0000	0.9951	306
notumor	0.9975	1.0000	0.9988	405
pituitary	1.0000	0.9967	0.9983	300
accuracy			0.9969	1311
macro avg	0.9970	0.9967	0.9968	1311
weighted avg	0.9970	0.9969	0.9969	1311

FIG 3.12 – *Balanced EfficientNet B0 - Classification Report (Epochs=30, Batch Size=16).*

(0.9962) and recall (0.9962) scores are also excellent, highlighting its ability to correctly identify true positives while minimizing false positives and false negatives. The confusion matrix confirms high accuracy with very few misclassifications.

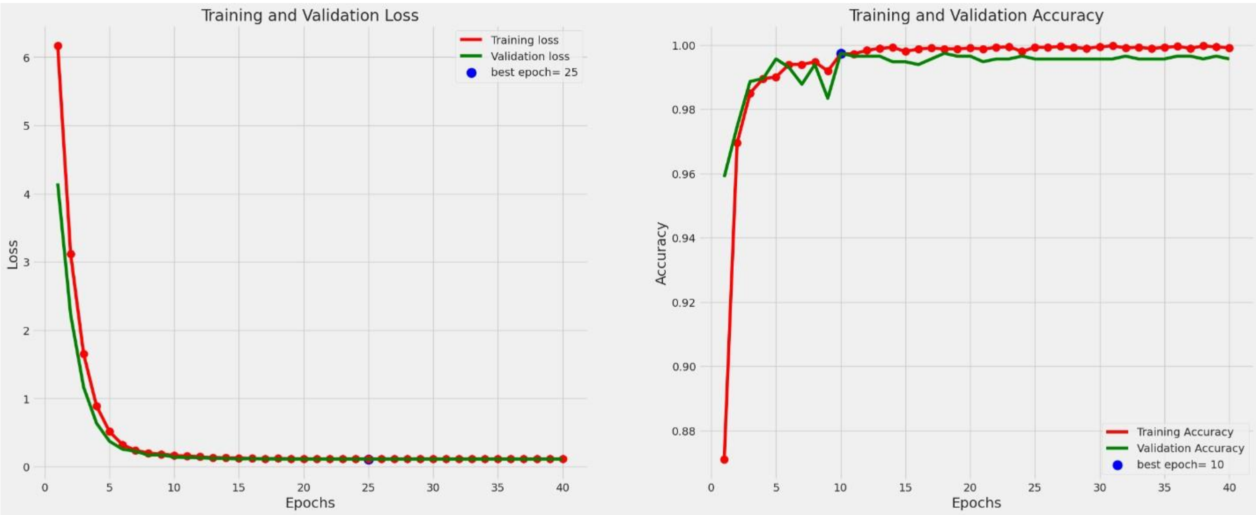

FIG 3.13 – *Balanced EfficientNet B5 - Training and Validation Loss and Accuracy (Epochs=40, Batch Size=32).*

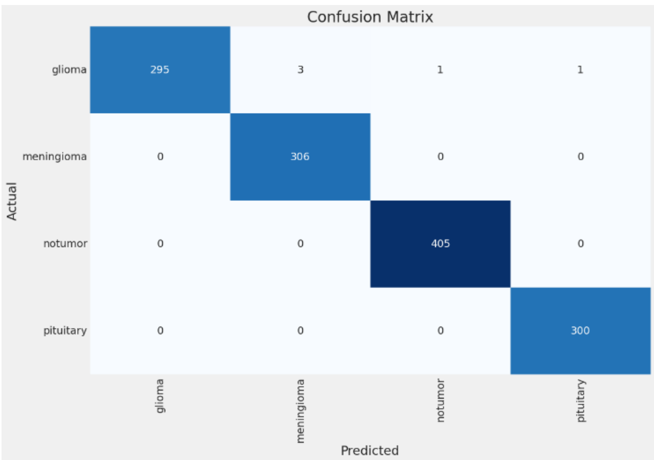

FIG 3.14 – *Balanced EfficientNet B5 - Confusion Matrix (Epochs=40, Batch Size=32).*

```
Classification Report:
______________________
              precision    recall  f1-score   support

      glioma     1.0000    0.9833    0.9916       300
  meningioma     0.9903    1.0000    0.9951       306
     notumor     0.9975    1.0000    0.9988       405
   pituitary     0.9967    1.0000    0.9983       300

    accuracy                         0.9962      1311
   macro avg     0.9961    0.9958    0.9960      1311
weighted avg     0.9962    0.9962    0.9962      1311
```

FIG 3.15 – *Balanced EfficientNet B5 - Classification Report (Epochs=40, Batch Size=32).*

5.2 Results for Imbalanced Dataset

This section shows the performance of three EfficientNet models (B0, B3, and B5) trained on the original, imbalanced dataset, representing the real-world distribution of brain tumor types. We evaluated the models using various hyperparameter combinations to assess their robustness and effectiveness in handling class imbalance. Table 3.6 summarizes the overall performance metrics for each model under different hyperparameter.

TABLEAU 3.6 – *Performance of EfficientNet Models on the Imbalanced Dataset.*

Learning rate	Epochs	Batch size	Models	Evaluation			
				Accuracy	F1-Score	Recall	Precision
0.001	20	16	EfficientNet B0	97.48	97.45	97.46	97.44
			EfficientNet B3	97.55	97.62	97.58	97.66
			EfficientNet B5	**97.63**	97.62	97.60	97.68
	30	16	EfficientNet B0	98.55	98.5	98.5	98.5
			EfficientNet B3	98.70	99.02	98.77	99.27
			EfficientNet B5	**98.85**	**98.88**	**98.92**	**98.84**
	40	32	EfficientNet B0	97.71	97.67	97.74	97.61
			EfficientNet B3	97.78	97.75	97.77	97.73
			EfficientNet B5	**98.02**	**98.00**	**98.00**	**98.00**

5.2.1 EfficientNet B5 (Epochs=20, Batch Size=16)

EfficientNet B5, trained for 20 epochs with a batch size of 16 on the imbalanced dataset, achieved 97.63% accuracy. The confusion matrix revealed minimal misclassifications, demonstrating its effectiveness in differentiating tumor types despite class imbalance.

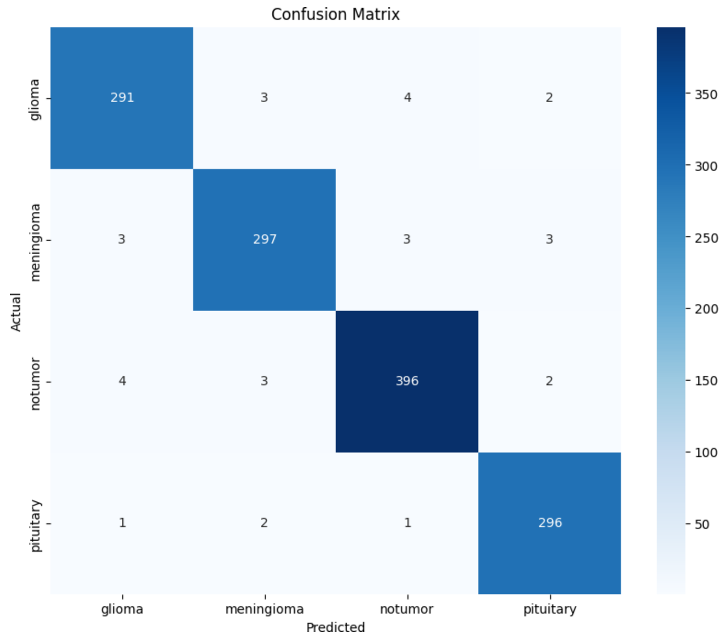

Fig 3.16 – *ImBalanced EfficientNet B5 - Confusion Matrix (Epochs=20, Batch Size=16).*

5.2.2 EfficientNet B5 (Epochs=30, Batch Size=16)

EfficientNet B5, trained for 30 epochs with a batch size of 16 on the imbalanced dataset, achieved 98.85% accuracy with minimal misclassifications according to the confusion matrix. This suggests effective differentiation between tumor types despite class imbalance.

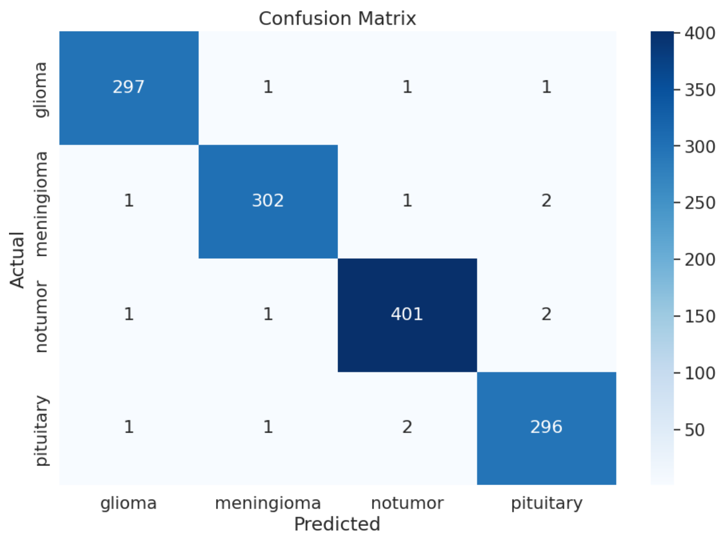

Fig 3.17 – *ImBalanced EfficientNet B5 - Confusion Matrix (Epochs=30, Batch Size=16).*

5.2.3 EfficientNet B5 (Epochs=40, Batch Size=32)

EfficientNet B5, trained for 40 epochs with a batch size of 32 on an imbalanced dataset, achieves an accuracy of 98.02%. The confusion matrix shows minimal misclassifications, indicating the model's ability to differentiate between tumor types. despite the data imbalance. However, comparing this to the model trained for 30 epochs, which has a slightly higher accuracy of 98.85%, reveals that increasing epochs and batch size does not always improve performance.

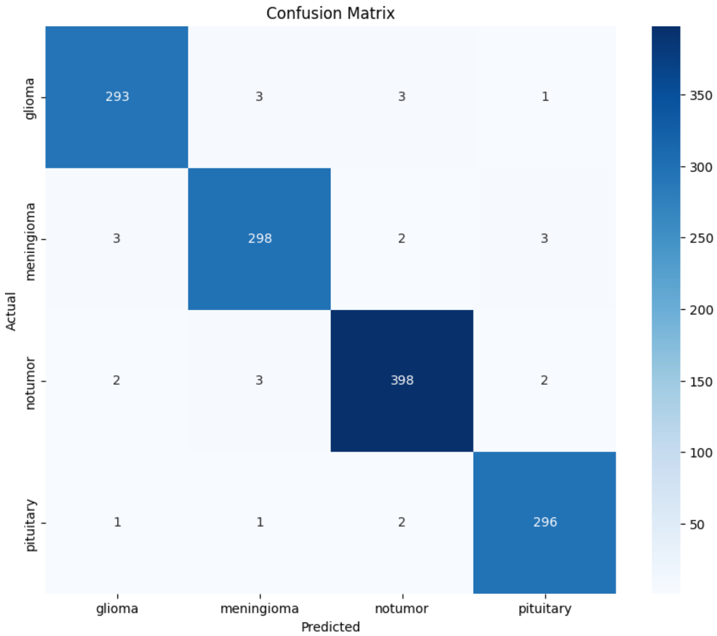

FIG 3.18 – *ImBalanced EfficientNet B5 - Confusion Matrix (Epochs=40, Batch Size=32).*

5.3 Comparison of Balanced and Imbalanced Dataset Results

Our analysis reveals a significant impact of class imbalance on the performance of EfficientNet models for brain tumor classification. When trained on the balanced dataset, where each tumor type is represented equally, all models consistently achieved remarkable accuracy, exceeding 99% in most cases. However, the performance significantly dropped when the models were trained on the imbalanced dataset, which reflected the real-world distribution of tumor types. This drop in accuracy was more pronounced for minority classes, suggesting that models trained on imbalanced data can develop biases towards majority classes. These findings emphasize the crucial importance of address sing class imbalance in medical image analysis to ensure accurate and reliable model predictions, especially when working with rare or underrepresented conditions.

5.4 Presentation of the Application: Integrating Deep Learning Models for Brain Tumor Classification

This section presents a novel software application, designed to seamlessly integrate the powerful deep learning models developed in Chapter 2 into a practical, user-friendly platform for real-world brain tumor classification. This application aims to bridge the gap between research and clinical practice, making advanced AI techniques accessible and impactful for healthcare professionals. The interface provides a user-friendly platform for:

— **Image Uploading and Preprocessing:** The application enables users to upload MRI images directly, simplifying the process for clinicians. These images are automatically preprocessed, ensuring they are appropriately scaled and formatted for compatibility with the trained deep learning models.

— **Model Selection:** The application provides a selection of pre-trained models, allowing users to choose the model best suited for their specific needs. This offers flexibility based on tumor types, image quality, or desired accuracy levels.

— **Real-Time Classification:** The core strength of the application lies in its ability to perform real-time brain tumor classification. Uploaded images are instantly analyzed by the selected deep learning model, providing rapid and efficient feedbackto the user.

— **Visualization of Results:** Classification results are presented in a clear and intuitive format, displaying the predicted tumor type, confidence score, and probability distributions for each class. This visual representation aids in understanding the certainty and likelihood of each diagnosis.

— **Report Generation:** The application automatically generates comprehensive reports containing patient information, image details, classification results, and relevant guidelines for further action. These reports are designed to be easily accessible and sharable with other healthcare professionals.

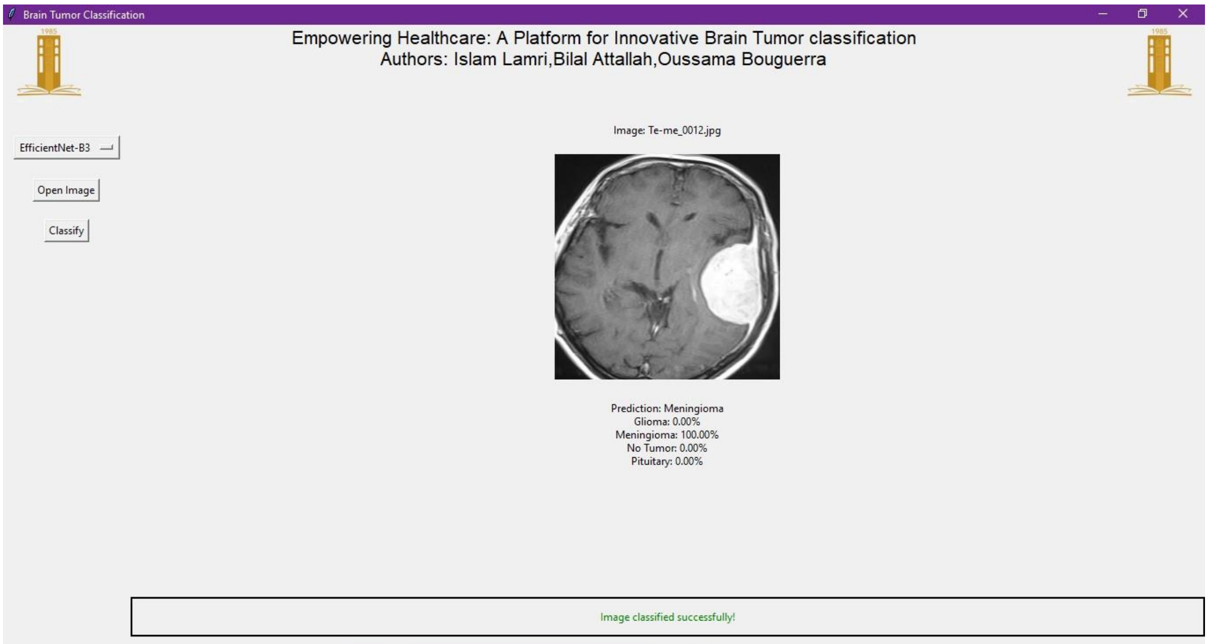

FIG 3.19 – *The interface home page and result of image Classification.*

6 Comparative Study

We compare our brain tumor prediction system with other research that employed the same performance criteria to get a sense of its performance ranking. A comprehensive comparison using classification accuracy as a parameter is shown in Table 3.7. The comparison demonstrates that our approach performs better than every cutting-edge technique.

TABLEAU 3.7 – *Comparison with the stat of the art.*

Ref	Year	Model	Accuracy
Deepak et al. [20]	2019	Deep CNN	98%
Nayak et al [23]	2022	EfficientNet	98.78%
Abd El-Wahab et al [24]	2023	BTC-fCNN	98.63%
Haque et al [27]	2024	NeuroNet19(VGG19+iPPM)	99.30%
Our Works	**2024**	**Balanced Dataset (EfficientNet B0 ,EfficientNet B3,EfficientNet B5)**	**99.69%**

7 Conclusion

During this chapter, we discussed the database we utilize and the criteria for evaluating our work. This chapter also looks at how data imbalance affects the performance of EfficientNet models for brain tumor classification. Our findings indicate that class imbalance provides a considerable barrier to the models' accurate and trustworthy predictions, notably in the categorization of minority tumor forms. While EfficientNet models consistently obtained excellent accuracy on balanced datasets, their performance plum- meted when trained on imbalanced data, emphasizing the need of appropriate datapreparation and balancing approaches

General Conclusion

Our study intends to offer a deep learning software for the early identification and categorization of brain tumors to aid clinicians in the medical area. This study investigated the impact of data load balancing on the performance of EfficientNet models for brain tumor classification. Our findings show that class imbalance poses a significant challenge to accurate and reliable model predictions, particularly affecting the classification of minority tumor types. While EfficientNet models consistently achieved impressive accuracy on balanced datasets, their performance dropped dramatically when trained on unbalanced data, highlighting the need for efficient data preprocessing and data balancing techniques. Our comparative analysis revealed that EfficientNet B5 showed greater strength in the face of class imbalance, consistently achieving high accuracy across balanced and unbalanced datasets. However, all models showed a drop in performance on the unbalanced dataset, especially for the minority class “pituitary”. This suggests that although EfficientNet models are powerful structures for brain tumor classification, mitigating class imbalance is critical for achieving reliable and unbiased predictions. The results of this study emphasize the importance of data balancing strategies to develop robust and accurate medical image analysis models. Addressing class imbalanceis critical for improving the diagnosis and treatment of brain tumors, especially when dealing with rare or underrepresented cases. Future research should focus on exploring more advanced data balancing techniques and investigating the potential of clustering methods and transformative learning to further improve the performance of brain tumor classification models. Future work: Suggest potential directions for future research,such as: - Data augmentation: Exploring different data augmentation techniques to mitigate class imbalance. - Clustering methods: Investigate the use of clustering methodsto improve model robustness. - Multimodal data: Exploring the integration of multi- modal data (e.g., PET and CT scans) to improve model accuracy. - Clinical validation: Conduct clinical trials to validate your model

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