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Dedication

I dedicate this work to my parents:

May they find here the testimony of my deep gratitude and acknowledgment their support and their prayers throughout my studies, their confidence.

To my dear fiance whose unwavering support, encouragement.

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BARKAT AYA

ملخص

يساهم التعلم العميق بشكل كبير في تبسيط وتنظيم حياتنا اليومية وصحتنا. مؤخراً، بدأ الأطباء في استخدام هذه التقنيات لعلاج أورام الدماغ بفضل قدراتها القوية في تحليل البيانات. يقترح هذا البحث نظاماً للكشف عن وتصنيف أورام الدماغ باستخدام نماذج التعلم العميق المتقدمة. باستخدام قاعدة بيانات ر٣٥س التي تحتوي على صور رنين مغناطيسي مصنفة إلى الورم الدبقي، الورم السحائي، الورم النخامي، وعدم وجود ورم، قمنا باختبار نماذج ضسته٥٠ط٢، وشبِلتط٢، ونستا١٦٩، بالإضافة إلى نموذجين مركبين. أظهرت النتائج دقة وكفاءة عالية في تصنيف أورام الدماغ.

كلمات مفتاحية: الاورام الدماغية، تصنيف الصور، التعلم العميق، الذكاء الاصطناعي، التصوير الطبي.

Abstract

Deep learning greatly enhances our daily lives and health. Recently, medical professionals have used these techniques to treat brain tumors due to their strong data analysis capabilities. This research proposes a system for detecting and classifying brain tumors using advanced deep learning models. Using the Br35H dataset with MRI images classified into glioma, meningioma, pituitary tumor, and no tumor, we tested ResNet50V2, MobileNetV2, DenseNet169, and two composite models. The results showed high accuracy and efficiency in classifying brain tumors.

Key words: *Brain tumor, image classification, deep learning, artificial intelligence, medical imaging.*

Résumé

Le deep learning améliore notre vie et notre santé. Récemment, des professionnels de la santé ont utilisé ces techniques pour traiter les tumeurs cérébrales grâce à leurs capacités d'analyse de données. Cette recherche propose un système de détection et de classification des tumeurs cérébrales avec des modèles de deep learning avancés. En utilisant le jeu de données Br35H et les modèles ResNet50V2, MobileNetV2, DenseNet169 et deux modèles composites, les résultats ont montré une grande précision et efficacité dans la classification des tumeurs cérébrales.

Mots clés : *les tumeurs cérébrales, classification d'images, apprentissage profond, intelligence artificielle, imagerie médicale.*

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List of Abbreviations

MRI: Magnetic Resonance Imaging
AI: Artificial Intelligence
DL: Deep Learning
ML: Machine Learning
CNN: Convolutional Neural Networks
TL: Transfer Learning
PET: Positron Emission Tomography
SPECT: Single-Photon Emission Computed Tomography
DT: Decision Trees
SVM: Support Vector Machine
KNN: K-Nearest Neighbors

General Introduction

Brain tumors represent one of the most severe and life-threatening types of cancer, requiring prompt and accurate identification for efficient treatment develop strategies. Traditional methods for diagnosis, like magnetic resonance imaging (MRI) and computed tomography (CT) scans, heavily depend on the expertise of radiologists. Despite being efficient, this manual interpretation procedure is frequently lengthy and prone to human mistakes, which could lead to delays in crucial treatment determinations and impact patient results. In recent years, the emergence of artificial intelligence (AI) and machine learning (ML) has contributed notable progress to the realm of medical diagnostics. Of these advancements, deep learning (DL) emerges as a notably potent instrument for audit medical images. Specifically, deep learning models, particularly convolutional neural networks (CNNs), have exhibited extraordinary capacities in tasks such as image classification, encompassing the intricate domain of medical image analysis [1, 2, 3, 4].

This study examines the utilization of integrated deep learning frameworks in the identification of brain tumors, with the goal of improving diagnostic precision and effectiveness [5, 6]. The strategy capitalizes on the capabilities of various CNN architectures—including ResNet50V2, MobileNetV2, and DenseNet169—to establish a resilient and all-encompassing diagnostic instrument [7]. Through the fusion of these varied frameworks, the investigation aims to harness their complementary attributes, thereby enhancing the overall efficiency of the brain tumor identification system.

The first chapter presents an overview on medical imaging and its importance for automated helping systems in healthcare [8]. Also, this chapter introduces the theoretical background of machine learning and explain the fundamental concepts associated with deep learning for medical image classification [9, 10]. We explain also the idea involved with deep learning for our proposed system, as well as the influence of AI in medical imaging.

The second chapter starts by providing a brief description of the dataset used for brain tumor detection [11]. Then, a literature review is conducted, covering recent advancements and studies in brain tumor diagnosis [12]. A detailed description of each component of our system is provided to give an overview of the methods, models, and techniques employed in this work [13].

Finally, chapter three evaluates and discusses various experiments conducted on the brain tumor detection dataset using multiple transfer learning models (such as ResNet50V2, MobileNetV2, and DenseNet169) [14]. We explore the performance of concatenated models such as MobileNetV2 and DenseNet169 and MobileNetV2 and ResNet50V2 [15]. The obtained results are expressed in terms of accuracy, precision, recall, and F1-score.
We conclude this dissertation with a general conclusion and some future perspectives.

Chapter 1

HEALTHCARE AND AI

1.1 INTRODUCTION

A tumor represents an anomalous and unregulated proliferation of cells within the organism. Within the sphere of brain neoplasms, this entails a swift and uninterrupted cellular replication resulting in the formation of aberrant tissue clusters in the cranial region. Timely detection and expeditious intervention for brain tumors markedly enhance the prospects of survival. The identification and diagnosis of brain tumors at an early stage are imperative for the efficient management of the ailment [16, 17].

Artificial Intelligence (AI) has revolutionized brain tumor research by significantly improving detection, diagnosis, and treatment efficacy [18, 19, 20, 21]. Through AI algorithms, medical imagery analysis is enhanced, enabling precise brain tumor diagnosis and facilitating prompt treatment decisions. AI aids in examining patient records, optimizing treatment strategies, and efficiently monitoring tumor progression, providing valuable insights for healthcare professionals. By meticulously scrutinizing images and offering tailored treatment suggestions, AI plays a crucial role in enhancing healthcare provision for brain tumor patients, ultimately increasing their chances of recovery. The integration of AI in brain tumor research showcases its potential to optimize patient outcomes and revolutionize the field of neurosurgery [22, 23].

Deep learning techniques like CNNs are instrumental in the realm of classification and identification by employing data mining methodologies to extract essential patterns and relationships from datasets. The utilization of machine learning (ML) and data mining techniques proves to be highly effective in the prompt detection and prevention of brain tumors.

Research on AI, Machine Learning (ML), and Deep Learning (DL) is centered on the development of cost-efficient, expedited, and non-intrusive methodologies to precisely detect brain tumors. This objective is attained through the utilization of sophisticated performance measurements such as sensitivity, recall, accuracy, F1-Score, precision, and specificity. The incorporation of machine and deep learning technologies empowers computers to recognize, calculate, and interpret relationships among different variables. Consequently, it advances the realm of preventive healthcare by employing analytical processes to optimize data representations. Deep learning methodologies can analyze extensive volumes of brain tumor data, facilitating the discovery of prognostic, diagnostic, and therapeutic interventions for diverse brain tumors [24].

1.2 THE CHALLENGES BEHIND BRAIN TUMORS

Brain tumors present a multifaceted challenge in medicine due to their complexity, including early diagnosis, accurate diagnosis and effective treatment A key issue is the difficulty in differentiating tumors between malignant and benign tumors by imaging alone, and often requires invasive procedures such as biopsies The area can be more difficult surgical intervention, which can result in loss of brain function the need is destroyed [13]. Despite advances in medical technology, survival for some types of brain tumors remains low, requiring highly effective therapeutic strategies and significant differences in genetic and environmental contributions brain tumors grow it logically and to s It integrates artificial intelligence, genetic research and new medical strategies [25].

1.3 BIOMEDICAL DATA

Biomedical data includes a wide range of information critical to understanding biological mechanisms, improving disease control strategies, and advancing healthcare delivery. This domain includes insights into molecules, physiological functions, patient medical histories, community health monitoring, genetic data, and other elements that collectively contribute to comprehensive biomedical knowledge [26, 27].

Managing extensive biological data presents challenges due to its diversity, advancing characteristics, and complex scientific context, complicating efficient organization and analysis [28].

Biomedical big data, derived from sources such as medical records, research data, social demographics, pharmaceutical innovation, disease monitoring, and meticulous health management. This data Motivate transformative shifts in medical methodologies, enhancing the quality and accessibility of healthcare [29]. Furthermore, the biology data book provides the scientific community with standardized biological constants, reference values, structured data on genetics, metabolism, environment, other factors essential for research and fostering correlations among biological phenomena [30].

1.4 MEDICAL IMAGING TYPES

The term "medical imaging" refers to various techniques used to observe specific areas of the human body, facilitating clinical diagnosis and medical intervention.

Medical imaging also allows for the visualization of tissue or organ functionality. This technology enables healthcare professionals to conduct comprehensive examinations of both the skeleton and membrane systems, aiding in the identification of medical conditions and Providing of effective treatments. Additionally, medical imaging is crucial for creating datasets necessary for studying human physiology and normal anatomical configurations. As a subset of biological imaging, medical imaging Includes a variety of techniques that aim to at capturing detailed visual representations of biological structures and processes [31].

1.4.1 Magnetic Resonance Imaging (MRI)

Magnetic resonance imaging (MRI) is a non-invasive medical imaging technique that produces detailed images of nearly every system in the human body, including organs, bones, muscles, and blood vessels. MRI scanners use a large magnet and radio waves to create these images. The MRI images are created by placing the patient within a large magnet that generates a high external magnetic field. This field causes the nuclei of various atoms in the body, particularly hydrogen, to align with the magnetic field. When a radio frequency (RF) signal is subsequently applied, the energy emitted by the body's atoms is detected and used by a computer to generate the MRI images, according to the figure 1.1.

Figure 1.1: The magnetic resonance imaging (MRI) scanner.

1.4.2 X-Ray Imaging

The X-ray imaging uses electromagnetic radiation emitted by electrons outside the nucleus of an atom, covering a spectrum of energies from 100 electron volts to 500 kilo-electron volts, allowing for deep penetration into dense materials [32]. This technology can enhance imaging speed and reduce radiation potion compared to traditional methods like computed tomography, by using algorithms for scatter removal and devices for optimal beam selection [33].

This imaging process involves generating X-ray radiation through the interaction between an electron beams and a target, moving the sample relative to the target, and detecting the emitted X-ray radiation [34].

X-ray imaging systems consist of various components: X-ray sources, converters for spatial data conversion, detectors, pattern generators for light and shadow patterns, image processors, and operation panels with sensors for signal output and liquid detection, See Figure 1.2 for details [35, 36].

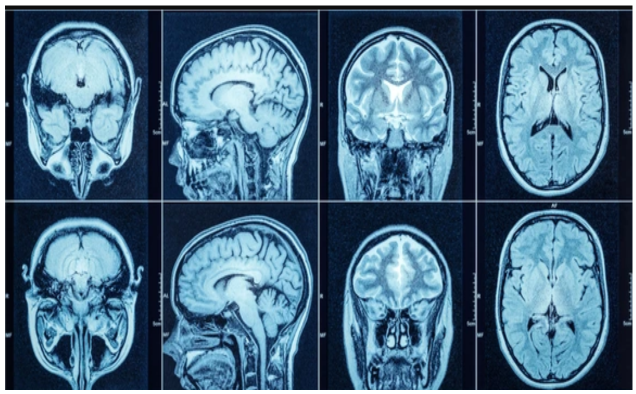


Figure 1.2: X-Ray images.

1.4.3 Positron Emission Tomography (PET) Imaging

The Positron Emission Tomography (PET) imaging plays a critical role in the non-invasive monitoring of physiological changes, as demonstrated in figure 1.3. Various strategies have been proposed to improve the quality of PET images. The kernelized expectation maximization (KEM) technique, along with the innovative regularized KEM (RKEM) approach, addresses challenges related to reconstruction variability and the preservation of image details [37]. Additionally, denoising methodologies such as spectral graph wavelet transform (SGWT) and denoising diffusion probabilistic models (DDPM) show potential in maintaining edge information while reducing noise in PET images [38, 39]. Furthermore, incorporating magnetic resonance (MR) prior knowledge into PET image reconstruction algorithms has proven beneficial in enhancing image quality and structural information [40]. These advancements highlight the ongoing efforts to improve PET images quality through innovative denoising and reconstruction techniques.

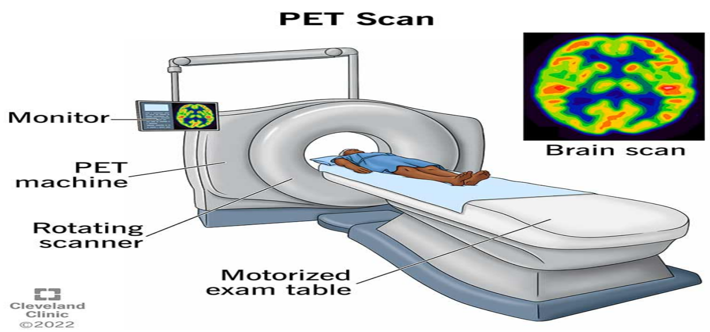
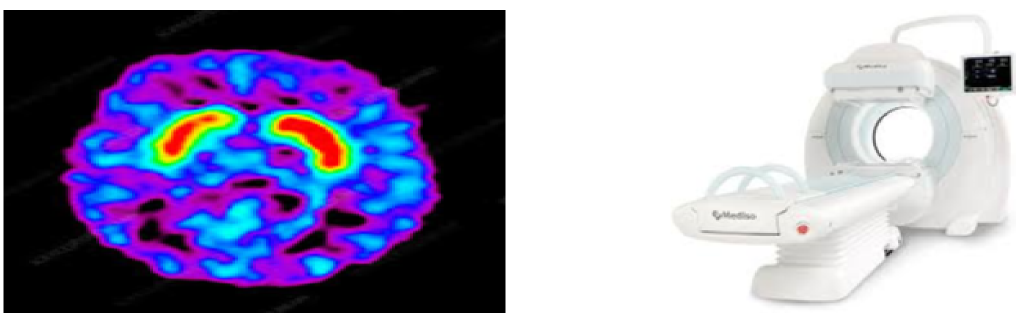


Figure 1.3: PET scan.

1.4.4 Single-Photon Emission Computed Tomography (SPECT) Imaging

The Single-Photon Emission Computed Tomography (SPECT) is an alternative nuclear medicine tomographic imaging technique that relies on gamma rays. SPECT provides three-dimensional data, usually visualized as cross-sectional segments of the body, which can be adjusted and transformed to meet specific needs, as demonstrated in the figure 1.4 [31].



(a) (b)

Figure 1.4: a) SPECT image from a brain healthy and b) SPECT scanner.

1.4.5 Microscopic Imaging

Microscopic imaging plays a pivotal role across various domains, particularly within biomedical research. Diverse methodologies have been developed to optimize the examination of these visual representations. Cellular automaton-centered segmentation strategies have been explored, with the von Neumann neighborhood technique demonstrating superior efficacy compared to the Moore neighborhood approach [41]. In addition, advanced deep learning architectures, such as generative adversarial networks (GANs) have been employed to enhance the resolution of individual images, achieving better results than standard networks for real-time microscopy resolution enhancement [42].

The analysis of biomedical images involves introductory processing and segmentation to address challenges such as noise interference and cell overlap. This includes the application of metrics for precision assessment and cell identification [43]. Moreover, advancements in microscopic visualization have led to the development of expansive field-of-view imaging using array objective lenses and imaging methodologies designed for comprehensive sample inclusivity [44], see figure 1.5 for more details.

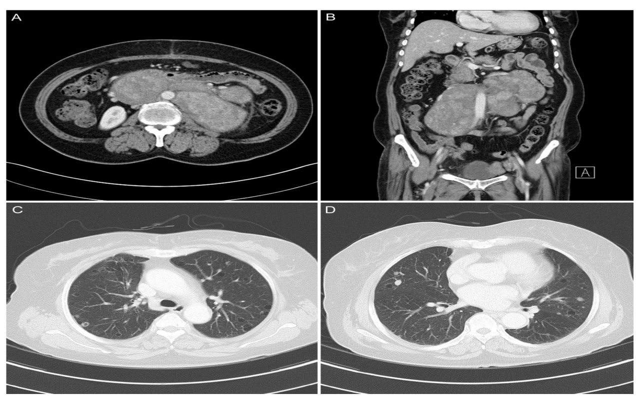


Figure 1.5: Computerized tomography (CT).

1.4.6 Ultrasound Imaging (Sonography)

The Ultrasound imaging, or sonography, uses ultrasound waves generated by piezoelectric materials to produce images of internal body structures [45]. This non-invasive imaging modality has been extensively studied, covering topics from the physics of wave propagation to algorithms for image reconstruction [46]. Recent advancements include techniques that improve the user-friendliness of ultrasound elastography, enhancing tissue characterization [47]. Moreover, novel ultrasound devices have been developed for the automatic identification of tissue boundaries, aiding in precise diagnosis and examination of various tissue types [48]. Overall, ultrasound imaging plays a crucial role in clinical diagnostics by providing detailed information on texture patterns, echogenic features, and quantitative tissue characterization, Check the figure 1.6 for a detailed.

Figure 1.6: Ultrasound scanner.

1.4.7 Endoscopy Imaging

Endoscopy involves the use of an endoscope, which typically comprises a video device located there are imaging optics, lighting mechanisms and image processing [49, 50, 51].

The endoscope captures images of internal body structures, which are processed through an electronic image recorder and image processing unit, then presented in real-time on a monitor [47]. Some endoscopes are equipped with solid-state image sensors to facilitate image signal output and additional features such as an image file unit for recording video signals and an alarm system for data retrieval [51], as shown in the figure 1.7. Furthermore, endoscopes can be outfitted with interchangeable outer pipes that house different lenses, allowing for various viewing angles and enhancing the device's adaptability during medical procedures.

1.4.8 Electrography

Electrography includes a variety of applications across different fields. In the realm of spatially resolved electrochemistry, "Glazunov" pioneered the use of electrography for imaging the surfaces of conducting solids and analyzing their electrochemical behavior [52].

In the medical domain, electrography systems employ electrodes to capture physiological electrical patterns for diagnostic purposes [53].

The advancement of digital technology in the late 1980s marked significant events such as the International Electrography and Copy Art Biennial, highlighting the intersection of art

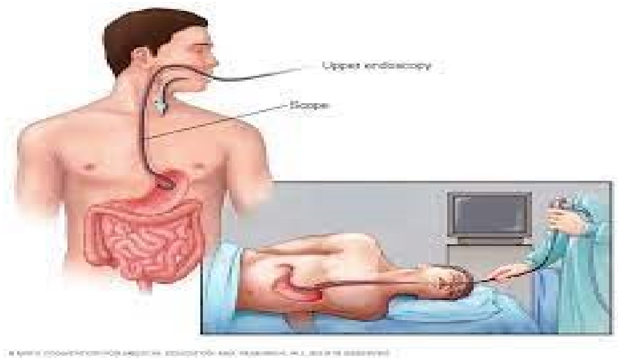


Figure 1.7: Endoscopy imaging.

and technology [54]. Furthermore, electrographic printers utilize ink capsules with specific viscosity ranges to effectively transfer images onto various media [55], according to the figure 1.8.

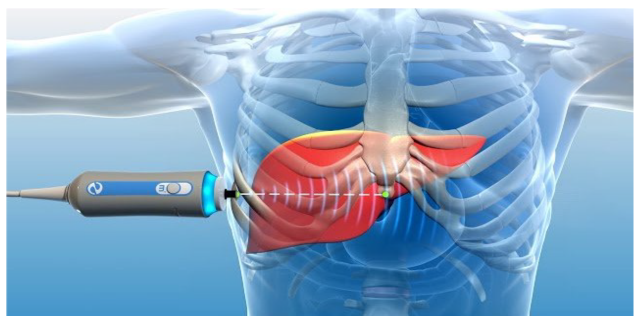


Figure 1.8: Elastography.

1.5 ARTIFICIAL INTELLIGENCE (AI)

1.5.1 Definition

Artificial intelligence (AI) refers to machines' cognitive abilities, including tasks like recognizing speech, understanding images, and translating languages [56, 57]. It's a tool created by humans to automate tasks that usually need human thinking, transforming many aspects of life [56, 58].

AI advertising, also called intelligent advertising, is a modern way of brand communication using AI, shifting from interactive to programmatic advertising since the 1990s [58]. This technological innovation mimics and enhances human thinking, creating a new field called intelligent advertising. In summary, AI represents a significant advancement in technology, allowing machines to understand, combine, and analyze information like humans do, (See figure 1.9).

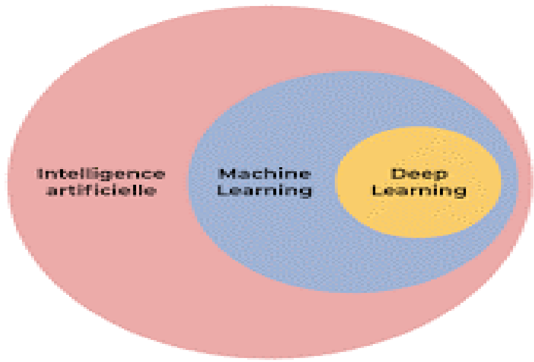


Figure 1.9: Artificial Intelligence.

1.5.2 History

The historical journey of artificial intelligence (AI) spans almost a century, marked by both successes and challenges [59].

AI's progress has shifted from rule-based methods to statistical and data-driven techniques in areas like computer vision, natural language processing, and machine learning [60, 61].

Two key paradigms, symbolism, and connectionism, have shaped AI research, highlighting the distinction between natural and artificial intelligence [62]. From 1940 to 2021, contemporary AI has seen significant advancements in hardware, software, algorithms, and technologies. Furthermore, AI's potential includes tasks like historical fact-checking and information completion, with advanced language models like GPT-4 showing promise in forecasting and validating historical events. This historical perspective emphasizes the need for ongoing exploration and collaboration in AI development to achieve effective human-machine cooperation.

1.5.3 Machine Learning (ML)

1.5.3.1 Definition

Machine Learning (ML) is a part of Artificial Intelligence (AI) that enables computers to learn from data without explicit programming [63, 64, 65]. It allows machines to improve their performance by processing more data, adapting, and enhancing their functions over time [66].

ML is particularly useful when manual programming is impractical due to task complexity or the need for adaptability to changing environments [67].

ML includes various methods like supervised, unsupervised, and reinforcement learning, enabling machines to learn from past experiences and make data-driven predictions and decisions , as presented in Figure 1.10.

The field of ML is constantly evolving, incorporating advanced techniques like deep learning and methods such as adversarial training and federated learning to address a wide range of problem domains.

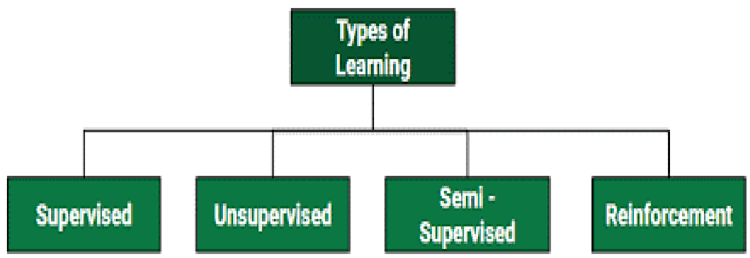


Figure 1.10: Machine learning types.

1.5.3.2 Machine learning types

a) Supervised Learning: Supervised learning involves training machine learning models with labeled data to accurately predict outputs [67, 68].

This approach is widely used across various fields, such as genetics, to predict gene characteristics using molecular interaction networks [69]. In supervised learning, the provided training data acts as a guide for the model to make accurate predictions based on the input data. This includes tasks like classification and regression , refining model parameters through techniques like cross-validation to ensure optimal alignment with the data.

The significance of supervised learning lies in its ability to address practical challenges like spam detection and gene classification, showcasing its versatility and effectiveness in various scenarios.

b) Unsupervised Learning: Unsupervised learning is a type of machine learning where algorithms find patterns in data without using predefined target labels. Unlike supervised learning, unsupervised learning focuses only on the raw input data to discover hidden relationships and insights [69, 70].

This method allows systems to understand the statistical structure of input patterns without specific target outputs or evaluations for each input. It uses existing biases to capture important aspects of the input's structure in the output [70].

The goal of unsupervised learning is to gain meaningful insights from data that does not have labeled responses, revealing the natural structure of the input data instead of task-specific understanding [70].

Common techniques used in unsupervised learning for pattern recognition and data representation include clustering methods like K-means and Hierarchical Clustering, as well as Principal Component Analysis (PCA).

c) Self-supervised Learning: Self-supervised learning (SSL) is a powerful method in machine learning that allows models to be pre-trained without needing labeled data [71, 72, 73]. This technique involves training models to predict certain parts of the input data itself, which helps them learn complex feature representations [73].

SSL not only helps compress information within the data but also improves later classification tasks by matching the learned features with meaningful labels. Recent progress in SSL has led to new methods like self-supervised explorative distillation (SSED), which aims to improve the quality of smaller models by ensuring they learn varied and accurate features. Additionally, SSL is especially useful for video data, where labeling can be very expensive. Research in this area focuses on factors like dataset size, complexity, and data noise, all to improve the effectiveness of representation learning.

d) Reinforcement Learning: Reinforcement Learning (RL) is a machine learning method where an agent learns to make decisions by interacting with an environment to maximize cumulative rewards [74, 75, 76].

RL is based on trial-and-error learning, where the agent receives feedback in the form of rewards for its actions, helping it figure out the best strategies without prior knowledge of the environment.

RL has been used in various fields, including game theory, robotic control, and even surpassing human performance in complex tasks. It serves as a versatile tool for experts in engineering, biology, and cognitive science to study goal-oriented behaviors and brain processes.

The choice between single-agent RL and multi-agent RL depends on the complexity of the problem and the need for coordination among agents.

1.5.4 Commonly Used Machine Learning Techniques

Various machine learning algorithms are used in medical concerns. A bench of the most commonly. A list of the most commonly used algorithms will be provided in the following:

1.5.4.1 Decision Trees (DTs)

Decision Trees (DTs) are prediction models represented as trees, where each node represents a characteristic and each edge indicates a potential value for that characteristic [77]. They are widely used for categorization and estimation tasks across various industries such as healthcare, finance, and commerce [78]. These models work by dividing the input space into subregions using a linear regression model, creating a tree structure where instances are organized from the root to terminal nodes [79], as illustrated in in Figure 1.11.

DTs are efficient in analyzing relationships within multidimensional data, as shown by their application in the electric power sector for developing statistical control techniques [80].

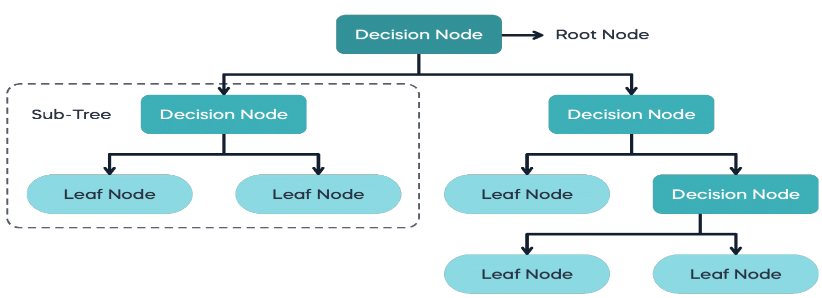


Figure 1.11: Decision tree (DT) architecture.

1.5.4.2 Support Vector Machine (SVM)

Support vector machine is a popular machine learning technique for classification and regression [81].

SVM is recognized as a highly efficient method in supervised learning [82], as presented in Figure 1.12.

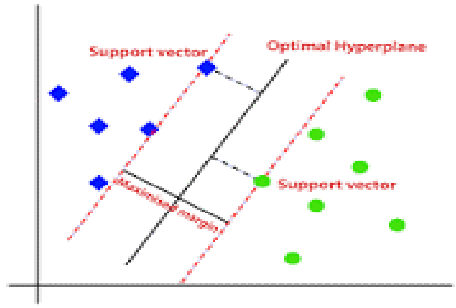


Figure 1.12: SVM principle.

1.5.4.3 K-nearest neighbors (KNN)

The K-nearest neighbors (KNN) algorithm is categorized as a non-generalizing technique known as "instance-based learning" or Known as a"lazy learning" method.

Instead of generating a detailed internal model, it preserves all instances linked to the training data in an n-dimensional space [81].

The fundamental principle of the KNN algorithm is that items sharing similarities tend to group closely together [?], as illustrated in Figure 1.13.

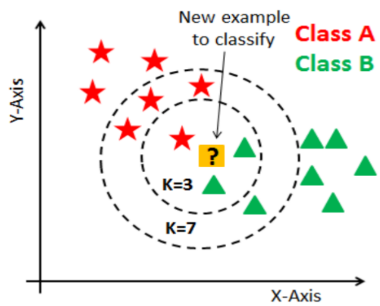


Figure 1.13: K-nearest neighbors process.

1.5.4.4 Artificial neural network

ANN, is a computational model inspired by biological processes, consists of numerous artificial neurons interconnected with coefficients, known as weights, which collectively form the neural architecture [83], as demonstrated in the figure 1.14.

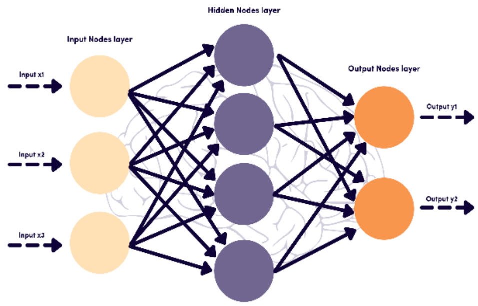


Figure 1.14: Artificial neural network.

1.5.5 Deep Learning (DL)

1.5.5.1 Definition

Deep learning, is a subset of machine learning, involving training artificial neural networks to comprehend and represent complex relationships between input data and output predictions [84, 85]. Its impact has been profound across various sectors, enabling tasks such as image recognition, natural language understanding, and speech interpretation [86, 87].

The use of deep learning techniques, including shallow Neural Networks (NNs), Recurrent Neural Network (RNNs),Graph Neural Networks (GNNs), and CNNs, aiming to process extensive and complex datasets to tackle issues like pattern recognition and precise diagnostics in fields such as bioinformatics [88]. This involves applying nonlinear transformations and sophisticated model abstractions within large data repositories, leading to significant advancements in areas like computer vision and language processing compared to traditional machine learning techniques. Guaranteed, deep learning mimics the organization and functioning of the human brain through interconnected elements to analyze data and make predictions, thus serving as a powerful tool for addressing complex challenges across various disciplines.

1.5.6 Deep Learning Techniques

This subsection discusses several well-known deep learning techniques, including Recursive Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and others [89].

1.5.6.1 Deep Neural Networks

A Deep Neural Network (DNN) is a type of artificial neural network with many hidden layers, allowing it to capture complex relationships between input and output variables [84, 85], as shown in figure 1.15. These networks, inspired by the architecture of the human brain, and they are crucial in deep learning, which are branch of machine learning that has led to significant progress in fields such as computer vision, natural language processing, and speech recognition [90].

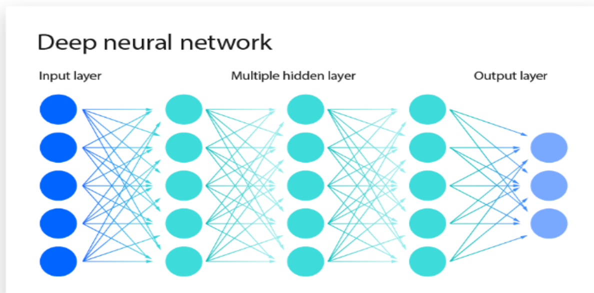


Figure 1.15: Deep neural network structure.

1.5.6.2 Restricted Boltzmann Machines (RBMs)

In 1986, the Restricted Boltzmann Machine (RBM) was proposed as a generative stochastic neural network. The RBM is a variation of the Boltzmann Machine and features a bipartite graph between the visible and hidden units. This structure improves the efficiency of training techniques, especially the gradient-based contrastive divergence method [91], as depicted in the image 1.16.

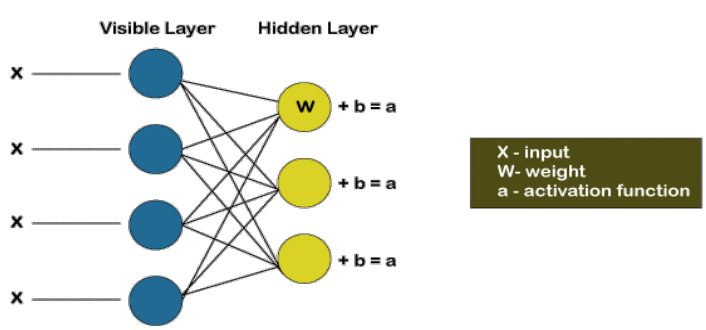


Figure 1.16: RBMs architecture.

In the following we will discuss these models in detail

a) Deep Belief Networks (DBNs): A Deep Belief Network (DBN) constitutes a deep learning architecture that consists of numerous layers of stochastic, latent variables. Said variables are usually binary in nature, constructing a network of interconnected "neurons" or units.

The training of DBNs entails a step-by-step method, frequently employing unsupervised pre-training, succeeded by fine-tuning through supervised learning methodologies [92, 93], as evident from Figure 1.17.

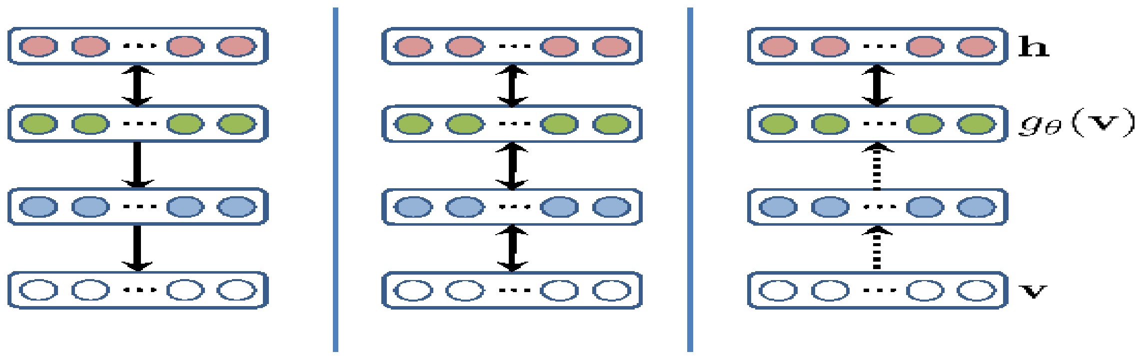


Figure 1.17: DBN models.

b) Deep Boltzmann Machines (DBMs): A Deep Boltzmann Machine (DBM) is a model with multiple hidden layers and undirected connections between the nodes [94].

c) Deep Energy Models (DEMs): Deep Energy Models (DEMs) combine multiple deterministic hidden layers with a single stochastic hidden layer. These models transform the input into a new representation using a feedforward neural network, and then model the output of this network with a single layer of stochastic hidden units [94].

1.5.6.3 Autoencoder

An autoencoder is a type of artificial neural network used for learning efficient data encodings. Instead of predicting a specific target output from the inputs, an autoencoder is trained to reconstruct its original inputs. The diagram in Figure 1.18 shows how an autoencoder works [91].

1.5.6.4 Convolutional Neural Networks (CNNs)

A Convolutional Neural Network (CNN) is a type of deep learning techniques, which is commonly used commonly used for image classification, segmentation, and recognition. CNNs

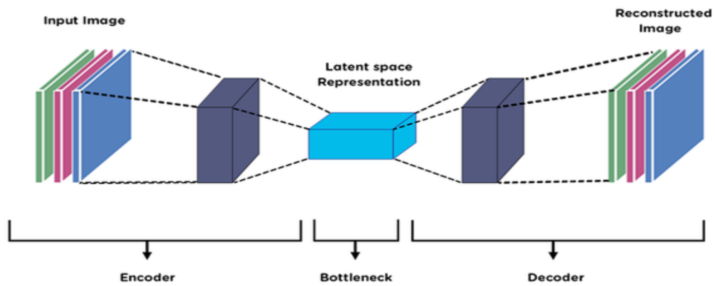


Figure 1.18: Autoencoder architecture.

are essential for classifying visual content, identifying objects in images, and grouping these objects.

The functionality of CNNs relies on the connections and weights among its components, followed by a subsampling process. A basic CNN architecture typically includes a convolutional layer, a pooling layer, and sometimes fully connected layers for supervised prediction [95]. Figure 1.19 shows the architecture of a simple CNN.

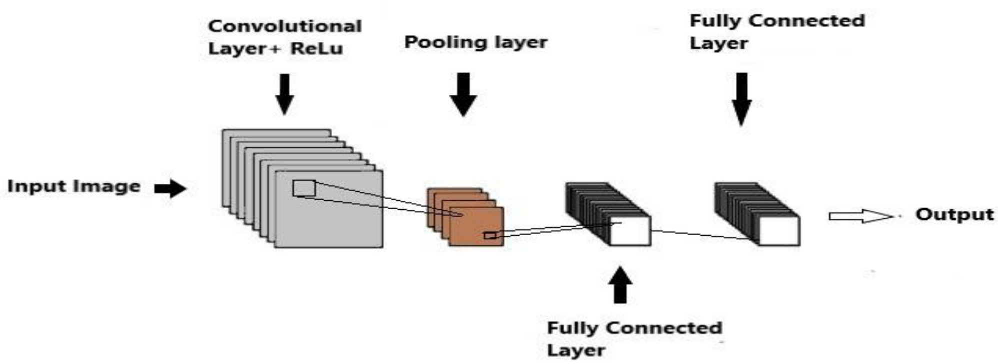


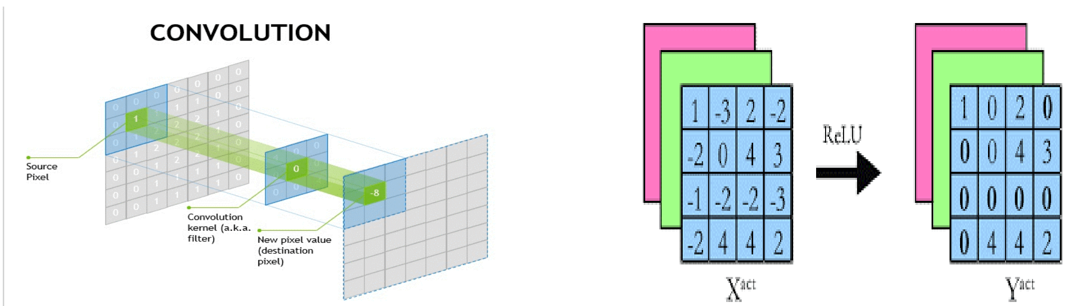
Figure 1.19: Architecture of a simple CNN.

a) Input layer :

The input layer in a CNN holds the image data. Image data is a three-dimensional matrix that needs to be reshaped into a single column before being fed into the network. Each layer's output serves as the input for the next layer [96].

b) Convolutional layer (Convo + ReLU) :

The Convolutional layer is the first active layer. It detects various features of an image, such as color, shape, and object components. Following the convolutional layer is the ReLU layer, which enhances the non-linear aspects of the image, allowing for higher-level feature extraction [96], as indicated in Figure 1.20.



(a) (b)

Figure 1.20: Convolution (a) and Relu (b) layers.

c) Pooling layer: After the convolutional layer, the pooling layer lowers the spatial volume of the input image [96], as illustrated in Figure 1.21.

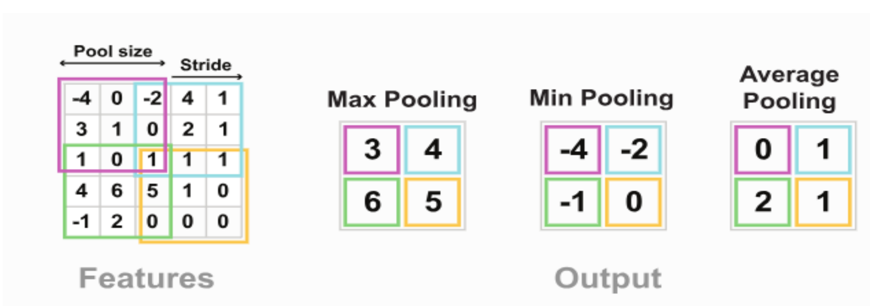


Figure 1.21: Diferenent aspects of the pooling layer.

d) Fully connected layers A fully connected layer is vital in deep learning models, especially for image classification tasks [97, 98]. It is crucial in areas like language restoration for patients with brain tumors [99], improving channel state information feedback in massive MIMO systems [98], and enhancing machine learning through multimodal data fusion [100], as indicated in the 1.22.

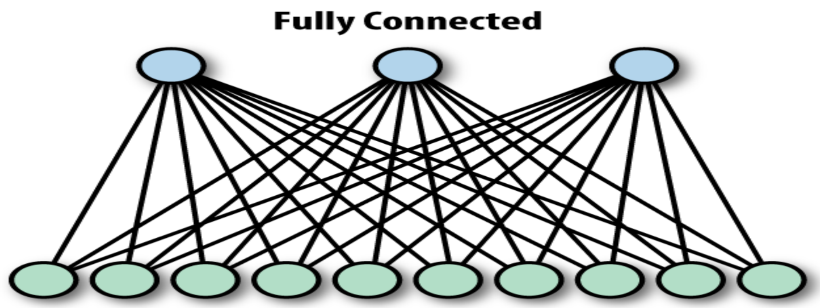


Figure 1.22: Fully connected layers (fc).

e) Softmax and output layers: These are the final layers of a CNN. After the Fully Connected (FC) layers comes the Softmax layer, used multi-class classification. The output layer then provides the final label for the input image [96].

1.5.7 CNN Models

1.5.7.1 AlexNet

AlexNet is a simple architecture made up of five convolutional layers combined with pooling, followed by three fully connected layers. It uses new techniques like data augmentation (DA), dropout, rectified linear units (ReLUs), local response normalization (LRN), and overlapping pooling. Figure 1.23 shows the AlexNet architecture [101].

1.5.7.2 GoogLeNet

GoogLeNet is a convolutional neural network; its structure is shown in Figure 1.24. The architecture was designed to capture detailed feature representations using a large dataset of millions of everyday object images, known as the ImageNet dataset. Figure 1.24 shows the Inception module with dimensionality reductions [102].

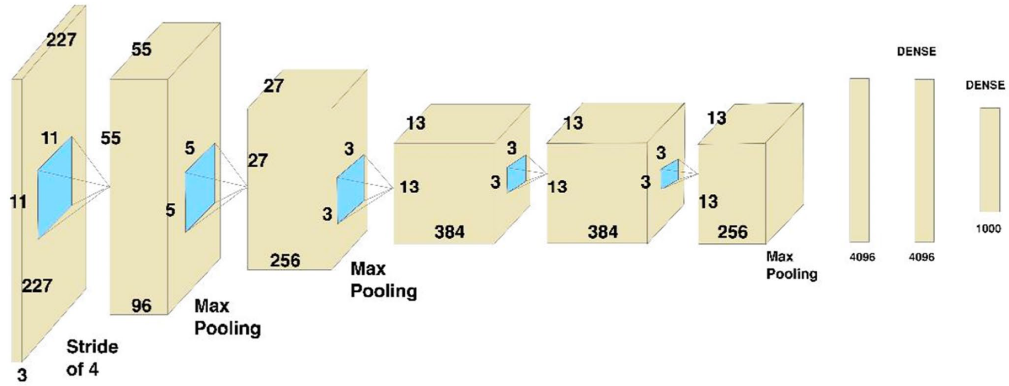


Figure 1.23: AlexNet architecture.

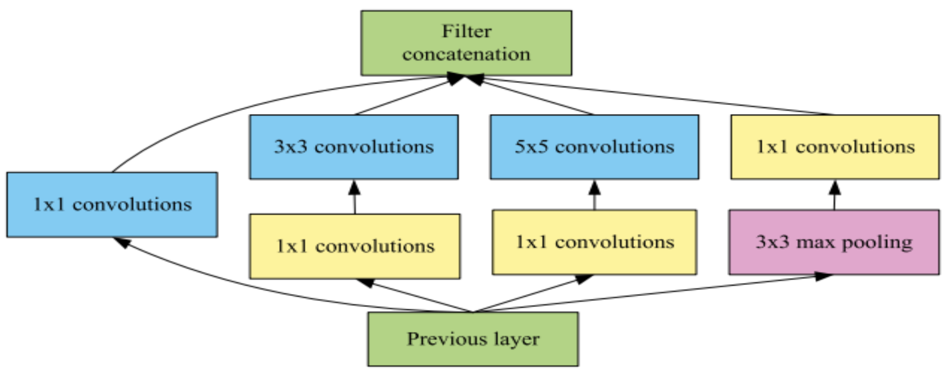


Figure 1.24: GoogLeNet architecture.

1.5.7.3 ResNet

ResNet is one of the most widely used architectures for image classification. When it was first introduced, it represented a major breakthrough and since then has become a fundamental model in various studies, often serving as a benchmark in research papers proposing new architectures [103]. Figure 1.25 shows the ResNet architecture.

1.5.7.4 VGG-Net

The VGG Network was introduced by the Visual Geometry Group at Oxford in the paper "Very Deep Convolutional Networks for Large-Scale Image Recognition" in 2014 [104]. A notable feature of this model is the use of many small filters, particularly 3x3 and 1x1 filters with a stride of one.

Most convolutional layers are followed by 2x2 max pooling layers, though not all. The architecture often stacks two, three, or even four convolutional layers before adding a max pooling layer. As the model gets deeper, the number of filters increases, leading to different

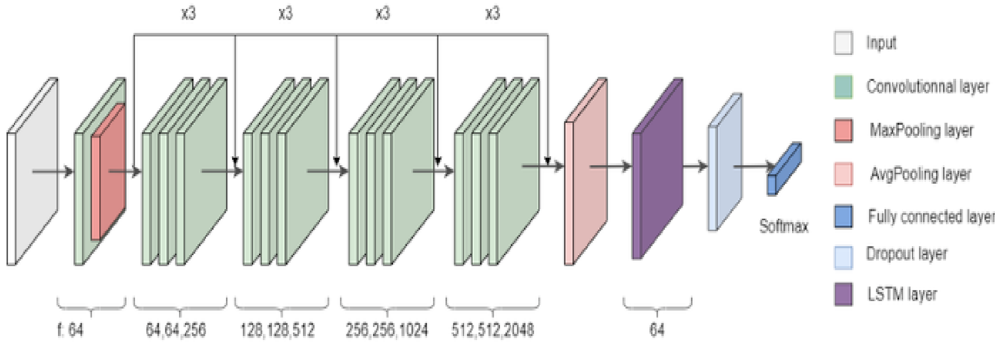


Figure 1.25: ResNet architecture.

versions of the model, each defined by the number of layers: VGG-16 and VGG-19 are two such versions [104]. Figure 1.26 shows the VGG-Net architecture.

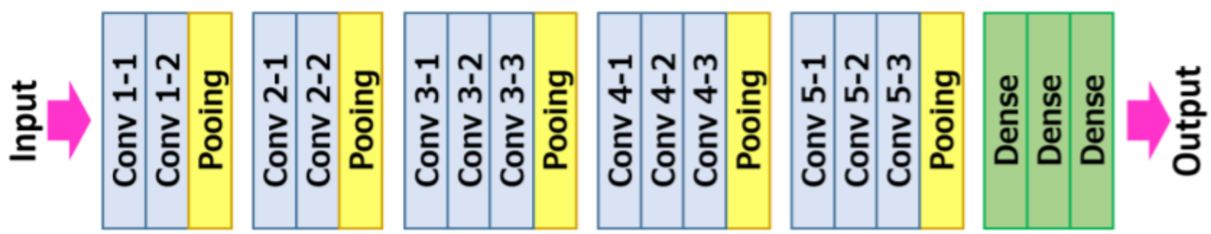


Figure 1.26: VGG-Net architecture.

1.5.8 Most Common CNN Approaches

1.5.8.1 Transfer Learning

Transfer learning involves using a model transformation approach designed for small datasets. This means transferring the parameters of a pretrained model, which has been trained on a large labeled dataset like ImageNet, to a new model. Even if the new dataset is large, starting with pretrained weights instead of random weights can be beneficial. In this case, the weights of the pretrained model are fine-tuned to fit the new model's needs [101], see figure 1.27 for details.

1.5.8.2 Fine-Tuning

Fine-tuning is the process of adjusting specific parameters in a model to improve its performance for a particular task. Several techniques have been proposed for efficient fine-tuning

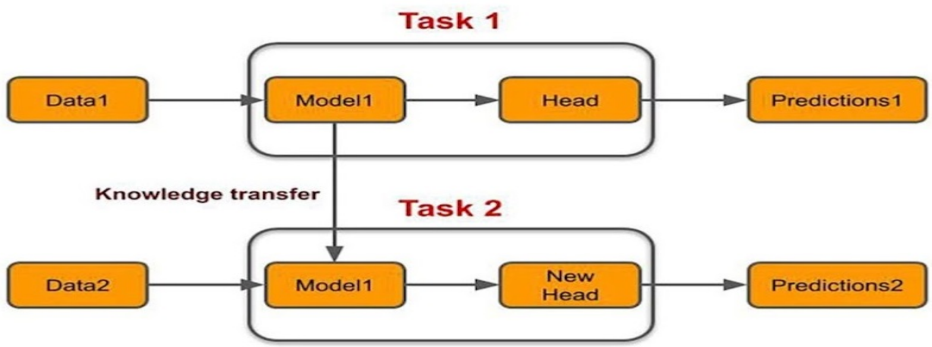


Figure 1.27: Transfer learning approach (TL).

[105]. One example is equi-tuning, which converts pretrained models into group equivariant models while minimizing L2 loss [106, 90]. See the figure 1.28 for a detailed analysis .

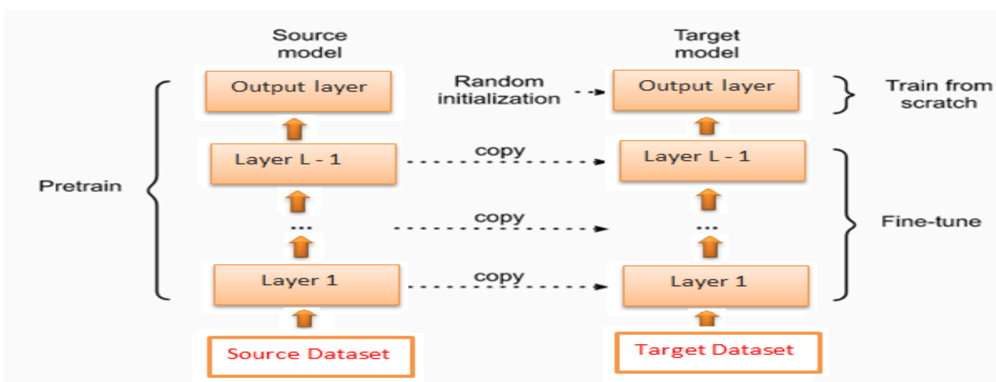


Figure 1.28: Fine tuning approach.

1.6 CONCLUSION

The promise of AI in the healthcare industry is clear from this literature. AI is becoming more useful at many levels, leading to better and faster patient outcomes. Artificial intelligence, machine learning, and deep learning can assist in surgeries, diagnose diseases like cancer at early stages, and more. With recent advancements in AI research and support and resources from governments, it is likely that the use of AI in healthcare will grow extensively, offering significant cost savings and improvements in the quality of healthcare services.

Chapter 2

PROPOSED SYSTEM

2.1 INTRODUCTION

In this chapter, the initial focus is on clarification the dataset employed in our research. Subsequently, an examination of the existing body of literature pertaining to brain tumor diagnosis over recent years is conducted. Furthermore, an exposition of our devised system for brain tumor diagnosis It is asked. A comprehensive clarification of each component of our system is furnished to impart an understanding of the methodologies and techniques deployed in this study.

2.2 DATA BASE

The experimental framework utilizes a brain tumor detection dataset Br35H using different deep transfer learning models. This dataset contains 7023 images of human brain MRI images which are classified into 4 classes: glioma - meningioma - no tumor and pituitary. Figure 2.1 shows some fundus images extracted from this dataset.

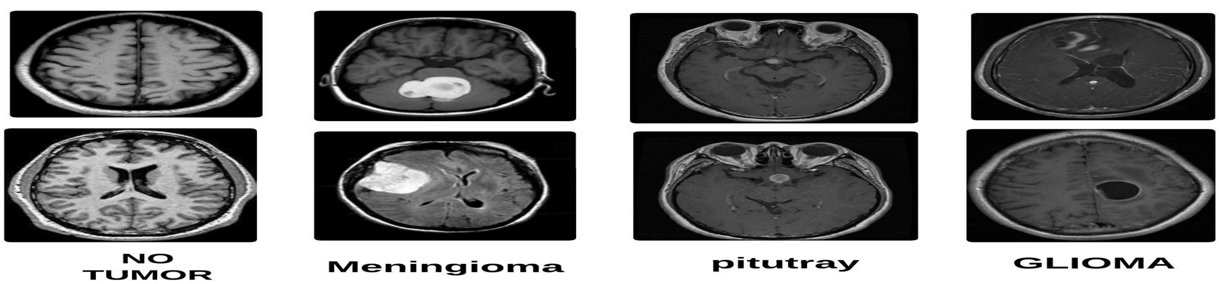


Figure 2.1: Some samples from different classes of Br35H.

2.3 RELATED WORKS

Brain tumors may result in significant implications, Depending upon diverse factors including their placement, dimensions, classification, and growth rate.Proper treatment and timely diagnosis can effectively obstructs the progression of the disease.

Various researchers have utilized artificial intelligence to achieve early identification of this particular ailment through the implementation of diverse methodologies. The forthcoming discourse will outline the key studies and findings from recent years.

Asif, S et al [107] utilized pre-trained deep learning models (Xception, NasNet Large, DenseNet121, InceptionResNetV2) for brain tumor diagnosis from MRI scans on two benchmark datasets. Models were trained using ADAM, SGD, and RMSprop optimizers and evaluated on accuracy, sensitivity, precision, specificity, and F1-score. The Xception model with ADAM optimizer outperformed others, achieving accuracy (99.67%), sensitivity (99.68%), specificity (99.66%), and F1-score(99.68%)on the MRI-large dataset. On MRI-small, it obtained accuracy(91.94%), sensitivity(96.55%), precision (87.50%), specificity (87.88%), and F1-score (91.80%). The results demonstrate the potential of transfer learning with deep CNN architectures like Xce ption for accurate brain tumor diagnosis from MRI data.

Gómez-Guzmán and colleagues [Gómez-Guzmán, 2023] examined seven CNN models (one generic and six pre-trained) using a dataset comprising 7023 brain MRI images categorized into four classes (three tumor types and healthy). Following preprocessing and training, the InceptionV3 model attained the highest average accuracy of 97.12% for the classification of brain tumors. This illustrates the capability of CNN techniques in assisting clinicians with the early detection of brain tumors from MRI data.

Selcuk,B et al [108] proposed a YOLOv8-based approach for brain tumor detection from MRI scans using the Br35h dataset with 800 annotated images. The model achieves high performance with 97.6% mean average precision, demonstrating its potential as an accurate and efficient tool for localizing and identifying brain tumors to aid clinical decision-making.

Islam, M. A et al [109] conducted a comparative analysis of deep Convolutional Neural Network (CNN) architectures (VGG16, ResNet50, MobileNet) for the purpose of detecting brain tumors from MRI images in the Br35h dataset. The accuracies obtained were 97%, 94.5%, and 99% for VGG16, ResNet50, and MobileNet, respectively. Introducing a modified CNN model that achieved an accuracy of 98.5% while utilizing fewer parameters and computational resources, demonstrating performance equivalent to or superior to the commonly employed models. The primary objective is to introduce an efficient model for computer-aided diagnosis of tumors while upholding a high level of accuracy.

Ata, M et al [110] proposed a features fusion model combining Gray Level Co-occurrence Matrix (GLCM) textural features extracted from brain MRI images, with features from a deep neural network (DNN) and a CNN model. The fused features are input to another DNN for tumor classification on the Br35H and FigShare datasets (binary and multi-class). The proposed methodology achieves superior performance compared to current state-of-the-art, with 98.22 % accuracy on Br35H and 98.01 % on FigShare, using metrics like accuracy, sensitivity, specificity, F-score, and training time. The model aims to effectively distinguish between no tumor and brain tumor types.

Gehad Abdullah Amran et al [111] introduced a novel hybrid learning framework, named

DeepTumorNetwork, designed for the categorization of binary brain tumors (BT). This framework merges the architecture of GoogLeNet with a Convolutional Neural Network (CNN), utilizing the Br35H Kaggle dataset. Results demonstrate superior performance compared to transfer learning frameworks such as ResNet, VGG-16, SqueezeNet, AlexNet, and MobileNet V2, as well as other machine and deep learning techniques, in terms of crucial performance metrics including accuracy (99.51%), precision (99%), recall (98.90%), and F1-score (98.50%). The hybrid methodology showcases exceptional classification accuracy, outperforming existing approaches for BT classification using MRI scans.

Mondal, A et al [112] compared the proposed PFpM model's performance with state-of-the-art deep CNN models (DenseNet201, InceptionV3, MobileNetV2, ResNet50, VGG19) and various activation functions (ReLU, LeakyReLU, GELU, Swish, Mish) on the Figshare and Br35H brain tumor datasets. Record-wise and subject-wise (patient-level) experiments were conducted using hold-out and 5-fold cross-validation. On Figshare, PFpM achieved accurcy (99.57%) (record-wise hold-out), 98.45% (record-wise 5-fold), 97.91% (subject-wise hold-out), and 97.26% (subject-wise 5-fold). On Br35H, PFpM attained 99% accuracy (record-wise hold-out) and 98.33% (record-wise 5-fold).

Vankdothu et al [113] proposed a model that detects and classifies brain tumor grades, including glioma, meningioma, pituitary tumor, and no tumor. They combined a CNN with a Long Short-Term Memory (STM) to extract the main brain features. Finally, the images have been classified and scored 89.39% accuracy in CNN, 90.02% in recurrent neural network (RNN), and 92% in the CNN-LSTM method.

Srikanth et al [114] introduced computer-assisted technology to detect and diagnose brain tumor disease automatically. Instead of using traditional machine learning algorithms (ML), they proposed a deep neural network based on the Visual Geometry Group (VGG-16) to improve the multi-classification accuracy value. Extensive experiments demonstrate that the updated VGG-16 model outperforms the current studies in terms of performance metrics.

Deshpande et al [115] proposed a fused algorithm to recognize a brain tumor based on a deep learning structure. Their framework has been merged with a Discrete Cosine Transform (DCT), CNN, and ResNet50 into one model to improve the recognition accuracy. The experimental results reveal that the proposed model scores the best in evaluating metrics.

Abirami et al [110] proposed a model called Border Collie Firefly Algorithm-based Generative Adversarial Network (BCFA-based GAN), which classifies the severity level of brain tumors effectively. They preprocessed the brain images using a Laplacian filter and then segmented them by a deep joint model. Furthermore, the main features have been extracted, including statistical and Texton and Karhunen-Loeve Transform-based features using slave nodes. Finally, the extracted features were classified using BCFAbased GAN and scored 97.51% of classification accuracy.

Irmak [116] introduced three distinct CNN architectures aimed aim to enhancing the automated and precise detection of brain tumors. The first CNN model partitions the dataset into five categories of brain tumors: normal, glioma, meningioma, pituitary, and metastatic. Furthermore, the second CNN model classifies brain tumors into Grade II, Grade III, and Grade IV, achieving classification accuracies of 92.6% and 98.14%, respectively, through hyperparameter tuning using a grid search optimization technique. Subsequently, in order to validate the reliability of the proposed model, a comparative analysis was conducted with established pre-trained models like ResNet-50, Alex Net, Inceptionv3, VGG-16, and GoogleNet, which revealed superior performance metrics.

2.4 PROPOSED SYSTEM

Figure 2.2 illustrates a comprehensive workflow for classifying brain tumors using deep convolutional neural networks (CNNs). Initially, MRI images of brain tumors are divided into training and testing sets. Three CNN architectures—ResNet50V2, MobileNetV2, and DenseNet169—are trained using the training part. After training, these models are validated using the testing set.

The proposed models are validated based on the Br35H dataset to accurately classify the images into one of four categories: Glioma, Pituitary, Meningioma, or No Tumor. Moreover, we combined these models to enhace brain tumor detection. This multi-model approach aims to leverage the strengths of different CNN architectures, enhancing the accuracy and reliability of brain tumor classification.

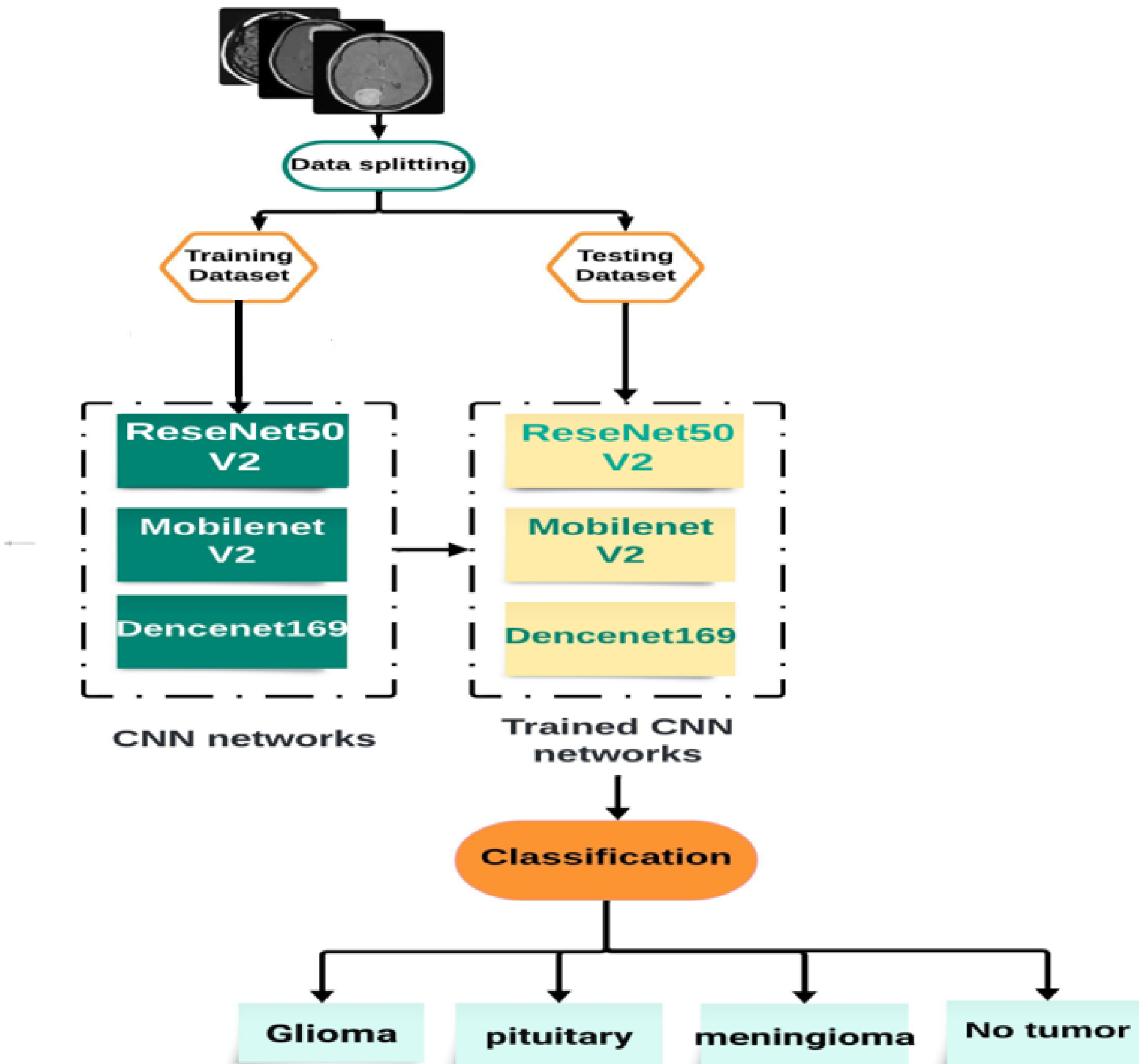


Figure 2.2: Proposed system.

2.4.1 Deep Pretrained CNN Networks

2.4.1.1 MobileNetV2

MobileNet V2 is a convolutional neural network architecture that has been specifically optimized for efficient performance on mobile devices. This architecture is built upon an inverted residual structure, which strategically places residual connections between bottleneck layers. Within the network, a lightweight depthwise convolution is utilized in the intermediate expansion layer to effectively filter features as non-linear sources.

The overall design of MobileNetV2 includes an initial fully convolutional layer comprising

32 filters, along with an additional 19 bottleneck layers, As shown in the figure 2.3 [117].

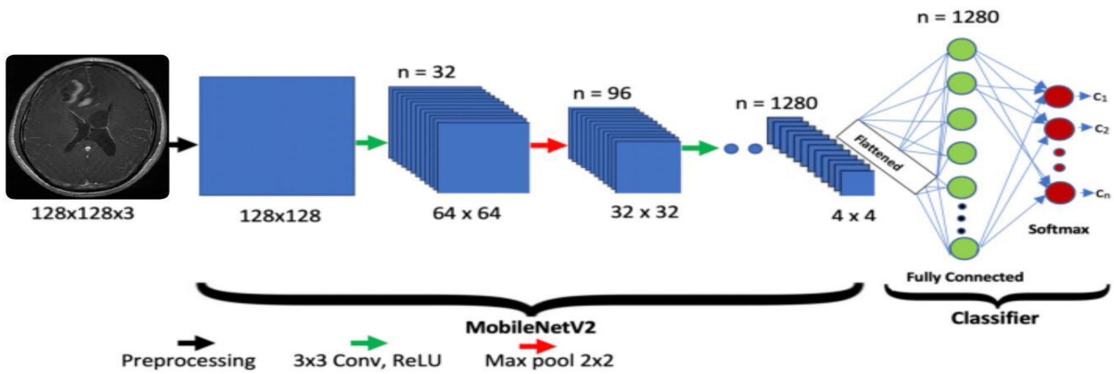


Figure 2.3: MobileNetV2 architecture.

2.4.1.2 DenseNet169

The DenseNet169 model is a deep learning architecture that is applied in a variety of fields for tasks such as crop pest and disease identification [118], stock price prediction [119], english accent classification, and diabetic retinopathy severity level detection [120].

An enhanced DenseNet model in crop pest and disease identification allows for real-time detection and early warning systems, achieving a notable recognition rate of 96.7% , As illustrated in figure 2.4 [120].

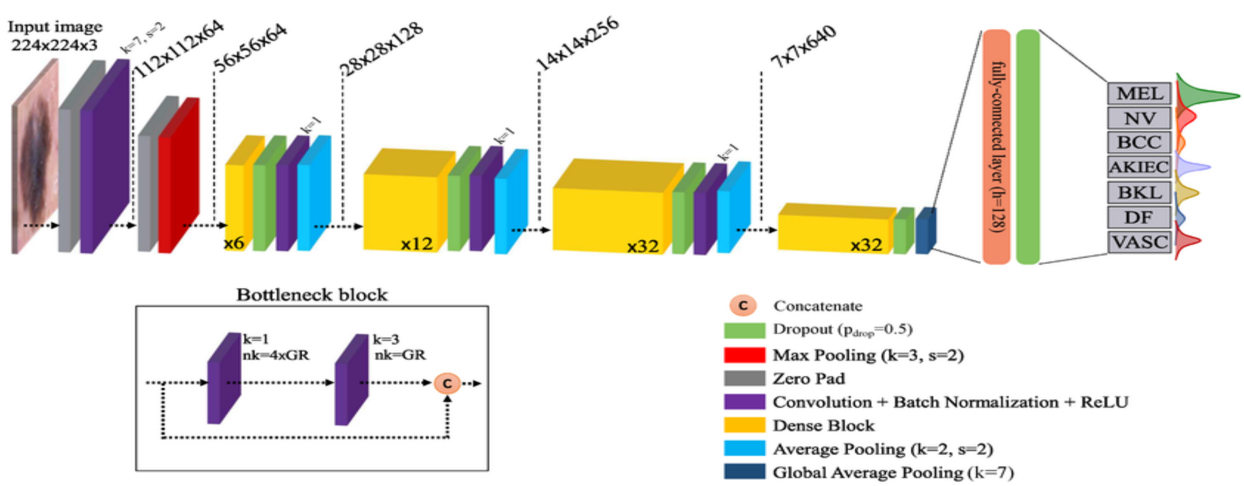


Figure 2.4: DenseNet169 architecture.

2.4.1.3 ResNet50V2

ResNet50 V2 denotes an adapted deep learning model that mergers the capabilities of Xception and ResNet50 architectures to enhance performance in areas like facial emotion recognition [121]. ResNet-50 stands out as a renowned deep learning structure recognized for its effective utilization in tasks such as image classification and emotional recognition [122, 123]. It presents benefits such as dependability, superior performance, and optimal utilization of computational resources, positioning it as a favorable option for diverse computer vision tasks. [123, 124] for specific networks, as depicted in figure 2.5.

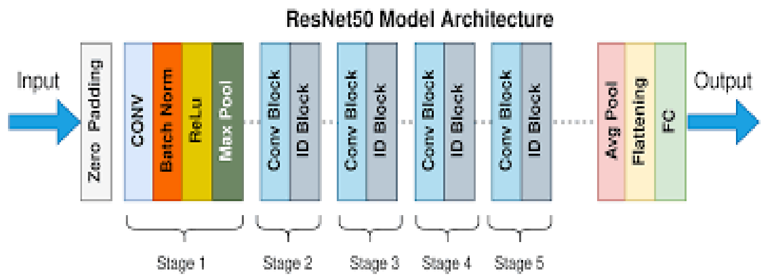


Figure 2.5: ResNet50 V2 architecture.

2.4.2 Feature Concatenation

Feature concatenation is the process of combining multiple features to enhance detection or recognition tasks [125]. Figure 2.6 illustrates the proposed concatenated deep CNN architecture designed for classifying brain tumor categories with the use of MRI images from the Br35H dataset.

Three different CNN networks including ResNet50V2, DenseNet169, and MobileNetV2 are employed to separately capture the relevant features from input images, producing features vector for each model (denoted as F1, F2, and F3 respectively). These latter are then combined to form one concatenated features vector, which will be fed into the fully connected layers (head) up to the output layer (softmax), functioning as a classifier that classifies the input into one of 4 classes (Glioma, Meningioma, Pituitary tumor, or No Tumor). This method leverages the strengths of multiple CNN architectures to improve the accuracy and robustness of brain tumor classification.

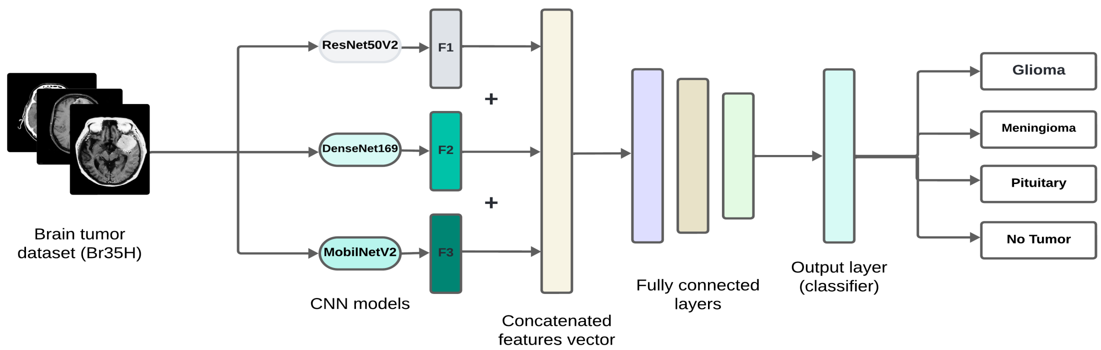


Figure 2.6: Concatenated deep learning models for enhanced performance.

2.5 CONCLUSION

In this chapter, the experimental framework for brain tumor detection using the Br35H dataset was elucidated, and explained three CNN models with theirs properties and theirs structures. In the next chapter, we will report the evaluation and the results of our experiments with quantitative and qualitative discussions to highlight the strengths and weaknesses of our system.

Chapter 3

EXPERIMENTAL RESULTS

3.1 INTRODUCTION

In this chapter, we evaluate and discuss many different experiments conducted on Br35H dataset using three transfer learning models (ResNet50V2, DensNet169, and MobileNetV2). Furthermore, the obtained results are expressed in term of accuracy, precision, recall and f1-score.

3.2 EXPERIMENTAL PROTOCOL

3.2.1 Data Distribution

Remodel this phrase, for example: The Br35H dataset was conducted in this study, containing 7023 images categorized under different labels. This dataset encompasses four distinct categories: Glioma, Meningioma, Pituitary, and No Tumor, as indicated in table 3.1. Each category is associated with a specific count of images in both the training and testing sets. The even distribution of images across categories and sets serves as a critical factor in ensuring that the models undergo training and testing on a representative dataset, thereby facilitating the attainment of precise and dependable outcomes in the context of brain tumor detection.

Table 3.1: Dataset distribution.

Dataset	N. of images	Labels	Training set	testing set
Br35H	7023	Glioma	1321	300
		Meningioma	1339	306
		pituitary	1457	300
		No tumor	1595	405

3.2.2 Evaluation Metrics

Evaluation metrics are crucial for assessing predictive models and classifiers, gauging their effectiveness across different applications [126, 127, 128]. Common metrics like accuracy, precision, recall, and F1-Score are widely used, while newer metrics like ROC/AUC and Kappa statistics provide deeper insights into model performance [129]. Developing standardized and comprehensive evaluation methodologies is a critical area for future exploration.

3.2.2.1 Confusion Matrix

A confusion matrix (see Figure 3.1) is an essential instrument in the assessment of model performance, offering a comprehensive overview of the model's predictions through a comparison of predicted class labels with actual class labels across all data instances[130]. This matrix allows for the calculation of various metrics like accuracy, precision, recall, and F1 score, which play a pivotal role in evaluating the efficiency of the model [131, 132].

N. of total samples		**Predicted**	
		No tumor	**Tumor**
Actual	**NO tumor**	***TN***	***FP***
	Tumor	***FN***	***TP***

Figure 3.1: Confusion matrix for binary classification tasks.

True Positive (TP): The number of cases in which the sample positively identifies the presence of a disease. For example, the properly identifies a person with a brain tumor as a tumor.

True Negative (TN): the number of cases in which the sample correctly shows no disease. For example, the properly identifies a healthy subject who does not have a tumor.

False Positive (FP): The number of cases in which the model incorrectly identifies a disease in a healthy individual. For example, the sample is incorrectly classified as the tumor of a healthy person.

False Negative (FN): The number of cases in which the model incorrectly predicts the absence of disease in a person who actually has the disease. For example, the model incorrectly classifies a person with epilepsy as healthy.

In order to evaluate the performance of our brain tumor detection model, we use several key metrics. These metrics include accuracy, precision, recall, specificity, and the F1 score.

3.2.2.2 Accuracy

Accuracy measures the proportion of true results (both true positives and true negatives) among the total number of cases examined [133, 134].

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.1}$$

3.2.2.3 Precision

Precision, also known as positive predictive value, is the proportion of true positives among all positive predictions [135, 136].

$$\text{Precision} = \frac{TP}{TP + FP} \tag{3.2}$$

3.2.2.4 Recall

Recall, also known as sensitivity, is the proportion of true positives among all actual positive cases [137].

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3.3}$$

3.2.2.5 F1-Score

The F1 Score is the harmonic mean of precision and recall, providing a single metric that balances both concerns [138, 139, 139].

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3.4}$$

3.2.2.6 The Receiver Operating Characteristic (ROC)

The Receiver Operating Characteristic (ROC) curve serves as a statistical instrument employed for the evaluation of the discriminatory capacity [140, 141]. It illustrates the relationship between sensitivity and specificity across different cut-off points, facilitating the identification of ideal thresholds, assessment of the overall effectiveness of the test, and comparison of numerous diagnostic tests [141].

3.3 RESULTS

3.3.1 Performance Assessment Using Pretrained Networks

A comprehensive overview of the performance exhibited by the pre-trained CNN networks, including MobileNetV2, DenseNet169, and ResNet50V2 models, across different training setups is presented in tables 3.2, 3.3, and 3.4, respectively. These models were evaluated using key metrics such as loss and accuracy in both training and testing phases, with their efficacy influenced by varying parameters like epochs, batch size, learning rate (LR), and optimizers. For MobileNetV2, using the Adam optimizer (LR = 0.0001, batch size = 16) yields high accuracy (100.0% in training, 97.63% in testing) and minimal losses. Alternative optimizers like SGD and RMSprop produce inconsistent outcomes. Similarly, DenseNet169 achieves notable accuracy (100.0% in training, 97.71% in testing) and minimal loss with Adam optimizer (LR = 0.0001, batch size = 16), while other optimizers yield inconsistent results. In the case of Resnest50V2, the Adam optimizer with the same parameters results in high accuracy (100.0% in training, 97.63% in testing) and minimal losses. Other optimizers lead to inconsistent outcomes, highlighting the importance of proper parameters and optimizer selection. However, the number of epochs also impacts accuracy, with models trained over 100 epochs generally outperforming those trained over 15 epochs.

Table 3.2: Performance assessment of the pre-trained MobileNeV2.

					Training		Testing	
Model	Optimizer	Epochs	Batch	LR	Loss	Accuracy	Loss	Accuracy
MobileNetV2	Adam	15	16	0.01	0.059	98.07	0.162	94.96
				0.001	0.032	98.81	0.114	96.49
				0.0001	0.006	99.98	0.089	97.10
			32	0.01	0.049	97.99	0.14	94.96
				0.001	0.008	99.79	0.093	96.49
				0.0001	0.013	99.98	0.089	96.56
			64	0.01	0.048	99.32	0.112	96.26
				0.001	0.0241	99.37	0.085	97.10
				0.0001	0.029	99.79	0.100	96.18
		100	16	0.0001	0.0005	100.0	0.074	97.63
	SGD	15	16	0.01	0.061	98.27	0.127	95.57
				0.001	0.230	92.42	0.295	89.16
				0.0001	0.492	84.72	0.561	80.54
			32	0.01	0.110	96.43	0.187	93.36
				0.001	0.288	0.906	0.3763	86.04
				0.0001	0.621	82.42	0.667	77.95
			64	0.01	0.162	94.57	0.221	91.83
				0.001	0.360	88.73	0.451	83.75
				0.0001	0.781	76.93	0.814	75.36
		100	32	0.1	0.0003	100.0	0.078	97.63
	RMSprop	15	16	0.01	0.144	96.97	0.210	93.21
				0.001	0.057	98.46	0.130	96.872
				0.0001	0.013	99.3	0.083	96.41
			32	0.01	0.139	97.29	0.266	94.27
				0.001	0.051	98.77	0.107	96.41
				0.0001	0.019	99.56	0.099	96.33
			64	0.01	0.128	96.64	0.172	94.81
				0.001	0.029	99.16	0.083	96.94
				0.0001	0.051	98.72	0.106	96.26
		100	64	0.001	5.4589e-06	100.0	0.099	97.40

Table 3.3: Performance assessment of the pre-trained DensNet169.

					Training		Testing	
Model	Optimizer	Epochs	Batch	LR	Loss	Accuracy	Loss	Accuracy
DensNet169	Adam	15	16	0.01	0.081	97.22	0.165	94.88
				0.001	0.034	98.77	0.099	96.64
				0.0001	0.016	99.86	0.0776	97.17
			32	0.01	0.098	96.67	0.117	95.80
				0.001	0.048	98.14	0.094	96.79
				0.0001	0.027	99.51	0.080	97.10
			64	0.01	0.069	97.30	0.101	96.56
				0.001	0.069	97.30	0.101	96.56
				0.0001	0.046	99.21	0.098	96.72
		100	16	0.0001	0.0001	100.0	0.067	97.71
	SGD	15	16	0.01	0.058	98.23	0.099	96.26
				0.001	0.209	93.24	0.271	89.77
				0.0001	0.466	86.34	0.533	82.68
			32	0.01	0.1001	97.04	0.14076	95.27
				0.001	0.2694	91.58	0.334	88.25
				0.0001	0.5722	83.77	0.6209	79.40
			64	0.01	0.148	95.27	0.206	92.37
				0.001	0.343	89.50	0.418	84.51
				0.0001	0.746	77.38	0.760	75.59
		100	32	0.1	2.7309e-04	100.0	0.069	97.55
	RMSprop	15	16	0.01	0.189	95.23	0.209	92.29
				0.001	0.063	98.03	0.111	96.10
				0.0001	0.029	99.03	0.848	97.11
			32	0.01	0.142	96.17	0.170	94.27
				0.001	0.0486	98.07	0.085	97.40
				0.0001	0.045	98.63	0.092	97.02
			64	0.01	0.126	95.90	0.1490	94.73
				0.001	0.062	97.75	0.080	96.94
				0.0001	0.075	97.81	0.099	96.49
		100	32	0.001	0.026	99.67	0.081	96.79

Table 3.4: Performance assessment of the pre-trained ResNet50V2.

					Training		Testing	
Model	Optimizer	Epochs	Batch	LR	Loss	Accuracy	Loss	Accuracy
ResNet50V2	Adam	15	16	0.01	0.050	98.48	0.214	95.34
				0.001	0.037	0.988	0.197	95.72
				0.0001	0.001	100.0	0.103	96.72
			32	0.01	0.026	99.11	0.303	94.12
				0.001	0.130	96.01	0.20	94.73
				0.0001	0.004	100.0	0.087	96.79
			64	0.01	0.048	98.2	0.193	95.34
				0.001	7.6692e-04	100.0	0.113	96.79
				0.0001	0.011	100.0	0.10	96.41
		100	16	0.0001	0.0005	100.0	0.074	97.63
	SGD		16	0.01	0.023	99.8	0.111	95.95
				0.001	0.174	94.78	0.258	91.53
				0.0001	0.425	85.8	0.506	82.30
			32	0.01	0.059	98.9	0.139	95.80
				0.001	0.2427	92.24	32.88	88.55
				0.0001	0.541	81.8	0.5996	77.65
			64	0.01	0.103	97.46	0.191	92.75
				0.001	0.311	86.49	0.398	82.66
				0.0001	0	77.45	0.699	73.07
		100	32	0.1	0.0003	100.0	0.078	97.63
	RMSprop	15	16	0.01	0.118	97.63	0.456	93.66
				0.001	0.026	99.2	0.284	96.10
				0.0001	0.003	99.92	0.132	95.72
			32	0.01	0.637	98.00	0.244	95.49
				0.001	0.0314	98.95	0.989	98.95
				0.0001	3.5383e-04	100.0	100.0	96.41
			64	0.01	0.084	97.93	0.733	90.99
				0.001	0.0149	99.56	0.170	95.57
				0.0001	0.022	99.63	0.091	96.94
		100	64	0.001	0.2335	96.52	0.122	96.85

3.3.2 Performance Assessment Using Different Concatenated CNN Networks

In this study, we combined several deep learning models to enhance the accuracy of brain tumor detection. By integrating MobileNetV2 with DenseNet169, we achieved the highest testing accuracy of 98.55% with a low loss of 0.071, outperforming the individual models, as depicted in Table 3.5. The combined model demonstrated superior performance in accurately classifying MRI images into glioma, meningioma, pituitary tumor, and no tumor categories. This approach underscores the potential of model fusion in leveraging the strengths of different architectures to improve diagnostic accuracy in medical image analysis.

Table 3.5: Performance assessment of Concatenated Deep CNN Models.

		Training		Testing	
Models	Parameters	Loss	Accuracy	Loss	Accuracy
MobileNetV2	LR=0.01, Epoch=100, Batch size= 16, Optimizer=SGD	0.0005	100.0	0.074	97.63
ResNet50V2	LR=0.0001, Epoch=100, Batch size= 16, Optimizer=Adam	0.0005	100.0	0.0741	97.63
DenseNet169	LR=0.1, Epoch=100, Batch size= 32, Optimizer=SGD	0.0001	100.0	0.0672	97.71
MobileNetV2+denseNet169	LR=0.01, Epoch=100, Batch size= 16, Optimizer=SGD	5.0627e-04	99.98	0.071	98.55
MobilNetV2+ResNet50V2	LR=0.01, Epoch=100, Batch size= 16, Optimizer=SGD	0.0081	99.88	0.2099	97.94

Figures (3.2, 3.3, 3.4, 3.5) provide the performance indicators of the best combination (MobileNetV2 and DensNet169). The classification report shows high precision, recall, and F1-scores across four classes: glioma, meningioma, no tumor, and pituitary, with an overall accuracy of 98.55%. The confusion matrix highlights minimal misclassifications, primarily between glioma and meningioma. The ROC curves further confirm the system's strong performance. These results underscore the system's high accuracy and robust diagnostic capabilities.

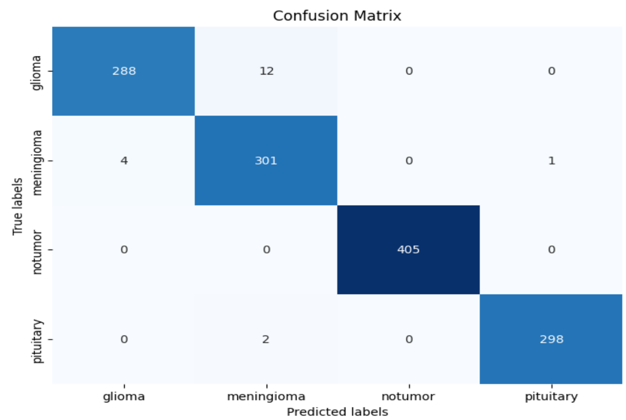


Figure 3.2: Confusion matrix of the best model.

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

           0     0.9863    0.9600    0.9730       300
           1     0.9556    0.9837    0.9694       306
           2     1.0000    1.0000    1.0000       405
           3     0.9967    0.9933    0.9950       300

    accuracy                         0.9855      1311
   macro avg     0.9846    0.9842    0.9843      1311
weighted avg     0.9857    0.9855    0.9855      1311
```

Figure 3.3: Classification report of the best model.

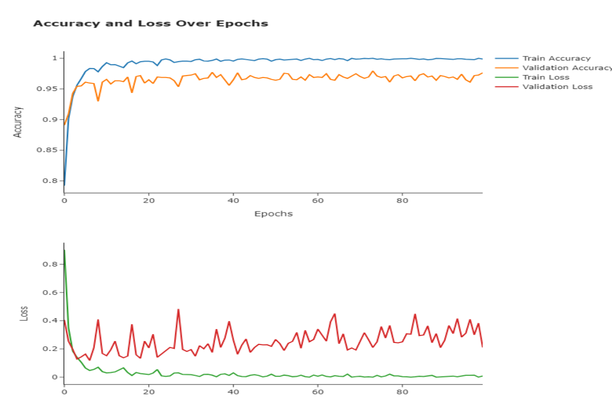


Figure 3.4: Accuracy, Loss curves during training and testing phases of the best model.

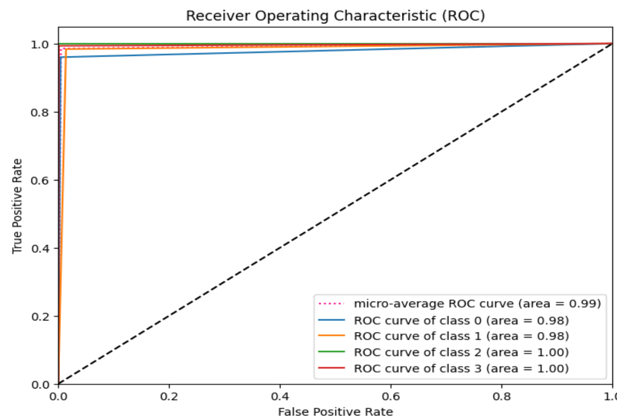


Figure 3.5: Receiver Operating Characteristic (ROC) of the best model.

3.4 Comparison With the The State of the Art

Table 3.6 provides a comprehensive overview of state-of-the-art techniques for brain tumor classification, including information on the authors, publication year, methodology used, number of classes considered, dataset employed, and corresponding accuracy levels achieved. The methodology proposed in our research, articulated herein, capitalizes on Transfer Learning utilizing MobileNet V2 in 2024, resulting in a competitive accuracy rate of 97.63% on the Br35H dataset. These collective findings serve to illustrate the continual progressions in methodologies for the classification of brain tumors, with a particular emphasis on the efficacy of deep learning techniques in producing elevated accuracies and robust performance on intricate medical imaging datasets.

Table 3.6: State-of-the-art methods for brain tumor classification.

Ref	Authors	year	Method	# of classes	# of data	Accuracy
[1]	MA Gómez-Guzmán et al	2023	CNN	4	Br35h	97.12%
[2]	Selcuk, B et al	2023	CNN	4	Br35h	97.6%
[3]	M. A. Islam et al	2023	CNN	4	Br35h	99%
[4]	Mohamed Maher Ata et al	2022	CNN/ DNN	4	Br35H	98.01%
[5]	Gehad Abdullah Amran et al	2022	CNN	4	Br35H	99.51%
[6]	Mondal, A., et al	2022	CNN	4	Br35H	99.57 %
[7]	Ours	2024	MobileNetV2+denseNet169	4	Br35H	98.55 %

3.5 CONCLUSION

The primary objective of this chapter was to design a robust system capable of distinguishing brain tumor cases from non-brain tumor cases and determining the severity of the tumors. Through a series of experiments, we tuned the parameters of each model and evaluated their performance across three levels to simulate real-world medical diagnosis scenarios. The results demonstrated the exceptional performance of concatenate MobileNetV2 and DensNet169, which achieved a high accuracy of 98.55%, surpassing other models and outperforming state-of-the-art techniques. This highlights the potential of concatenate MobileNetV2 and DensNet169 as a highly effective tool for brain tumor detection and severity classification.

General Conclusion

In this work, we have proposed an automated system for brain tumor detection using deep learning techniques. We have discussed the advantages of early brain tumor detection using advanced imaging techniques [142, 143]. The late detection of brain tumors, often resulting from manual diagnostic protocols, can lead to severe complications and reduced survival rates. However, automated diagnosis systems have garnered significant interest for facilitating early detection of brain tumors using deep neural network models. Our study evaluates the performance of various models, including ResNet50V2, MobileNetV2, and DenseNet169, as well as their concatenated versions, to determine the most effective approach for accurate and timely diagnosis [144].

For this purpose, we have proposed a solution for overcoming the drawback of traditional diagnosis systems by using three different models including ResNet50V2, MobileNetV2, and DenseNet169 to extract representative features from brain tumor images [145].

As dataset, we used the well-known Br35H . In addition, we have used various evaluation metrics such as accuracy, precision, recall, and F1 score to assess the performance of our proposed system [146]. These statistics enabled us to analyze our models' outcomes and improve detection performance.

As experimental results, we have employed hierarchical decisions that closely mimic the medical protocols used by healthcare professionals. In the context of brain tumor detection, the medical protocol first involves determining whether a patient has a brain tumor or not. If a tumor is detected, the medical procedure then focuses on assessing the tumor's type and severity [147]. At this stage, we have divided the tumor types into four types.

The future perspectives that can be proposed to improve this system would be to incorporate one of these principles:

- Apply Preprocessing Technique.
- Advanced Diagnostic Techniques.
- Create my own system and use two defferent dataset.

- Exploration of the latest methods for tumor detection.

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