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Using Deep Learning for Cerebral Gliomas Classification (HGG, LGG) Based on MRI

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Abstract

Gliomas are serious diseases that require early detection and diagnosis due to their seriousness and its great impact on health. In this thesis, we conducted a comprehensive research on gliomas and their classification as well as the tools and techniques used to classify these tumors.

To perform this task several Convolutional Neural Network models were used including ResNet50, VGG16 and Xception which were trained on the BraTS2018 dataset added to BraTS2019 in order to overcome the challenge of data scarcity. The modeling architecture consists of the base models (ResNet50, VGG16, Xception) with additional layers such as Dense Layers, Batch Normalization and Dropout that was used to avoid overfitting. The Adam optimizer was used to train the models while Sparse Categorical Crossentropy Loss and Accuracy metrics were used to evaluate them.

The results of our work were very promising as it showed the superiority of ResNet50 with a training accuracy of up to 99% and a validation accuracy of 98% compared to VGG16 which gave 97% in training accuracy and 95% in validation accuracy which also gave Xception a training accuracy that reached 96% and Validation accuracy equal to 94% During 35 epoch. This makes the ResNet50 model a reliable choice for classifying gliomas.

In general our thesis highlights the importance of using technology such as deep learning in the health field to help doctors and patients and reduce the impact of gliomas. The results of this research open the way for the development of new automatic diagnostic systems and provide a solid basis for future research in this direction.

Keywords: Gliomas, classification, Convolutional Neural Network, VGG16, XCEPTION, RESNET50, BraTS2018, BraTS2019, Dense Layer, Batch Normalization, Dropout, Adam optimizer,Sparse Categorical Crossentropy Loss, Accuracy.

Résumé

Les gliomes sont des maladies graves qui nécessitent une détection et un diagnostic précoces en raison de leur impact sur la santé. Dans ce mémoire, nous avons mené une recherche exhaustive sur les gliomes et leur classification ainsi que les techniques utilisées pour classifier ces tumeurs.

Pour la classification de ces tumeurs, plusieurs modèles CNNs ont été utilisés, notamment VGG16, Xception et ResNet50, qui ont été entraînés sur notre base d'images BraTS2018 et BraTS2019 .Nous avons utilisées trois modèles de base (VGG16, Xception, ResNet50) avec des couches supplémentaires telles que Dense Layers, Batch Normalization et Dropout qui ont été utilisées pour éviter le surapprentissage. L'optimiseur Adam a été utilisé pour entraîner les modèles, tandis que les mesures de perte et de précision ont été utilisées pour les évaluer.

Les résultats de notre travail étaient très prometteurs et ils ont montrés a la fiabilité de ResNet50 pour la classification des gliomes avec une précision d'apprentissage allant jusqu'à 99% et une précision de validation de 98% par rapport : à VGG16 qui a donné 97% de précision d'apprentissage et 95% de précision de validation et à Xception qui a donné une précision d'apprentissage de 96% et une précision de validation égale à 94% Pendant 35 époque.

Notre travail montre l'importance d'utiliser les technologies de l'apprentissage profond dans le domaine de la santé pour l'aide au diagnostic médical. Les résultats de ce travail ouvrent la voie au développement d'autres systèmes de diagnostic automatique et fournissent une base pour les futures recherches dans ce sujet.

Mots-clés : Gliomes, classification, VGG16, XCEPTION, RESNET50, BraTS2018, BraTS2019, Couche Dense, Abandon, Optimiseur Adam, Précision.

ملخص

تُعد الأورام الدبقية من الأمراض الخطيرة التي تستدعي الكشف و التشخيص المبكر نظراً لخطورتها وتأثيرها الكبير على الصحة. في هذه الأطروحة ،قمنا بإجراء بحث شامل حول الأورام الدبقية و تصنيفها و كذلك الأدوات و التقنيات المستخدمة في تصنيف هذه الأورام .

لأداء هذه المهمة تم إستخدام العديد من نماذج الشبكات العصبية الملتفة بما في ذلك VGG16 , ResNet50 , Xception ، و التي تم تدريبها على مجموعة بيانات BraTS2018 مضافة لBraTS2019 و ذلك من اجل التغلب على تحدي ندرة البيانات . تتكون هندسة النماذج من نماذج الأساس(Xception , VGG16 ,ResNet50) مع طبقات إضافية مثل Dense Layers وBatch Normalization و Dropout الذي تم إستخدامه لتجنب الإفراط في التجهيز . تم إستخدام Adam optimizer أثناء تدريب النماذج ، في حين تم إستخدام Sparse Categorical Crossentropy Loss و Accuracy metrics لتقييمها .

كانت نتائج عملنا واعدة للغاية ، حيث أظهرت تفوق ResNet50 بدقة تدريب تصل إلى ٪99 و دقة التحقق من الصحة ٪98 مقارنة ب VGG16 التي أعطت 97 ٪ في دقة التدريب و ٪95 في دقة التحقق مما أعطت كذلك Xception دقة تدريب وصلت إلى 96 ٪ و دقة تحقق تعادل ٪94 خلال 35 epoch و هذا يجعل نموذج ResNet50 خيارا موثوقا لتصنيف الأورام الدبقية .

بشكل عام، تسلط أطروحتنا الضوء على أهمية استخدام التكنولوجيا مثل التعلم العميق في المجال الصحي لمساعدة الأطباء والمرضى والتقليل من تأثير الأورام الدبقية. تفتح نتائج هذا البحث المجال لتطوير أنظمة تشخيص تلقائية جديدة وتوفر أرضية قوية لأبحاث مستقبلية في هذا الاتجاه.

الكلمات المفتاحية:الأورام الدبقية، التصنيف، الشبكة العصبية التلافيفية، VGG16، XCEPTION، RESNET50، BraTS2018، BraTS2019، Dense Layers، Batch Normalization ، Drpout، Adam optimizer، Sparse Categorical Crossentropy Loss، Accuracy.

Acknowledgment

الحمد لله

We would like to begin by expressing our immense gratitude to ***ALLAH***, who has endowed us with determination and granted us good health, providing us with the courage, strength, and patience necessary to accomplish this work.

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We would like to thank all the teachers who have contributed to our education throughout our years of study, and we express our sincere thanks and deep respect to them.

Our sincere thanks and profound respect go to all the individuals who have contributed to our success.

Dedications

شكرا

I dedicate this work to the spirit of ***my father***, who is still present in the heart of his little daughter, and I pray to God to grant him mercy and forgiveness.

I am honored to do this work for ***my mother***, the source of my happiness, and I would like to thank her for her sacrifices, trust, love, and splendor. From this platform, I tell her that she is the best and most wonderful mother that history has ever seen. I pray to God to protect her.

To ***my brother Zino, my sister Faiza*** , and the source of my happiness, the little children of the family, ***Nourssine, Tasnim***, the dearest soul to my heart. They have always been a source of love and happiness.

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To my feisty friend,***C. Sanna***, my lifelong and childhood friend, I pray for her good luck and success.

To my partner for this work, ***D.Manar***, I tell her we have done a tremendous job. We thank God for it and for our support and standing together throughout the journey. I pray for her success after graduation.

And finally, thanks to every soul I know from near or far.

"Believe in your self "

Wassila

Dedications

To my beloved ***father***, my friend , and dear love, your daughter is here today thanks to your faith in me, your love, and your support. I will always remember your constant reminders me to stay ambitious, different, and outstanding. I love you Dad.

To my dear ***mother***, the source of my knowledge and the light of my path, I have always proudly followed you. Today, I dedicate my graduation joy to you, grateful for you to be proud of me and my achievements that wouldn't have existed without your care, intelligence, knowledge, and constant encouragement. I love you Mom.

To my dear brother ***Souhaib***, the only one in my heart, I thank you for all the efforts you have made for me. May God reward you with the best of what you have.

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To ***my friends*** and loved ones, to everyone who stood by me in my failures before my successes, To everyone who has played a part, big or small, in my academic journey, I extend my sincere appreciation. Your contributions have helped shape my growth, and I am truly grateful for your presence in my life.
"Life doesn't show mercy to anyone. Only those who fight to live get to survive."

MANAR

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List of Acronyms

Adam	Adaptive Moment Estimation
AI	Artificial Intelligence
ANN	Artificial Neural Network
CAD	Computer-Aided Design
CNN	Convolutional Neural Network
CNS	Central Nervous System
CSF	Circulation of Cerebrospinal Fluid
DL	Deep Learning
DNNs	Deep Neural Networks
DSC	Dice Similarity Coefficient
DWI	Diffusion-Weighted Imaging
DWT	Deadweight Tonnage
FC	Fully Connected
FCM	Fuzzy C-Means clustering
fMRI	Functional Magnetic Resonance Imaging
FOTM	Fuzzy Otsuthresholding Morphology
GANs	Generative Adversarial Networks
HGG	High-Grade Gliomas
IoU	Intersection over Union
LGG	Low-Grade Gliomas
LSVRC	ImageNet Large Scale Visual Recognition Challenge
ML	Machine Learning
MLP	Multilayer Perceptron

MRA-UNet	Multiscale Residual Attention UNet
MRI	Magnetic Resonance Imaging
NMR	Nuclear Magnetic Resonance
PCA	Principal Component Analysis
RBMs	Restricted Boltzmann Machines
ReLU	Rectified Linear Unit
ResNet	Residual Network
RF	RadioFrequency
RGB	Red, Green, Blue
RNNs	Recurrent Neural Networks
SVM	Support Vector Machine
TL	Transfer Learning
TML	Traditional Machine Learning
VGG	Visual Geometry Group
Xception	Extreme Inception

Introduction

In the medical field, Gliomas pose a major challenge to doctors and medical professionals as they affect the lives of millions of people around the world and have a significant impact on the quality of life of patients and those around them. Early detection and accurate classification of gliomas is decisive for effective treatment planning and timely intervention. Traditionally, diagnosis is based on clinical assessment, medical history and various cognitive tests. However these methods can sometimes be subjective time consuming and are not always accurate.

In recent years advancements in deep learning techniques offers new avenues for improving the diagnostic process and reducing human errors by analyzing large quantities of data, and training them in algorithms in order to be able to accurately classifying gliomas with better precision.

In this thesis we aim to harness the power of deep learning in the classification of gliomas (HGG, LGG) using MRI images. Especially development of multiple convolutional neural networks models such as ResNet50, VGG16 and Xception using transfer learning techniques to ensure high accuracy. Each CNN model is independently trained on labeled dataset containing MRI images of HGG and LGG allowing the models to learn discriminative features and patterns associated with each class.

The thesis is structured as follows:
Chapter 1 provides a comprehensive overview of the medecal context, including the human brain and its anatomy, MRI, and cerebral pathologies.
Chapter 2 presents various techniques used in our work, including machine learning, deep learning, convolutional neural networks and its known models, State of the art related on brain tumor detection or classification.
Chapter 3 delves into the implementation details of our proposed gliomas classification approach, including the methodologies, datasets, and evaluation metrics employed.
Finally the conclusion summarizes the key findings and presents avenues for future research.

By leveraging the power of deep learning and image analysis this thesis aims to make some of contributions to the area of neuro-oncology specifically focusing on gliomas classification. The potential benefits of such systems include early diagnosis of gliomas, personalized treatment strategies and improved patient management practices. Ultimately these advancements could lead to better patient outcomes, improved treatment efficacy and significant contributions to medical research and healthcare.

Chapter 1

Brain Anatomy, MRI and Cerebral Pathologies

1.1 Introduction

The human brain is part of the human central nervous system, and widely recognized as the most important and complex part of the human body controlling the functions and thought processes. It is essential in areas of neurology, psychiatry.

Anatomy of the human brain deals with the investigation of its variety of components, including the gray and white matter which make up the general structure of the brain including the cerebrum, cerebellum, the brain stem and the cerebral cortex.These brain regions play crucial roles in sensory processing, control of voluntary muscle movements, cognitive functions and executive function.

Cerebral pathologies refer to illnesses that affect the brain and cerebral nerves, these are ailments such as stroke, alzheimer's disease as well as tumors. If not diagnosed and treated, the aforementioned conditions become a major threat to living of a individual, especially in advanced stages. Tumors can be divided into primary tumors, which form and develop inside the brain, and secondary tumors, which form in part of a person's body and move to the brain.Among these, gliomas are classified as a subgroup of brain tumors derived from glial cells. They can be categorized into high grade glioma and low grade glioma, both of which pose unique challenges in their clinical management.

MRI is the best modality in determining and further monitoring of brain diseases or disorders. This imaging provides enhanced definition and detail of the structures in the brain, diseases can be detected earlier, allowing for better interventions.Advances in MRI technology have significantly enhanced our ability to detect abnormalities and study the brain's intricate workings.

1.2 Brain

The brain a complicated organ coordinates essential physiological Characteristics vital for human survival such as cognition, reminiscence emotion, tactile perception, motor talents, visual methoding, breathing regulation, thermal homeostasis and urge for food manage. Together with the contiguous spinal wire the brain forms the central nervous system.

Figure 1.1: the Brain [1]

Weighing approximately three pounds and comprising 60% lipids and 40% water, protein, carbs and salts the brain homes neurons and glial cells. Roleing as a command middle it communicates via chemical and electric signals, overseeing various physiological processes . This complicated messaging machine includes inner and external communique influencing each inner capabilities and the body's extremities. With billions of neurons , the brain serves as the epicenter for cognitive emotional and physiological regulation within the central nervous system. [24]

Figure 1.2: Brain from Above [1]

1.3 Brain Anatomy

1.3.1 Meninges

The meninges constitute three protective layers enveloping and safeguarding the brain and spinal cord. These layers arranged from the outermost to the innermost are the dura mater arachnoid mater and pia mater.

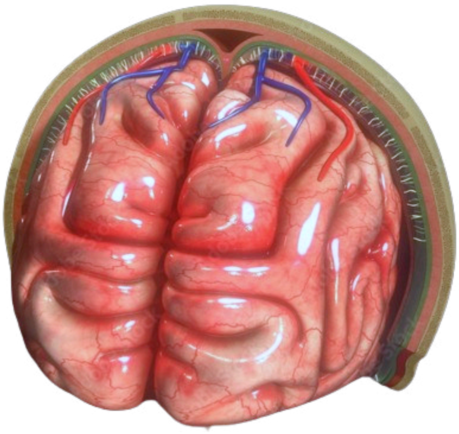

Figure 1.3: the Meninges Of The Brain [2]

1.3.1.1 Dura Mater

The dura mater is a robust and thick membrane that lines the interior of the skull closely. Comprising two layers - the periosteal and meningeal dura - they fuse and separate only to form venous sinuses. This durable membrane makes folds and compartments within the skull. Two notable dural folds the falx and the tentorium serve specific Roles. The falx separates the right and left hemispheres of the brain while the tentorium divides the cerebrum from the cerebellum.

1.3.1.2 Arachnoid Mater

The arachnoid mater is a delicate web-like membrane extending across the entire brain. Composed of Elastic material it contributes to the protective layers surrounding the central nervous system. The space between the dura and arachnoid membranes is known as the subdural space.

1.3.1.3 Pia Mater

This is a membrane that intimately adheres to the surface of the brain, accurately following its grooves as well as folds. This layer has many blood vessels which penetrate deep into the brain tissue forming an interconnecting network. The space between pia mater and arachnoid is known as subarachnoid space. This crucial site contains cerebrospinal fluid, which creates a vital milieu that surrounds, protects and props up the brain. Cerebrospinal fluid is important in maintaining a steady internal environment; it cushions against sudden jolts and helps in transportation of food within central nervous system. [25]

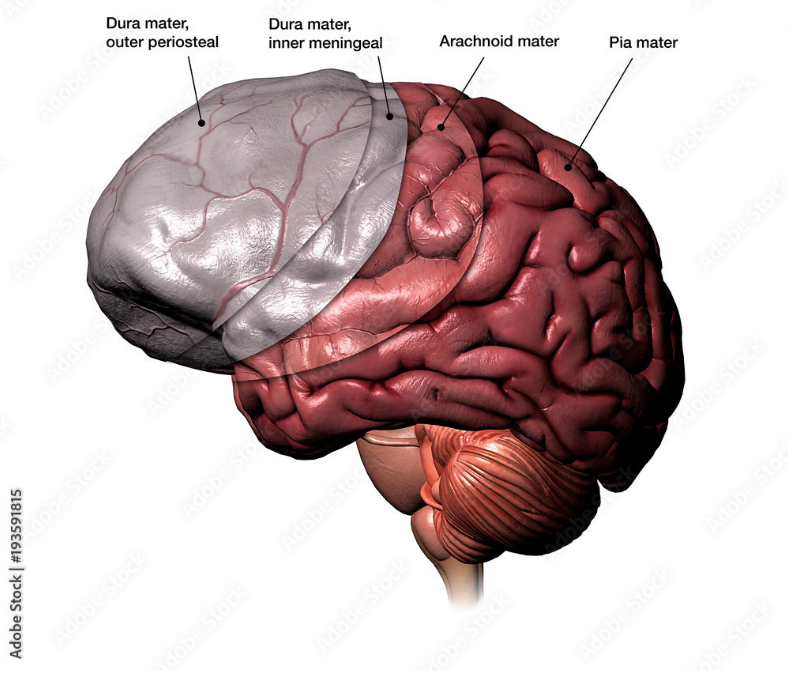

Figure 1.4: The Meninges [2]

1.3.2 Gray And White Matter

The central nervous system comprises two distinct regions known as gray and white matter. In the brain gray matter constitutes the darker outer layer while white matter makes up the lighter inner section underneath.

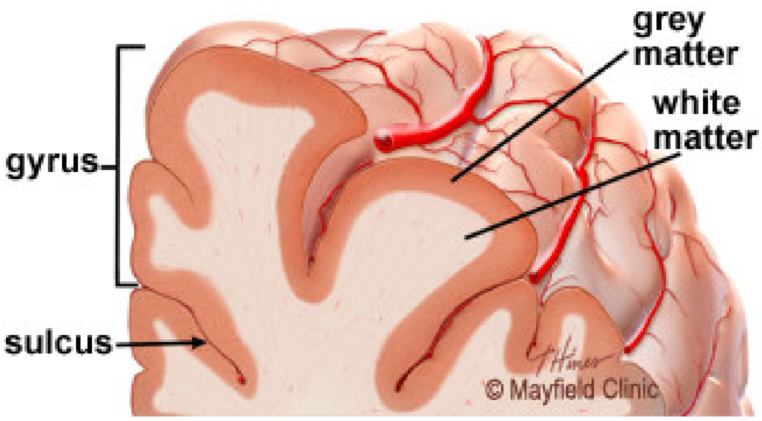

Figure 1.5: Gray and white matter of the brain [3]

Neuron cell bodies (rounded central cell structures) are the main component of gray matter while white matter consists mostly of axons (elongated projections that connect neurons) encased in a protective myelin layer. The distinct composition of neuronal Parts is the reason behind the contrasting shades observed in certain scans.

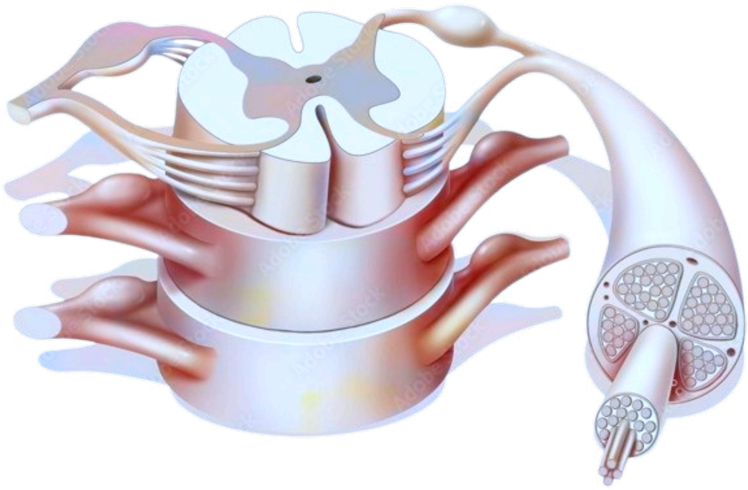

Figure 1.6: Gray and white matter of the Spinal Cord [2]

In the spinal cord, this order is reversed with white matter on the outside, and gray matter on the inside. [24]

1.3.3 The Structure Of The Brain

1.3.3.1 Main Division Of The Brain

The brain is a team of one that works synchronously with each other but at the same time has very different duties. The brain can be clustered into three basic parts: the forebrain, midbrain, and hindbrain. Every expert in this exclusive cluster possesses his or her own skill set; these are specialization roles performed by cerebral divisions.

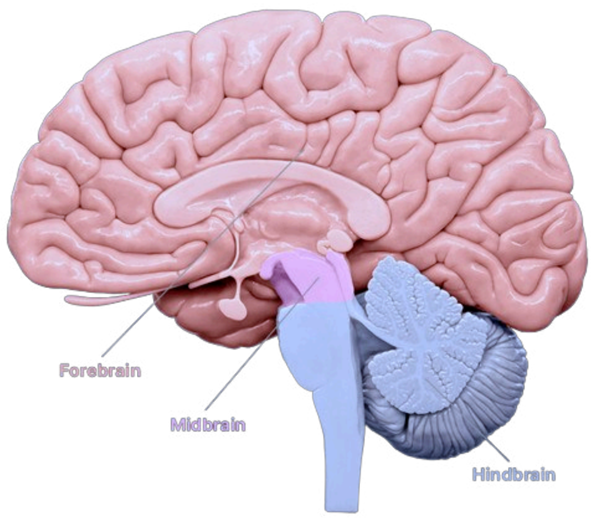

Figure 1.7: Main Division Of The Brain [2]

1. **The Hindbrain** includes the upper part of the spinal cord pons , medulla

and cerebellum. It controls the body's vital functions like respiration, blood pressure and and heart rate.

2. **The Midbrain** At the top of the brainstem , overseeing reflex actions and contributing to the circuit for controlling eye movements and other voluntary actions. Serving as a bridge between the lower and upper brain, the midbrain regulates movement and responds to sensory stimuli.

3. **The Forebrain** is the primary and most advanced segment of the brain primarily comprising the cerebrum and its underlying structures (see "The Inner Brain"). This region incorporates the cerebral cortex responsible for managing cognitive processes like thinking and planning serving as a decisive element for advanced mental functions. [26]

1.3.3.2 Cerebrum

The cerebrum constituting the largest part of the brain characteristics a surface characterized by depressions or grooves known as sulci and raised areas termed gyri. This structural arrangement serves to augment the surface area of the cerebrum without necessitating an increase in overall brain size. Grey matter approximately 2 to 4 mm thick ,envelops the outer surface of the cerebrum. This region processes and Combines information received from the white matter fiber tracts that constitute the inner surface of the cerebrum.

Figure 1.8: The Cerebrum [2]

The cerebrum is bilaterally divided into two hemispheres namely the right hemisphere and the left hemisphere separated by a deep fissure. The corpus callosum bridges the gap between these hemispheres facilitating communication between the two sides of the brain. Each hemisphere predominantly connects to the contralateral side of the body , meaning the left hemisphere of the cerebrum receives information from the right side of the body ,thereby influencing motor control of the right side and vice versa.

Further organizational division occurs within the hemispheres resulting in the formation of four lobes. These lobes play specific roles in cognitive and sensory functions, contributing to the overall complicatedity of the cerebrum. [27]

1.3.3.3 Cerebellum

The cerebellum often called the ”Little Brain” is a decisive structure located at the back of the brain. Occupying about 10 % of the brain’s total size but housing over 50 % of its neurons , it is the largest part of the hindbrain. Structurally it consists of two hemispheres connected by a median vermis linked to the brainstem by three cerebellar peduncles .

Figure 1.9: The Cerebellum [2]

From a functional standpoint, the cerebellum plays an important and vital role in coordinating voluntary movements, such as hand and leg movement and other examples, and in maintaining balance and ensuring precise and smooth movements. It collects data from the sensory organs and spine. The spinal cord and other parts of the brain, and thus corrects the production of motor commands. Although it is the smallest part of the brain, the cerebellum is indispensable for daily activities such as writing, playing the piano, or expressing the skill of playing any musical instrument by balancing the body in those activities. [27]

1.3.3.4 Brainstem

This part is called the brainstem, it lies in the center of the brain and acts as a vital link between cerebrum and spinal cord. Midbrain, pons and medulla make up this structure, which plays various significant roles in physiology.

Figure 1.10: The Brainstem [2]

1. **Midbrain** It is a highly complex structure consisting of different neuron clusters such as nuclei and colliculi along with neural pathways as we have seen earlier(page 2). This intricacy supports processes like auditory perception, voluntary motor movements and adaptive responses to environmental changes. Notably, substantia nigra which exists within midbrain consists of many neurons that are rich in dopamine content making part of basal ganglia involved in movement coordination.

2. **Pons** Named for the latin word "bridge" the pons acts as a vital connection between the midbrain and the medulla. It serves as the origin for four out of the 12 cranial nerves playing a decisive role in activities like tear production chewing blinking vision focus balance hearing and facial expression.

3. **Medulla** Situated at the base of the brainstem where it meets the spinal cord the medulla is indispensable for survival. It regulates essential bodily roles including heart rhythm ,breathing , blood flow and the levels of oxygen and carbon dioxide. also the medulla oversees reflexive activities like sneezing vomiting coughing and swallowing.

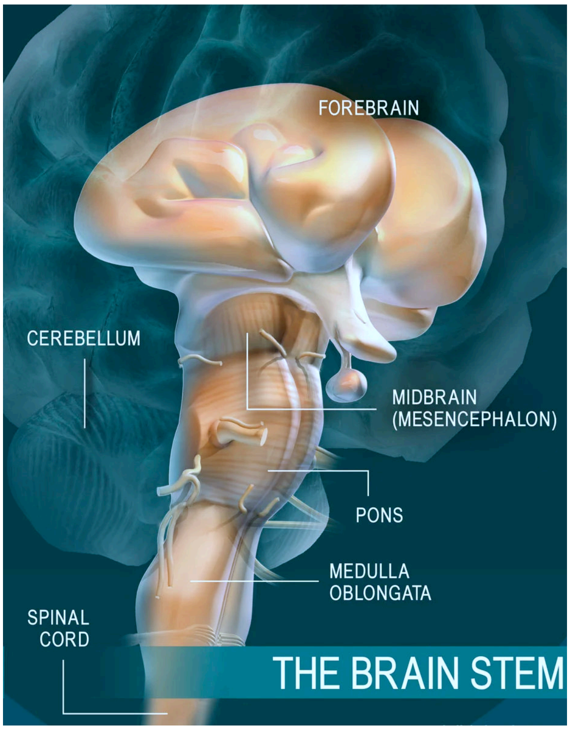

Figure 1.11: Midbrain , Pons, Medulla [4]

The spinal cord extends from the base of the medulla and passes through the lower opening at the base of the skull. It is supported by vertebrae. The spinal cord acts as a decisive communication pathway between the brain and the body transmitting messages to and from different parts of the body. This enables coordinated answers and eases voluntary movements. [24]

1.3.3.5 Cerebral Cortex

Enveloping the cerebrum and cerebellum is a decisive layer of tissue, akin to the thickness of two or three dimes stacked together known as the cortex. This term originates from the Latin word for bark. The cerebral cortex is where the majority of information Methoding occurs in the brain. When people refer to "gray matter" in the brain they are specifically referring to the cortex. The gray color results from the absence of insulation on nerves in this region unlike other brain areas that appear white.

The intricate folds in the brain Add to an expanded surface area amplifying the extent of gray matter and enhancing the brain's capaMetropolis for information Methoding. Essentially the cortex serves as the hub for various cognitive Roles and its unique characteristics enable the brain to efficiently manage and Explain a vast volume of information. [26]

1.3.4 Geography Of Thought

Each cerebral hemisphere is segmented into specialized sections known as lobes, each dedicated to distinct functions. Let's explore the cerebral hemispheres and understand the unique roles of each lobe. [26]

1.3.4.1 Frontal Lobes

Among the most frontwards lobe areas located right behind have the forehead are two frontal lobes. These lobes are of vital significance, since you make a to do list, imagine the future or engage in thinking and acting in a logical way . The primary task of the frontal lobes is their participation in the activity of memory cache where the visual, auditory or motor information is held. This helps one image how diverse ideas can be related to each other while they are being processed.

Frontal Lobe is where Broca's area is located whose functioning is speech ability. [26]

Figure 1.12: Frontal Lobes [2]

1. **Motor Cortex** Situated in the rear section of each frontal lobe is the motor cortex a region decisive for orchestrating regulating and carrying out voluntary movements. Whether it's the motion of your arm or the action of kicking a ball the motor cortex actively participates in the planning and execution of these intentional physical activities. [26]

1.3.4.2 Parietal Lobes

Taste appreciation happens when parietals in the back of the frontal lobes are utilized and one can savor the noisy food and detect its smell, taste and texture. Sensory processing areas such as the parietal lobes make not only the sensory experience of food perfect but also allow the activities like reading and arithmetic to work smoothly. Taking this on, the parietal lobes come into play in the area of spatial awareness with their ability to help you move about and relate with your surroundings properly. its diverse roles promote its importance in the fields of sensory perception as well as cognitive processes and regulation. [26]

Figure 1.13: Parietal Lobes [2]

1. **Somatosensory Cortex** The anterior regions of these lobes situated immediately behind the motor areas ,house the somatosensory cortex. These regions receive input regarding temperature, flavor, tactile sensations and motion from the entire body. [26]

1.3.4.3 Occipital Lobes

While you observe the words and images on this page two regions at the posterior part of the brain are actively engaged. Referred to as the occipital lobes ,these areas Examine visual stimuli received from the eyes and associate this information with images stored in memory. Impairments or injuries affecting the occipital lobes can result in visual deficits or blindness. [26]

Figure 1.14: Occipital Lobes [2]

1.3.4.4 Temporal Lobes

The final lobes in our exploration of the cerebral hemispheres are the temporal lobes positioned anterior to the visual areas and nestled beneath the parietal and frontal lobes. Regardless of your musical preferences whether it be symphonies or rock music these lobes orchestrate your brain's Answer. At the summit of each temporal lobe is a region tasked with receiving information from the ears. The underside of each temporal lobe assumes a pivotal role in the creation and retrieval of memories encompassing those linked to music. Other segments of this lobe amalgamate memories and sensations related to taste sound sight and touch. [26]

Figure 1.15: Temporal Lobes [2]

1.3.5 Ventricular System

The ventricular system in the brain comprises four connected sinuses that help function of the brain and also serve to cushion the brain from injuries through the circulation of CSF around the brain. [28]

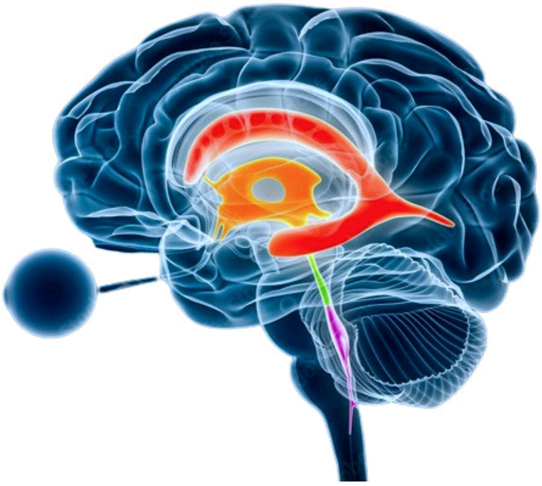

Figure 1.16: The Ventricular System [2]

1.3.5.1 Lateral Ventricle

The lateral ventricle a C-shaped cavity within each cerebral hemisphere is lined by ependyma and filled with CSF. Its central part extending from the interventricular foramen to the splenium of the corpus callosum forms the roof with the inferior surface of the corpus callosum. The floor concave in shape is formed by structures like the caudate nucleus thalamostriate vein and thalamus.

The lateral ventricle has three horns: anterior, posterior and inferior ,extending into the frontal occipital and temporal lobes ,respectively. [28]

1.3.5.2 Foramen Of Monroe

connects the lateral ventricle with the third ventricle and its size and shape depend on ventricular size. [28]

1.3.5.3 Third Ventricle

Situated as a median slit-like cavity between the thalami and part of the hypothalamus the third ventricle communicates with the lateral ventricles anteriorly and the fourth ventricle posteriorly through the cerebral aqueduct of Sylvius. It is lined by ependyma and traversed by the interthalamic adhesion or Massa intermedia.

The third ventricle has a roof covered by tela choroidea walls formed by various structures and a floor descending ventrally through structures like the optic chiasma ,tuber cinereum ,mammillary body, posterior perforated substance and tegmentum of the midbrain. Five recesses protrude into the surrounding structures including the infundibular, optic, anterior, pineal and suprapineal recesses. [28]

1.3.5.4 Aqueduct Of Sylvius

The Sylvian aqueduct which is the narrowest point in the ventricular system and is of the approximate length of 18 mm has a very important role of connecting the third to fourth ventricle with sometimes blockade when both ventricles coexist. As the encircling neural tissue develops, the diameter of the aqueduct gradually diminishes during the second fetal month . [28]

1.3.5.5 Fourth Ventricle

The fourth ventricle is a broad tent-like cavity in the hindbrain filled with CSF and bounded anteriorly by the pons and cranial half of the medulla and posteriorly by the cerebellum. It appears triangular on sagittal section and rhomboidal on a horizontal section. It is continuous with the cerebral aqueduct superiorly and the central canal of the spinal cord inferiorly.

Recesses in the fourth ventricle include lateral recesses a medial dorsal recess extending into the white core of the cerebellum and two lateral dorsal recesses on either side of the median dorsal recess above the inferior medullary velum.

In summary the ventricular system is a Complicated network decisive for maintaining the brain's environment with each ventricle playing specific roles and housing recesses that Add to its overall Roleality. [28]

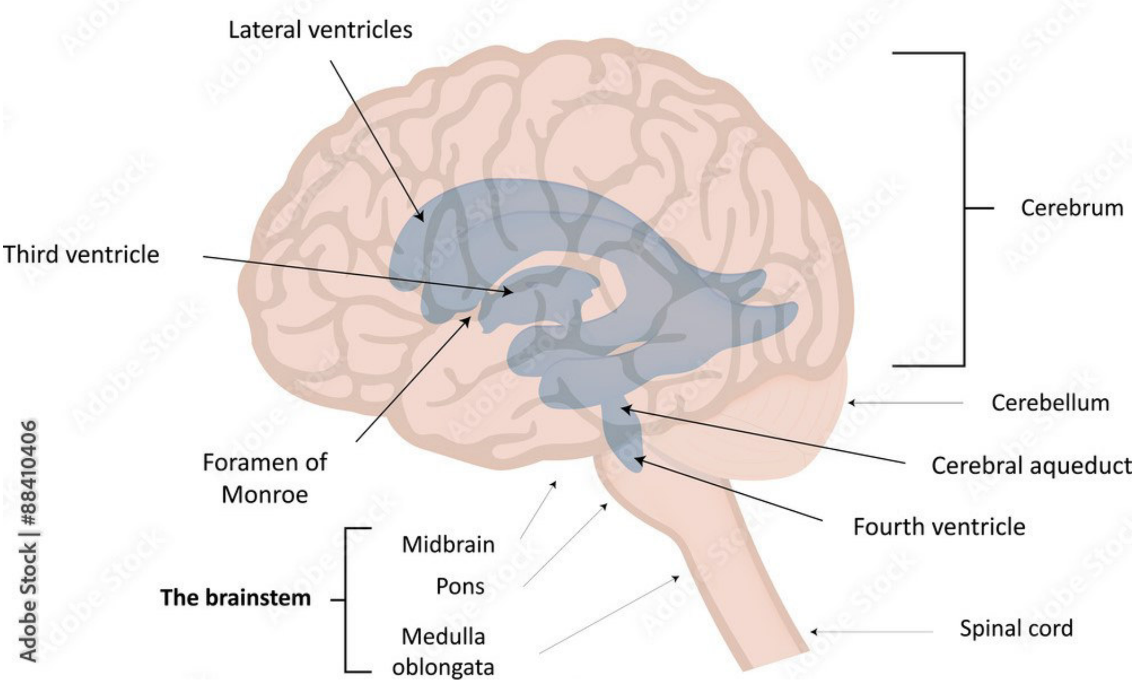

Figure 1.17: The most important elements of The Ventricular System [2]

1.4 MRI

Magnetic Resonance Imaging (MRI) is a next-gen medical imaging technique based on the underlying principles of nuclear and magnetic physics providing superior body's internal details as compared to a traditional x-ray. First starts the patient inside the MR that is provided with a magnet and radiofrequency coils by which signals are noticed. A magnetic field with a substantial force is generated, which influences the hydrogen atoms in the body, causing them to align in a particular direction. [29]

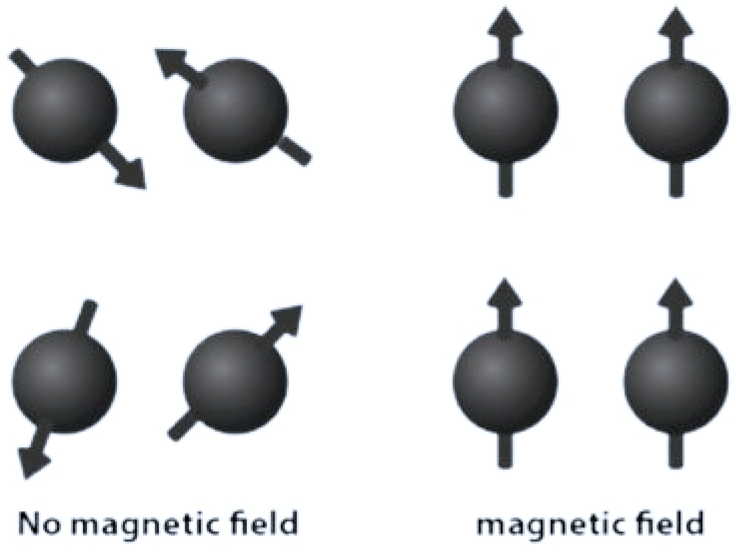

Figure 1.18: Illustration depicting the alignment of hydrogen atoms in a specific direction under the influence of a strong magnetic field [5]

These hydrogen atoms begin to spin around their atomic in the magnetic field's direction in a way that is described as 'spinning' in atomic orbital terms. they also engage in an additional rotational movement termed "precession" due to presence of an external magnetic field. [29]

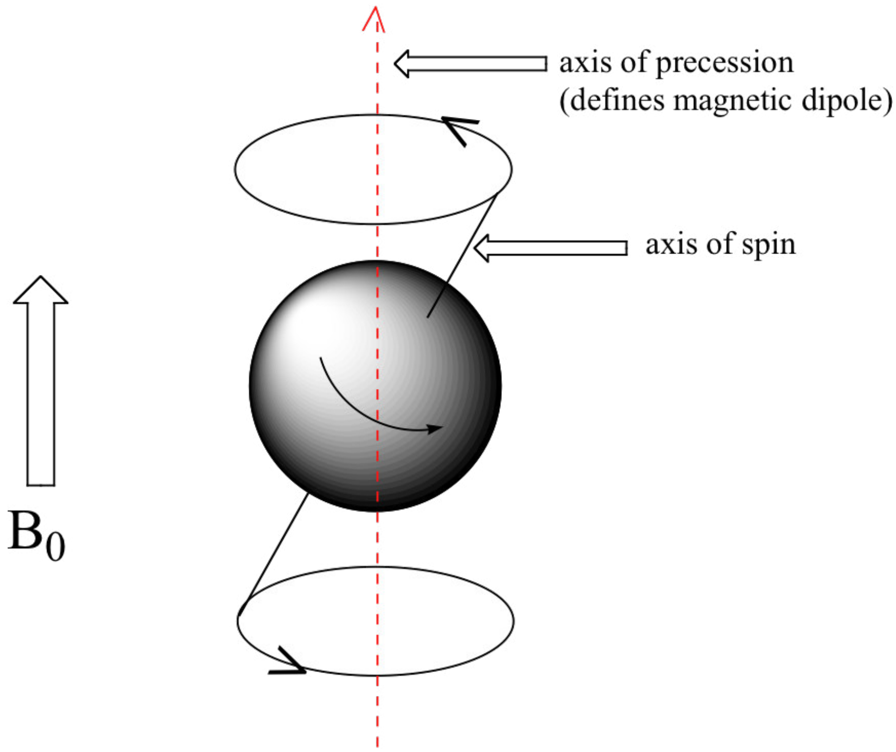

Figure 1.19: Explanation of Spinning and Precession Phenomena in MRI Imaging [6]

In magnetic resonance imaging, the speed at which the protons ' spin ' around the field is fittingly referred to as the Larmor frequency which in turn depends on the strength of the magnetic . This is quite fitting in Larmor equation which accounts for the magnetic fields strength and gives the direct relationship between the Larmor frequency and the field's strength.[29]

$$\omega = \gamma B_0$$

Figure 1.20: the Larmor equation [7]

MRI optically takes the principles of nuclear magnetic resonance(NMR) phenomenon concealed in nuclei, having certain nuclei property called the spin. Hence, MRI facilitates imaging by providing an atomic-scale view. In MR imaging the hydrogen proton nuclei are the principal nuclei variously breasted in the body tissues due to the considerable presence of water and fats.

The proton behavior in these atoms is so perfectly controlled by two such necessary processes – T1 and T2 relaxation. Definitionally, T1 relaxation (also known as longitudinal relaxation) is a mechanism where protons return to their initial audong ment with the magnetic field following perturbation by RF excitation pulses . T2 relaxation, or transverse relaxation, is the process of losing the consistency between proton's spin directions because of neighbor atoms' interactions. [29]

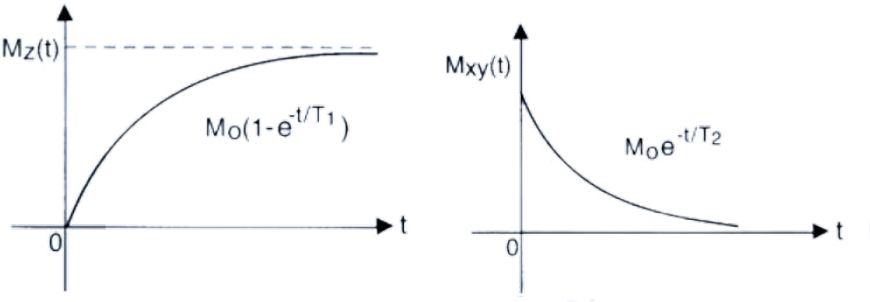

Figure 1.21: MRI essentials: T1 (realignment) and T2 (spin coherence loss) [8]

When a MR image is assembled during an MRI scan, the tissue is undergoing a process of being affected by the RF excitation pulses which disturb the equilibrium alignment of the protons. Protons under consideration of these pulses are ejected from the nucleus, and at the same time, these protons get energy to move to a higher energy state. Furthermore, these MRIs respond to the applied magnetic field, magnetizing again, and emitting radiofrequency signals that can be detected by the scanners receiver coils. When the troubled protons reach equilibrium, T1 and T2 relaxation time, which respectively depends on the tissue type and physiological conditions, determines how long that will take. [29]

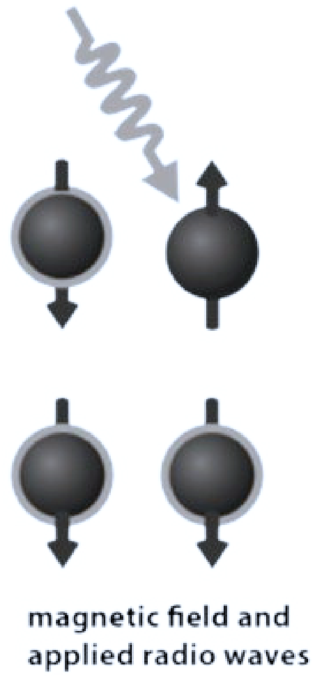

Figure 1.22: Application of Radiofrequency (RF) Pulse on Protons in MRI Imaging [5]

These signals are therefrom decoded by the computer and turned into 3D cross-sectional pictures of tissues and organs. These images give the highest resolution imaging information about tissues and structure , physicians benefit from it in making diagnosis and customizing treatment.[29]

Figure 1.23: Review images obtained through MRI [2]

MRI technology was defined by its double characteristics of safety of the patients by the detailed images without surgery and it does not involve the use of harmful radiation . They are the indications of the way forward toward a better healthcare quality and setting standards of treatment for a patient.[29]

Figure 1.24: The external appearance of the MRI [2]

1.4.1 Advances in Brain MRI

Recently magnetic resonance imaging (MRI) technology for the brain has undergone significant advancements in medicine and medical imaging. Continuous Improvements in MRI hardware and software have enabled the acquisition of highly precise brain images with unprecedented clarity. These Improvements have Eased better exploration of the brain's Complicated structure and Improved analysis of its Role. important advancements include the adoption of three-dimensional imaging techniques and multi-contrast imaging which have Improved image precision and the Findion of fine details. also Roleal imaging methods such as fMRI and DWI have been Constructed to understand brain biological Methodes and assess the impact of diseases and injuries. These Improvements have led to more accurate diagnosis of neurological disorders and faster more effective treatment determination.[30]

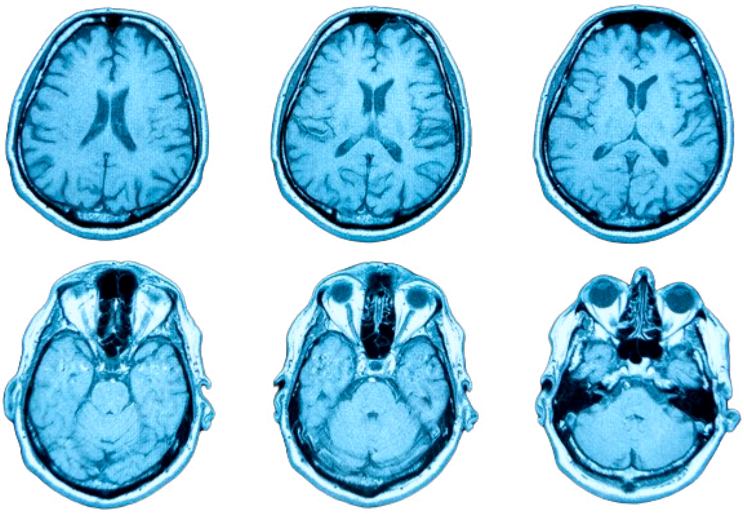

Figure 1.25: Magnetic resonance image (MRI) of the human brain [1]

1.5 Cerebral Pathologies

Cerebro-pathology group together a heterogeneous collection of brain diseases that either damage or interfere with normal brain functioning and pathways. They can range from occurrences such as stroke, blockage of the blood vessels, to neurodegenerative diseases for example Alzheimer and Parkinson, congenital disorders and developmental delays, to presence of brain tumors. they represent a continuum of disease and disorder with different levels of severity, which are characterised by specific pathological features and tend to affect structural, functional and connectivity aspects of the brain.

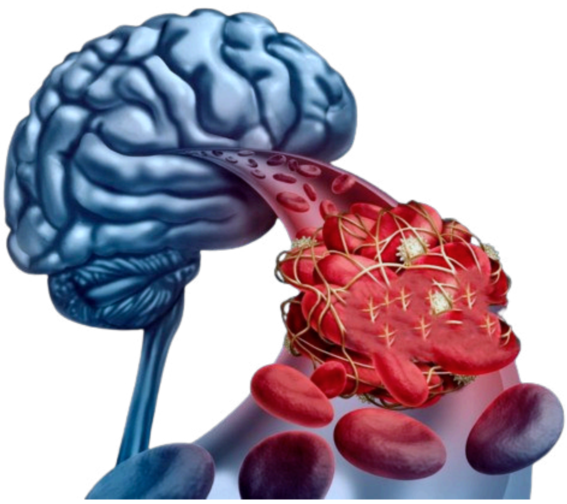

Figure 1.26: A metaphorical drawing representing Cerebral Pathologies [1]

Detecting the causative mechanisms is an essential thing in diagnostics, therapy, and management. What is even more, those cerebral pathologies pose significant challenges not only for the patients yet also for the medical professionals, hence the requirement for multidisciplinary strategies in managing and interventions thus becomes vital.

1.5.1 Stroke

A stroke is an emergency problem which happens as a result of blood supply's interruption to a specified part of the brain either due to veins' blockade or hemorrhage. This deprivation system promotes cell damage in the territory affected, disturbing the functions of the brain in the area pertaining to such functions as movement and speech. Stroke is a dire medical condition that necessitates immediate care so that a patient can have reasonable chances of recovery.[31]

1.5.2 Alzheimer

Alzheimer's disease is a chronic progressive neurodegradative condition with the main manifestations of cognitive impairment, severe memory loss and alterations in one's behaviour. It primarily affects the elderly population where the inclusion of the abnormal protein aggregates within the brain is both intracellularly and extracellularly observed.This pathological process results in neuronal loss and disrupted neurotransmitter signaling pathways. Consequently, the whole high intellectual functions initially are decreased gradually that give way to malfunction of the activities of daily living as well as loss of self-care autonomy.[32]

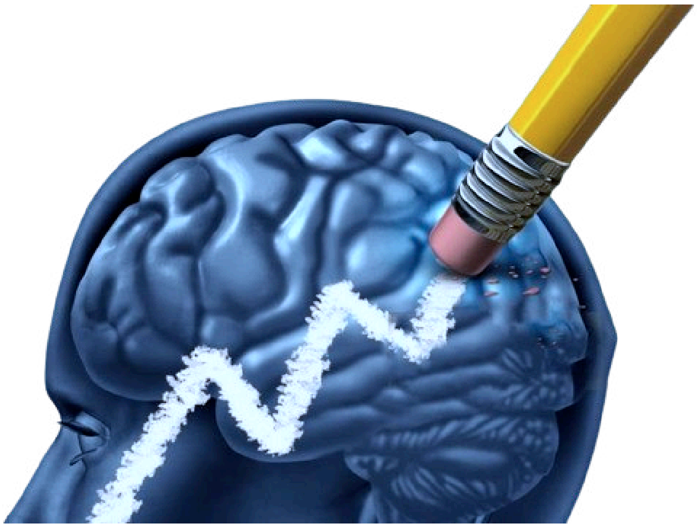

Figure 1.27: A metaphorical drawing representing Alzheimer's disease [1]

1.5.3 Tumors

Brain tumors are classified as abnormal clusters of neuronal cells or brain-supporting cells that proliferate irregularly within brain tissues or surrounding tissues. These tumors vary in behavior and development, ranging from benign tumors that are non-life-threatening to malignant tumors that can be dangerous and life-threatening. These tumors are classified according to their type and characteristics into different grades, and require systematic management and treatment depending on the diagnosis and disease progression.[33]

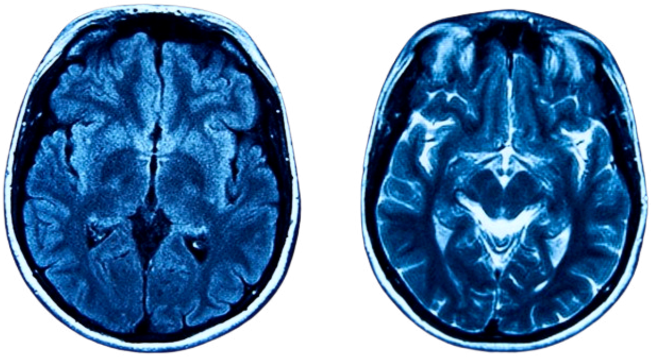

Figure 1.28: Magnetic resonance image (MRI) of BRAIN TUMOR . [9]

1.5.3.1 Benign and malignant brain tumors

Benign tumors or neoplasms of the brain are composed of benign cells that grow very slowly within the brain or surrounding tissues . They occur only in a cluster that is limited to particular regions of the brain without spreading to other areas of the body. These tumours generally are benign but can rarely become cancerous. Such tumours are almost plus completely removable in surgery with a very low chance of getting recurrent.

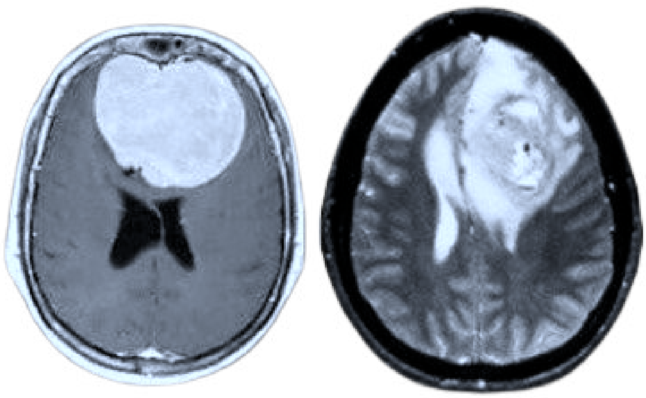

Figure 1.29: Magnetic resonance images (MRI) of a benign brain tumor (left) and a malignant brain tumor (right) [10]

The common type, the malignant brain tumor, differs from the non-cancerous benign brain tumor because this malignant sort of tumor rapidly grows and can invade other parts of the body. These swellings are a deadly groupand staying away from surgery, chemotherapy, radiotherapy, would be unproductive. Cancerous cell escape from the tissue of the original tumor through the blood vessels or lymphatic system to the distant internal organs with which the treatment becomes complex, and patients' chances of survival diminish. [34]

1.5.3.2 Primary and Secondary brain tumours

Primary tumors are that, tumors are sited in the brain or in the spinal cord, and are made up of communities of cancerous cells. These tumors are made out of the brain cells itself, they are found within the central nervous system, where brain lies.

Another form known as secondary brain tumors rather is a mass of cancer cells that metastasizes to the brain from other areas of the body. The cells from the primary site, which might be in the lungs or breasts, can migrate to the brain too through blood or lymphatic system, and locally grow to form the secondary tumors in the brain. [35]

1.5.3.3 Gliomas

Gliomas , which can occur from the glial cells in the central nervous system including the brain and the spinal cord, encompasses a very wide range of neurological tumors that differ in their place of origin and cell of origin. The nature of these tumors is not uniform; though mostly they originate from astrocytes, oligodendrocytes, and ependymal cells. The ability of them to penetrate the brain tissue surrounding and their tendency to recur even beyond treatment characterizes them. Gliomas are classified according to the histological type, tumor grade as being high-grade or low-grade and by other factors such as sites of origin in the brain or spinal cord, presence of molecular markers or presentation in patients. This categorization label assists in finding the type of brain tumor (the nature, aggressiveness and treatment approach etc..), which can vastly differ depending upon the individual patient factors and the tumor itself.

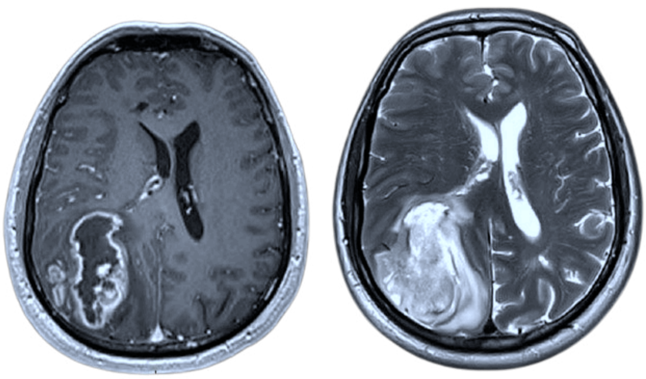

Figure 1.30: Magnetic resonance imaging showing a typical glioblastoma with central necrosis and peripheral enhancement on contrast-enhanced T1-weighted imaging (left), and surrounding oedema and midline shift on T2-weighted imaging (right) [11]

1. **Possible Causes of Gliomas**

   (a) **Genetic Factors**Some studies show genetic factors to be the cause of this malignancy as first-degree relatives of glioma patients are found to have a high chance of brain tumors, which increases the risk.

   (b) **Exposure to Ionizing Radiation** The data that come from the studies say that ionizing radiation either from nuclear explosions or medical treatments may increase the risk of glioma.

   (c) **Immune and Inflammatory Factors** One of the possible relations was found to exist between glioma risk and allergies affected by immune function. If this finding proves accurate, patients with allergies will have a lower risk of getting glioma than people without such a problem.

   (d) **Genetic & Epigenetic Changes** There is an idea that genetic and epigenetic modifications leading to reduced rates of cell division or immune system evasion, may be responsible for glioma development. [36]

2. **Classification of Gliomas**

   the classification of gliomas is generally based on several factors when diagnosing a patient's condition:

   (a) **Histological Type** Gliomas are histologically classified based on the type of neural cells from which they originate. The main histological types include; Astrocytomas, oligodendrogliomas, ependymomas, and mixed gliomas.

   (b) **HGG and LGG** Gliomas comprises two general levels: HGG and LGG. These categories are named according to the degree of malignancy of the tumor. Such gliomas that are categorized as grade 3 and 4 are highly malignant (HGG)and are growths that are fast growing. On the other hand, low-grade gliomas or gliomas that fall under the scale of 1 or 2 (LGG)are growing at a generally slow rate and are less aggressive. It is therefore imperative to: differentiate and diagnose HGG and LGG in order to correctly identify the type of tumor and classify the tumor grade; and know the treatment choice for each type of tumor grade.

   (c) **Tumor Location**The location of the tumor also within the brain or spinal cord may be considered in classification of tumors. Gliomas arise in these areas of the central nervous system – cerebral hemispheres, brainstem, cerebellum, and spinal cord.

   (d) **Molecular Markers** Recent improvements in molecular diagnostics have resulted in the discovery of certain specific types of gliomas' genetic mutations and molecular markers. These markers are useful in prognosis and recommendations on treatment as well as in typing gliomas into sub classes based on molecular differences.

   (e) **Clinical Presentation**of disease and Magnetic Resonance Image or Computed Tomography Scan result plays an important role in the assessment regarding Glioma.

   In broad terms, glioma classification is multi-dimensional and incorporates all those aforementioned parameters including histology, molecular pathology, imaging, and clinical factors to determine the diagnosis and classification of this disease which is then used to define treatment as well as prognostic assessments. [36]

3. **Radiation and Chemotherapy Treatment for Gliomas**

   Radiation therapy is further used to treat Glioma tumors by focusing high energy and accuracy on the cancer cells thereby killing them or reducing the cells' growth without damaging the surrounding parts. There are several phases in the radiation therapy and they include identification of the best site and areas of radiation that are to be targeted together with the radiation dose and time taken for treatment and also the monitoring of the response and side effects of radiation. Latest methods like stereotactic radiation therapy involve the refinement in the targeting of the cancerous region as well as minimizing the effect of the surrounding tissues.

   Chemotherapy in Glioma is a process in which chemical substances that are capable of controlling or killing cells are employed for depleting cancer cells in tumors. Chemotherapy is one of the treatments that should me used to treat Glioma patients either alone or in conjunction with other treatments such as; Radiotherapy or Surgery. Chemotherapeutic drugs are used in the present day in the already established treatment guidelines for glioma tumors as part of treatment therefore boosting treatment outcomes and prolonging survival in glioma patients.[36]

Figure 1.31: A small warrior in a big battle: A brave child fighting cancer with a smile. [12]

نسأل الله أن يشفي جميع مرضى السرطان

1.6 Conclusion

In conclusion, this chapter has provided a comprehensive overview of brain anatomy, MRI technology advancements, and various cerebral pathologies. We explored the intricate structures of the brain, including the meninges, gray and white matter, and essential brain divisions.

Additionally, the chapter covered the significance of MRI in diagnosing brain disorders, highlighting its evolution and pivotal role in clinical practice. We discussed common cerebral pathologies such as stroke, Alzheimer's disease, and tumors, with a specific focus on gliomas—emphasizing their classification and management challenges.

The Machine learning and deep learning have transformed the fight against gliomas. As it processes and analyses extensive medical datasets, such as Magnetic Resonance Imaging scans, Deep Learning has unmatched comprehension of this complex tumour.Deep learning can tell apart aggressive high-grade gliomas from low-grade ones that grow at a slower rate , giving physicians specific information.Equipped with this new found clarity, doctors can now create individual treatment plans for each tumor.Surgery, radiation or targeted therapies are personalized scenarios that generate favorable results for glioma patients.

In the next chapter, we will explain what is meant by machine learning and deep learning and how it is useful for the diagnosis and treatment of gliomas in much detail. This paper will demonstrate how these technologies improve tumor classification, prognosticate outcome, and optimize treatment. The goal will be achieved by focusing on examples of a particular algorithm and its utilization in mri and data analysis for unraveling the advantages and disadvantages of these innovative solutions in gliomas treatment.

Chapter 2

Image Classification, Deep learning and Convolutional Neural Network

2.1 Introduction

We live in a thrilling era that is usually called the information age, where the amount of data on earth is undergoing exponential growth and this expansion can be clearly seen in visual data, which has been spiraling high in terms of photos and videos. In addition to the above mentioned case,there is also exponential increase in textual and visual digital information within the healthcare system.

These irreversible increase in the amount of data, makes the application of Artificial Intelligence one of the most promising areas of health innovation especially in medical imaging, a broad term that describes computer science field dedicated to developing processes that analyze their environment and perform actions in order to optimize success towards a desired goal.[37]

AI has been transforming clinical decision making in oncology paving way for personalized medicine. It simplifies data extraction assisting in treatment planning and post treatment follow up. Further AI improves efficiency by fast image analysis to pick out findings visible and invisible to the naked eye hence optimizing health care workflow.

In medical imaging analysis, supervised learning a machine learning technique classifies images such as gliomas MRI into different classes like LGG or HGG. Traditional ML methodologies had feature extraction done on them, but Deep Learning breakthroughs particularly Convolutional Neural Networks, automate it now improving both accuracy and efficiency of the process. CNNs are inspired by biological neural networks that can automatically learn complex patterns from raw image data aiding in radiology and neurology tasks.

This chapter delves into the significance of ML and its types, and models particularly ANNs , in advancing medical image classification, showcasing the transformative potential of CNNs and challenges that we face in DL and alternate solutions should we take. Then we descus about related works on Brain Tumor detection or classification.

2.2 Machine Learning

Machine learning, a subfield of AI invented by Arthur Samuel in 1959,that gives computers the ability to learn without being explicitly programmed. Instead of relying on explicit instructions, machine learning algorithms learn from data, identify patterns, and make predictions or decisions.[37]

By leveraging vast datasets, machine learning algorithms can detect patterns and anomalies in medical images with remarkable accuracy, aiding clinicians in early disease detection and personalized patient care.

These algorithms can be classified into different types , each with its own strengths and weaknesses. Some common types of machine learning algorithms include:

2.2.1 Supervised Learning

In supervised learning, the algorithm is trained on a human-labeled data, where each input is associated with a corresponding target label. The algorithm learns to map inputs to outputs, making predictions or decisions based on new, unseen data.

This type of learning is divided into two methods: classification and regression. [38]

2.2.1.1 Classification

Classification is a method of grouping similar datasets together based on shared attributes this is done using classifiers that predict the characteristic features for each class label. The main purpose of this process is to determine the appropriate class for different types of data.

Traditional Machine Learning methodologies require feature extraction in order to be able to perform, which raises issues related to selecting proper fea- tures,relying heavily on domain expertise.

Deep Learning, however has changed all that. It does away with the need for pre-determined features that traditional techniques may have limitedly relied on.

Medical image classification is especially advantaged by these developments. TML techniques often struggle with complex medical images where extensive feature selection and extraction are required. In this area, powerful solutions have been developed through DL methods like Convolutional Neural Networks which can automatically learn complex patterns and features from raw image data, achieving high levels of accuracy and efficiency. We will discussing of this powerful technique on detail in 4.1. [23]

2.2.1.2 Regression

In regression, the algorithm predicts a continuous value for a target variable based on the input features. It is used when the target variable is continuous, and the goal is to predict a quantitative outcome. [38]

2.2.2 Unsupervised Learning

In unsupervised learning,the algorithm is trained on unlabeled dataset that are unknown to humans. This means that the data is not categorized, and the algorithm must learn to find patterns in the data on its own. This type of learning is particularly useful for discovering hidden structures or relationships within the data and it is divided into two major methods : clustering and association. [38]

2.2.3 Reinforcement learning

In reinforcement learning, an agent learns to make decisions by interacting with an environment. It was inspired by how human beings learn skills through trial and error. The agent receives feedback in the form of rewards or penalties based on its actions, allowing it to learn the optimal behavior through trial and error.[39]

2.3 Artificial Neural Network

Artificial neural networks is one of the most famous machine learning models . They were initially introduced in 1943 by Warren McCulloch and Walter Pitts to imitate biological neurons using mathematical models.The Mark I Perceptron, the first neurocomputer, showed rudimentary pattern recognition capabilities. Over the years, advances in data accessibility and algorithms have led to increased neuronetwork technology as well as more advanced models like deep neural networks.

Neurons in ANNs are nodes, like cell bodies, which communicate through connections similar to axons and dendrites inspired by how biological neural networks work. Within ANNs weighted connections change over time as they become more effective in achieving desired outcomes just like synapse strengthening in biological networks. ANNs mimic the way information is processed by neurons as it undergoes mathematical transformations within them leading to output signals thus making it possible for them to solve complicated problems effectively.[40]

2.3.1 Basic Architecture of Artificial Neural Networks

[40]

The architecture of an ANN indicates how its neurons are placed and arranged, in relation to each other.

In general an ANN can be segmented into three distinct layers:

1. **Input layer**

   This layer serves as the receiver of information such as signals,Characteristics or measurements originating from the external environment.

2. **Hidden Layers**

   These layers positioned between the input layer and the corresponding output layer,which extract the majority of the information performing computations that are not directly visible to the user. They are often referred to as intermediate, or invisible layers.

3. **Output Layer**

   This layer is responsible for generating and presenting the final outputs.

2.3.1.1 Single-Layer Feedforward

This neural network configuration consists of a single input layer and a single neural layer, which also functions as the output layer.Data flow in this architecture is unidirectional, solely progressing from the input layer to the output layer.

Within the feedforward architecture, one prominent network type is the Perceptron.

1. **Perceptron**

   A perceptron is the most basic form of artificial neural network, consisting of a single layer of input neurons and an output neuron. It's used for binary classification tasks .

   From the analysis of Figure 2.1, it becomes apparent that each of the input variables, denoted as Xi, undergoes an initial weighting process by synaptic weights Wi in order to quantify the importance of these inputs . Subsequently, the resultant value obtained from the summation of all inputs weighted by their respective synaptic weights, coupled with the activation threshold or bias b, serves as input for the activation function f(.). This activation function computes the output value, denoted as y, which is the ultimate output produced by the Perceptron. In mathematical terms, the internal operation executed by the Perceptron is encapsulated by the subsequent expressions:

$$U=\Sigma(Wi * Xi)+ b$$
$$Y=f(U)$$

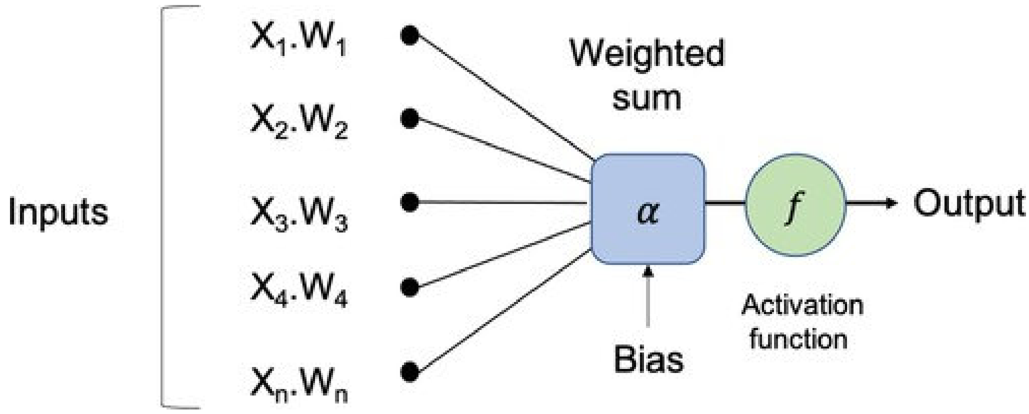

Figure 2.1: Perceptron basic Architecture . [13]

2.3.1.2 Multiple-Layer Feedforward

Feedforward networks with multiple layers are comprised of one or more hidden neural layers.

Within the Multiple-Layer feedforward architecture, one prominent network type is Multilayer Neural Network

1. **Multilayer Neural Network**

   The Multilayer Perceptron network includes at least one intermediate (hidden) neural layer.

   From the analysis of Figure 2.2, it becomes evident that every input of the network, propagated layer-by-layer toward the output layer. Consequently, the outputs of neurons from the initial neural layer serve as inputs for neurons within the subsequent hidden neural layer, neurons from the second hidden neural layer become the inputs for neurons within the output neural layer, and so it continues until we reach the end of the network.

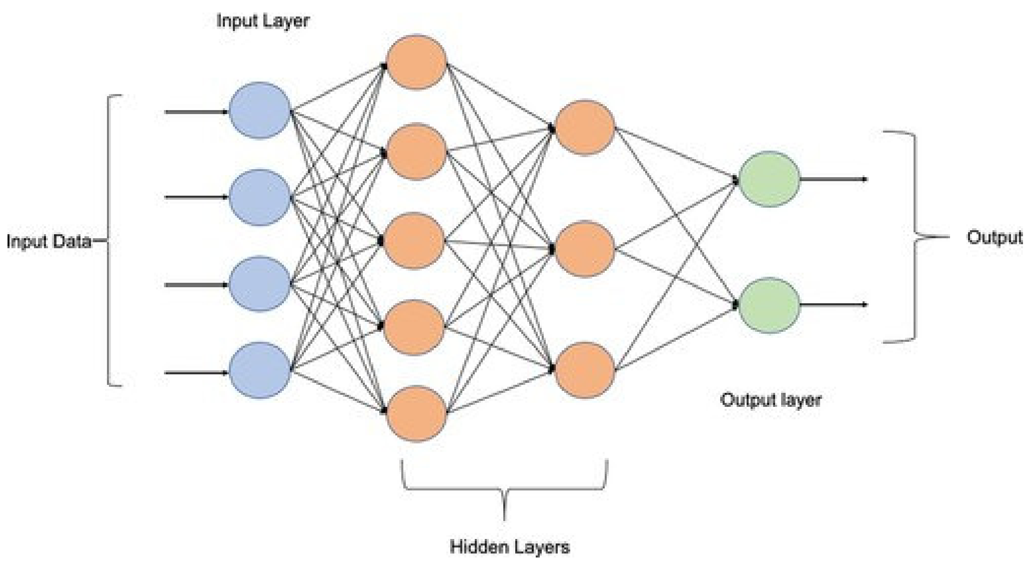

Figure 2.2: MLP basic Architecture . [13]

2.3.2 Training Process of ANN

Training in a single-layer neural network is relatively easy since the error function or loss function can directly be computed with respect to weights thereby simplifying gradient computations. However, training multilayer networks becomes challenging as the loss becomes a complex composite of prior weights. This complexity is addressed by utilizing backpropagation algorithm for computing the gradients of this composition function. The algorithm has two main phases: forward and backward phases, which facilitate efficient computation of gradients across the network's layers. [41]

2.3.2.1 Forward propagation

[40]

Forward propagation involves the sequential processing of input data through the network's layers to produce an output prediction. At each layer, the input is transformed using a weighted sum of the previous layer's outputs, followed by an activation function to introduce non-linearity. Mathematically, for a given layer l , the forward propagation process can be represented as:

$$Z(l)=W(l)*A(l-1)+b(l)$$

where:

- Z(l) is the pre-activation output of layer l ,

- W(l) represents the weight matrix of layer l ,

- A(l-1) denotes the activation output of the previous layer,

- b(l) is the bias vector of layer l .

Then, this pre-activation output is passed through an activation function, such as the sigmoid function, ReLU (Rectified Linear Unit), or tanh (hyperbolic tangent), to produce the activation output of the current layer:

$$A(l)=f(Z(l))$$

where f(.) is the activation function.

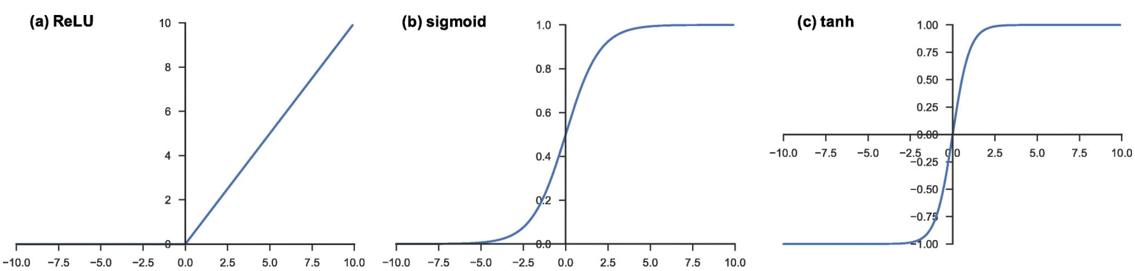

Figure 2.3: Known activation functions applied to neural networks . [14]

Finally, after the forward propagation is completed, the loss function is applied to measure the discrepancy between the predicted output and the actual target output. The loss function quantifies the error of the model's prediction and provides a scalar value representing the difference between predictions and ground truth.

$$L=\text{Loss}(Y \text{ true} , Y \text{ pred})$$

Where (Y true) is the true label and (Y pred) is the predicted output of the network.

Commonly used loss functions include :

- Cross entropy for multiclass classification tasks.
- Mean squared error for regression tasks.[17]

This process is repeated for each layer until the output layer is reached, where the final output of the network is obtained.[40]

2.3.2.2 Backward propagation

Backpropagation, or backward propagation, is the phase used after forward propagation involves modifying the weights and biases of the network in response to changes in the error or cost function. This adjustment phase relies on computing partial derivatives or gradients, which indicate how the error varies with respect to the weights and biases, respectively.

These are determined using local errors through backpropagation, which then adjusts these weights accordingly. The aim here is to minimize differences between actual outputs and predicted outputs in order to optimize performance.

These gradients guide updates through optimization algorithms such as gradient descent, Momentum and Adam. [17]

Gradient descent, a widely employed optimization algorithm, iteratively updates the network parameters in the opposite direction of the gradient to minimize the loss function. The gradient of the loss function provides the direction of steepest increase, and each parameter is adjusted in the negative direction of the gradient, guided by the learning rate hyperparameter. This updating process is facilitated through network backpropagation, where the gradient at each neuron is propagated backward to all neurons in the preceding layer. By iteratively adjusting the parameters based on the gradient, the network aims to converge toward an optimal solution and improve its overall performance. [14]

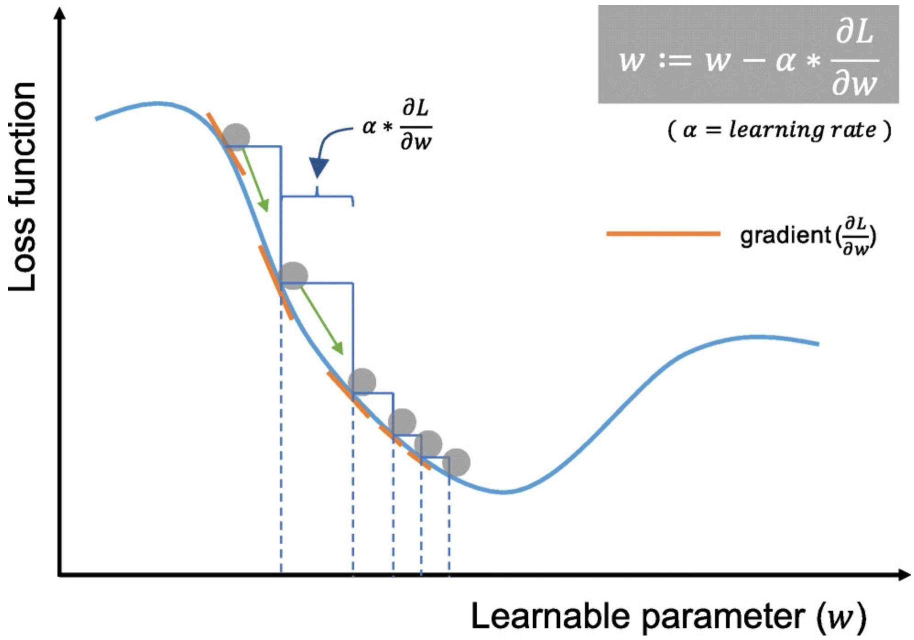

Figure 2.4: Gradient Descent . [14]

2.4 Deep Learning

Deep learning is a variant of ANN that adds complexity by using multiple "deep" layers of an artificial neural network. In deep learning, the computers learn useful representations and features automatically, directly from the raw data, by-passing this manual and difficult step, Discovering features and performing a task is merged into one problem, and therefore both improved during the same training process.

Deep learning has revolutionized the field of medicine and medical analysis by enabling unprecedented advancements in image processing, diagnosis, and classification tasks. With its ability to automatically extract complex features directly from raw data, deep learning algorithms have significantly enhanced the accuracy and efficiency of medical image analysis. [38]

DL can be classified into different categories :
Deep supervised learning such as : Recurrent Neural Networks, Convolutional Neural Networks, and Deep Neural Networks.
Deep unsupervised learning such as : Restricted Boltzmann Machines, auto-encoders and Generative Adversarial Networks.
Deep reinforcement learning . [17]

2.5 Convolutional neural networks

CNNs are widely recognized as the most established deep learning algorithm. Their true turning point occurred during the 2012 ImageNet challenge.[14]

These networks are capable of automatically learning hierarchical representations of features directly from raw pixel data. Imaging data is processed into reduced representations of features using mathematical transformations, most fundamentally kernel convolution, followed by additional methods for dimensionality reduction. CNNs have demonstrated remarkable performance in various applications, including image classification, object detection, and image segmentation. [42]

2.5.1 CNN Architecture

[17][41][43][15]

CNN consists of multiple layers of interconnected neurons, work together to extract features from the input data and perform classification . The basic CNN architecture along with its several layers is illustrated in Figure 2.5.

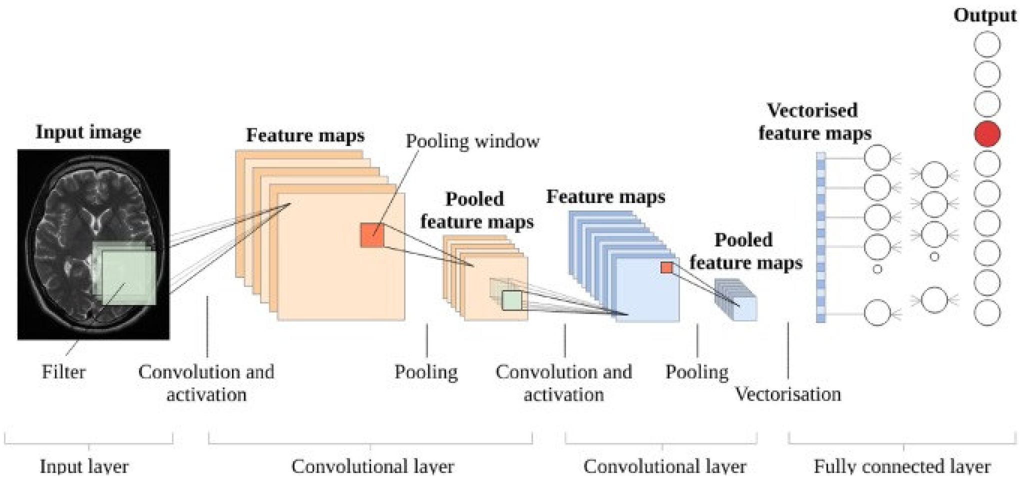

Figure 2.5: The basic architecture of CNN . [15]

2.5.1.1 Convolution Layer (Convo+ReLU)

The first layer and the fundamental building block of CNN architecture is the convolution layer and it is where the majority of computation occurs. that is responsible for extracting features from the given input image which is represented as 4D tensors (height, width, number of samples, number of color channels or depth) (depth=1 for gray-scale images and for RGB images depth=3) using the convolution filters.

1. **The filter**

   A filter, often referred to as a kernel, is a small matrix that is used to extract the features from the input image. Each filter is designed to detect certain features, such as edges, textures, or patterns. The kernel performs a specialized linear operation called convolution.

   The values within the filter are the parameters that the network learns during training. These parameters determine how the filter interacts with the input data, and they are adjusted through the process of backpropagation and gradient descent to optimize the network's performance on the given task.

2. **Convolution Operation**

   The convolution operation involves sliding the filter/kernel over the input image by a stride value and computing the element-wise multiplication between the filter and the overlapping region of the input image. At each position, the results are summed up to produce a single value in the output feature map.This process is repeated for every position in the input image, producing the entire feature map also known as an activation map .

   The convolution operation relies on two critical hyperparameters:

   - Kernel size, typically represented as 3x3, 5x5, or 7x7, dictates the dimensions of the filter used .
   - the number of kernels determines the depth of the resulting feature maps.

3. **Stride**

   Stride refers to the number of pixels by which the filter/kernel is shifted or "slid" over the input image during convolution.

4. **Padding**

   Typically, when performing convolution, the output feature map's height and width are decreased compared to the input image. To overcome this challenge, padding—often implemented as zero padding—is applied. This involves inserting rows and columns of zeros into the input image, ensuring consistent dimensions throughout the convolution proces.

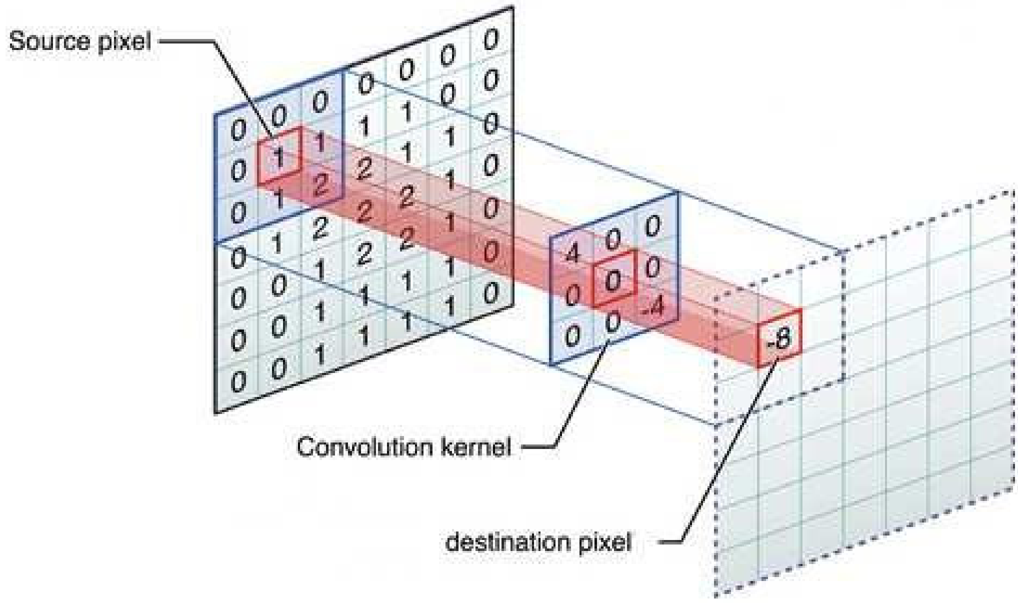

Figure 2.6: Kernel Application and Feature Map Generation in Convolutional Layer . [16]

5. **Non Linearity(ReLU)**

   After each convolution operation, a CNN applies a Rectified Linear Unit transformation to the feature map, introducing nonlinearity to the model wich replaces all negative values in the feature map by zero using a simple formula :

$$f(x)\text{ReLU} = \max(0, x)$$

   whereas, x is an input parameter .

2.5.1.2 Poolig Layer

Pooling layers, often referred to as downsampling, play a pivotal role in dimensionality reduction, effectively trimming down the number of parameters in the input. Much like their counterpart, the convolutional layer, pooling operations involve traversing a filter across the entire input data. However, unlike convolutional layers, these filters dont have weights. Instead, they apply an aggregation function to the values within their receptive fields, thereby populating the output array.

There exist three primary types of pooling:

1. **Max pooling**

   In this method, as the filter traverses the input, it cherry-picks the pixel with the highest value, channeling it to the output array. Notably, this technique is more prevalent compared to average pooling.

2. **Average pooling**

   Contrasting with max pooling, average pooling computes the mean value within the receptive field as the filter sweeps across the input, then forwards it to the output array.

3. **Global Average Pooling**

   This method computes the average value of each feature map in the previous layer. It collapses the entire spatial dimensions into a single value per feature map, effectively reducing the size of the data.

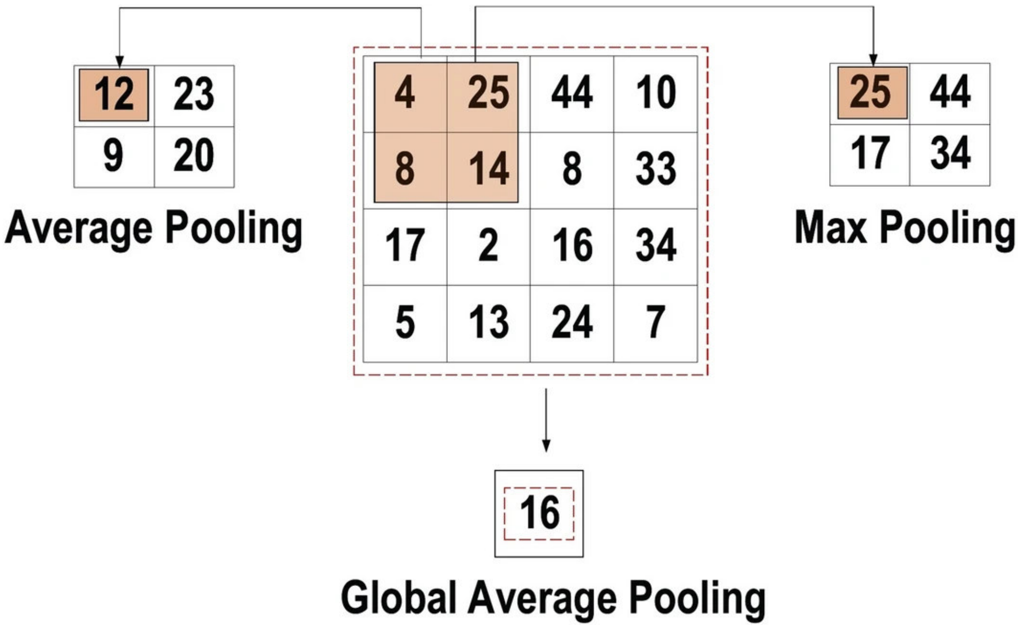

Figure 2.7: Three types of pooling operations. [17]

2.5.1.3 Fully Connected Layer

The fully connected layer, also known as a dense layer , serves as the final stage in a CNN, functions as the classifier. It operates in a feed-forward manner akin to a conventional multi-layer perceptron neural network.

Each neuron within this layer establishes connections with all neurons from the preceding layer. The input to the FC layer is a vector derived from the flattened feature maps extracted from the prior pooling or convolutional layers. Through the computation of the dot product between the weight vector and input vector, the FC layer generates the ultimate output of the network.

Typically, the final FC layer comprises the same number of output nodes as the classes in classification tasks, where it produces the final prediction or decision based on the learned features.

2.5.2 Training Process in CNN

Like we see in 3.2 (Training Process of ANN) the training is a process that involves the optimization of paramaters to minimize the difference between predicted outputs and ground truth labels on a training dataset. In CNN these paramaters are kernels in convolution layers and weights in fully connected layers.

2.5.3 Known CNN Models

The evolution of Convolutional Neural Networks has been profoundly shaped by the ImageNet Large Scale Visual Recognition Challenge.

- **ILSVRC** an annual competition renowned for catalyzing groundbreaking advancements in image classification. Notable models such as AlexNet, VGGNet, Inception and ResNet emerged as frontrunners from this competition each introducing novel architectural innovations that pushed the boundaries of effectiveness and efficiency.

These models extensively trained on vast datasets including ImageNet are commonly referred to as pre-trained CNN models.

- **ImageNet** comprises more than 15 million high-resolution images categorized into approximately 22,000 distinct categories. These images were sourced from the internet and meticulously labeled by human annotators utilizing Amazon's Mechanical Turk crowd-sourcing platform serves as a cornerstone for training and fine-tuning these specialized CNN models.[18] [15]

2.5.3.1 AlexNet

[18]

AlexNet proposed by Krizhevesky et al won the ImageNet Large Scale Visual Recognition Challenge 2012. It revolutionized deep learning with its creative Structure and training techniques leveraging the power of GPUs for training efficiency and operation Improvement.

1. **Architecture**

   The architecture of AlexNet consists of eight layers with weights :
   five convolutional layers , three max-pooling layers , two fully-connected layers and one SoftMax layer.

   The first convolutional layer processes the 224x224x3 input image with 96 kernels of size 11x11x3 employing a stride of 4 pixels.
   Subsequent layers refine feature representations with the second convolutional layer filtering the output of the first layer with 256 kernels of size 5x5x48.
   The third, fourth, and fifth convolutional layers maintain connectivity without intervening pooling or normalization each employing kernels of specific sizes and connecting to previous layer outputs accordingly.

   Finally the fully-connected layers in AlexNet consist of 4096 neurons each enabling high-dimensional feature transformation and classification.

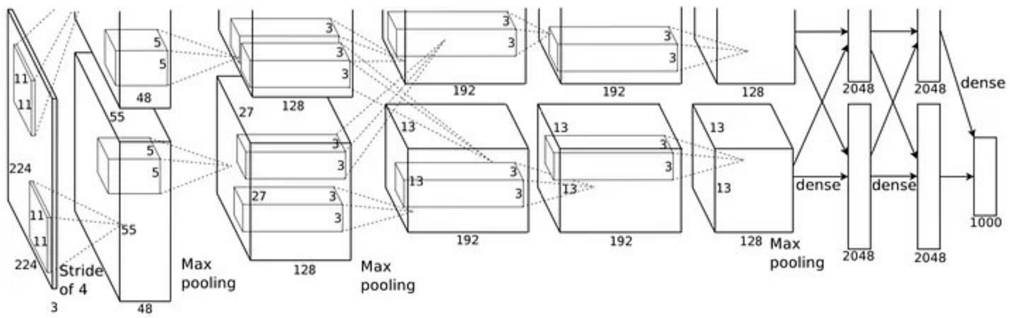

Figure 2.8: The AlexNet Architecture. [18]

2.5.3.2 Visual Geometry Group (VGG)

[44]

The Visual Geometry Group network proposed by Karen Simonyan and Andrew Zisserman It is renowned for its deep structure.

VGG has multiple variants including VGG11, VGG13, VGG16 and VGG19 each with a different number of layers. The most generally used variants are VGG16 and VGG19 which have 16 and 19 layers respectively. These deeper structures enable VGGNet to learn intricate features from input images leading to improved effectiveness in image classification tasks.

1. **VGG Architecture**

   (a) Input Layer
   The input to VGG ConvNets is a fixed-size 224 × 224 RGB image.

   (b) Convolutional Layers
   VGG employs a stack of convolutional layers with small receptive field each followed by a ReLU activation function. These layers use small 3x3 filters with a stride of 1 and same padding. The number of filters starts at 64 in the first layer and increases to 512 in subsequent layers. It also includes 1 × 1 convolution filters for linear transformations of input channels.

   (c) Pooling Layers
   Spatial pooling is carried out by max-pooling layers for spatial downsampling over a 2 × 2 pixel window with a stride of 2 reducing the spatial dimensions of the feature maps by half.

   (d) Fully Connected Layers
   The convolutional layers are followed by two fully connected layers each with 4096 neurons. Each fully connected layer is followed by a ReLU activation function except for the last one.

   (e) Output Layer
   The final fully connected layer has 1000 neurons corresponding to the 1000 classes in the ImageNet dataset. It is followed by a softmax activation function to compute the probabilities of each class.

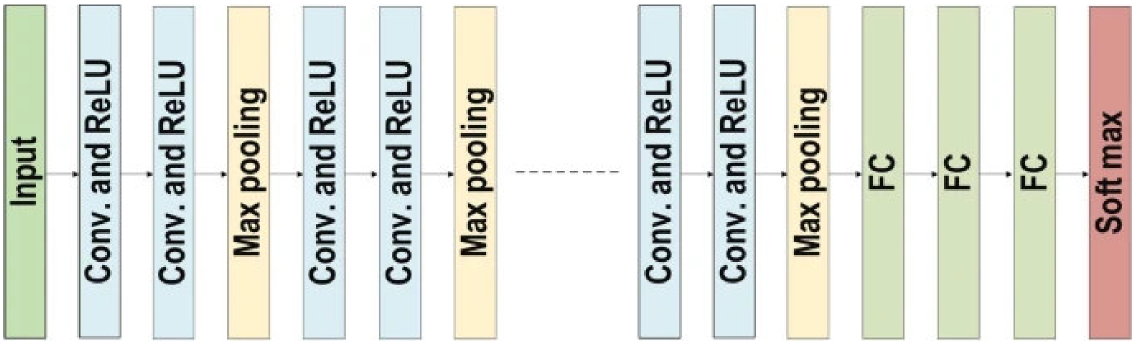

Figure 2.9: Architecture of VGG . [17]

2. **VGG16**

VGG16 is a variant of the VGG architecture specifically comprising 16 weight layers including 13 convolutional layers and 3 fully connected layers.It achieved important recognition for its performance in image classification tasks despite its computational cost.

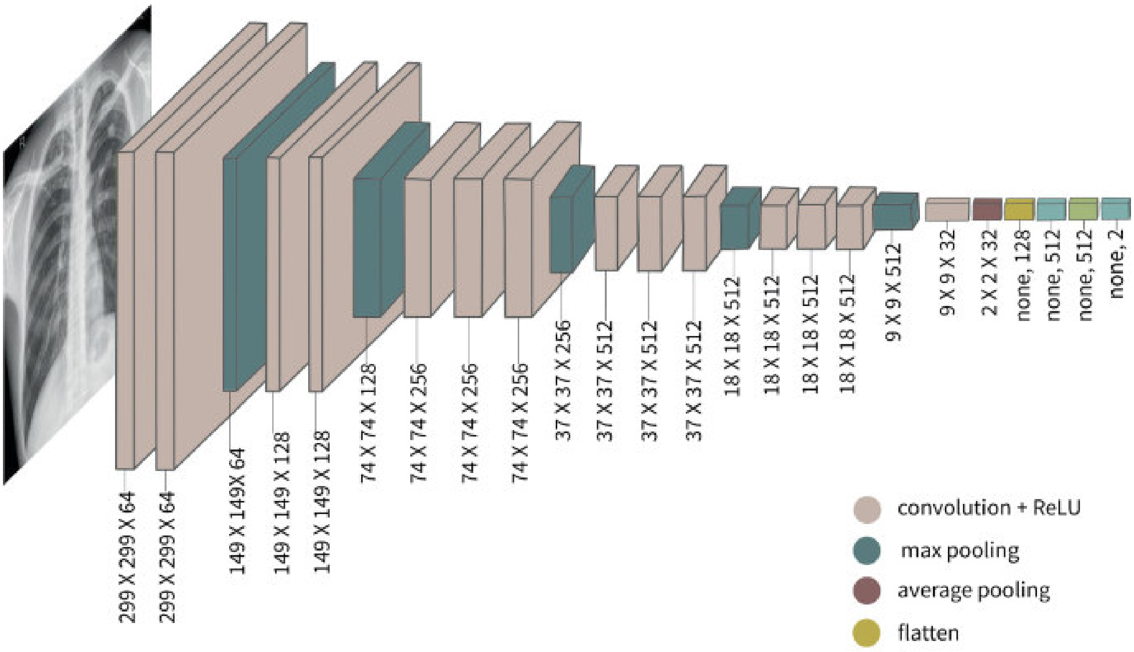

Figure 2.10: VGG16 Architecture . [19]

The figure presents the architecture of VGG16.

3. **VGG19**

VGG19 extends VGG16 with an additional three convolutional layers making it deeper and further enhancing its representational capacity. While VGG19 offers improved effectiveness in tasks like image recognition and classification compared to VGG16 it comes with increased computational cost.

2.5.3.3 Inception

[20].

Inception developed by researchers at Google. The primary motivation behind the inception architecture was to construct deeper networks while maintaining computational efficiency. Inception does this by introducing a special building block called an ”inception module” which is actually an increase in network depth.

This architecture aims to improve the performance of image classification tasks by effectively capturing features at various spatial scales.

The popular versions of inception networks are as follows:

- Inception v1 or GoogLeNet .
- Inception v2 and Inceptionv3.
- Inception v4 and Inception-ResNet.

1. **Inception Module**

   The cornerstone of the Inception architecture is the inception module. consists of parallel convolutional operations with varying filter sizes enabling the network to capture features at different spatial resolutions simultaneously. These parallel operations typically include 1x1, 3x3 and 5x5 convolutions as well as max-pooling operations. By combining multiple convolutional operations in parallel inception modules allow the network to learn diverse and discriminative features from input data efficiently.

   The below image is the “naive” inception module. It executes convolution on an input using filters of three different sizes (1x1, 3x3, 5x5) alongside max pooling. The resulting outputs are concatenated and forwarded to the subsequent inception module.

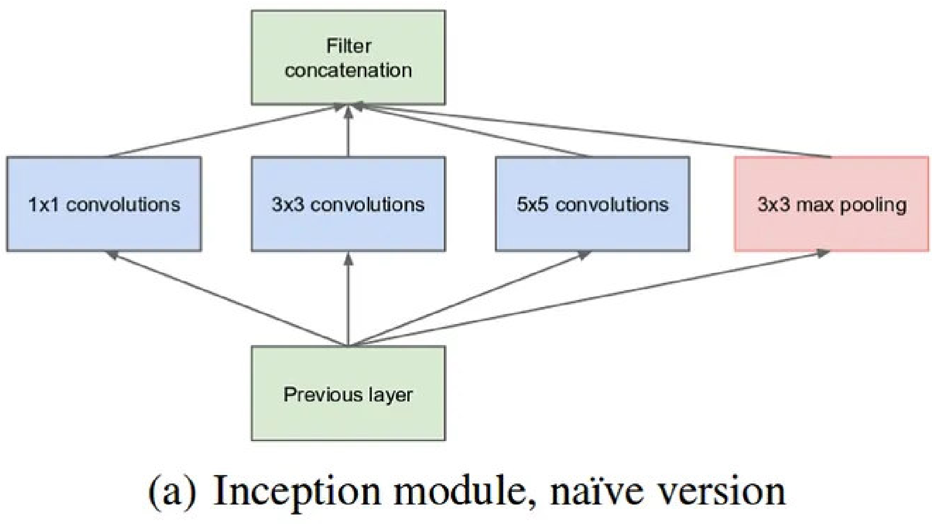

Figure 2.11: The naive inception module. [20]

To alleviate the computational load of deep neural networks a reduction in the number of input channels is implemented by incorporating an extra 1x1 convolution before the 3x3 and 5x5 convolutions. Despite appearing to increase complexity 1x1 convolutions require significantly fewer computations compared to 5x5 convolutions, and the decrease in input channels proves advantageous. Importantly the 1x1 convolution is applied after max pooling rather than before it.

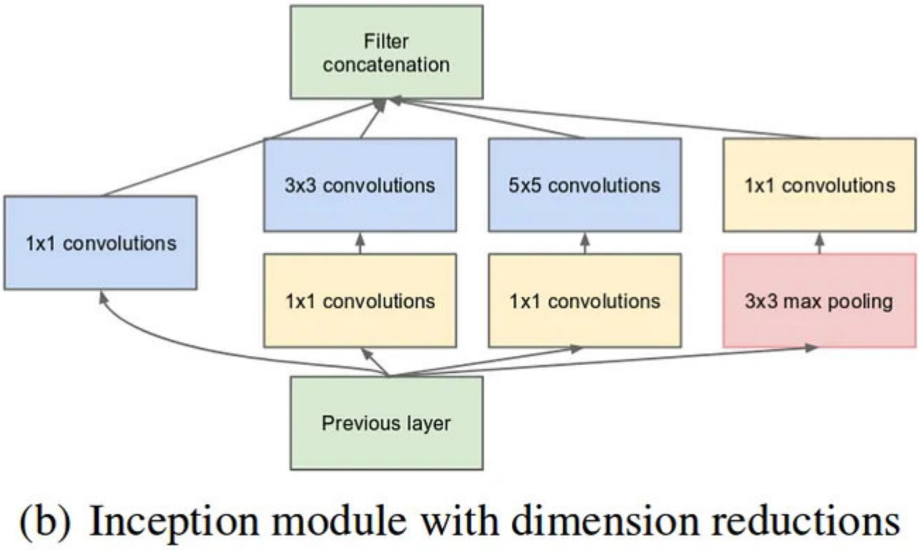

Figure 2.12: Inception module with dimension reduction. [20]

2.5.3.4 Xception

Xception an abbreviation for "Extreme Inception" proposed by François Chollet in 2017 built entirely on depthwise separable convolution layers. It considered an "extreme" version of the Inception architecture suggesting it takes a more radical approach.

The core idea behind this approach is that information about different aspects of an image like how features relate to each other across color channels (crosschannel correlations) and how they are arranged within the image (spatial correlations) can be learned independently.

This novel approach to convolutional operations significantly reduces the number of parameters and computational complexity while maintaining expressive power making Xception a highly efficient and effective model for various computer vision tasks. [21]

1. **Architecture**

   The Xception model starts with an image size 299x299 pixels and the last fully connected layer of Xception architecture has been connected to the Softmax layer to classify the image into 18 different categories (using 18 neurons).

   Xception architecture can be divided into three main parts:
   the Entry Flow, the Middle Flow and the Exit Flow .

This architecture contains 36 convolutional layers which are structured into 14 modules Each module uses a special type of convolution called ”depthwise separable convolution” that’s more efficient than standard convolutions.
To improve the model’s learning ability most of these modules (except the first and last) have special connections that allow information to flow directly from earlier parts of the network to later parts.

In simpler terms Xception is a series of these efficient convolution modules stacked on top of each other with connections that help information flow throughout the network. [45]

A complete description of these network is given in Figure 2.15 .

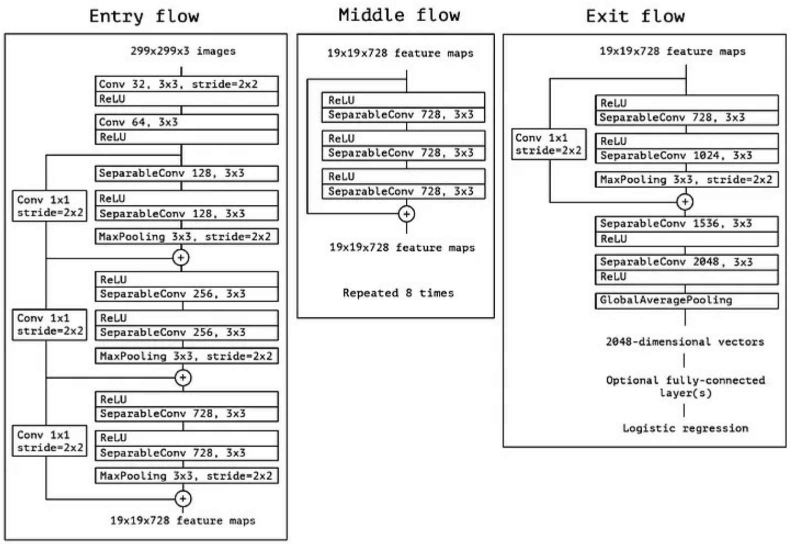

Figure 2.13: The Xception architecture . [21]

2.5.3.5 ResNet

[46]

Deep networks have revolutionized image classification and provide more complex features, By stacking more and more layers. However there is a limit to how a deep network can be. As networks get deeper it becomes more difficult to train them because of vanishing and exploding gradient types of problems and their accuracy can even start to degrade.

ResNet short for Residual Network introduced by Kaiming He et al. in 2015. Which is one of the common architectures of CNN allowed us to train extremely deep neural networks and address the degradation problem by introducing a new way to connect layers in the network.

1. **Residual Learning**

   The core idea of ResNets is residual learning. Instead of learning a mapping from an input x to an output y directly ResNets learn a residual function F(x) that is added to the input x. This can be written as:

$$y = F(x) + x$$

This reformulation makes it easier for the network to learn complex functions. If the residual function F(x) is zero then the output y is simply the input x. This means that the network can easily learn the identity function which is a good starting point for learning more complex functions.

2. **Shortcut Connections**

   ResNets use shortcut connections to implement residual learning. These connections skip over one or more layers in the network and add the input to the output of the skipped layers. This allows the network to directly propagate information from earlier layers to later layers.

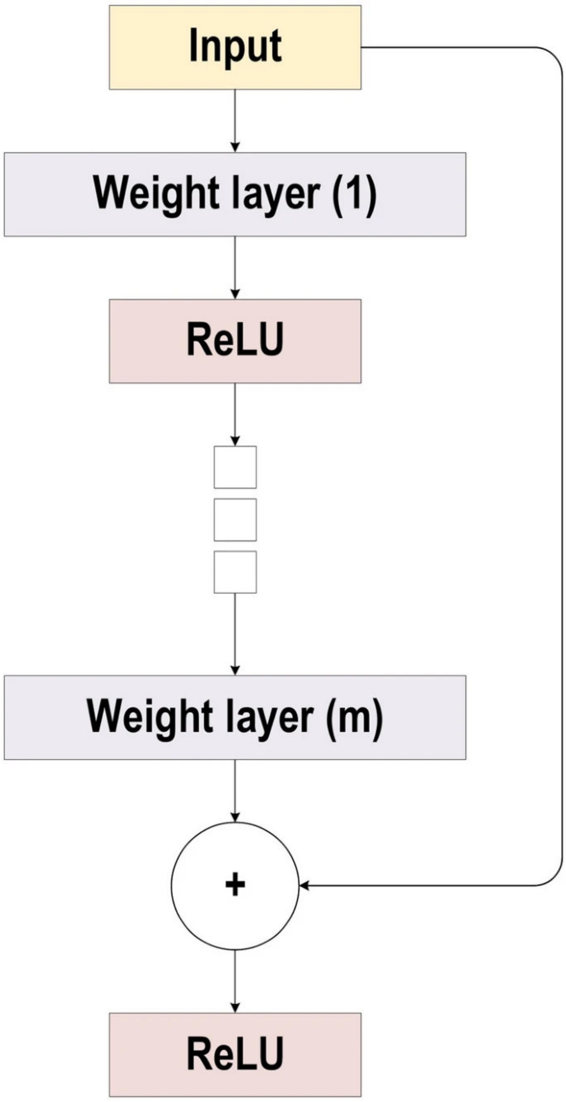

Figure 2.14: Residual learning: a building block. [17]

2.6 Challenges of DL and alternate solutions

[17]

In the realm of deep learning, numerous challenges are frequently contemplated. The most daunting ones are outlined below along with corresponding alternative solutions.

2.6.1 Lack of training data

Deep learning typically requires a substantial amount of data to develop a reliable performance model. As the quantity of data increases the likelihood of achieving a well-behaved performance model also rises. Usually the data available is adequate for creating a satisfactory performance model. Nonetheless there are occasions when there's a deficiency in data making direct application of deep learning challenging.

To effectively tackle this matter there are these proposed approaches:

2.6.1.1 Transfer learning

Transfer learning is a method in which an already developed model trained on one task with large volumes of data is repurposed or fine-tuned on a second related task on a small request dataset.

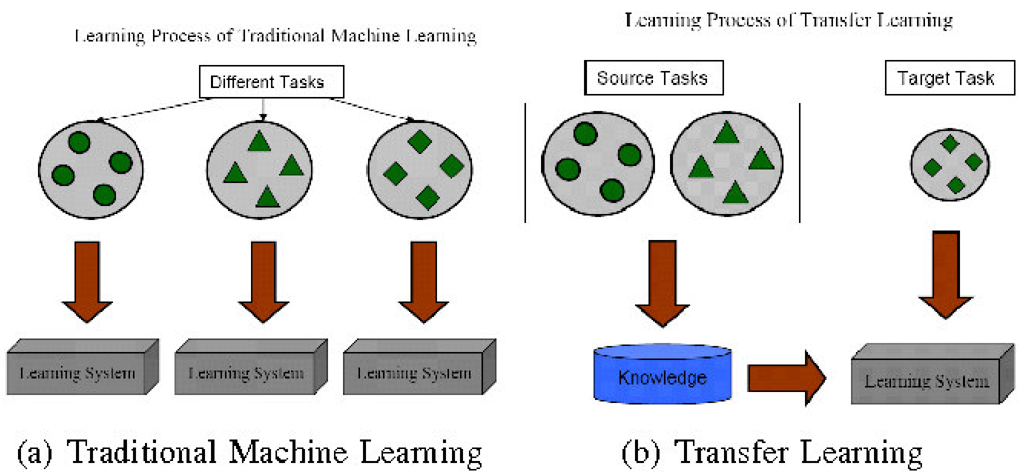

Figure 2.15: Different Learning Processes between Traditional ML and TL . [22]

2.6.1.2 Data augmentation

Data augmentation comprises a set of techniques aimed at enhancing both the characteristics and the volume of training datasets. It involves applying various transformations to the existing data samples to create modified versions while preserving the original label or class.

Here are some common data augmentation alternate techniques: Flipping ,Rotation,Translation.

2.6.2 Overfitting

Overfitting occurs when a model learns statistical patterns unique to the training dataset essentially memorizing irrelevant noise instead of capturing the signal.As an result it tends to exhibit reduced performance when applied to new datasets.
It becomes extremely good at being able to classify or predict on data that was included in the training sets but is not really good at classifying data that it wasn't trained on (test sets).[14]

To effectively tackle this matter there are these categories :
The initial category influences both the model's architecture and its parameters encompassing well-known techniques like weight decay, batch normalization and dropout.
The second category focuses on manipulating model inputs involving actions like data corruption and data augmentation.

2.6.2.1 Batch normalization

Batch normalization serves as an additional layer that dynamically normalizes the input values of layers that come after it.This method improves gradient flow across the network enables the use of higher learning rates and reduces the need for initialization .

2.6.2.2 Dropout

Dropout is a regularization technique where during training a random fraction of input units are temporarily set to zero effectively "dropping out" or "turning off" these units along with their connections. This helps prevent overfitting by forcing the network to learn more robust features. The dropped neuron will not be a part of back-propagation or forward-propagation. By contrast at test time no units are dropped out but the output values are scaled down to maintain expected values.[14]

2.6.3 Vanishing gradient problem

When using gradient-based learning and backpropagation approaches to train Artificial Neural Networks one of the biggest challenges they face is the vanishing gradient problem. The network's weights are iteratively updated during the training phase using the partial derivative of the error function and the current weight. A vanishingly small gradient on the other hand may prevent this weight updating from happening in some cases which can make the network stopped completely.
A contributing factor to this problem lies in the choice of activation functions such as the sigmoid function, which compresses a broad input range into a narrow output range. Consequently the derivative of the sigmoid function tends to be diminutive particularly when there is substantial input variation resulting in minor output changes.

To address these problem various techniques have been proposed including the use of alternative activation functions such as ReLU and its variants as well as more sophisticated initialization methods and optimization algorithms. These approaches aim to mitigate the diminishing gradient issue and facilitate more effective training of deep neural networks.

2.6.4 Exploding gradient problem

The Opposite to the vanishing gradient problem, Large error gradients are specifically accumulated during backpropagation wich cause the network's weights to be updated in a very large way that make the model losing its ability to learn effectively .
Some potential solutions include:

1. Implementing various weight regularization techniques.
2. Redesigning the architecture of the network model.

2.7 State of the art: related works on Brain Tumor detection or classification

At this momentous juncture, we find ourselves on the brink of delving into the evolution of science and artificial intelligence in the detection of gliomas, a form of brain cancer. Let us embark on this journey through the years, spanning from 2010 to 2023, witnessing the emergence of myriad innovations and challenges that have revolutionized patient care and early disease detection. The primary objective of this study is to review and comprehend the global strategies for classifying and detecting brain tumors developed during this period. [23]

2.7.1 MRI Brain Tumor Segmentation

Table 2.1: Summary of Brain Tumor Segmentation Techniques [23]

Year	Author	Technique & Method	Dataset Used	Performance Metrics
2010	Gordillo et al.	Region-based / Fuzzy logic structure utilizing MR image features and expert knowledge	NON & GBM & MEN	Accuracy 71% , 93%
2016	Pereira et al.	DL / CNN architecture with small three-by-three kernels	BRATS	DSC 88.00%
2017	Abbasi and Tajeripour	NN / Multistage approach involving contrast improvement, data reduction, LBP, and random forest classifier	MRI 3D images	Jaccard 87% and DSC , 93%
2018	Gupta et al.	Region-Based / CAD system using super pixels and FCM-clustering technique	Gliomas	Accuracy 98.00%
2019	Razzak et al.	DL / Two-pathway-group CNN architecture	BRATS	DSC 89.20%
2021	Karayegen and Aksahin	DL / Semantic segmentation approach using CNN for BRATS image datasets	BRATS	IoU 91.72%
2022	Ullah et al.	DL / Multiscale residual attention CNN (MRA-UNet)	BRATS-2020	DSC 98.18%
2023	Wisaeng and Sa-Ngiamvibool	region-based / Fuzzy Otsu thresholding morphology (FOTM) approach	Brain MRI images	Accuracy 93.77%

2.7.2 MRI Brain Tumor Classification Using ML

Classification of brain tumors using MRI images through machine learning has been extensively researched. This involves several key steps in the machine learning process, including data cleaning, feature extraction, and feature selection. Building a machine learning model based on labeled samples represents the final stage. Table 2.2 provides a summary of MRI brain tumor classification using machine learning techniques. [23]

Table 2.2: MRI brain Tumor Classification Using ML. [23]

Year	Author	Feature Extraction / Selection	Dataset Used	Classification
2010	El-Dahshan, E.-S.A.; Hosny, T.; Salem, A.-B.M.	DWT / PCA	70 brain MR images	ANN with acc 98% and KNN with acc 97%
2011	Zhang, Y.; Dong, Z.; Wu, L.; Wang, S.	wavelet / PCA	66 MR images	Back-propagation NN with acc 100%
2013	Sachdeva, J.; et al	Intensity and texture /PCA	428 T1 MR images from 55 individuals	ANN with acc 85.50%
2015	Arakeri and Reddy	Texture and shape / ICA	T1- and T2-weighted MR images of 550 patients	SVM with acc 99.09%
2020	Ullah, Z.; Farooq, M.U.; Lee, S.-H.; An, D.	DWT / Mean and standard deviation	brain MRI images obtained from the Harvard Medical School website	DNN with acc 95.8 %

2.7.3 MRI Brain Tumor Classification Using DL

Deep learning techniques have emerged as powerful tools for the classification of brain tumors using MRI images. Unlike traditional machine learning approaches, deep learning methods automatically learn hierarchical representations from raw data, eliminating the need for manual feature extraction. This allows deep learning models to capture complex patterns and relationships within the data, leading to improved classification accuracy. Table 2.3 and 2.4 summarizes the classification of brain tumors using deep learning techniques

Table 2.3: MRI brain Tumor Classification Using DL. [23]

Year	Author	Method	objective	Dataset Used	Performance Metrics
2015	Sultan et al.	Custom-CNN	divide the severity of gliomas into two categories: low severity or high severity, as well as multiple grades of severity (Grades II, III, and IV).	Publicly available datasets	Accuracy 96.00%
2018	Yang and Yan, Lin-Feng and Wang, Wen	AlexNet	classify gliomas (brain tumors)	131 patients with glioma	Accuracy 90.90%
2019	Sultan et al.	Custom-CNN	classify different kinds of brain tumors using two publicly available datasets . The first divides cancers into meningioma, pituitary, and glioma tumors. The other one distinguishes among Grade II, III, and IV gliomas.	Publicly available datasets	Accuracy 98.70%
2019	Rehman, A. et al	VGG16	describes three experiments that classified brain malignancies such as meningiomas, gliomas, and pituitary tumors using three designs of CNN	Brain tumor dataset from Figshare	Accuracy 98.69%
2020	Khan, H.A. et al	VGG-16, Inception-v3, ResNet-50	classify brain MRI scan images into malignant and benign	253 brain MRI images	Accuracy 96% 75% 89%
2020	Isunuri, B.V.; Kakarla, J.	Seven-Layer CNN	A seven-layer CNN was suggested to assist with the three-class categorization of brain MR images	Publicly available dataset	Accuracy 97.52%
2021	Ozcan, H., Emiroglu, B. G ,et al	AlexNet, GoogleNet, SqueezeNet	Accurate prediction of glioma grade	(50 LGGs, 54 HGGs)	Accuracy 97.10%
2021	Ruqian et al.	Custom-CNN	classify brain tumors	MRI training dataset and baseline validation dataset	ROC 82.89%

Table 2.4: MRI brain Tumor Classification Using DL (follows (table2.3)). [23]

Year	Author	Method	objective	Dataset Used	Performance Metrics
2021	El Hamdaoui, H.; et al	Multi-CNN Structure	for identifying and categorizing brain tumors using images from the risk of malignancy index.	BRATS	Precision 98.67% F1 score 98.06% Precision 98.33% Sensitivity 98.06%
2021	Kaur, T.; Gandhi, T.K	Alexnet	evaluate the performance of several pretrained CNNs for image classification tasks related to brain tumors.	Data from the clinical, Harvard, and Figshare repositories	Accuracy 100.00%
2022	Khazaee et al	EfficientNetB0	Evaluation and classification of human brain gliomas using sequences from MR images	BRATS-2019	Accuracy 98.80%
2022	Amou, M.A.; Xia, K.; Kamhi, S.; Mouhafid, M.	Custom-CNN	Improving the performance of neural networks in classifying different types of brain cancer by classifying 3064 images of different types of brain tumors	3064 T1 images	Accuracy 98.70%
2023	Deepa, S.; Janet, J.; Sumathi, S.; Ananth, J.P.	CNN	for the segmentation and classification of brain tumors.	BRATS-2018	Accuracy 92.10%

2.8 Conclusion

In the exploration of machine learning and its evolution into the latest advancements in deep learning techniques, a detailed analysis begins from the fundamentals, starting with machine learning types such as supervised, unsupervised and reinforcement learning. As the discussion Continues, attention turns towards artificial neural networks (ANNs), Explaining their architecture and training processes, paving the way for understanding deep learning techniques.

The discussion turn to the realm of deep learning, focusing specifically on convolutional neural networks (CNNs) and their pivotal role in image classification tasks. Known CNN models like AlexNet, VGGNet, Inception, and ResNet are deeply Studied, highlighting their advances and contributions to the field. Additionally, the significance of datasets such as ImageNet and competitions like ILSVRC in driving advancements in image classification is underlined.

Additionally, difficulties that may arise when training DL models, particularly CNN models, are discussed, along with alternative approaches that may be used to resolve these problems.

Moreover, these insights will serve as a foundation for our work on utilizing Deep Learning for the classification of cerebral gliomas (HGG & LGG) based on MRI.

Chapter 3

Deep learning for Gliomas classification : Principles and applications

3.1 Introduction

In this chapter we will delve into the study and Layout of a deep learning model for the classification of Gliomas. A comprehensive description of the dataset preprocessing steps, model architecture, and training and evaluation procedures will be provided.. Our goal is to develop a robust model capable of accurately classifying different types of gliomas using data from the well-known BraTS dataset.

We will explore the data preprocessing steps required to prepare the data for the model and the various techniques used in building the model such as ResNet 50 layers, flattening ,dropout, batch normalization and dense layers. in addition we will compare the performance of ResNet 50 with different systems to understand its strengths and weaknesses in gliomas classification.

Furthermore we will detail how to load and preprocess the data in a Colab environment along with the steps involved in defining, freezing layers, and compiling the model. The training process and evaluation of the model will be discussed including the loss function , accuracy metrics and the results of the model training. last we will summarize the general flow of the proposed approach in a block diagram where it shows the steps involved in training the model and using it for prediction.3.9

In addition we will test the model and develop a user interface using the Django framework to create an interactive front-end that facilitates the practical application of the model.

3.2 Dataset description

3.2.1 BraTS Dataset

The images used in the study are from BraTS _2019 with BraTS _2018 following images of gliomas (High Grade Glioma (HGG) and Low Grade Glioma (LGG)). This dataset is available on Kaggle and contains over 1400 images of HGG and LGG gliomas. There are images for training and for validation, where 80 % of the images is for training and only 20 % is for validation.

3.2.2 Preprocessing 1

To preprocess the dataset for deep learning, some arrangements were made as shown below. First of all, the images with NII format were transformed into the JPG format in order to improve their manageability. We then split the data into training and validation sets. We also reshaped the images from gray-scale to rgb so that they could be fed into our models. Also, we normalized the pixel values of the images to a scale of 0-1 (we added this step in our models as an additional layer). This step is critical for two reasons, firstly, to resize the images to a common size and secondly to normalize the pixel values, which enhances the deep learning algorithms.

3.3 Model Architecture

In this section we provide a detailed description of the deep learning model used in the study to classify gliomas to HGG and LGG . We used the BraTS_Dataset which contains images of gliomas hgg and lgg . We used the ResNet 50 (VGG16 Xception)architecture as the base model which was pre-trained on the ImageNet dataset. we froze the weights of the layers of the base model and trained the remaining layers on our dataset. The ResNet 50 (VGG16 & Xception) consists of the following layers:

3.3.1 ResNet 50

The ResNet layer is the base model that was pre-trained on the ImageNet dataset. it consists of multiple convolutional layers that extract features from the input image.

3.3.2 Flatten

The Flatten layer in TensorFlow / Keras model is used to flatten the multi-dimensional array output from of preceding layers and pass on the resultant one dimensional flattened array in order to fed into dense layers that require input in a flat vector format

3.3.3 BatchNormalization

The ‘BatchNormalization‘ layer in TensorFlow/Keras Improves the performance and stability of deep neural networks by normalizing the outputs of previous layers. this standardization accelerates training stabilizes the learning process and reduces overfitting by rescaling and shifting the data using learnable parameters.

3.3.4 Dropout

The Dropout layer randomly drops out a fraction of the neurons in the previous layer during training to prevent overfitting.In our study, we used dropout with a rate of 0.6.

3.3.5 Dense

The Dense layer is a fully connected layer that takes the output from the previous layer as input and applies a rectified linear unit (ReLU) activation function. we used 512 neurons in this layer.

3.3.6 Dense (Output)

The final Dense layer is a fully connected layer that takes the output from the Dense(512) layer as input and applies a softmax activation function. We used 2 neurons in this layer, which corresponds to the number of classes in our dataset.

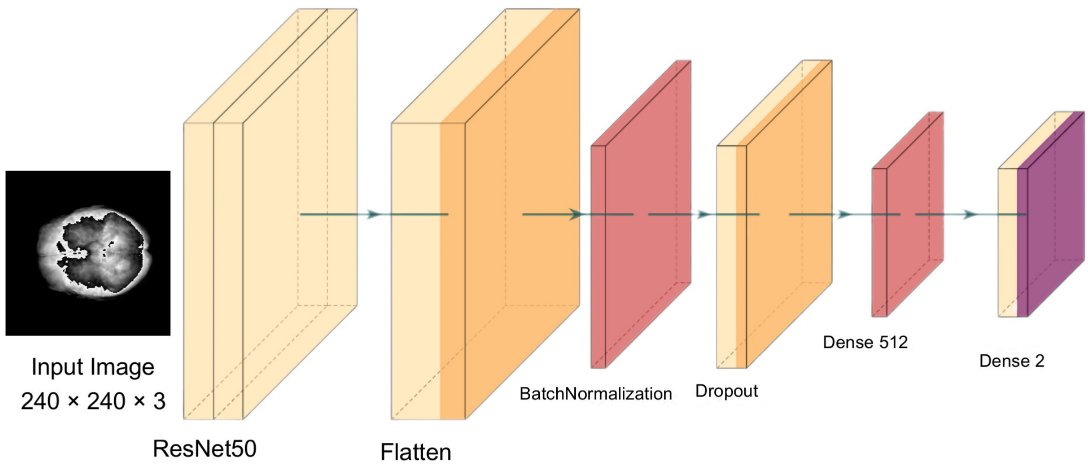

Figure 3.1: Model’s Architecture

3.4 Code Source

3.4.1 Dataset on Colab

We downloaded and set up the BRATS 2018/2019 dataset from Kaggle on Google Colab. First, the kaggle.json file containing authentication information is uploaded, then a hidden folder .kaggle is created, and the file is copied into it with its permissions adjusted. After that, the dataset is downloaded using Kaggle commands and unzipped to be ready for use.

```
# download of dataset
from google.colab import files
# Upload kaggle.json file
uploaded = files.upload()
# Make directory for Kaggle
!mkdir ~/.kaggle
# Copy kaggle.json to the Kaggle directory
!cp kaggle.json ~/.kaggle/
# Change the permissions of the file
!chmod 600 ~/.kaggle/kaggle.json
# Download the BRATS dataset
!kaggle datasets download -d memoiremw/datamix
# Unzip the downloaded dataset
!unzip datamix.zip
```

Algorithm 3.1: Python code for downloaded and set up the dataset from Kaggle on Google Colab

3.4.2 Data Loading

we have uploaded our `training` and `validation` datasets present at their respective directories on Colab using TensorFlow. It resizes the images to 240×240 pixels and sets the batch size to 10. The images are loaded from the "/content/DATA/train" directory for the training set and from the "/content/DATA/valid" directory for the validation set, preparing the data for use in training deep learning model

```
train_dataset = tf.keras.preprocessing.
   image_dataset_from_directory(
    "/content/DATA/train",
    image_size=[240, 240],
    batch_size=10,
)
val_dataset = tf.keras.preprocessing.
   image_dataset_from_directory(
    "/content/DATA/valid",
    image_size=[240, 240],
    batch_size=5,
)
```

Algorithm 3.2: Python code for Data Loading

3.4.3 Preprocessing 2

For deep learning model preparation we used TensorFlow to organize train and validation dataset. We defined two data classes, namely ‘HGG’ and ‘LGG’ and then converted their labels into one-hot encoding format using ‘tf.one_hot‘ function. After that, I extended this function to each element in the datasets by using ’map ’to change the form of the labels that is recognizable by the model. It made performance optimizable whenever operations were performed concurrently by employing AUTOTUNE. The purpose of this step was to clean the data so that it is in a form most suitable for the model training stage.

```python
AUTOTUNE = tf.data.experimental.AUTOTUNE
class_names = ['HGG', 'LGG']
train_dataset.class_names = class_names
val_dataset.class_names = class_names
NUM_CLASSES = len(class_names)

def one_hot_label(image, label):
    label = tf.one_hot(label, NUM_CLASSES)
    return image, label

train_dataset = train_dataset.map(one_hot_label,
    num_parallel_calls=AUTOTUNE)
val_dataset = val_dataset.map(one_hot_label, num_parallel_calls=
    AUTOTUNE)
```

Algorithm 3.3: Python code for one-hot encoding format

Here we processed the images in the training and validation datasets. we converted single-channel (grayscale) images to three-channel (rgb) images using ‘tf.image.grayscale_to_rgb‘. Subsequently we filtered out any images that did not have three channels ensuring that all images in both datasets had the same number of channels. we used the ‘map‘ and ‘filter‘functions to reach this preprocessing step before training the model.

```python
def preprocess_image(image, label):
    if image.shape[-1] == 1:
        image = tf.image.grayscale_to_rgb(image)
    return image, label

train_dataset = train_dataset.map(preprocess_image,
    num_parallel_calls=AUTOTUNE).filter(lambda x, y: tf.shape(x)
    [-1] == 3)
val_dataset = val_dataset.map(preprocess_image,
    num_parallel_calls=AUTOTUNE).filter(lambda x, y: tf.shape(x)
    [-1] == 3)
```

Algorithm 3.4: Python code for grayscale$_t o_r gb$

3.4.4 Models Definition

The pretrained_model_1 , 2 and 3 variables is created by instantiating the ResNet50 model , Xception model and VGG16 model respectively with pre-trained weights from the ImageNet dataset. the include_top parameter is set to False to exclude the fully connected layers at the top of the network. The input_shape is set to (240, 240, 3) to match the input image dimensions.

```
resnet_model = Sequential()
pretrained_model_1 = tf.keras.applications.ResNet50(include_top=False,
                    input_shape=(240,240, 3),
                    pooling='avg',
                    classes=2,
                    weights='imagenet')
```

Algorithm 3.5: Python code for Model Definition

3.4.5 Freezing Layers and Model Architecture

The layers of the `pretrained_model` are frozen by setting their `trainable` attribute to False. this ensures that these layers' weights are not updated during training. The final model architecture is created by stacking the `pretrained_model` with a Flatten layer , a dropout layer with a dropout rate of 0.6 , a BatchNormalization layer , a dense layer with 512 units and ReLU activation and a dense layer with 2 units (corresponding to the number of classes) and softmax activation.

```
for layer in pretrained_model_1.layers:
  layer.trainable=False
resnet_model.add(pretrained_model_1)
resnet_model.add(tf.keras.layers.Flatten())
resnet_model.add(tf.keras.layers.BatchNormalization())
resnet_model.add(tf.keras.layers.Dropout(0.6))
resnet_model.add(tf.keras.layers.Dense(512, activation='relu'))
resnet_model.add(tf.keras.layers.Dense(2, activation='softmax'))
```

Algorithm 3.6: Python code for Freezing Layers and Model Architecture

3.4.6 Model Compilation

The model is compiled using the Adam optimizer with a learning rate of 0.001. The loss function is set to `'tf.losses.CategoricalCrossentropy()'` since the labels are provided as one-hot encoded vectors. The accuracy metric is also specified for evaluation.

```
resnet_model.compile(
        optimizer=Adam(learning_rate=0.001),
        loss=tf.losses.CategoricalCrossentropy(),
        metrics=[tf.keras.metrics.AUC(name='auc')])
```

Algorithm 3.7: Python code for the Model Compilation

3.4.7 Model Training

A list of callbacks is defined to monitor the training process. the `EarlyStopping` callback stops the training if the validation loss does not improve for ten consecutive epochs. The `ModelCheckpoint` callback saves the model with the lowest validation loss during training. the `TensorBoard` callback logs the training progress for visualization.

```
my_callbacks = [
    tf.keras.callbacks.EarlyStopping(patience=10),
    tf.keras.callbacks.ModelCheckpoint(filepath='/kaggle/working
       /model.{epoch:02d}-{val_loss:.2f}.h5'),
    tf.keras.callbacks.TensorBoard(log_dir='./logs'),
]
history = resnet_model.fit(
    train_dataset,
    validation_data=val_dataset,
    epochs=35,
   callbacks=my_callbacks
)
```

Algorithm 3.8: Python code for the Model Training

The model is trained using the `fit()` method with the `train_dataset` as the training data, `val_dataset` as the validation data, 35 epochs, and the defined callbacks. The training history is stored in the `history` variable for further analysis.

Optimizer	Adam
Learning Rate	0.001
Loss Function	losses.CategoricalCrossentropy()
Regularization Techniques	Early Stopping
Model Checkpointing	Yes
Epochs	35
Batch Size	10

Table 3.1: Training Details

3.5 Training and Evaluation

3.5.1 Overview of the Training Process

In this study, we used deep learning models to classify gliomas as HGG or LGG. The training included data processing and optimization techniques.

3.5.2 Loss Function and Accuracy Metric

the model was compiled with the Adam optimizer with a learning rate of 0.001..the loss function used was losses.CategoricalCrossentropy(), the accuracy metric was employed to evaluate the model's performance.

3.5.3 Results of Model Training and Evaluation

The model was trained for 35 epochs in total with early stopping and model checkpoint callbacks as well. The training process yielded the following results:

Metric	Train	valid
Accuracy	99.54%	98.99%
Precision	-	96%
Recall	-	95%

Table 3.2: Model performance metrics

The plot below explains the change in both train and validation accuracy and loss during the training epochs:

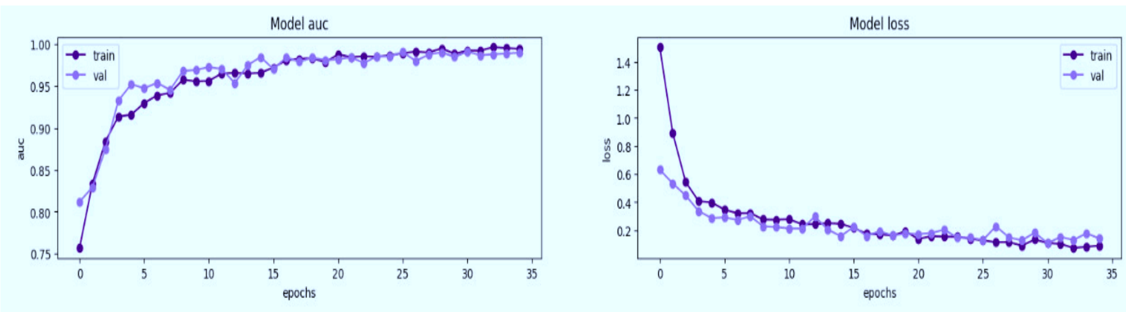

Figure 3.2: Train and Validation Loss and Train and Validation Accuracy

to summarize the results of model training and evaluation we present a table to show the accuracy and loss of the model during the training and validation process. The results are shown in Table 3.3.

Metric	Training	Validation
Accuracy	0.9945	0.9899
Loss	0.0914	0.1423

Table 3.3: Training and validation accuracy and loss

3.5.4 Analysis of Model Performance

In this model, the accuracy level was much higher, reaching 99.45% on the training set whereas on test set 98.99% and this show batter generalization ability. The precision and the recall also turned out to be good at 96%, 95% and this statistic gave an impression that the proposed model was capable of classifying gliomas as either HGG or LGG.

However there may still be potential sources of error and areas for Improvement. for exemple the model might gain from foster fine-tuning of the hyperparameters such as the learning rate and the number of layers in the neural network. also incorporating more diverse and representative data samples could further Improve the model's Effectiveness.

3.5.5 Model Predictions for gliomas classification

Results To classify gliomas into HGG and LGG using images as input, we report the results of our deep learning model in this section. We tested the performance of our model on many images of gliomas, and reached with an accuracy of 98%. Here is a figure to illustrate the performance of our model a visual example of 6 sample images along with their true label and predicted label from our model.

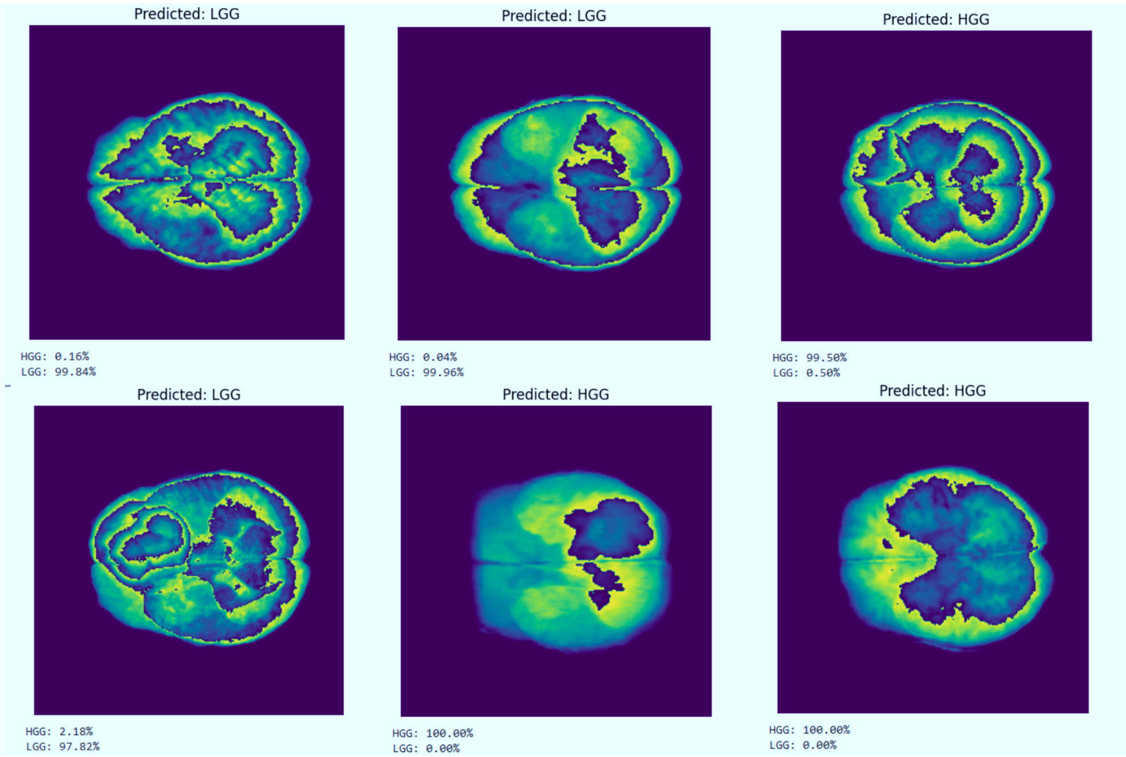

Figure 3.3: predicted label from our model

As shown in Figure 3.3, our model was able to accurately predict the calss of gliomas (HGG or LGG) for each of the six sample images. The first image, which shows a LGG Gliomas , was correctly identified by our model as LGG With probability 99.84%. The second image, which shows also a LGG Gliomas , was correctly identified by our model as LGG With probability 97.82% . the fourth image, which shows a HGG Gliomas , was correctly identified by our model as HGG With probability 100% .Finally,we say that our model was able to correctly classify all six images with a high probability of them belonging to the appropriate category

3.6 Realization

In this section we provide a comprehensive overview of our work in developing a Django web application designed to test our ResNet model and create an interactive user interface.This interface will facilitate the practical application of the model by allowing users to easily upload MRI images and receive classification results. By integrating our machine learning model into a web application we aim to provide an accessible and user-friendly tool for classifying Gliomas into High-Grade Gliomas (HGG) or Low-Grade Gliomas (LGG) with the percentage of each.

3.6.1 Django Environment

Django is a powerful web framework for building efficient and scalable web applications built on Python. It is free and open source, it offers a plethora of features that make it an ideal choice for web development.[47]
For our project we used Django version 3.2.25 which provides a stable and feature-rich platform for development of our web application.

3.6.2 Our Web Application

Our Django web application is designed to provide a seamless interface for classifying MRI images of Gliomas. It integrates the pre-trained ResNet model to predict whether the Gliomas is high-grade or low-grade based on the uploaded image.
The application divided into the below several categories : Home page, About Us Page, Our Services Page, Registration Page, Login Page and Classification Page.

1. **Home Page**

   In the home page of our "🧠 Brain Care" web application we provide a professional introduction to our platform. The page features a clean and modern design contain a header that includes our logo and navigation links to essential sections such as "Home" "About" and "Services" along with a "Login" button for user access.

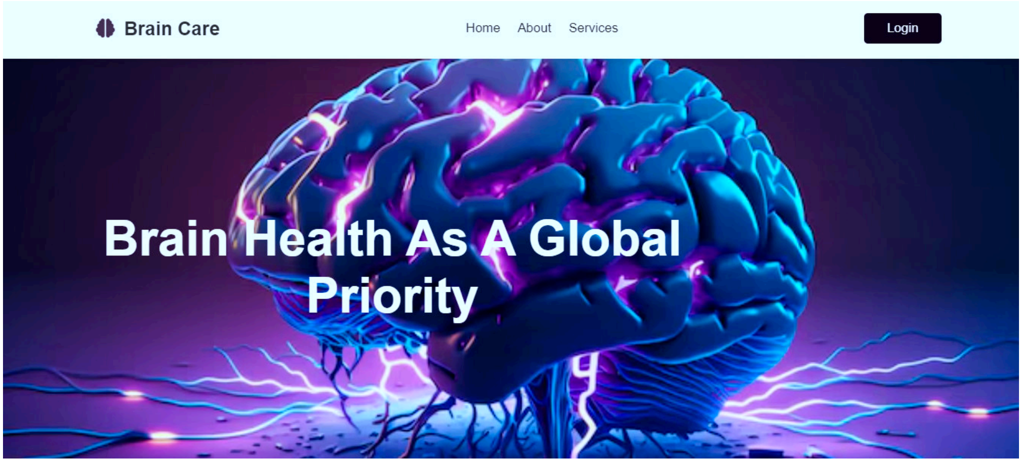

Figure 3.4: Home Page

2. **Login Page**

   For the "Login" page of our "🧠 Brain Care" web application, we ensure secure and user-friendly access to our advanced diagnostic tools and services, it offers two type of inputs email and password.

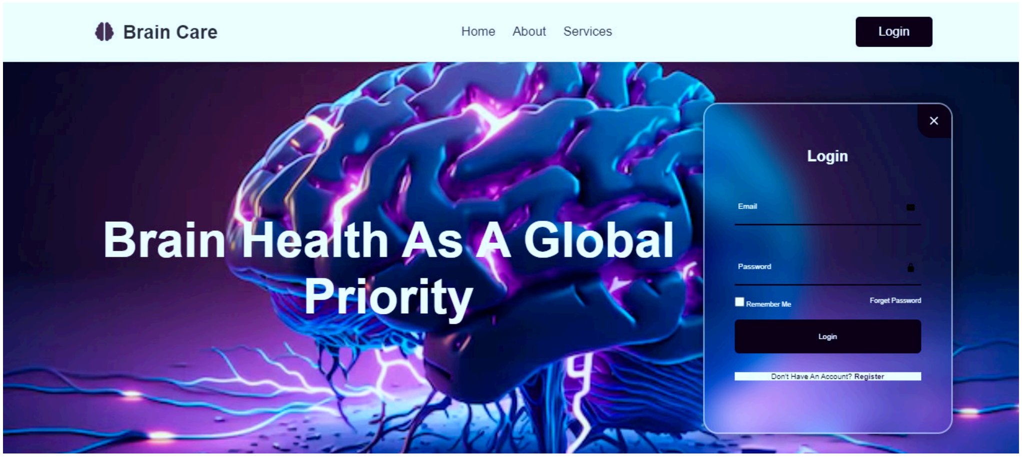

Figure 3.5: Login Page

3. **Classification Page**

   For the "Classification" page of our "🧠 Brain Care" web application, we offer an advanced interface where users can upload MRI images and button to classify it using our pre-trained model.

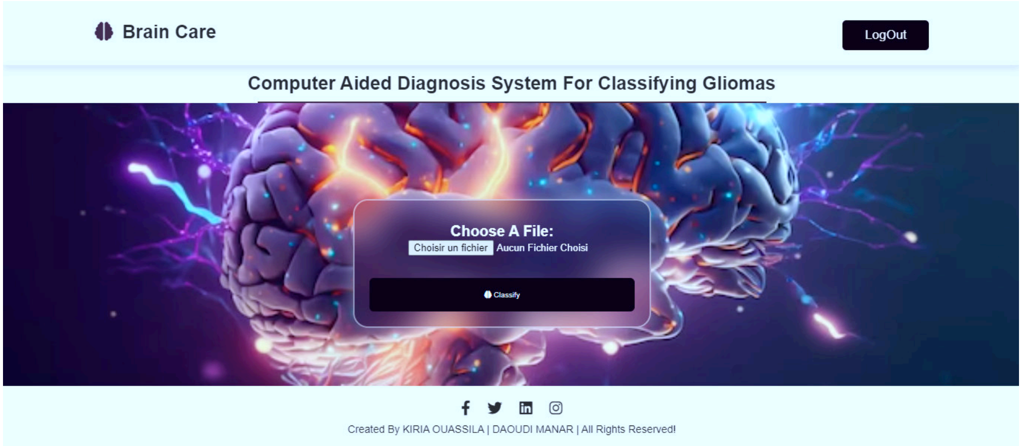

Figure 3.6: Classification Page

Upon clicking the button the form for uploading the image disappears and the classification results are displayed on the same page. These results include the predicted gliomas type and the corresponding percentages for high-grade gliomas and low-grade gliomas . A "Refresh" button is also provided allowing users to reset the page and display the upload form again for a new classification.
Figure 3.7 and Figure 3.8 illustrate examples of the system's capability to accurately distinguish between different gliomas grades.

Figure 3.7: System Prediction of Low-Grade Gliomas

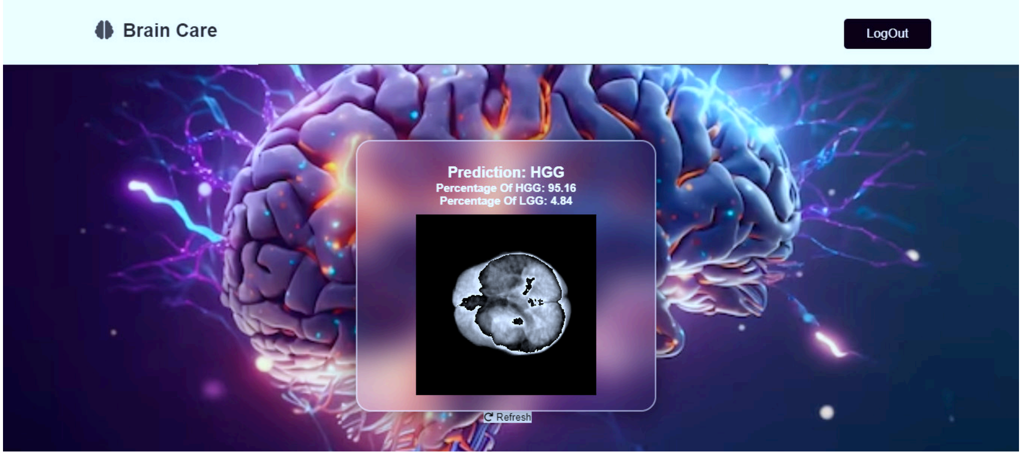

Figure 3.8: System Prediction of High-Grade Gliomas

3.7 Discussion

3.7.1 Approach Overview

Figure 3.9 illustrates the block diagram of the proposed approach for gliomas classification.

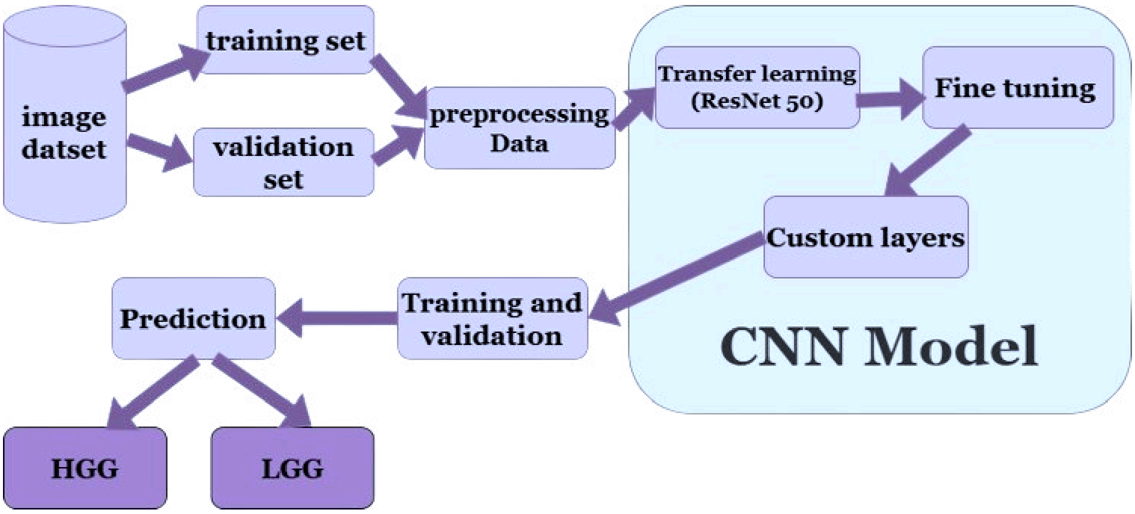

Figure 3.9: Block diagram of the proposed approach for gliomas classification.

This block diagram outlines the overall flow of the proposed approach, showcasing the steps involved in training a model for gliomas classification and using it to make predictions on new, unseen gliomas images.

3.7.2 Interpretation of Results

The results of our study indicate that the deep learning model we developed is highly effective in classifying gliomas . With a train accuracy of 99.81% and a test accuracy of 98.80%, the model demonstrates a strong ability to generalize to new data. These results provide a positive answer to our first research question: deep learning techniques can indeed be used to accurately classify gliomas.

The precision and recall scores of 98.50% , 97.30% further support the model's effectiveness. High precision indicates that the model is correctly identifying the true positive cases, while high recall suggests that it is capturing most of the true positive cases. This balance between precision and recall is crucial for a reliable gliomas classification system, as it ensures that the model is both accurate and comprehensive in its predictions.

3.7.3 Comparison with Other Approaches

In our implementation we used the ResNet architecture and conducted comparative experiments with VGG and XCeption models. we evaluated the performance of these models by varying the number of epochs to 35, 50, and 60. In all tested configurations ResNet consistently demonstrated superior performance.

We used the same architecture for all models in our experiments which included a Flatten layer a Dropout layer with a rate of 0.6 a Batch Normalization layer a Dense layer with 512 units and ReLU activation and a final Dense layer with 2 units and softmax activation for classification. ResNet proved to be the most robust and efficient in handling our specific application maintaining higher accuracy and performance metrics compared to vgg and xception models across all tested epochs.

Table 3.4: ResNet vs Xception vs Vgg

epoches	models	accu train	accu valid
35	ResNet	99.45%	98.99%
	Xception	96.23%	94.39%
	vgg	97.70%	95.04%
50	ResNet	99.64%	98.63%
	Xception	98.34%	97.04%
	vgg	98.01%	96.14%
60	ResNet	99.84%	97.24%
	Xception	98.75%	97.65%
	vgg	98.53%	96.46%

Compared to previous studies in the classification of gliomas into HGG and LGG our study outperformed many such as the study by Ozcan H. Emiroglu B. G., et al. in 2021 which used the AlexNet model and achieved an accuracy of 97.10%. In our study, we achieved an accuracy of 99% demonstrating the superior efficiency and effectiveness of our approach.These previous studies were discussed in detail at the end of Chapter 2.

3.7.4 Limitations and Future Research

Although we obtained good results, our study has some limitations and potential biases that should be recognized. The first shortcoming which needs to be overcame is concerned with the limitation of study's dataset in terms of not covering all the gliomas cases and their various types. Increasing diversity of samples in the dataset might enhance the performance and generalization of the model.

Second, the choice of the ResNet architecture, while effective, may not be the optimal solution for this task. Future research could explore other deep learning architectures, such as AlexNet or Inception, to determine if they offer better performance or efficiency.

Additionally, our model may be susceptible to biases present in the training data, such as over-representation of certain category (HGG or LGG)or under-representation of other. Addressing these biases through data balancing techniques or incorporating additional data sources could further improve the model's performance.

Lastly ,Future studies are poised to revolutionize the identification and classification of gliomas through advancements in imaging technology and artificial intelligence. these studies may leverage cutting-edge techniques ,such as multimodal imaging combining MRI ,PET scans, and advanced radiomics analyses.By integrating these technologies with deep learning models, researchers can potentially achieve more precise delineation of tumor boundaries, characterization of tumor heterogeneity and prediction of patient outcomes. such as advancements hold promise for optimizing treatment strategies.

3.8 Conclusion

In this study, we developed a deep learning model for gliomas classification and achieved high accuracy and generalization performance. our model which is based on the ResNet 50 architecture and leverages transfer learning techniques outperformed traditional machine learning methods and many existing deep learning-based approaches.

we began by introducing the principles and applications of deep learning in gliomas classification. Our dataset including the BraTS dataset was thoroughly described and we detailed our preprocessing steps to prepare the data for modeling.

We discussed the model architecture highlighting the layers and configurations used such as Flatten, Dropout ,BatchNormalization and Dense layers. The code implementation was presented, including steps for dataset loading, preprocessing, model definition, and training.

Our training and evaluation section provided an overview of the training process, the loss function, and accuracy metrics used. the results of model training and evaluation were presented, including the performance analysis. Model predictions for gliomas classification were also discussed.

In the discussion section we interpreted our results compared our approach with other methods and acknowledged the limitations and potential biases in our study. We also suggested directions for future research to further improve glioma classification.

In conclusion our study highlights the efficacy of deep learning and transfer learning in glioma classification presenting a robust model that can support clinical decision-making and treatment planning.

Conclusion and Perspectives

In this thesis we tackled the challenge of classifying gliomas (HGG and LGG) using deep learning particularly Convolutional Neural Networks, the primary objective of this research was to develop a highly accurate and efficient model for automated gliomas diagnosis with the ultimate goal of enhancing clinical decision-making and improving patient outcomes.

Through the application of deep learning algorithms especially convolutional neural networks within the ResNet 50 architecture we achieved significant advancements in gliomas classification, our model utilizing the BraTS dataset and transfer learning demonstrated a remarkable accuracy rate which underscores the potential of deep learning as a transformative tool in medical image analysis providing a reliable and automated approach for gliomas classification.

An important aspect of this research was the development of a user-friendly web application using the Django framework, this interface facilitates the practical application of our model by allowing users to easily upload MRI images and receive classification results.

while our research has shown promising results it is essential to acknowledge certain limitations and challenges encountered, one significant limitation is the computational resources required for training and deploying deep learning models. High-performance hardware is necessary which may not be accessible in all clinical settings potentially limiting the model's applicability, additionally the preprocessing and normalization of MRI images to standardize data input is a time-consuming process that can introduce variability and affect model performance.

Looking forward several promising directions for future research in gliomas classification using deep learning are evident. Exploring novel CNN architectures such as 3D CNNs or capsule networks holds potential to capture spatial and contextual information more effectively enhancing the accuracy of glioma classification, additionally integrating hybrid deep learning models that combine CNNs with other architectures like Recurrent Neural Networks or Transformer mod- els could improve the model's ability to capture both spatial features from images and sequential patterns from clinical data thereby advancing the state-of-the-art in medical imaging analysis.

In conclusion this research has demonstrated the substantial potential of deep learning techniques in gliomas classification through MRI image analysis. while further advancements are necessary to overcome existing limitations and broaden the scope of the model, the findings of this study contribute to the ongoing efforts in medical diagnostics, healthcare innovation and the enhancement of patient care.

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Abstract

Gliomas are serious diseases that require early detection and diagnosis due to their seriousness and its great impact on health. In this thesis, we conducted a comprehensive research on gliomas and their classification as well as the tools and techniques used to classify these tumors.

To perform this task several Convolutional Neural Network models were used including ResNet50, VGG16 and Xception which were trained on the BraTS2018 dataset added to BraTS2019 in order to overcome the challenge of data scarcity. The modeling architecture consists of the base models (ResNet50, VGG16, Xception) with additional layers such as Dense Layers, Batch Normalization and Dropout that was used to avoid overfitting. The Adam optimizer was used to train the models while Sparse Categorical Crossentropy Loss and Accuracy metrics were used to evaluate them.

The results of our work were very promising as it showed the superiority of ResNet50 with a training accuracy of up to 99% and a validation accuracy of 98% compared to VGG16 which gave 97% in training accuracy and 95% in validation accuracy which also gave Xception a training accuracy that reached 96% and Validation accuracy equal to 94% During 35 epoch. This makes the ResNet50 model a reliable choice for classifying gliomas.

In general our thesis highlights the importance of using technology such as deep learning in the health field to help doctors and patients and reduce the impact of gliomas. The results of this research open the way for the development of new automatic diagnostic systems and provide a solid basis for future research in this direction.

Keywords: Gliomas, classification, Convolutional Neural Network, VGG16, XCEPTION, RESNET50, BraTS2018, BraTS2019, Dense Layer, Batch Normalization, Dropout, Adam optimizer,Sparse Categorical Crossentropy Loss, Accuracy.

Résumé

Les gliomes sont des maladies graves qui nécessitent une détection et un diagnostic précoces en raison de leur impact sur la santé. Dans ce mémoire, nous avons mené une recherche exhaustive sur les gliomes et leur classification ainsi que les techniques utilisées pour classifier ces tumeurs.

Pour la classification de ces tumeurs, plusieurs modèles CNNs ont été utilisés, notamment VGG16, Xception et ResNet50, qui ont été entraînés sur notre base d’images BraTS2018 et BraTS2019 .Nous avons utilisées trois modèles de base (VGG16, Xception, ResNet50) avec des couches supplémentaires telles que Dense Layers, Batch Normalization et Dropout qui ont été utilisées pour éviter le surapprentissage. L’optimiseur Adam a été utilisé pour entraîner les modèles, tandis que les mesures de perte et de précision ont été utilisées pour les évaluer.

Les résultats de notre travail étaient très prometteurs et ils ont montrés a la fiabilité de ResNet50 pour la classification des gliomes avec une précision d’apprentissage allant jusqu’à 99% et une précision de validation de 98% par rapport : à VGG16 qui a donné 97% de précision d’apprentissage et 95% de précision de validation et à Xception qui a donné une précision d’apprentissage de 96% et une précision de validation égale à 94% Pendant 35 époque.

Notre travail montre l’importance d’utiliser les technologies de l’apprentissage profond dans le domaine de la santé pour l’aide au diagnostic médical. Les résultats de ce travail ouvrent la voie au développement d’autres systèmes de diagnostic automatique et fournissent une base pour les futures recherches dans ce sujet.

Mots-clés : Gliomes, classification, VGG16, XCEPTION, RESNET50, BraTS2018, BraTS2019, Couche Dense, Abandon, Optimiseur Adam, Précision.