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Enhancing Brain Tumor Classification Accuracy through Multi-Modal MRI Analysis and Advanced Ensemble Deep Learning

S

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Lastly, to those who were the secret of my success through their prayers: my parents and my siblings, I owe my utmost and most sincere gratitude.

Dedication

This thesis is dedicated with warmly gratitude to those who made it possible.

To my dear parents, the source of my strength,
for their unconditional love and sacrifices.

To my wonderful brothers and sisters,
for their unwavering support and encouragement.

And with deep respect, I also dedicate this to my supervisors,
***Dr. Bilal Attallah** and **Dr. Oussama Bouguerra**,*
whose guidance was not only academic
but also a source of great personal motivation.

Abstract

In an attempt to apply state-of-the-art deep learning techniques for brain tumor classification, which is a medical imaging domain, accurate multi-class diagnosis can dramatically affect treatment choices and patient outcomes, two modern CNN architectures EfficientNet-B3 and ConvNeXt-Tiny were evaluated for the classification of 44 different brain tumor types through Magnetic Resonance Imaging (MRI) data. The dataset, sourced from Kaggle. To redress class imbalance and enhance the generalization aspect, several data augmentation methods . Transfer learning was implemented by employing pretrained weights, and both models were fine-tuned with customized classifier heads that have Batch Normalization, Dropout and Dense layers for training. The same hyperparameters were used to train all models, and the evaluation was done with Accuracy, F1-Score, Recall, and Precision. The results demonstrate that EfficientNet-B3 reached an accuracy of **96.85%**, F1-Score **96.74%**, Recall **96.85%**, and Precision **96.94%**, while ConvNeXt-Tiny got accuracy of **95.88%** ,F1-Score **95.86%**, Recall **95.88%**, and Precision **96.16%**. A weighted ensemble approach was also used to combine the two models. This ensemble model attained the highest classification accuracy of **97.07%**, which shows that weighted averaging is a good way to improve performance. Such outcomes demonstrate the strong points of present deep learning architectures and ensemble methods in dealing with fine-grained multi-class brain tumor classification. The findings confirm that hybrid approaches have the capability to surpass accuracy in addressing difficult diagnostic tasks from medical imaging data.

الملخص

في محاولة لتطبيق أحدث تقنيات التعلم العميق في تصنيف أورام الدماغ، وهو مجال من مجالات التصوير الطبي، تم تقييم معماريتين حديثتين من الشبكات العصبية الالتفافية(CNN) ، وهما EfficientNet-B3 وConvNeXt-Tiny، لتصنيف 44 نوعاً مختلفاً من أورام الدماغ باستخدام بيانات التصوير بالرنين المغناطيسي (MRI). وقد تم الحصول على مجموعة البيانات من منصةKaggle .

ولمعالجة اختلال توازن الفئات وتعزيز قدرة النماذج على التعميم، تم استخدام عدة تقنيات لزيادة البيانات. كما تم اعتماد أسلوب التعلم بالنقل (Transfer Learning) من خلال الاستفادة من الأوزان المدربة مسبقاً، مع تعديل رؤوس المصنفات لكلا النموذجين لتشمل طبقات Batch Normalizationو Dropout و Dense أثناء التدريب.

تم استخدام نفس القيم الفائقة (Hyperparameters) لتدريب جميع النماذج، وتم تقييم الأداء باستخدام مؤشرات الدقة(Accuracy) ، ومعدل الدقة التوافقي(F1-Score) ، والاسترجاع (Recall)، والدقة(Precision) .

أظهرت النتائج أن نموذج EfficientNet-B3 حقق دقة تصنيف بلغت 96.85%، ومعدل F1- Scoreقدره 96.74%، واسترجاعاً بنسبة 96.85%، ودقة تصنيف بلغت 96.94%، في حين أن نموذج ConvNeXt-Tiny حقق دقة قدرها 95.88%، و F1-Score بنسبة 95.86%، واسترجاعاً 95.88%، ودقة 96.16% .

كما تم استخدام نهج التجميع الوزني (Weighted Ensemble) لدمج نتائج النموذجين، وقد حقق هذا النموذج المجمع أعلى دقة تصنيف بلغت 97.07%، مما يدل على أن المتوسط الوزني يُعدّ وسيلة فعّالة لتحسين الأداء.

تؤكد هذه النتائج على فعالية المعماريات الحديثة في التعلم العميق، بالإضافة إلى أهمية أساليب التجميع في معالجة مهام التصنيف الدقيقة والمتعددة الفئات لأورام الدماغ. كما تُبرز النتائج قدرة النهج الهجينة على تحقيق أداء يتجاوز الأساليب التقليدية في المهام التشخيصية المعقدة اعتماداً على بيانات التصوير الطبي.

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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

Summary

Introduction

Brain tumors are the most hazardous and fatal diseases that affect the central nervous system. Their timely detection and accurate categorization are necessary for choosing the proper treatment and raising patient survival. Because of the diverse nature of brain tumors, their different subtypes, and often faint radiological characteristics, reliable diagnosis is still a significant problem in clinical work. Magnetic Resonance Imaging (MRI) depicts the brain non-invasively and is the most commonly used method for identifying abnormalities in brain structures. The human hand's work in MRI scan interpretation, however, is very time-consuming for radiologists, it is prone to human mistakes, and there is a variance in observers. Never before was the impact of AI, particularly DL, in the area of medical image revolution so big. CNNs, a group of deep learning models, have made a significant breakthrough on image classification tasks, for example, in the case of brain tumor detection and classifying, they have even outperformed humans. Through learning hierarchical features right from the data, CNNs get rid of the need for hand-crafted features and give the possibility of having robust, automated analysis pipelines that support radiologists in reaching more accurate and timely diagnoses. This thesis presents the deep learning approach for brain tumor classification on MRI images. The primary aim, which is double, in the first place is to increase the accuracy of classification and secondly to carry out a comparison of different CNN architectures' effectiveness. The study focuses on two powerful neural network models namely EfficientNet-B3 and ConvNeXt-Tiny. The dataset that was utilized to train these models consists of 4,479 brain MRI images that were provided by the Kaggle website, allowing for extensive data augmentation that balances the classes and increases the generalization capability of this research. Among others, the problem of imbalance is one of the top issues that deep learning algorithms face to the extent that they are only capable of offering predictions that are biased toward the majority classes. The Dropout regularization and augmentation techniques were introduced to solve the issue of imbalanced data. Similarly, the overfitting problem which is frequently encountered in deep learning was tackled by using fine-tuning strategies, batch normalization, and dropout layers. Going beyond individual model evaluation, the authors of this paper suggest an ensemble-based method that harnesses the capabilities of EfficientNet-B3 and ConvNeXt-Tiny using a weighted fusion of their prediction probabilities and a score-level fusion of their latent representations of brain

tumor images. According to the experimental results, EfficientNet-B3 generally outperformed ConvNeXt-Tiny alone, However, the ensemble model outdid the individual models in terms of accuracy, precision, recall, and F1-score. The finding underscores the importance of ensemble strategies in raising model robustness and diagnostic reliability. The structure of this thesis is as follows: The first chapter introduces the medical and biological background of brain tumors, outlining their types, symptoms, and treatment modalities, as well as a brief overview of artificial intelligence , AI applications in healthcare,Machine learning and Deep learning The second chapter reviews recent studies on brain tumor classification and presents the methodology, including dataset preprocessing, model architecture, and training procedures. The final chapter presents experimental results, evaluation metrics, and a comparative analysis of the models, concluding with insights into the strengths of the proposed hybrid model and recommendations for future work.

By leveraging the power of deep learning and ensemble learning, this work contributes to the ongoing efforts to enhance automated brain tumor classification, with the ultimate goal of supporting clinical decision-making and improving patient care.

CHAPTER 1

OVERVIEW TO BRAIN TUMORS AND ARTIFICIAL INTELLIGENCE

1 Introduction

The fear of brain tumors is really terrifying and life changing. Once a brain tumor is diagnosed by the doctor, it is important to consult an expert who has the expertise to correct this condition. The brain is complex and one of the most critical centers in your body and the treatment usually causes life-altering alterations after a long time. Research is ongoing on brain tumor treatment; therefore, it becomes paramount that you know the latest medical information regarding the available treatments for that particular type of brain tumor you have as well as opinions of experts concerning your treatment strategy [27].

Thus, the chapter intends to raise our understanding of brain tumors through research into their basic causes showing common symptoms and other types and the way they are treated as well as how they affect the everyday lives of people across the world, Medical Imaging Overview, and we will be talking about the application of machine learning, deep learning, and other architectures.

2 Brain Tumor Overview

A brain tumor is an abnormal growth of cells within the brain or the central spinal canal. These tumors can be benign (non-cancerous) or malignant (cancerous). However, brain tumors will compromise brain function one way or another if size permits them to exert pressure on adjacent tissues, damaging healthy brain tissue, and disrupting normal brain activity. Brain tumors can be treated in many ways [28]. Figure 1.1 illustrates an image of the brain with tumor location.

2.1 Brain Tumor Type:

There are different types of tumors that can grow in the brain. Depending on the type of cells that make up the tumor, the tumor is classified. Information about the specific cells might get from giving tests on the tumor cells in laboratory conditions.

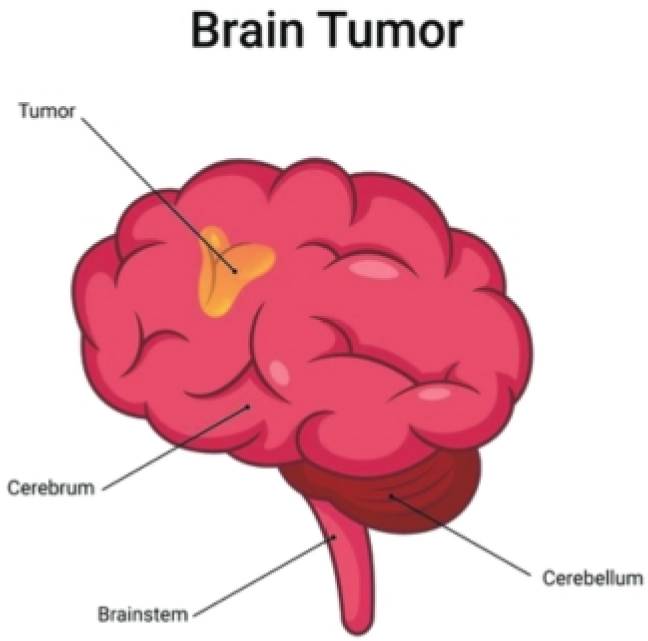


Fig 1.1: Brain tumor [1].

Certain varieties of brain tumors are usually not malignant. These are called nonmalignant brain tumors or benign brain tumors. Some varieties of brain tumors are always malignant. These are called brain cancer or malignant brain tumors. Certain types of brain tumors could be benign or malignant.

Benign brain tumors are generally considered to be slow-growing brain tumors; malignant brain tumors are considered usually fast-growing.[29]

Glioma tumor: A glioma ranks second amongst adult brain tumors. The CBTRUS estimated about 20,000 new cases of gliomas in 2015 in the United States. Approximately half of all gliomas are glioblastomas. Gliomas may occur in all four lobes of the brain: frontal (23.6%), temporal (17.4%), parietal (10.6%), occipital (2.8%), and less frequent in the brain stem, cerebellum, and spinal cord.[27] As shown in Figure 1.2, the tumor can appear in various regions of the brain

Meningioma tumor: Meningiomas are the commonest brain tumors in adults, covering approximately 36% of all brain tumors in the Central Brain Tumor Registry of the United States (CBTRUS). In 2015, CBTRUS estimated about 24,000 new meningiomas

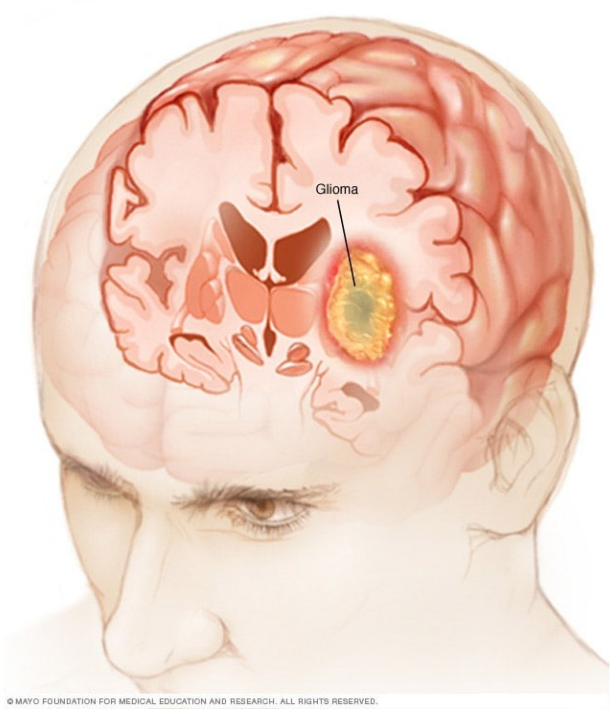


Fig 1.2: Glioma tumor [2].

diagnosed in the United States. The incidence of meningioma increases steadily with age, being twice as common in women as in men and 20% more prevalent in blacks than in whites. Most meningiomas are benign (grade I), with 5–20% atypical (grade II), and 1–3% malignant in type (grade III).[27] As shown in Figure 1.3.

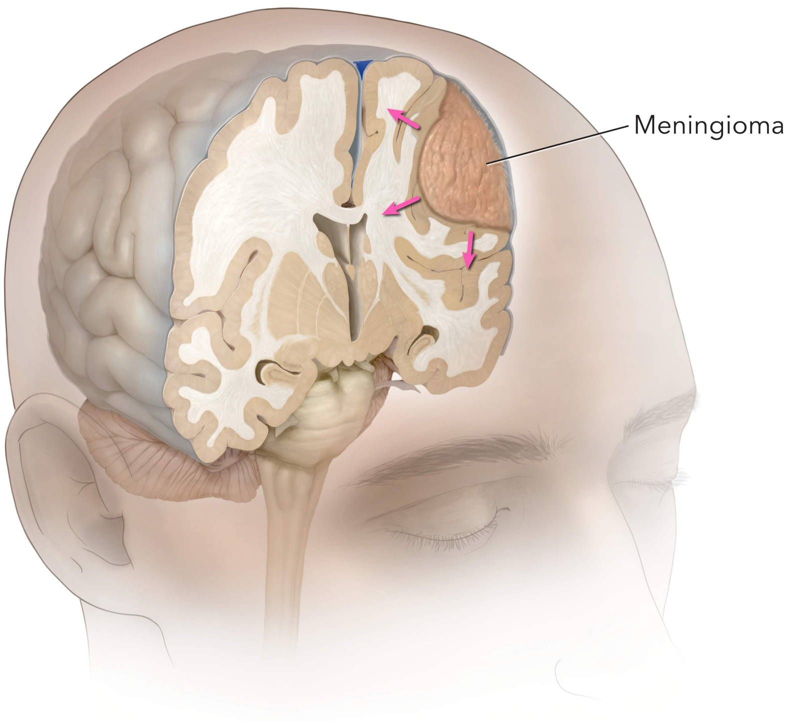


Fig 1.3: Meningioma tumor [3].

Pituitary tumor: Pituitary tumors, the third most common brain tumors, account for approximately 15%. Most brain tumors are benign adenomas. Symptoms might arise in even the nonfunctioning tumors because of the intracranial mass effect. This implies tumor growth may be stimulated by substance affecting the secretion of functional hormones of the normal pituitary ,As shown in Figure 1.4, growth factors involved in normal fetal pituitary development.[29]

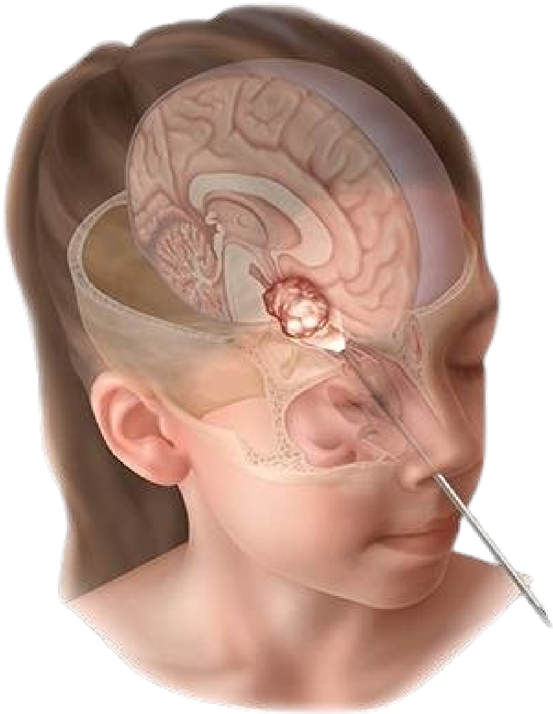


Fig 1.4: Pituitary tumor [4].

2.2 Brain Tumor Symptoms:

Some individuals with a brain tumor do not experience any symptoms, especially when it is tiny. Signs and symptoms of a brain tumor vary according to the location, size, and type of the tumor, and may include:[30]

(i) Persistent headaches

(ii) Nausea or vomiting

(iii) Seizures

(iv) Memory loss

(v) Vision problems

(vi) Speech difficulties

2.3 Brain Tumor Causes

Researchers understand that brain tumors develop when genes responsible for functioning on the chromosomes of a cell are damaged, yet why this happens remains uncertain. Your chromosomes carry DNA for your cells throughout the body to tell them what to do — to grow, to divide or multiply and/or to die. As soon as the DNA of the brain cell undergoes a change, the brain cell comes to know different instructions. Abnormal brain cells arise, which grow and multiply and occasionally linger on longer than normal. Some individuals are born with mutations in one or more of these genes; in other instances, environmental factors may have triggered the injury to the genes.[30]

2.4 Treatments for brain tumors

It depended on:

(i) Where the tumor is located, what it is, and its size.

(ii) How many tumors are present.

(iii) Age and general health condition of the patient.[30]

There are many benign tumors that can be removed through surgery and do not recur, depending on where it is located and the safety of the procedure.

Under five years old found more susceptible to treatment with side effects yet manifest apparent causes from radiation.[30]

- **Brain surgery (craniotomy):** If feasible, surgeons remove the tumor. They perform very careful surgery, sometimes with the patient awake (with no pain at all), to limit damage to functioning areas of the brain.
- **Treatment with radiation:** Exposure to high levels of X-rays destroys brain tumor cells or shrinks the tumor in this kind of treatment.
- **Chemotherapy:** includes drugs that kill cancer cells in your brain and other regions of your body. You might receive chemotherapy through an injection into a vein or take it as a pill. Your healthcare provider may recommend chemotherapy after surgery to kill any cancer cells left after surgery or to stop any remaining tumor cells from growing.[30]

3 Medical Imaging Overview

Medical imaging comprises techniques and processes employed for originating imaging of the human body, both at a individual and clinical level. This is a really significant area of medical imaging in regard to brain tumors, which helps in diagnosis and management. Medical imaging plays a role in tumor detection, localization, characterization, as well as treatment planning.[31]

(i) Computed Tomography (CT).

(ii) Positron Emission Tomography (PET).

(iii) Single-photon Emission Computed Tomography (SPECT).

(iv) Magnetic Resonance Imaging (MRI).

(v) Magnetic Resonance Spectroscopy (MRS)

3.1 Methodology of MRI

MRI alias magnetic resonance imaging is one of the most modern methods of examining tissue. That said, it is an emerging imaging diagnostic method that is capable of visualizing the human body structure internally without any interference. It provides high-clarity images of human tissue and organs, translating into more intuitive image information on the internal structure of the human body, thus providing the clinician with richer and meaningful diagnostic and treatment information.[32] The appearance of an MRI machine is shown in Figure 1.5.

Fig 1.5: MRI Imaging machine.[5]

Our research 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. A high magnetic field generates acoustic signals from water molecules in the body, while a transmitter/receiver in the equipment broadcasts and receives radio waves to produce CT MRI pictures. Examples of MRI scan images are shown in Figure 1.6.

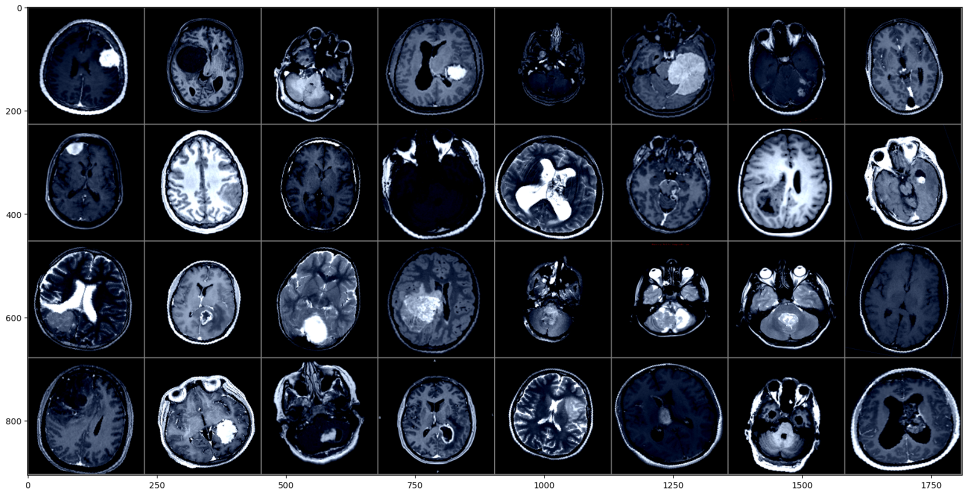


Fig 1.6: Brain tumor MRI scans.

4 Artificial Intelligence (AI)

4.1 Definition of Artificial Intelligence (AI)

Artificial Intelligence (AI) is a branch of computer science that builds systems for carrying out tasks that normally would require human intelligence: these tasks include problem-solving, reasoning, learning, perception, and understanding natural language. AI technologies, therefore, seek to mimic the human cognitive behaviors of making machines perform highly complex work autonomously.

For AI-qualifying systems, to make sense of the user parameter, simple rules developed from knowledge expressed in descriptive language were introduced to deal with large numbers of restrictions. The AI systems have advanced and evolved, especially in the last couple of decades, going from simple rule-based systems to optimized learning models that can change according to data. Thus, AI comprises lots of applications such as machine learning (ML), deep learning (DL), and natural language processing (NLP) as widely studied subject areas. With an enormous amount of data and an algorithm to learn from, AI systems gradually improve at completing their task as they make more and more decisions or predictions.[33] The relationship between AI, ML, and DL is illustrated in Figure 1.7.

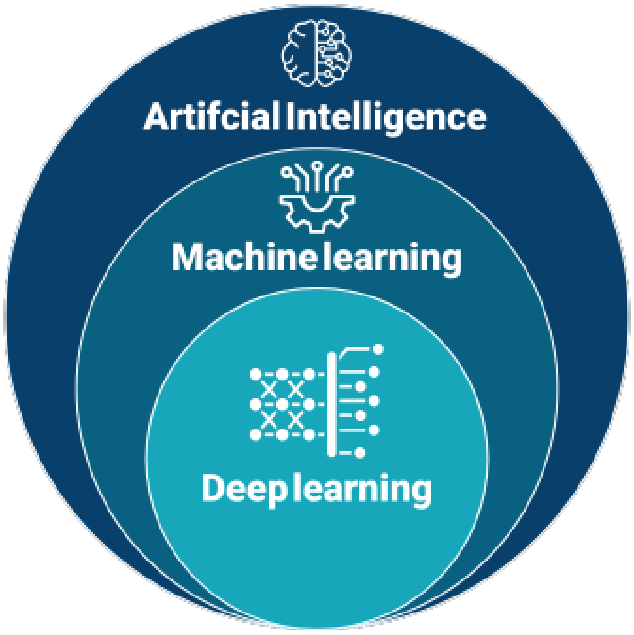


Fig 1.7: Artificial intelligence (AI). [6]

4.2 The importance of artificial intelligence in medical imaging

There has been enormous development regarding artificial intelligence (AI) in the medical field over the years. It can ensure the highest quality patient care with optimum decision-making in health care and medicine from their corresponding prevention, detection, diagnosis, and treatment of diseases. It also advances medical imaging by enhancing diagnostic accuracy, speed, and efficiency. It helps the radiologist in accurately detecting those anomalies like a tumor, fracture, or infection. AI algorithms allow very speedy analysis of massive cascading piles of imaging data, diminishing human error, thus supporting the early identification of diseases.[34] Applications of AI in the medical field are illustrated in Figure 1.8.

5 Machine Learning (ML)

Machine learning (ML) is a subfield of artificial intelligence (AI) that provides various methods of creating algorithms and statistical models to enable computer systems improve their capacity on a specific task as time rolls. Therefore, we could refer to machine learning as a method of building an artificial intelligence system.[33] Machine

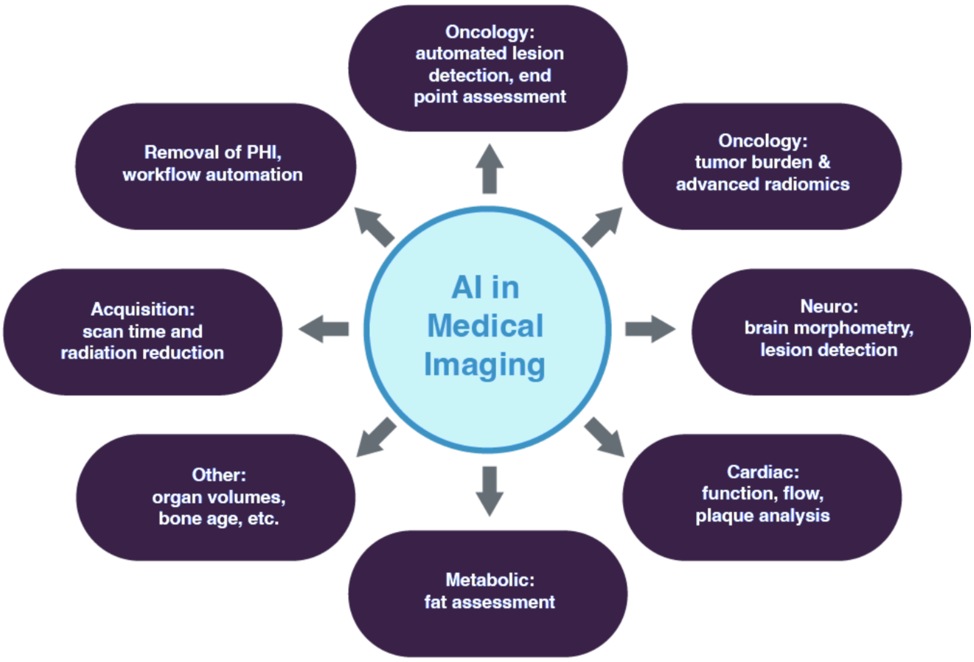


Fig 1.8: Applications of AI in medical imaging. [7]

learning is based on algorithms and statistical models which are meant to enable a computer to learn-based decision making processes derived from data without having been programmed clearly. Generally, machine learning algorithms identify some patterns and capabilities in data and use the used insights to predict or decide on new data.[35]

5.1 Types of machine learning Algorithms

Machine learning has grown extremely wider in terms with numerous varied perspectives and various applications, it can be classified into following categories : [33]

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

An overview of machine learning types and their typical applications is presented in Figure 1.9.

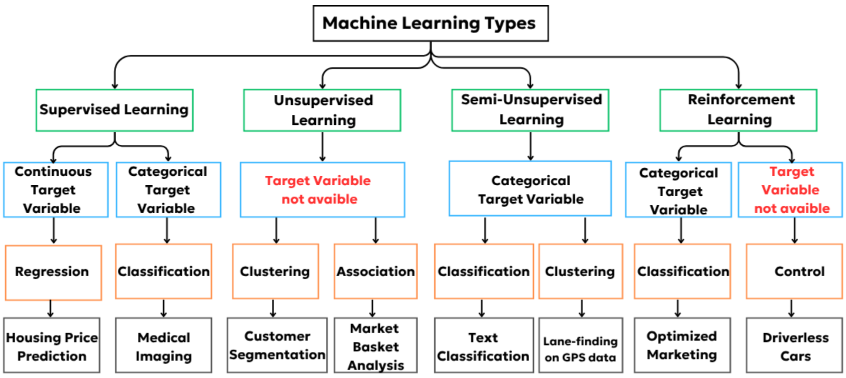


Fig 1.9: Types of Machine Learning. [8]

5.1.1 Supervised learning

in which the machine trained on labeled data to see the relationship between the input data and the output data. The learning of an algorithm takes place, using a labeled dataset, one that has a known correct output for every possible input. Hence, the algorithm will then learn to predict by correlating different inputs to the produced outputs in this learned mapping using a pattern in the data. [36] The process is illustrated in Figure 1.10.

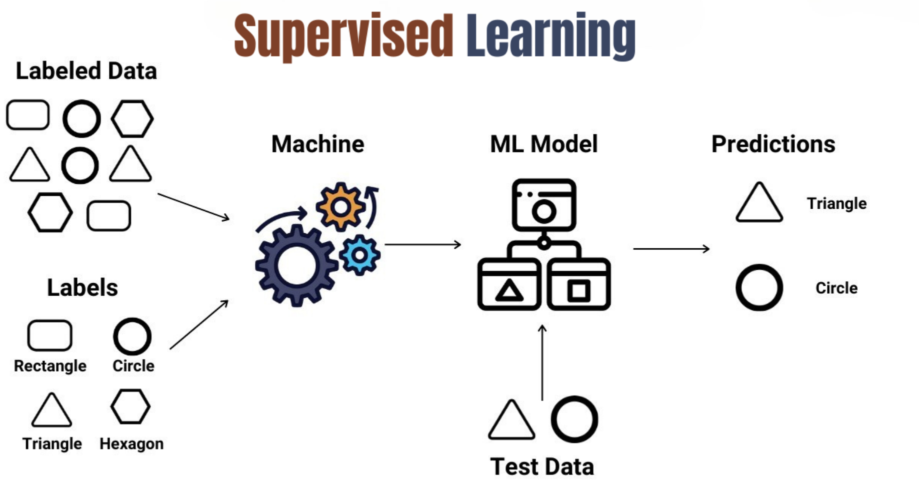


Fig 1.10: Supervised Machine Learning.[9]

5.1.2 Unsupervised Learning

The machine can be trained with unlabeled data which can lead to pattern or structure discovery in the data. This exercise involves training an algorithm with an unlabeled dataset and without specifying what the expected output is for each input. Thus, the algorithm identifies data patterns and relationships by itself without being told what to search for. [36] The process is illustrated in Figure 1.11.

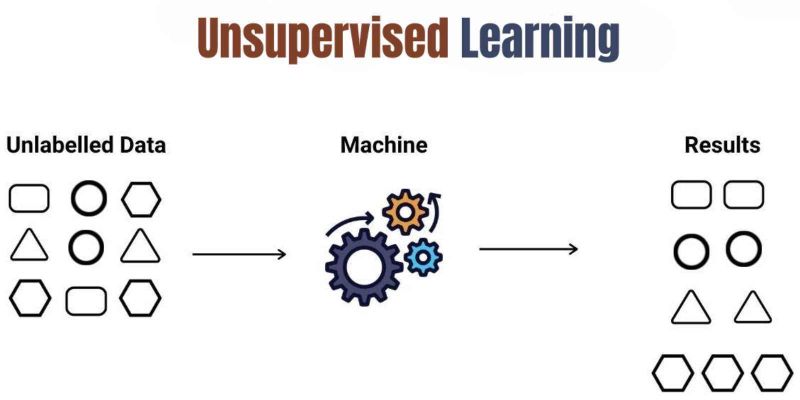


Fig 1.11: Unsupervised Learning.[10]

5.1.3 Semi-supervised Learning

Learning techniques that combine both supervised and unsupervised learning methods are grouped within this classification. While unlabelled data is available, the process of discovering labelled data is tasking and very tedious. This technique is commonly used in the data mining field. [36] The process is illustrated in Figure 1.12.

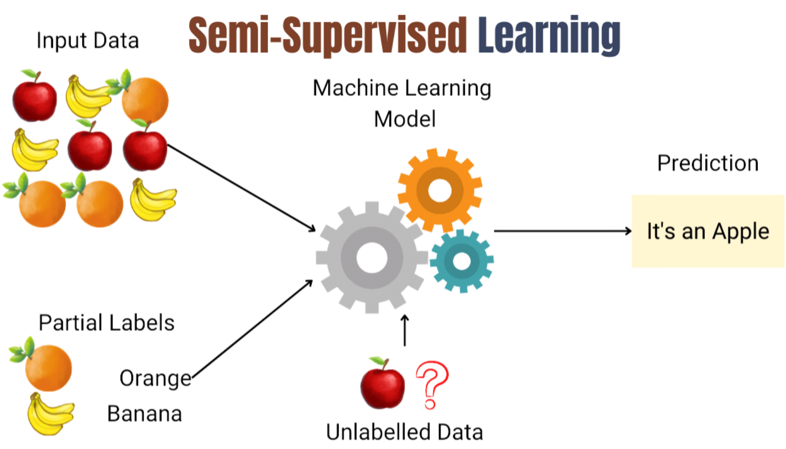


Fig 1.12: Semi-supervised Learning. [11]

5.1.4 Reinforcement Learning

in which the machine learning by interacting with the environment by rewarding or punishing certain actions. Basically, an algorithm is trained to make a decision based on the feedback from the environment. The algorithm maximizes a reward signal by taking actions that yield positive outcomes while avoiding actions that yield negative outcomes. [36] The process is illustrated in Figure 1.13.

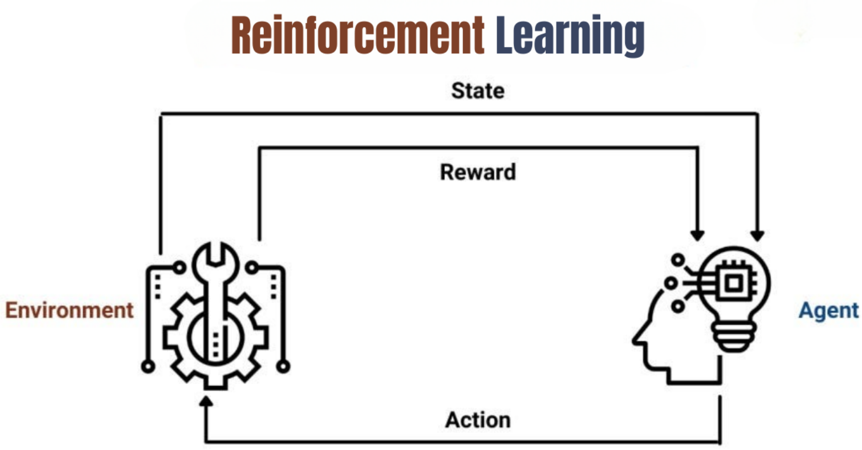


Fig 1.13: Reinforcement Learning.[12]

5.2 The challenges faced during the machine learning process

In machine learning, the model is trained based on some features. Sometimes our model has a low accuracy in the newly presented data. The two types of issues that may come into play here are: overfitting and underfitting. [37]

Underfitting : Underfitting results when given few features to train the model and sometimes unknown data is incorrectly identified. To reduce the underfitting problem, increase feature selection. [37]

Overfitting : Overfitting results if the model has been trained on a large number of features. It was also shown that a further training of the model on even fewer numbers of features makes the machine too biased, and indeed with that, the model receives an underfitting problem. But actually training on more features will lead to one more problem. The problem will come, if the trained model has many more features, the variance in the picture will become more and then the model identification will be very low, leading to worse performance of the model. This is called overfitting problem. [37]

Table 1.14 summarizes the main differences between underfitting and overfitting.

6 Deep Learning (DL)

Deep Learning (DL), is one of the subsets of machine learning in which artificial neural networks are used, with the term ”deep” indicating multiple layers. In these deep neural networks, large volumes of data can be processed and automatically learned-with little or no human and can automatically learn from raw data images, text, etc.-without bringing in feature extraction and representation explicitly. Deep learning has revolutionized AI by achieving remarkable performance in complex tasks like image and speech recognition. Just like humans, deep learning processes information in multiple

Techniques to fight underfitting and overfitting

Underfitting	Overfitting
More complex model	More simple model
Less regularization	More regularization
Larger quantity of features	Smaller quantity of features
More data can't help	More data can help

Fig 1.14: Underfitting and Overfitting. [13]

layers of networks, with each layer understanding more abstract features of the data so that eventually, the DL models learn complex patterns.[33]

6.1 Deep Neural Networks

Deep Neural Networks (DNNs) are a specific variant of multilayer feed-forward artificial neural networks in which several hidden layers are inserted between the input and output layers. Moreover, the number of hidden neurons is the same for each of the hidden layers. The benefit of using extra hidden layers in the network enables the composition of features from lower layers. These features potentially model complex data with fewer units.[38] The architecture of a DNN is illustrated in Figure 1.15.

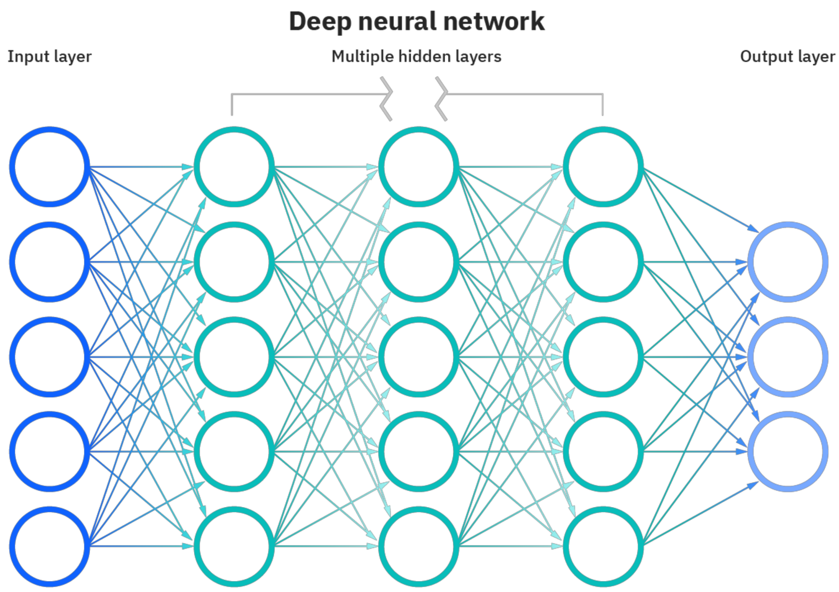


Fig 1.15: Architecture diagram DNN [14]

6.2 Convolutional Neural Networks

CNNs are deep learning models. These are mainly applied in the processing of data that is mainly in form of a grid, for example-images. They basically consist of convolutional layers which learn automatically and adaptively hierarchical organization of spatial features from input images. Throughout medical images-brain tumor being MRI detected-they have proved to be important potential tools in their well-illustrated capabilities of capturing spatial and structural features of the data.[39] The architecture of a CNN is illustrated in Figure 1.16.

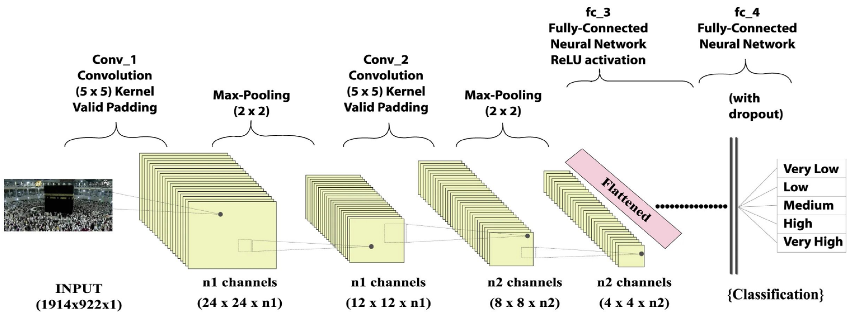


Fig 1.16: Architecture diagram CNN [15]

6.3 Recurrent neural networks

The RNN structure is tailored towards information processing in a sequential manner, be it along the lines of time series or language. By retaining the memory of previous inputs in internal states, RNNs could learn the temporal relationship. Traditional RNNs were traditionally afflicted by the vanishing gradient dilemma, giving rise to more advanced architectures such as LSTM and GRU.[39] The architecture of a RNN is illustrated in Figure 1.17.

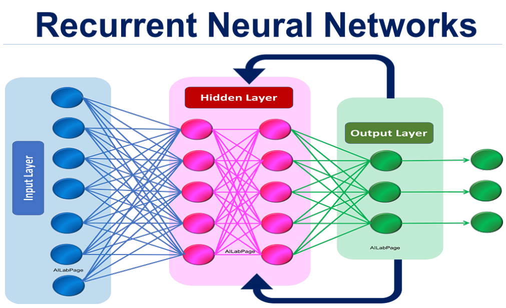


Fig 1.17: Architecture diagram RNN [16]

7 Conclusion

In this chapter, we provide an overview of brain tumors, including their origins, basic classification, common symptoms, and impact on people's lives around the world. We also discuss how emerging technologies have contributed to the field of artificial intelligence through machine learning, deep learning, and various architectures designed for research purposes.

CHAPTER 2

SYSTEM AND METHODOLOGY FOR BRAIN TUMOR DIAGNOSIS

1 Introduction

In this chapter, an overview of the brain tumor will be given, along with a presentation of our newly invented system which is aimed specifically for your purpose related to brain tumors. Recent trends in brain tumor research will be considered first. we will delve into the components and functionalities of our system, elaborating on techniques and strategies that the system employs. By the end of the chapter, the readers would have a good knowledge of brain tumors and the novel intervention developed within our system.

2 A literature survey on brain tumor classification techniques

- In this paper, the authors proposed a method to classify brain tumors into four types using a modified VGG-16 model with transfer learning. The MRI dataset used contained 7023 images from three views: axial, sagittal, and coronal. They applied image preprocessing like resizing, contrast enhancement, and region-of-interest extraction. The model showed good performance with an accuracy of 98.5% and AUC of 99%.[40]
- This study presents a new deep learning model for classifying brain tumors using a custom three-branch CNN (3B Net) combined with EfficientNetB2. The model was trained and tested on several public MRI datasets covering binary, three-class, and four-class classifications. Data augmentation and fine-tuning of EfficientNetB2 helped improve performance and reduce overfitting. The model achieved 99.50% accuracy in binary classification, 98.72% in three-class, and 97.80% in four-class classification tasks.[41]
- This study proposes a deep learning framework for classifying 15 brain tumor types using MRI images. The method uses a deformable convolutional network (DCN) combined with a hierarchical multi-scale attention module. The dataset

from Kaggle and included expert-annotated MR images of various tumor categories. Data augmentation and saliency mapping were applied to improve classification . The model achieved a classification accuracy of 96.35%.[42]

- This study introduces a deep learning method for multi-class brain tumor classification using EfficientNetV2 and Vision Transformer (ViT). The dataset used includes 7,023 MRI images split into training and testing sets. EfficientNetV2 achieved 95% accuracy, while ViT reached 90%. Using a geometric mean ensemble of both models, the final accuracy improved to 96%.[43]
- This paper presents RDXNet, a hybrid deep learning model combining ResNet101, DenseNet121, and Xception for multi-class brain tumor classification. The model was trained on 7,023 MRI images from Br35H, Figshare, and Radiopaedia datasets. It classifies four tumor types. Using feature fusion and transfer learning, RDXNet achieved 91.23% accuracy. The model outperformed individual networks while reducing overfitting.[44]
- This study introduces a brain tumor classification model using DenseNet-169 optimized with the manta-ray foraging optimizer (MRFO). The approach includes hyperparameter tuning and enhanced residual blocks to improve feature extraction. The model was tested on four datasets including Kaggle and BR35H, covering both binary and multi-class tasks. It achieved 96.40% accuracy on the main dataset and up to 99.10% on others. The method improves feature representation and outperforms several existing models.[45]
- This study proposes a brain tumor classification model using EfficientNet-B4 with customized layers and global average pooling. The model was trained on a Kaggle MRI dataset includes 7,023 brain MRI images multi-class, with batch normalization and dropout to prevent overfitting. Seven optimizers were tested, and AdamW gave the best results. It achieved 99.24% accuracy, with precision, recall, and F1-score of 99.22%. The lowest-performing optimizer was AdamX, with 98.55% accuracy.[46]
- This paper presents a brain tumor classification method using transfer learning combined with co-evolutionary genetic algorithms (CEGA). EfficientNetB3 and DenseNet121 were fine-tuned and optimized using CEGA to classify four tumor types from a Kaggle MRI dataset. The goal was to improve hyperparameter tuning and model accuracy. CEGA-EfficientNetB3 achieved 99.39% accuracy, while CEGA-DenseNet121 reached 99.01%. Both models performed well without data augmentation.[47]
- This study presents an ensemble deep learning approach for brain tumor classification using MRI images. It combines MobileNetV1, MobileNetV2, and ResNet50V2 with optimal weight allocation using a Differential Evolution (DE)

algorithm. The model outputs are integrated via a weighted average to improve accuracy. It achieved 98% accuracy on a binary dataset and 97.03% on a multi-class dataset. [48]

- This study presents a brain tumor classification model using EfficientNetB3V2 combined with a MaxEnt classifier. The model classifies MRI images into four types: pituitary, meningioma, glioma, and no tumor. It achieved 99.76% training accuracy, 99.35% validation accuracy, and 98.47% testing accuracy .[49]

A comprehensive summary of the brain tumor classification methods discussed above is provided Table 2.1.

Table 2.1: Literature Survey (based on selected articles).

Ref, Year	Dataset	Technique and Model	Classification	Results
[40], 2025	Br35H, Figshare,datasets (7023 images)	Modified VGG-16 with transfer learning, preprocessing	Multi Classification (4-classes)	Accuracy: 98.5% f1-score: 98.3 % recall: 99.0 % precision: 98.3%
[41], 2025	Multiple public MRI datasets	Custom three-branch CNN (3B Net) + EfficientNetB2, data augmentation and fine-tuning	Binary,Multi Classification (3,4-classes)	Accuracy: 99.50% (binary), 98.72% (3-class), 97.80% (4-class)
[42], 2025	Kaggle MRI dataset	Deformable CNN with hierarchical multi-scale attention, data augmentation	Multi Classification (15-classes)	Accuracy: 96.35% f1-score: 96.43 % recall: 97.22 % precision: 95.67%
[43], 2025	Br35H, Figshare,datasets (7023 images)	EfficientNetV2 and Vision Transformer (ViT), ensemble approach	Multi Classification (4-classes)	Accuracy: 96% (ensemble), 95% (EfficientNetV2), 90% (ViT)
[44], 2025	Br35H, Figshare,datasets (7023 images)	Hybrid DL: ResNet101 + DenseNet121 + Xception, feature fusion, transfer learning	Multi Classification (4-classes)	Accuracy: 91.23% f1-score: 91.00 % recall: 91.00 % precision: 91.00%
[45], 2025	Kaggle, BR35H, MSID, Gastro datasets	DenseNet-169 + Manta Ray Foraging Optimizer + enhanced residual blocks	Multi Classification (4-classes)	Accuracy: 96.40% f1-score: // recall: // precision: //
[46], 2025	Kaggle MRI dataset (7023 images)	EfficientNet-B4	Multi Classification (4-classes)	Accuracy: 99.24% f1-score: 99.22 % recall: 99.22 % precision: 99.22%
[47], 2025	Br35H, Figshare,datasets (7023 images)	CEGA DenseNet121,CEGA EfficientNetB3	Multi Classification (4-classes)	Accuracy:CEGA-DNet121 (99.24%), CEGA-EffNet-B3(99.01%)
[48], 2025	BR35H dataset	Ensemble of MobileNetV1, V2, ResNet50V2 + DE algorithm	Binary,Multi Classification (4-classes)	Accuracy: 98% (binary), 97.03% (multi-class)
[49], 2025	Br35H, Figshare,datasets (7023 images)	EfficientNetB3V2 + MaxEnt classifier	Multi Classification (4-classes)	Accuracy : 98.47% f1-score: // recall: // precision: //

3 Techniques for training neural networks

Training a neural network is all about tweaking its parameters in iterations such that the value of a particular loss function is minimized. This step is important for the network to generalize well to new inputs and perform well on different tasks as well. [50]

3.1 Loss function

The loss function is essential in training machine or deep learning models by measuring the difference between predictions and known target results, thus providing a clear metric for performance evaluation. It aids the back-propagation process in using the gradient of the loss function to modify the parameters, thus minimizing loss on the prediction and improving accuracy. Moreover, a good loss function balances bias and variance to help prevent overfitting.[51] An illustrative diagram of the loss functions role and position in a neural network is shown in Figure 2.1.

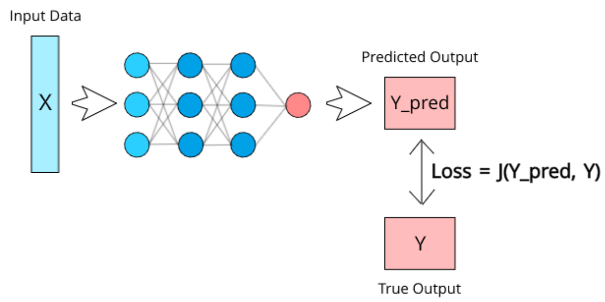


Fig 2.1: Loss Function.[17]

3.2 Dropout

Dropout is one of the most commonly used regularization methods to avoid deep learning models overfitting. [52] Some percent of the activations in the network are dropped by randomly eliminating or zeroing some of the neurons in the neural network during training, thus encouraging the network to learn more robust features and combating the tendency to focus on any particular attribute.[52] An illustrative diagram of the Dropout role is shown in Figure 2.2.

3.3 Batch normalization

Batch normalization is the process of initializing the weights of a neural network.[53] These normalizations are used just before the activation layer to reduce the internal covariance shift of the activation layers, improving training stability and speed. [52]

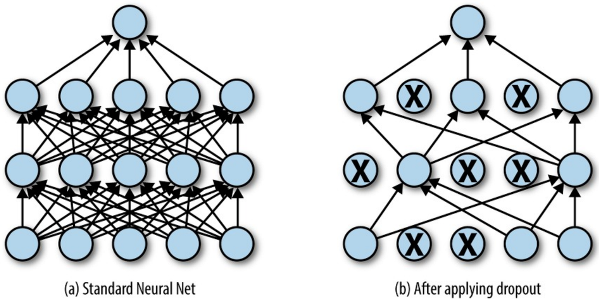


Fig 2.2: Dropout Regularization. [18]

3.4 Hyperparameters

Hyperparameters in CNN are all immensely important parameters that are defined before model training, governing its learning process and impacting performance. In CNN, these parameters define architecture, hidden layers, dropout rates, learning algorithms, etc., affecting different parameters such as feature extraction and avoidance of overfitting. The effective tuning of hyperparameters is vital for optimizing the CNN structure and training so as to enhance performance and accuracy .[54]

3.4.1 Batch Size

Batch size determines how many samples are processed together during gradient estimation. While larger batches may slow convergence due to memory constraints, very small batches can harm performance due to noisy gradient estimates. Commonly used batch sizes include 16, 32, and 64, which are selected in conjunction with other hyperparameters [54]. A comparison between small, medium, and large batch sizes and their impact is summarized in Table 2.3.

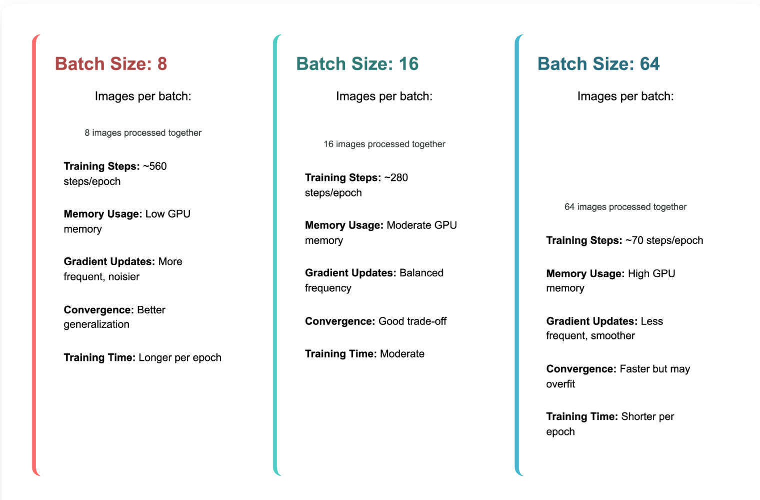


Fig 2.3: Batch Size.[18]

3.4.2 Optimizer

Training of neural networks demands optimizers that manipulate network weights and learning rates so that the hard loss function can be minimized. The most common optimizers include Adam,SGD and RMSprop [54] . A comparison between Adam,SGD and RMSprop and their impact is summarized in Table 2.4.

Feature	SGD	RMSprop	Adam
Learning Rate	Fixed or decayed	Adaptive	Adaptive
Momentum	Optional	Uses moving average	Yes (with momentum & RMS)
Speed	Slow	Faster	Fastest
Memory Usage	Low	Medium	High
Best for	Simple problems	Recurrent models	Most problems

Fig 2.4: Comparison Between Optimizer Adam,SGD and RMSprop.

3.4.3 Learning Rate

The LR determines the frequency of parameter revisions for optimal results, If set incorrectly, it can harm performance. The effect of increasing learning rates is to accelerate convergence in cases when consecutive steps align in the same gradient direction.[54] as shown in Table 2.5.

3.4.4 Epochs

Epochs represent how many times the entire dataset is passed to a neural network for training,forward and backward passes. The dataset may need to be input multiple times to improve generalization. However, too many epochs can lead to overfitting, so choosing the right number of epochs is crucial to avoid this problem.[54] A comparison between small and large Epochs and their impact is summarized in Table 2.6.

3.5 Activation Function

Activation functions are integral components of neural networks and thus serve important purposes for learning and modeling complex relationships in data. Understanding these purposes is crucial for designing effective neural network architectures and optimizing their performance. Its primary purpose in the neural network is to

Fig 2.5: Learning Rate.

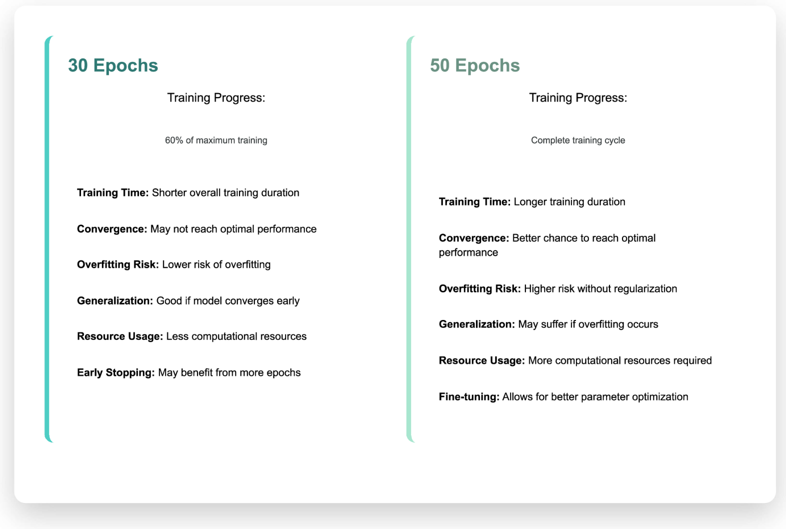


Fig 2.6: Epochs.

incorporate nonlinearity, without which the neural network would operate as a linear regression model. To activate a neuron, apply an activation function to the weighted sum of its inputs, including the bias factor, as follows [55].

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

- **A:** Output of a neuron.
- **G:** Activation Function.
- **W:** Weights.
- **Xi:** Features.

- **B:** Bias.

It affects the performance of neural networks and the process of their training. Examples of these activation functions are sigmoid, tanh, and ReLU with their own unique properties and applications.An illustration of commonly used activation functions—Sigmoid,Tanh and ReLU—is shown in Figure 2.7.

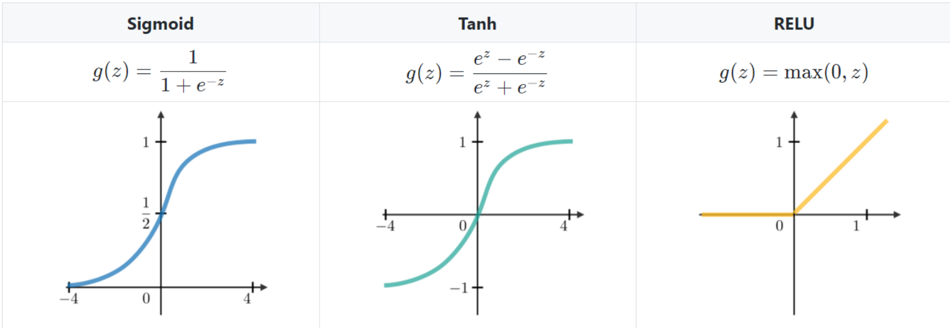


Fig 2.7: Sigmoid vs Tanh vs RelU Activations Functions. [19]

4 Methods in classification of brain tumors

4.1 An Overview on Convolutional Neural Networks

A convolutional neural network (CNN), also called a ConvNet, is a particular type of artificial neural network (ANN) with a deep feed-forward architecture. CNNs are known for their remarkable generalization ability as compared to other architectures with fully connected layers: they can learn highly abstracted features of objects, especially in the spatial domain, and recognize those features more efficiently. Deep CNN models basically consist of a finite set of processing layers that learn to extract various features of input data (such as image) with multiple levels of abstraction. There are five different layers in CNN : [52], as illustrated in Figure 2.8. There are five different

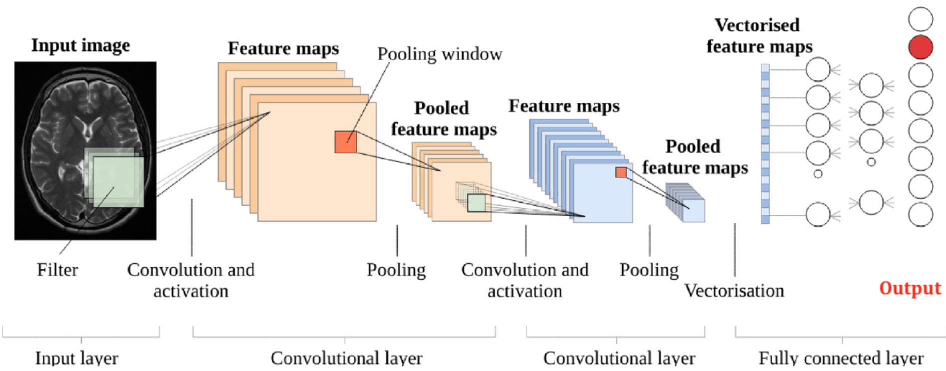


Fig 2.8: Convolutional neural network layers.[20]

layers in CNN:

– Input layer.

– Conv layer (Convo+ReLU).

– Pooling layer.

– Fully connected (FC) layer.

– Output layer (soft-max).

4.1.1 Input layer

The input layer consists of 2D image data with the following dimensions: [width, height, and number of channels]. It is a matrix containing pixel values that represent the intensity or color information of each point in the image.

4.1.2 Convolution layer

Convolutional layer is the key to feature extraction from the input data such as images, maintained within convolutional neural networks (CNNs). This systems work by applying set of filters, also termed "kernels." These filters then convoluted across the spatial dimensions of an input, producing feature maps. Each filter is specifically tuned to get activated with the presence of certain visual features in the input, such as edges or textures.[53] , as illustrated in Figure 2.9.

Filters: A filter is small matrix weights that are being moved throughout input data. In the forward pass, a filter performs an element-wise multiplication to some part of the input then sums up all these values to produce one output value. This process is done all over the input so that the network can identify patterns regardless of the position at which the object exists. The weights of such filters are randomly initialized and then optimized through training during backpropagation to minimize the loss function.[52]
Kernel Size: The kernel size describes the dimensions (height and width) of the filter. Typical kernel sizes include 3×3, 5×5, and 7×7. The choice of the kernel size directly affects the receptive field of the filter, which is defined as the area of the input that the filter covers; hence, it will also affect the amount of detail that it can attract. Small kernels can focus on details, while large kernels cover more general features.[52]

Stride: The stride defines the kernel's step size as it slides through the picture.[56]

Padding: is a phrase used in convolutional neural networks to represent the number of pixels added to an image during processing by the kernel.[56]

Relu Activation Function: This type of activation function is one of the non-linear varieties. It produces an output of 0 if the input is less than 0 and an output equal to the input for positive values. In large neural networks, Rectified Linear Unit (ReLU) can operate much faster than any other activation function [53]. In this layer, every

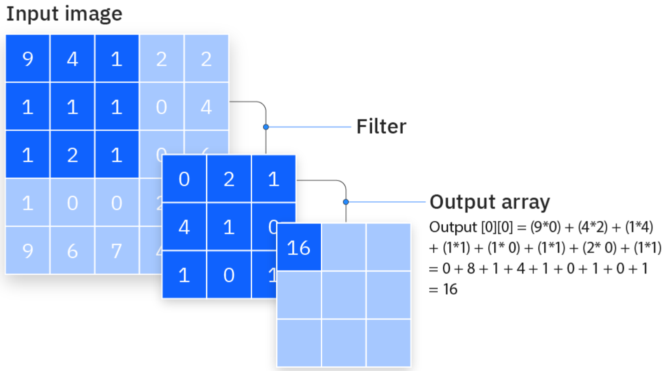


Fig 2.9: Convolutional layer operation. [23]

negative value from the filtered picture is eliminated and replaced with zero [57], as illustrated in Figure 2.10.

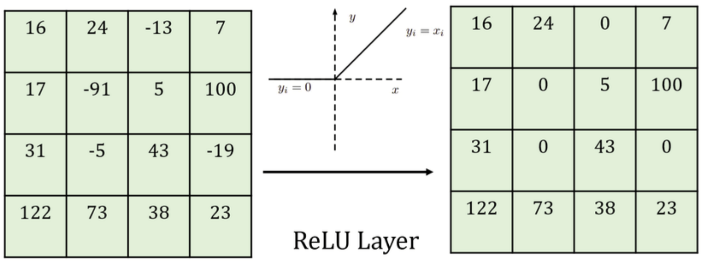


Fig 2.10: Relu operation. [21]

4.1.3 Pooling layer

Pooling layers, also known as down-sampling layers, reduce the dimensionality of the feature maps while retaining the most vital information. In the pooling layer, a filter performs the pooling operation on the input data by sliding over it (max, min, avg). In literature, maximum pooling has the greatest notoriety [56], as illustrated in Figure 2.11.

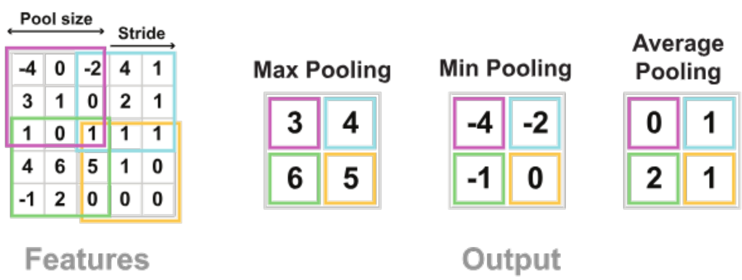


Fig 2.11: Max-pooling and Avg-pooling and Min-pooling layers.[22]

4.1.4 Fully-Connected Layer

The fully connected layer, commonly called the convolutional output layer, uses the features obtained from the previous layers and filters to perform categorization. This layer links each neuron from the previous layer to every neuron in the current layer, forming a densely connected network. Based on the extracted features, the fully connected layer classifies or predicts the input image. Importantly, the final classification considers the knowledge learned at earlier levels [52], as illustrated in Figure 2.12.

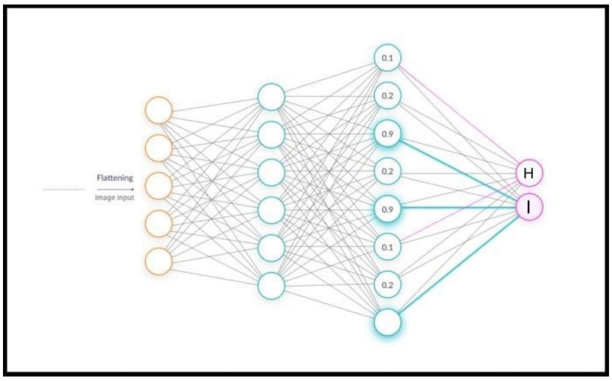


Fig 2.12: fully connected layer.[23]

4.1.5 Output layer

In neural networks, the output layer is the last layer in the series of neurons that gives the final output of the network concerning a particular input. The number of neurons in the output section depends on the application of the network.

4.2 Transfer Learning

Transfer learning is a way to reduce time for the model training neural network. It is a part or subfield of artificial intelligence and machine learning whereby one applies what he/she learned from one task to another but somewhat similar task. New model transferred learning improves its performance even when training it with a lesser amount of data [58], as shown in Figure 2.13.

Advantages:

- Transfer learning enables the bringing essentially new datasets to the pre-trained models, reducing the resources and data needed for training purposes.

Disadvantages:

- Transfer learning brings overfitting to the pre-training dataset and, thus, requires an extravagant tuning of the network to become optimally efficient in new datasets.

5 Proposed Brain Tumor Classification System

This research study illustrates a profound learning-centered approach to brain tumor imaging through MRI in a complicated large-scale multi-class domain which consisted

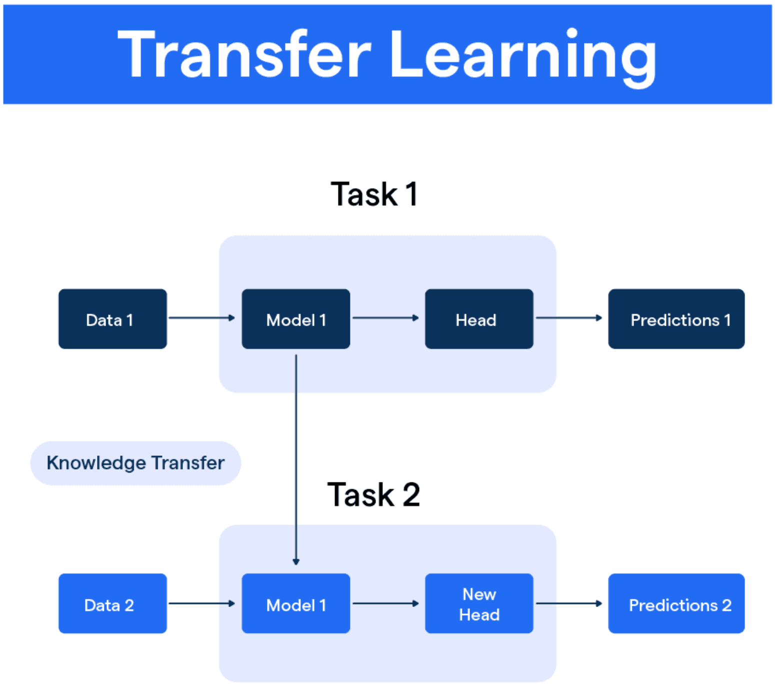


Fig 2.13: Transfer Learning. [24]

of 44 classes. Two modern convolutional neural networks, EfficientNetB3 and ConvNeXt, were separately fine-tuned and retrained on the dataset that is more appropriate. Subsequently, an ensemble strategy was utilized to integrate their forecasting potentials, searching for a better classification performance in total. The next performance measures - accuracy, precision, recall, and F1-score - were used to evaluate the models. This work utilizes the complementarity of the two architectures through hybrid fusion for reinforcing the accuracy and the reliability of the brain tumor diagnosis, hence the clinical decision-making to be more informed. as illustrated in Figure 2.14.

5.1 Preprocessing

In Brain Tumor analysis and detection systems, preprocessing is a necessary step. Preprocessing typically betterizes image quality. Several preprocessing techniques in image processing are hence implemented for the betterization of MRI images. Then:
Resizing: The input images were resized to `224×224×3` to match the required input dimensions of the pre-trained models.
Normalization: Images were normalized using the mean and standard deviation values `[0.485, 0.456, 0.406]` and `[0.229, 0.224, 0.225]` respectively for the RGB channels, which is a standard preprocessing step for models trained on ImageNet.
Total Dataset:

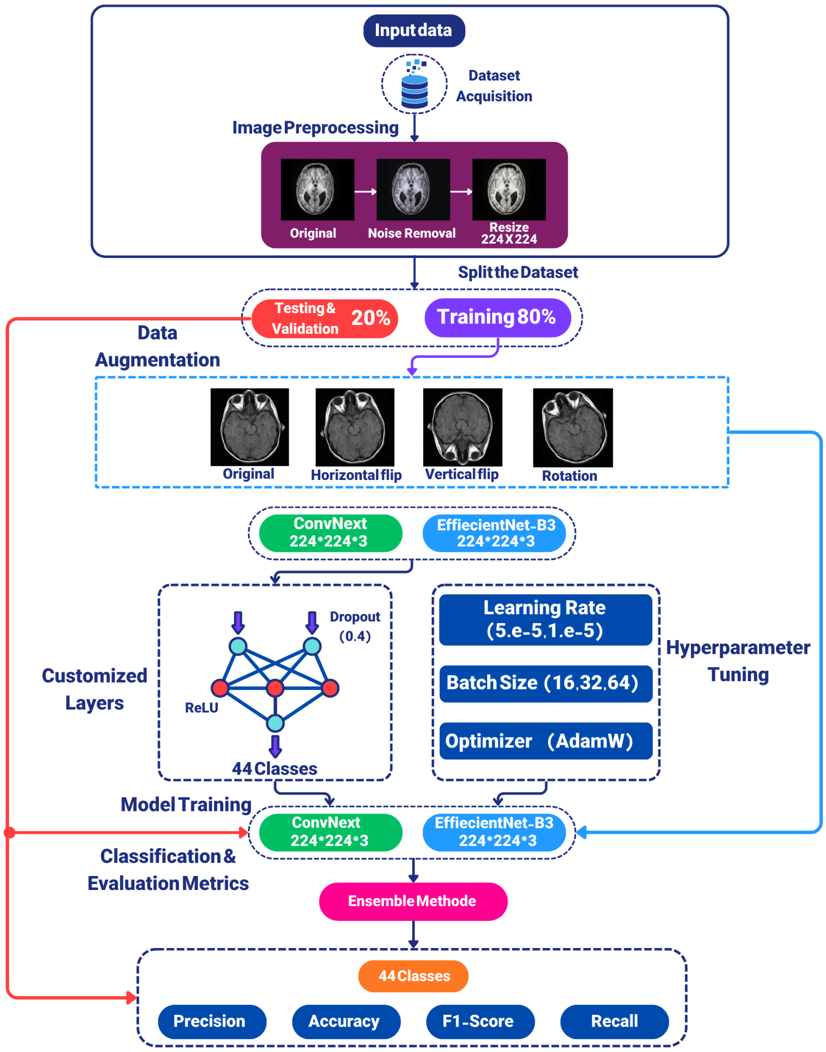


Fig 2.14: shows the suggested Brain Tumor Classification system.

- 44 distinct tumor classes
- 4,479 total images (RGB, varying resolutions)

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

- **Training data:** was utilized to fit the model, Number of images 3,557.
- **Validation & Testing data:** Test and adjust the model, Number of images 922.

5.2 Understanding Model Architectures

Deep-learning image classification, selecting the best model architecture that performance, accuracy, and computational efficiency is on the top of the list of customers' requirements. The experiment involved two modern CNNs: EfficientNet-B3, which proportionally scales depth, width, and resolution for high accuracy with the least number of parameters. To compare the other side, we used ConvNeXt-Tiny is a current architecture, inspired by the design of transformers, but transformed for CNNs, incorporating features, such as large kernel sizes and layer normalization, for improved performance. Both models, pre-trained on ImageNet, allowed faster training and better performance with less data. They were compared in an experiment to see how effective they are in classifying 44 types of brain tumors.

5.2.1 ConvNeXt Architecture

ConvNeXt is a new model for brain tumor detection that adopts a CNN structure to draw out deep features whole-brain images like MRI scans. Training this architecture on greyscale or RGB brain images would allow the model to recognize distinguishing and novel features of the tumors. The model, at first, would have been designed using a pre-trained ConvNeXt backbone. An extended training, later on, would be done through transfer learning on the brain tumor dataset. Several architectures make up the models consisting of depthwise separated convolution layers, followed by global average pooling, and then fully connected layers with sigmoid or softmax for binary or multi-class classification. This not only improves accuracy and generalization but also reduces training time, which fits the criteria of not only detecting and classifying brain tumors with quite small datasets and quick computing but also making it relevant for clinical settings [59]. The ConvNeXt model used in this study is shown in Figure 2.15.

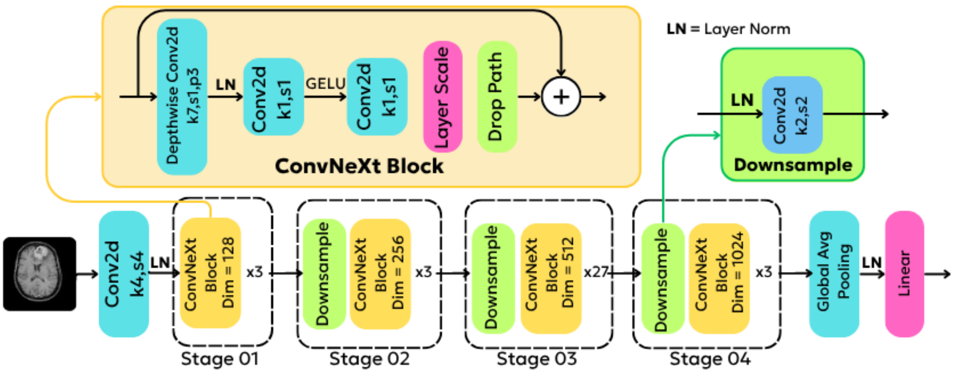


Fig 2.15: ConvNext Architecture.

5.2.2 EfficientNet-B3 Architecture

EfficientNet B3 is a convolutional neural network model that has been widely recognized as a perfect balance between the model size and the performance. This model is from the EfficientNet family where both accuracy and efficiency were optimized. The architecture itself is a series of stacked blocks composed of depth-wise separable convolutions and inverted residual connections. The Backbone of EfficientNet B3 is constructed of several stages, with the resolution and depth going up as you travel deeper [60]. The schematic representation of the EfficientNet B3 architectural design used herein is depicted in Figure 2.16.

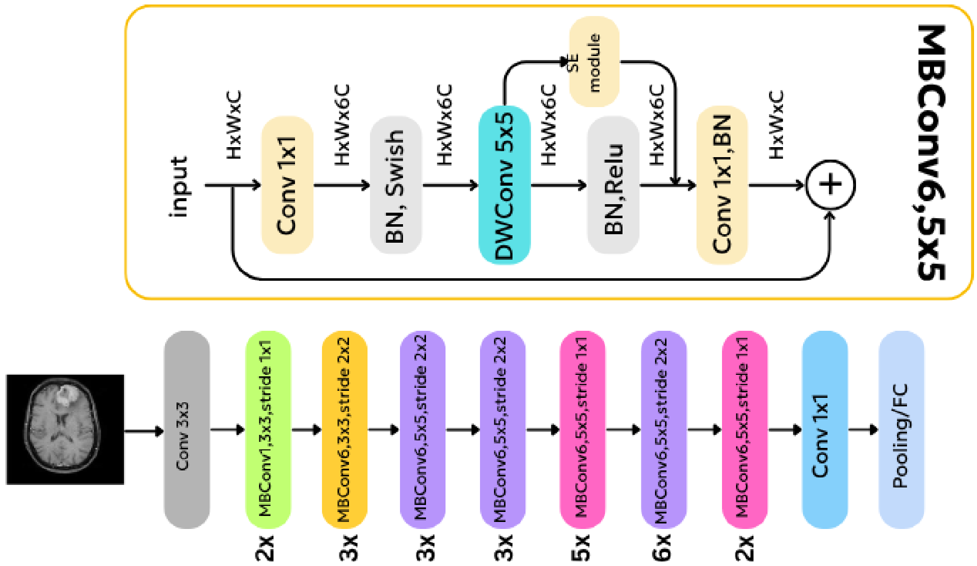


Fig 2.16: EfficientNet Architecture.

Table 2.2: Comparison between of ConvNext-Tiny and EfficientNet-B3

Suggested Model	Parameters (ImageNet) (Million	Accuracy	Depth Multiplier	Width Multiplier	Input Size
ConvNeXt-Tiny-224	28.6M	82.1%	1.0	1.0	224x224x3
EfficientNet-B3	12M	81.6%	2.2	1.4	300x300x3

5.3 Architecture of the transfer learning models used in our work

In this suggested setup, we opted for two models (EfficineNet-B3 and ConvNeXt-Tiny).We want to show the instruments and tech employed to develop our system.EfficineNet-B3 and ConvNeXt-Tiny Model Models consist of multiple layers.

5.4 Adaptation of ConvNeXt for Brain Tumor Classification

Our classification model is basically a pre-trained ConvNeXt-Tiny network, which has set a record for top-notch performance in large-scale image recognition tasks such as ImageNet. However, the original model is intended for general-purpose classification and is not specialized for the fine-grained distinctions needed to identify 44 different types of brain tumors from medical images. So, we decided to use this strong architecture for our domain only and selected a transfer learning approach. We got rid of the original top classification layer of the ConvNeXt model and only used its convolutional backbone as a feature extractor. Instead, we added a custom classification head. The new head is a sequence of layers - a fully connected (Linear) layer that increases the feature dimension from 768 to 1024, a ReLU activation function for non-linearity, a Dropout layer with the rate 0.3 to deal with overfitting, and a final Linear layer that assigns the features to the 44 brain tumor classes. This change enables the model to utilize the strong, general features learned from the ImageNet dataset while training a new, specialized classifier that is designed to recognize the subtle and complex patterns unique to brain tumor pathology.

The table below outlines the architecture of the final `ConvNextTumorClassifier`, detailing the flow from the input image to the final class prediction.

Table 2.3: Layer-by-layer structure of the modified ConvNeXt model for brain tumor classification. The letter 'B' in the Output Shape column denotes the batch size.

Layer / Block	Description	Output Shape
Input Image	A 3-channel brain tumor image tensor, resized to the model's expected input size.	(B, 3, 224, 224)
ConvNeXt-Tiny Backbone	The pre-trained `facebook/convnext-tiny-224` model, used as a feature extractor. It processes the input image to generate a high-level feature vector.	(B, 768)
	— Custom Classifier Head —	
1. Linear Layer	A fully connected layer that transforms the 768-dimensional feature vector from the backbone into a 1024-dimensional space.	(B, 1024)
2. ReLU Activation	A non-linear activation function that introduces complexity, allowing the model to learn more intricate patterns.	(B, 1024)
3. Dropout (p=0.3)	A regularization technique that randomly sets 30% of neuron activations to zero during training to prevent overfitting.	(B, 1024)
4. Output Linear Layer	The final classification layer. It maps the 1024-dimensional vector to raw output scores (logits) for each of the 44 tumor classes.	(B, 44)
Softmax (Implicit)	This function is typically applied after the final layer (often within the loss function) to convert the raw logits into class probabilities.	(B, 44)

5.5 Adaptation of EfficientNet-B3 for Brain Tumor Classification

In parallel with our work on ConvNeXt, we also adapted the EfficientNet-B3 architecture, a model renowned for its exceptional balance between computational efficiency and high accuracy. Employing a similar transfer learning strategy, we repurposed the pre-trained EfficientNet-B3 model to serve as a specialized feature extractor for our task. The original, final classification layer of the network was surgically removed and replaced with an `nn.Identity` layer, which effectively truncates the model, allowing it to output the high-dimensional feature map generated by its convolutional blocks. To this feature extractor, we attached the same custom classifier head used for the ConvNeXt model. This head first transforms the 1536-dimensional feature vector from the EfficientNet backbone into a 1024-dimensional space using a Linear layer, followed by a ReLU activation and a Dropout layer (p=0.3) for regularization. A final Linear layer then maps these processed features to the 44 target brain tumor classes. This approach enables us to harness the sophisticated feature representations learned by EfficientNet-B3 while fine-tuning a new classifier specifically for the nuanced domain of brain tumor pathology.

The table below provides a detailed breakdown of the `EfficientNetTumorClassifier` architecture, from the input image to the final classification output.

Table 2.4: Layer-by-layer structure of the modified EfficientNet-B3 model. The letter 'B' in the Output Shape column denotes the batch size.

Layer / Block	Description	Output Shape
Input Image	A 3-channel brain tumor image tensor, resized to the model's expected input size (e.g., 224x224 for B3).	(B, 3, 224, 224)
EfficientNet-B3 Backbone	The pre-trained `efficientnet_b3` model, with its final classifier replaced by an `nn.Identity` layer to act as a feature extractor.	(B, 1536)
	— Custom Classifier Head —	
1. Linear Layer	A fully connected layer that transforms the 1536-dimensional feature vector from the backbone into a 1024-dimensional space.	(B, 1024)
2. ReLU Activation	A non-linear activation function that introduces complexity, allowing the model to learn more intricate patterns.	(B, 1024)
3. Dropout (p=0.3)	A regularization technique that randomly sets 30% of neuron activations to zero during training to prevent overfitting.	(B, 1024)
4. Output Linear Layer	The final classification layer. It maps the 1024-dimensional vector to raw output scores (logits) for each of the 44 tumor classes.	(B, 44)
Softmax (Implicit)	This function is typically applied after the final layer (often within the loss function) to convert the raw logits into class probabilities.	(B, 44)

5.6 Ensemble classifier methods

In this work, we propose a novel approach for combining the predictions of multiple models. Our approach is based on the idea of Ensemble Learning, which involves combining the prediction probabilities from the different models to produce a fused score. Figure 2.17 shows the Principles of Ensemble Learning utilized in the developed system.

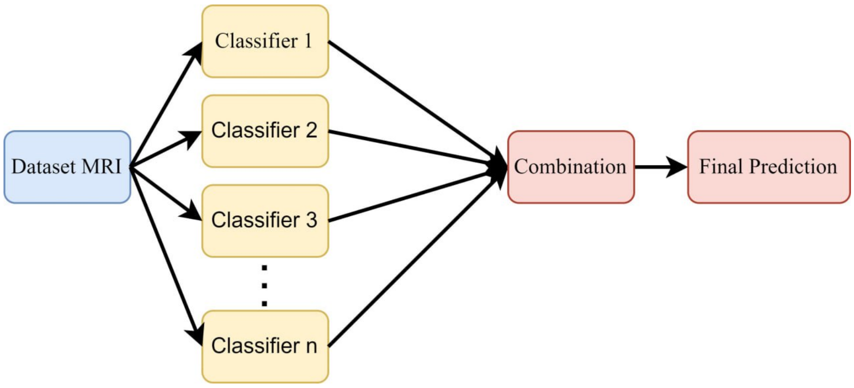


Fig 2.17: Principles of Ensemble Learning [25]

5.6.1 Weighted sum

The weighted sum is a simple method used for data fusion or combining multiple scores/values. It involves multiplying each input score by a weighting factor and then summing up the resulting weighted scores. see Equation (1). The weighting factors determine the relative contribution or importance of each input score [25].

$$\text{Final class prediction} = \sum_{i=1}^{n} W_i S_i \tag{1}$$

6 Conclusion

This chapter gives the foundation concepts about brain tumors, focusing on their classification and application of neural network training strategies. The next chapter deals with the data pre-processing, followed by a detailed introduction to the classification models used. Finally, the results are presented, backed by quantitative and qualitative analyses, depicting the merits and demerits of the proposed system.

CHAPTER 3

RESULT AND DISCUSSION

1 Introduction

This chapter gives a thorough overview of the database that was used in our study. We explain the evaluation methods and also describe our current achievements with a mixture of numerical and descriptive arguments that reflect the advantages and weaknesses of the system. Besides, We also conduct comparative studies that provide further information on the efficacy of our system.

2 Dataset Description

2.1 Dataset used

One of the sources from which we have drawn data for our study is the Kaggle dataset ”Brain Tumor MRI Images (44 Classes).” [61] This dataset is a selection of MRI images, consisting of T1-weighted, contrast-enhanced T1, and T2-weighted types, that have been labeled with 44 brain tumor classes for classification. The classification of the tumors considers cells of tumors such as astrocytoma, carcinoma, ependymoma, ganglioglioma, germinoma, glioblastoma, granuloma, medulloblastoma, meningioma, neurocytoma, oligodendroglioma, papilloma, schwannoma, and tuberculoma, to mention a few.Here are some samples from the data set in Figure 3.1. The images in this dataset are anonymous and utterly devoid of any information that can identify a patient, and the experts who have interpreted and provided the labels for the images are radiologists. A detailed breakdown of the number of MRI images per tumor class in is Table 3.1.

3 Evaluation Metrics

In machine learning, the confusion matrix is the primary type of metric used to test the performance of a classification model. CM is a table having two dimensions (”Pre-

Table 3.1: Description of The Brain Tumor Dataset 44 Classes.

Class	**Total Images**	**Class**	**Total Images**
Astrocitoma T1	176	Meduloblastoma T1C+	67
Astrocitoma T1C+	232	Meduloblastoma T2	41
Astrocitoma T2	171	Meningioma T1	272
Carcinoma T1	66	Meningioma T1C+	369
Carcinoma T1C+	112	Meningioma T2	233
Carcinoma T2	73	Neurocitoma T1	130
Ependimoma T1	45	Neurocitoma T1C+	223
Ependimoma T1C+	48	Neurocitoma T2	104
Ependimoma T2	57	Oligodendroglioma T1	86
Ganglioglioma T1	20	Oligodendroglioma T1C+	72
Ganglioglioma T1C+	18	Oligodendroglioma T2	66
Ganglioglioma T2	23	Papiloma T1	66
Germinoma T1	27	Papiloma T1C+	108
Germinoma T1C+	40	Papiloma T2	63
Germinoma T2	33	Schwannoma T1	148
Glioblastoma T1	55	Schwannoma T1C+	194
Glioblastoma T1C+	94	Schwannoma T2	123
Glioblastoma T2	55	Tuberculoma T1	28
Granuloma T1	30	Tuberculoma T1C+	84
Granuloma T1C+	31	Tuberculoma T2	33
Granuloma T2	17	_NORMAL T1	251
Meduloblastoma T1	23	_NORMAL T2	271

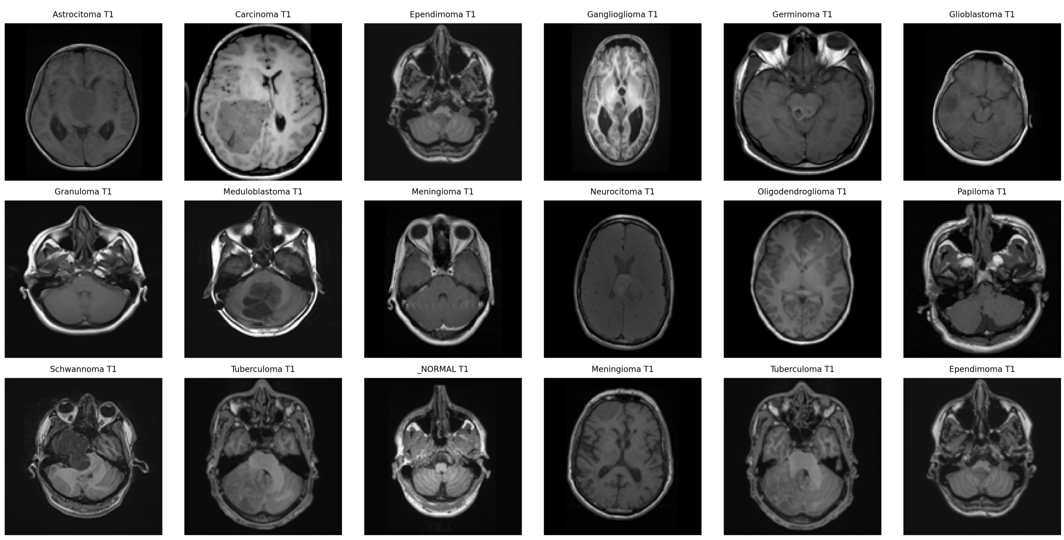


Fig 3.1: Samples from the dataset.

dicted" and "Actual") with many "classes" in each dimension. Our predicted classes are rows, while the actual classifications are columns. This matrix gives us a look inside-how the predictions of the model compared to reality, thus gaining a full impression of the pros and cons of the model, rather than simply gazing at how accurate it was.[62]

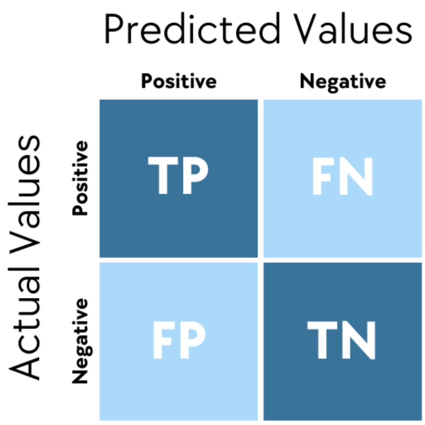


Fig 3.2: Confusion matrix. [26]

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 has a negative class, although the expected class is positive.
FN: Despite predictions that it would be negative, the instance's actual 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 an interpreted, high-level, general-purpose language that is free and easy to learn. Being dynamically typed and garbage-collected, developers often call Python ”batteries included,” which translates into having a vast standard collection of tools and libraries to address different issues. Initially developed in 1991 by Guido van Rossum, Python has attracted usage in many varied domains.[63]

4.2 Pytorch

PyTorch is a Python program library meant to foster deep learning programs. This freedom and ease that are found in make PyTorch convenient for developing deep neural networks. It has a relatively broad scope and is applied to many usages. Because Python is a programming language, PyTorch could either be an excellent introductory tool to deep learning or a tool usable by professionals in real-world applications.[64]

4.3 kaggle

Kaggle Notebooks are cloud-based environments provided by Kaggle, now owned by Google, and are popular for data science and machine learning competitions. Users write Python code and execute it straight through the browser without having to set anything locally.Unrestricted use of GPUs and TPUs is available, along with integration for popular datasets and libraries, forming a perfect environment for deep learning, data analysis, and prototype model building.It gifts the ease of doing public data search and sharing and collaborating on notebooks making it a an excellent platform for learning, as well as researching AI.

5 Result and Discussion

This part of the study shows the results of our study about the identification of brain tumor types from an excellent granularity set of 44 classes. We test and analyze the results of two top deep learning models, namely ConvNeXt-Tiny and EfficientNet-B3. Additionally, to realize the full classification potential and tap the complementary advantages of individual models, we also come up with an ensemble-based approach grounded in weighted probability . The test was done on a collection of 4,479 brain MRI pictures and applied data augmentation methods to balance the classes and allow the models to generalize better. The comparative evaluation is the most prominent showcase of ensemble learning capability of gaining superior results over the use of single models.

5.1 Results of the used models

The performance of two models, effcientNet-B3 and ConvNeXt-Tiny, trained on the dataset representing the real-world distribution of tumor types, is shown here. The models were proven with various hyperparameter permutations to observe whether they are robust and capable of handling class imbalance. Table 3.2 presents the summary of the overall performance metrics of each model with different hyperparameter combinations.

Table 3.2: Performance of ConvNeXt Tiny and EfficientNet B3 Models.

Learning Rate	Optimizer	epochs	Batch Size	Model	Testing Evalution			
					Accuracy	Precision	Recall	F1-Score
0.00001	AdamW	30	16	**ConvNext-Tiny**	**95.88%**	**96.16%**	**95.88%**	**95.68%**
				EffiecientNet-B3	96.09%	96.19%	96.09%	96.00%
			32	ConvNext-Tiny	87.85%	87.41%	87.85%	86.69%
				EffiecientNet-B3	**96.85%**	**96.94%**	**96.85%**	**96.74%**
			64	ConvNext-Tiny	90.67%	89.83%	90.67%	91.00%
				EffiecientNet-B3	96.52%	96.59%	96.53%	96.42%
0.00005	AdamW	30	16	ConvNext-Tiny	94.69%	95.01%	94.69%	94.49
				EffiecientNet-B3	94.68%	94.87%	94.68%	94.52%
			32	**ConvNext-Tiny**	**95.88%**	**96.06%**	**95.88%**	**95.70%**
				EffiecientNet-B3	**96.42%**	**96.43%**	**96.42%**	**96.36%**
			64	ConvNext-Tiny	95.01%	95.34%	95.01%	94.77%
				EffiecientNet-B3	96.09%	96.14%	96.09%	95.98%

5.1.1 EfficientNetB3(Lr=0.00001,BatchSize=32)

The EfficientNetB3 model that was trained with a learning rate of 0.00001 and a batch size of 32 recorded the highest classification performance across all the configurations tested. Its accuracy was 96.85%, precision 96.94%, recall 96.85%, and F1-score 96.74% were all outstanding. The results of these experiments show that the model has a great generalization power and its agility in recognizing the 44 brain tumor classes is not weakened due to the dataset that is unbalanced. The top precision and recall values in this instance suggest that the model can cut down the number of false positives as well as false negatives, thus, it turns into a very reliable classifier in the medical imaging circumstances of multiple-classes. The present arrangement also emphasizes the accomplishment of a moderate batch size and a low learning rate combination for tuning the pre-trained models to the tionmost challenging classification tasks.The training dynamics of the model, as illustrated in the accuracy and loss curves (Figure 3.3), confirm stable convergence and minimal overfitting. Moreover, the confusion matrix (Figure 3.4) demonstrates the model's high discriminative capability across the different tumor types.

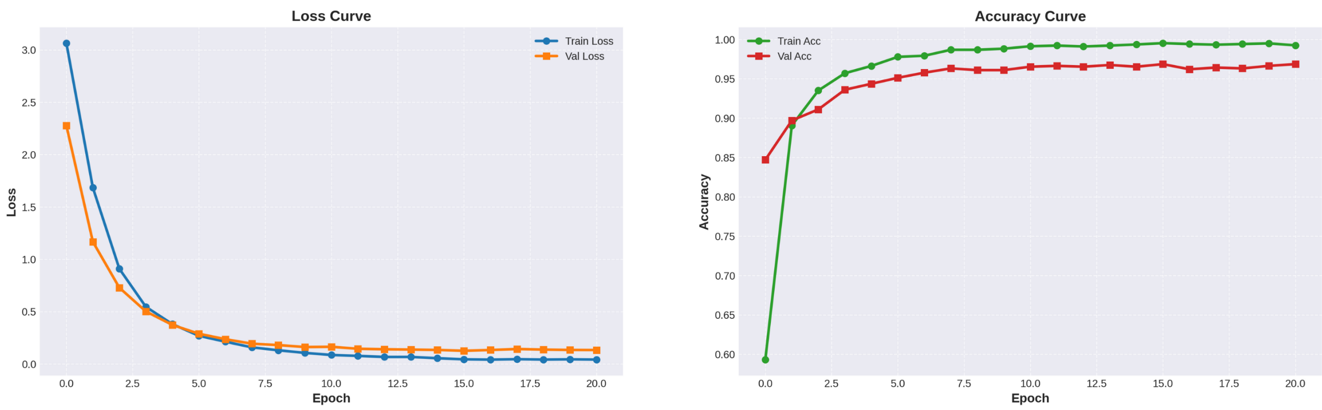


Fig 3.3: EfficientNet B3 - Training and Validation Loss and Accuracy curve.

5.1.2 ConvNeXt-Tiny (Lr = 0.00001, Batch Size = 16)

The ConvNeXt-Tiny model, trained with a learning rate of 0.00001 and a batch size of 16, achieved its best performance with this setup. It got a 95.88% accuracy with a precision of 96.16%,a recall of 95.88%, and an F1-score of 95.68%. These are the indications that the model is capable of efficiently managing the multi-class brain tumor classification that is complex, although it is smaller in the architecture, compared to EfficientNetB3. The high precision and recall figures confirm that the model is capable of detecting true positives efficiently while keeping the false positive and false negative rates at a minimum. ConvNeXt-Tiny is a competitive and efficient option, although it is worse than EfficientNetB3, especially for use cases where computational resources are limited. The training progress of ConvNeXt-Tiny is visualized in the loss and accuracy curves (Figure 3.5), which show smooth convergence and generalization capability. Additionally, the confusion matrix (Figure 3.6) highlights the model's performance across all tumor classes and its ability to distinguish between them accurately.

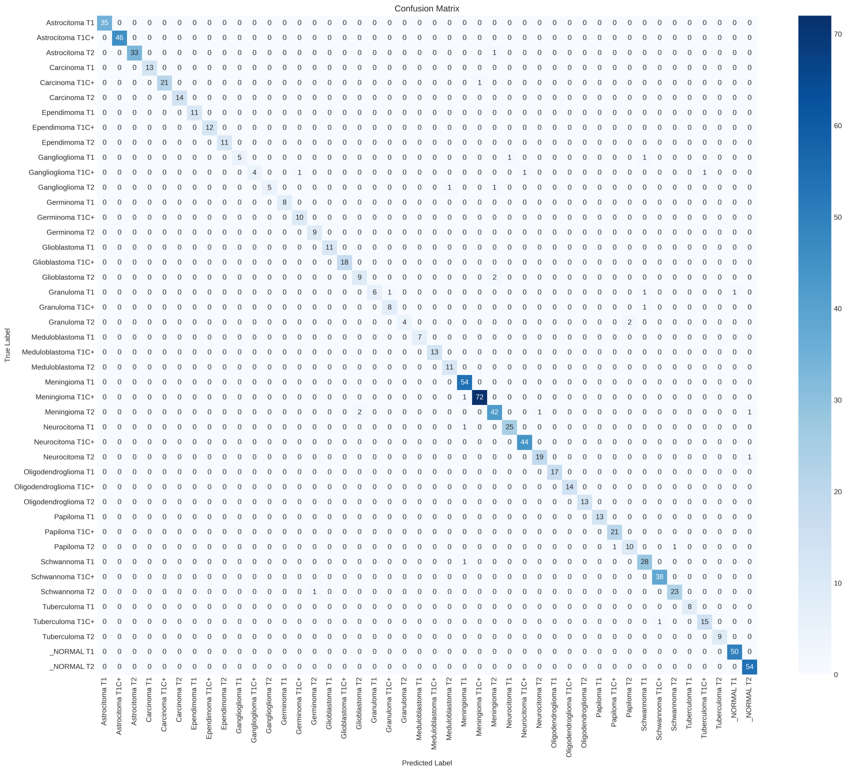


Fig 3.4: EfficientNet B3 - Confusion Matrix.

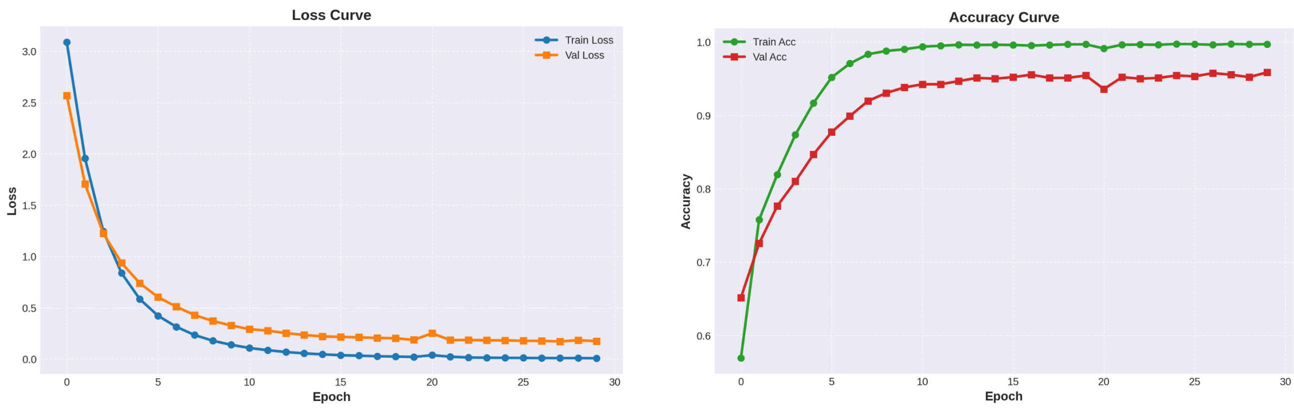


Fig 3.5: ConvNeXt-Tiny - Training and Validation Loss and Accuracy curve.

5.2 Results of Ensemble Methode

A weighted average ensemble combining EfficientNet-B3 (60%) and ConvNeXt-Tiny (40%) was implemented to enhance classification accuracy. This approach effectively leveraged the strengths of both models and achieved an accuracy of **97.07%**, outperforming each model. The results confirm the effectiveness of ensemble strategies in improving robustness and generalization for multi-class brain tumor classification.

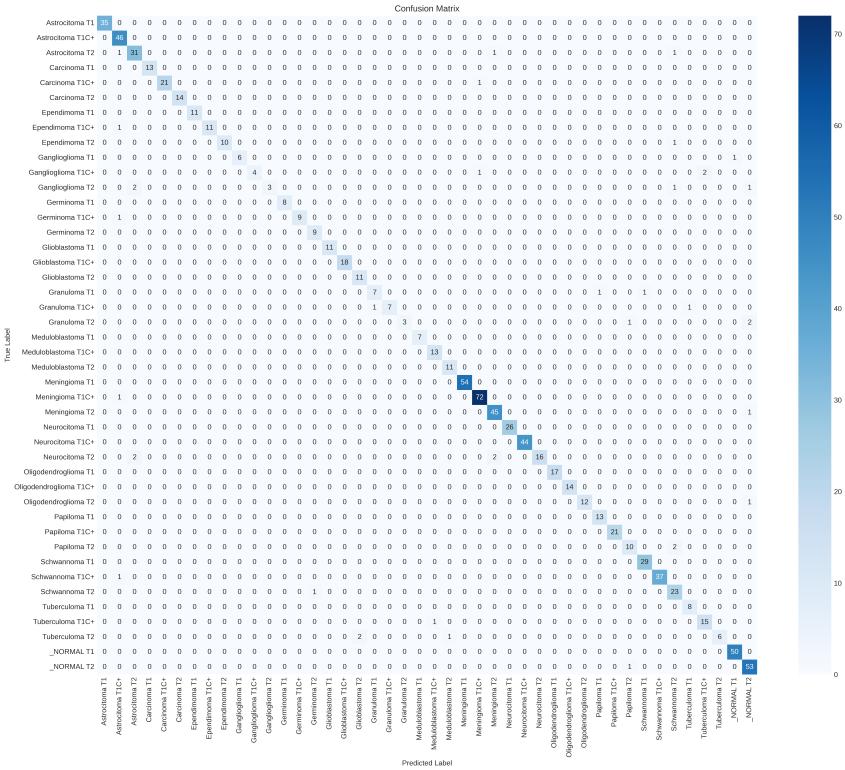


Fig 3.6: ConvNeXt-Tiny - Confusion Matrix.

5.3 Comparison of the used models and Ensemble Methode Results

This part of the article illustrates the results on experiments of the brain tumor locating task with ConvNeXt-Tiny, EfficientNet-B3 and a sample fusion method. The individual models were able to classify the original database very well. However, EfficientNet-B3 was better than ConvNeXt-Tiny in any of the metrics used, the most important were accuracy, precision, recall, and F1-score. The latter one is the most balanced metric. To improve the classification performance even more and to overcome the possible drawbacks of single-model predictions we proposed a solution in the form of an ensemble strategy based on weighted probability fusion. This method is a marriage of the two thus leading to improved robustness and generalization. The ensemble model significantly outperformed all the standalone models, thus underlining the fact that blending complementary feature representations can go a long way in the task of diagnostic accuracy in complex multi-class classification such as brain tumor detection. These results are indicative of the usefulness of ensemble learning in one of its main performances, which is that it is capable of taking advantage of the strengths of diversified CNN architecture to enhance the reliability of the medical image analysis field.The detailed comparison between ConvNeXt-Tiny, EfficientNet-B3, and the proposed hybrid ensemble model is presented in Table 3.3.

Table 3.3: Comparison of ConvNeXt Tiny,EfficientNet B3 and Ensemble Methode Results.

Model	Accuracy	Precision	Recall	F1-Score
ConvNext-Tiny	95,88%	96,16%	95,88%	95,68%
EffiecientNet-B3	96,85%	96,94%	96,85%	96,74%
Hybrid model	**97,07%**	**97.15%**	**97.07%**	**96.98%**

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

This section of the website highlights the "MTC AI" application, which is an integrated and innovative software platform that utilizes deep learning models of high capability to classify 44 different types of brain tumors. This app is an attempt to establish a connection between innovative AI research and the clinical practice of doctors on a daily basis by handing over a strong, safe, and easy-to-use tool to medical practitioners.

The platform is equipped with a professional user interface that offers a range of core features:

- **Secure Authentication:** The software starts with a login interface that is secure and creates a professional environment in which the utmost care is taken in the handling of medical data and patient information. Such a system guarantees that only those with the proper credentials can access the platform, Consequently, the security and confidentiality of medical records are improved.

- **Comprehensive Dashboard:** After the user logs in successfully, he or she is welcomed with an interactive dashboard that gives a quick and comprehensive overview of primary activities. The dashboard not only presents essential statistics such as the total number of patients, total scans performed, and detected positive cases but also the "Quick Actions" buttons that make the workflow more straightforward to use like, for example, registering a new patient or uploading MRI (Magnetic Resonance Imaging) scans.

- **Integrated Patient Management:** The software is not only for analysis but also provides a patient management system that is an integral part of the whole software. Users have the possibility of smoothly registering new patients, reading their records, and tracking their medical history, hence making the platform a centralized solution for organizing patient data and their associated examinations.

- **Real-Time AI-Powered Analysis:** The application is a real-time analysis of MRI scans ability that makes it powerful. The user selects a patient, uploads the image, and then starts the analysis with one click. The system relies on a pre-trained deep learning model to provide an accurate diagnosis by showing the predicted tumor type and the confidence level of the result.

- **Automated Report Generation:** After the analysis is finished, the app becomes the one that automatically creates all those medical reports in detail. In every report the patient's data, the analysis part (tumor type, confidence level), the recommendations of doctors, as well as the physician's notes are included. Those reports are made in such a way that they are understandable, professional, and easy to share with friends or keep in the patient's record.

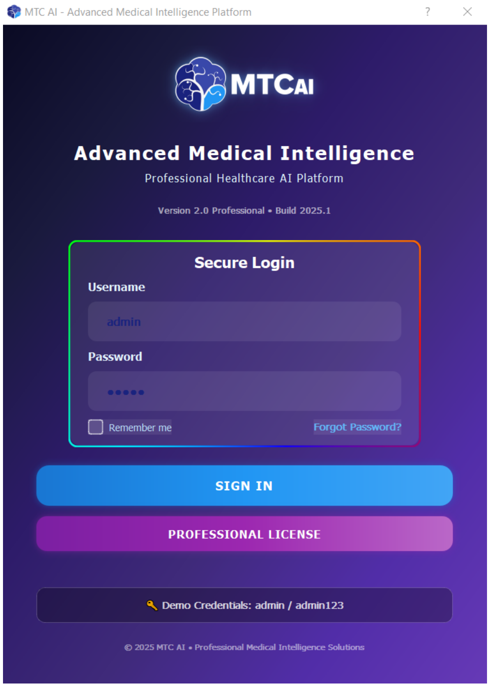


Fig 3.7: The interface of login.

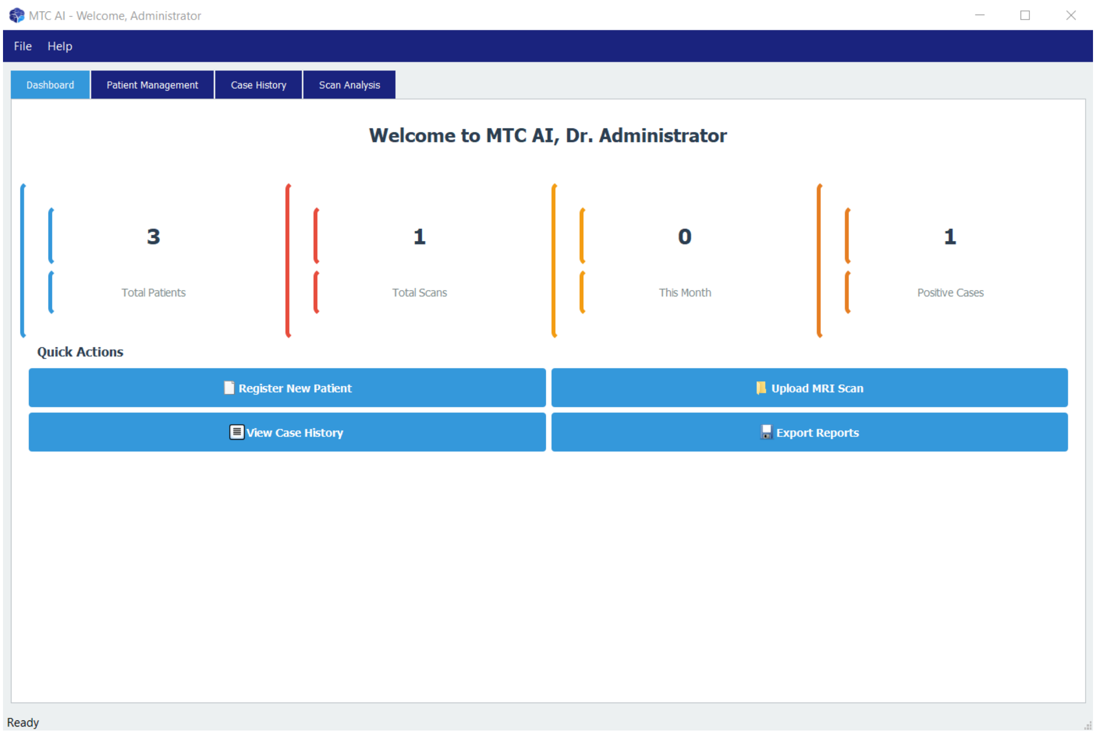


Fig 3.8: The interface of Home (Dashboard).

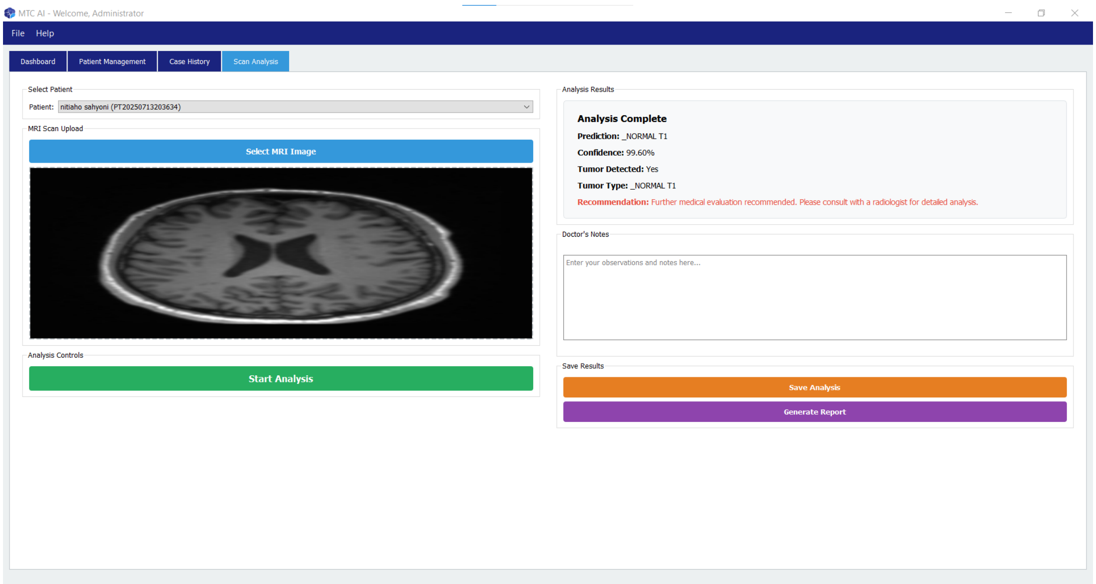
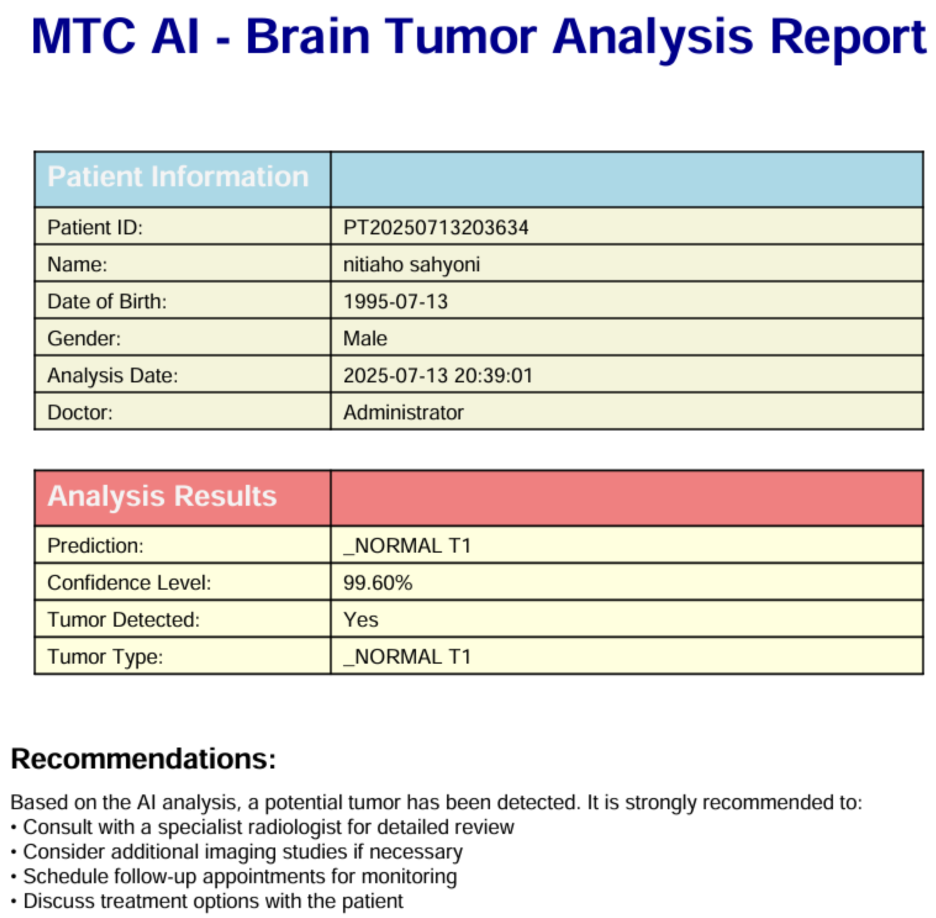


Fig 3.9: The interface of Scan & Classification.



MTC AI - Brain Tumor Analysis Report

Patient Information	
Patient ID:	PT20250713203634
Name:	nitiaho sahyoni
Date of Birth:	1995-07-13
Gender:	Male
Analysis Date:	2025-07-13 20:39:01
Doctor:	Administrator

Analysis Results	
Prediction:	_NORMAL T1
Confidence Level:	99.60%
Tumor Detected:	Yes
Tumor Type:	_NORMAL T1

Recommendations:

Based on the AI analysis, a potential tumor has been detected. It is strongly recommended to:
- Consult with a specialist radiologist for detailed review
- Consider additional imaging studies if necessary
- Schedule follow-up appointments for monitoring
- Discuss treatment options with the patient

Fig 3.10: Analysis Report.

6 Comparative Study

In order to gauge how well our system performs, we have done an evaluation and compared it with the current best research studies using classification accuracy as the primary measure. The outcome, presented in Table 3.4 , reveals that the designed model of our team gets an accuracy of 97.07%. This result not only leads the pack of all other models in the comparison but also beats the best one of 96.06% from Gasmi et al. (2024). So, the evidence confirms that our ensemble method stands for a breakthrough in the field over the existing state of the art.

Table 3.4: Comparison with the state of the art.

Ref	Year	Model	Accuracy
[65]	2024	Deep CNN	94.75%
[66]	2024	deep CNN models	94.97%
[67]	2024	EfficientNet v2s	95.6%
[68]	2024	EfficientNet v2 and ViT v2	96.06%
[69]	2025	Fibonacci-based Lightweight CNN Model v2	96.2%
Our Works	**2025**	**Ensemble methodes (EfficientNet-B3 with ConvNeXt-Tiny)**	**97.07%**

7 Conclusion

This study successfully A deep learning system with high performance was built in this study to identify 44 types of brain tumors. The weighted ensemble of the EfficientNet-B3 and ConvNeXt-Tiny models led to the realization of a state-of-the-art accuracy of 97.07%, which is beyond the previous results. This powerful model was then packaged into a user-friendly and practical app called "MTC AI" that can act as a trustworthy aid for diagnosticians to work more efficiently and with greater accuracy The accomplishment of our work illustrates the influence that ensemble strategies can have in the improvement of the precision of medical images Analysis for tricky oncological diagnoses.

Conclusion

Our study suggested a deep learning-based system that is capable of practical application in the multi-class classification of brain tumors from MRI images. The experiment's primary aim was to increase the accuracy of a classification and to solve some essential problems, such as class imbalance and overfitting by using convolutional neural networks (CNN) and ensemble fusion strategies, which are very good hardware.

In our study, we focused on the EfficiencyNet-B3 and ConvNeXt-Tiny deep learning models most recent and performing best. Experimental results illustrate that EfficiencyNet-B3 was more consistent than ConvNeXt-Tiny in accuracy under various training setups. However, the models individually are somewhat limited in their capacity to learn and are prone to failing tasks especially when they face 44 tumor class complexity.

In order to get rid of those types of restrictions, we came up with an ensemble fusion method that was based only on weighted averaging of the predicted probabilities, where 60% weight was given to EfficientNet-B3 and 40% to ConvNeXt-Tiny. This method allowed us to achieve superior classification performance, with a peak accuracy of **97.07%**, exceeding the results obtained by the individual models.The ensemble technique efficiently utilized the strengths of both architectures, thus improving the overall robustness and the ability to generalize, especially with respect to the minority classes.

The results of our research show that ensemble learning can be used to solve complicated problems of medical image classification and stress the importance of eliminating such data-related problems as class imbalance. Instead of applying explicit data rebalancing techniques, our work illustrated that architectural strategies, for example, model fusion, can be a practical alternative.

In the future, the model integration method could be improved using more advanced techniques, and more accurate data augmentation methods could be used to support rare tumor types. It's also possible to integrate other medical images, such as CT scans, to improve results, while focusing on making the model more interpretable and evaluating it in a real-world clinical setting.

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