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Abstract:

In recent years, Artificial Intelligence (AI), and more specifically Deep Learning, has become a fundamental tool driving transformative advancements across various fields, particularly in healthcare. This study focuses on designing an intelligent model based on Convolutional Neural Networks (CNN), one of the most prominent techniques in deep learning, to classify brain Magnetic Resonance Imaging (MRI) scans and automatically detect tumors. The significance of this work lies in addressing the challenges of conventional diagnosis, such as delays and inconsistencies in interpretation among physicians. The proposed model follows a structured process involving image preprocessing, training, and classification. Results have shown that the model effectively accelerates the diagnostic workflow, making it a promising supportive tool in clinical practice. The model achieved an accuracy of 97.71%, confirming its high reliability and effectiveness in tumor detection.

Key words :Artificial Intelligence (AI), Medical image processing, Deep Learning (DL), Convolutional Neural Network (CNN).

Résumé:

Ces dernières années, l'intelligence artificielle (IA), et plus particulièrement l'apprentissage profond (Deep Learning), est devenue un outil fondamental à l'origine d'avancées majeures dans divers domaines, notamment dans le secteur de la santé. Cette étude vise à concevoir un modèle intelligent basé sur les réseaux de neurones convolutifs (CNN), l'une des techniques les plus puissantes de l'apprentissage profond, afin de classer les images par résonance magnétique (IRM) du cerveau et de détecter automatiquement les tumeurs. L'importance de ce travail réside dans sa capacité à répondre aux défis du diagnostic traditionnel, tels que les retards et les divergences d'interprétation entre les médecins. Le modèle proposé suit un processus structuré comprenant le prétraitement des images, l'entraînement et la classification. Les résultats ont montré que le modèle permet d'accélérer efficacement le flux de travail diagnostique, ce qui en fait un outil d'assistance prometteur dans la pratique clinique. Le modèle a atteint une précision de 97,71 %, confirmant sa grande fiabilité et son efficacité dans la détection des tumeurs.

Les mots clés: Intelligence Artificielle (IA), traitement d'images médicales, Deep Learning (DL), réseaux de neurones convolutifs (CNN)

الملخص:

في السنوات الأخيرة، أصبح الذكاء الاصطناعي (AI) ، وتحديدًا التعلم العميق، أداة أساسية لدفع عجلة التقدم التحويلي في مختلف المجالات، لا سيما في مجال الرعاية الصحية. تركز هذه الدراسة على تصميم نموذج ذكي قائم على الشبكات العصبية التلافيفية (CNN) ، إحدى أبرز تقنيات التعلم العميق، لتصنيف فحوصات التصوير بالرنين المغناطيسي للدماغ (MRI) والكشف التلقائي عن الأورام. تكمن أهمية هذا العمل في معالجة تحديات التشخيص التقليدي، مثل التأخير والتناقضات في التفسير بين الأطباء. ينبع النموذج المقترح عملية منظمة تتضمن معالجة الصور مسبقًا والتدريب والتصنيف. أظهرت النتائج أن النموذج يُسرّع سير العمل التشخيصي بفعالية، مما يجعله أداة داعمة واعدة في الممارسة السريرية. حقق النموذج دقةً بلغت 97.71%، مما يؤكد موثوقيته العالية وفعاليته في الكشف عن الأورام.

الكلمات المفتاحية: معالجة الصور الطبية، التعلم العميق (DL)، الشبكات العصبية التلافيفية (CNN)، الذكاء الاصطناعي (AI).

Dedication

I dedicate this work to Allah, the Most Merciful, whose guidance and blessings made every step of this journey possible.

To my mother and father, whose love, strength, and sacrifices have shaped my path.

To my siblings, my constant support and comfort through every high and low.

To my teachers, whose guidance and belief in me helped me grow.

To my friends, whose kindness and laughter made the journey lighter. And finally, to myself—for not giving up, for holding on, and for turning challenges into strength.

TOUATI BRAHIM Selma

إهداء

(وَكَانَ فَضْلُ اللَّهِ عَلَيْكَ عَظِيمًا)

ما سلكت البدايات إلا بتيسيره، وما بلغت النهايات إلا بتوفيقه ، وما حققت الغايات إلا بفضلته، فالحمد لله قولا وعملا ، والحمد لله على التمام والإنجاز .
إلى الأيادي التي أزالت عن طريقي أشواك الفشل إلى من ساندني بكل حب عند ضعفي إلى من رسموا إلي المستقبل بخطوط من الثقة والحب إلى عائلتي .
إلى النور الذي أنار دربي والسراج الذي لا ينطفئ نوره إلى العزيز الذي حملت اسمه فخراً داعمي الأول في مسيرتي وسندي والدي العزيز .
أهدى فرحة تخرجني إلى تلك الإنسانية العظيمة، إلى من جعل الله الجنة تحت أقدامها وسهلت لي الشدائد بدعائها والدتي العزيزة .
إلى خيرة أيامي وصفوتها، إلى ضلعي الثابت وأمان أيامي إخواني وأخواتي ، جدتي .
إلى الذين يبهجهم نجاحي ، وكانوا عوناً وسنداً في هذا الطريق رفقاء السنين وأصحاب الشدائد والأزمات صديقاتي .
وأخيراً الشكر موصول لنفسي على الصبر والعزيمة والإصرار ، راجية من الله تعالى أن ينفعني بما علمني وأن يعل مني ما أجهل ويجعله حجةً لي لا على .

Chebrou Rokaia

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Abbreviations List :

AI : Artificial Intelligence

DL : Deep Learning

ML : Machine Learning

CNN : Convolutional Neural Networks

MRI :Magnetic resonance image

CT :Computer Tomography

GPU :Graphics Processing Unit

RNN:Recurrent Neural Network

HOG: Histograms of Oriented Gradients

SIFT : Scale-Invariant Feature Transform

SVM :Support Vector Machines

ReLU :Rectified Linear Unit

SGDM : Stochastic Gradient Descent with Momentum

Adam :Adaptive Moment Estimation

General Introduction

In recent years, Artificial Intelligence (AI) has become one of the fundamental pillars supporting technological advancement across various sectors, especially in healthcare. Medical imaging stands out as one of the most prominent applications of AI, where techniques such as X-rays, Magnetic Resonance Imaging (MRI), and Computed Tomography (CT) are employed to provide essential and accurate insights into the internal structure of the human body.

Despite progress in medical imaging technologies, the interpretation of these images remains a major challenge. It often requires significant time, effort, and expert knowledge, which can result to delays in diagnosis, especially in critical conditions such as brain tumors. Physicians typically rely on manual analysis of DICOM images using advanced software tools, which exposes the process to variability between doctors in interpreting the results. Such inconsistencies may negatively impact the quality of medical decisions and the effectiveness of treatment.

This study aims to explore the potential of artificial intelligence—particularly deep learning techniques—by designing a model that can classify medical images and evaluate its diagnostic performance by calculating accuracy on different datasets. Special attention is given to Convolutional Neural Networks (CNNs), which have proven to be highly effective in image analysis and classification tasks.

In this context, an intelligent system was design based on a CNN model capable of automatically and accurately classifying brain MRI images into four categories : “tumor(glioma, meningioma, or pituitary)” or “no tumor.” This system helps automate the diagnostic workflow, reducing the time required for diagnosis and improving its accuracy, thus assisting medical professionals in making data-driven and objective decisions.

This study is structured into three main chapters as follows :

- **The first chapter** : Introduces generalities on the AI, provides an overview of medical image processing, and discusses the role of AI in this domain.
- **The second chapter** : Focuses on the functioning of Convolutional Neural Networks and presents commonly used architectures in image analysis.
- **The third chapter** : Demonstrates the practical implementation of the proposed model, detailing the tools and datasets used, as well as the results obtained.

Chapter I

AI and Medical image processing

1. Introduction :

Medical image processing is an advanced field that combines computer technologies and medicine to analyze medical images. Its main goal is to enhance image quality and extract accurate information to assist doctors in diagnosis. With the advancement of artificial intelligence (AI), techniques such as deep learning and machine learning have become crucial in this field. AI can analyze vast amounts of medical data, improving diagnostic accuracy and efficiency.

In this chapter, we studied an overview of AI and medical image processing, and finally, the role of AI in diagnosing and processing medical images.

2. Artificial intelligence :

2.1. Definition AI:

AI is the study of how to build or program computer to enable them to do what mind can do [1].

2.2. Historical development of AI :

➤ Before (1950s)

- AI started as an idea from math and logic.
- Scientists wondered :Can machines think like humans ?
- Alan Turing (1950) created the Turing Test to check if a machine could talk like a person.

➤ (1950s)

- Computers could solve basic math problems and play simple games.
- They followed strict rules and couldn't learn from experience.
- AI worked by trying many options (trial-and-error) to find answers.

➤ (1960s)

- AI couldn't think on its own or recognize patterns well.
- Programs were slow and only worked for specific tasks.
- Scientists worked on new problem-solving methods to make AI smarter.

➤ (1970s–1980s)

- AI became expert systems, meaning it used stored knowledge to make decisions.
- These systems helped in medicine, engineering, and business.
- But AI still couldn't improve by itself—humans had to update it.

➤ (1980s–1990s)

- Scientists created neural networks, inspired by how the human brain works.
- AI could now recognize speech and images by finding patterns.
- Instead of following fixed rules, AI learned from examples (machine learning).

➤ (2000s–Today)

- AI got even better with deep learning, allowing it to learn from huge amounts of data.
- Now AI is used in self-driving cars, virtual assistants (Siri, Alexa), and even hospitals.
- AI keeps learning and improving without human help[2].

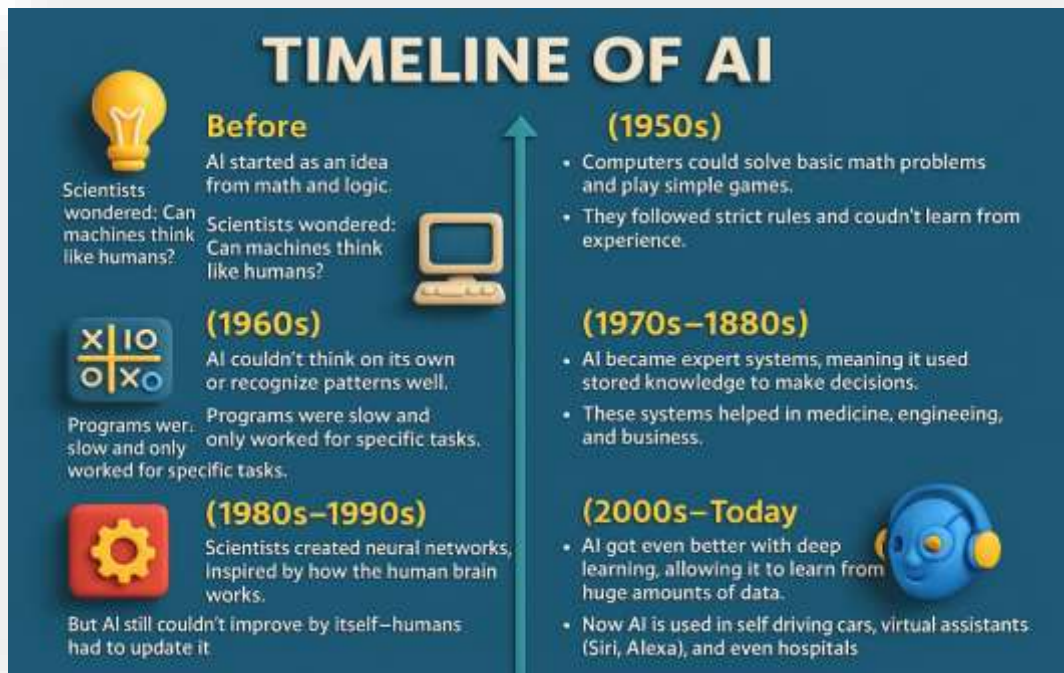


Figure I.1: Historical development of AI

2.3. Fields of Application of AI:

At the core of modern AI are two closely related fields [3] :

- **Machine Learning (ML)** : A subfield of AI that enables computers to learn from data without being explicitly programmed. Instead of following hard-coded rules, ML systems improve their performance by identifying patterns and making predictions from data.
- **Deep Learning (DL)** : A specialized branch of machine learning that uses artificial neural networks with multiple layers (deep neural networks). Deep learning is especially powerful for processing complex data such as images, sound, and natural language.

These technologies are now applied in a wide variety of real-world domains. The following sections present the most prominent fields where AI, ML, and DL are making significant impact.

- **Healthcare and Medicine** :AI is widely applied in medical diagnostics, personalized medicine, drug discovery, and medical imaging.

Key Applications :

- Medical imaging (e.g., MRI, CT scan analysis)
 - Disease prediction and diagnosis
 - Robotic surgery
- **Finance and Economics :** AI is used in algorithmic trading, fraud detection, risk management, and customer service automation.

Key Applications :

- Fraud detection
 - Stock market forecasting
 - Robo-advisors
- **Autonomous Systems and Robotics :** AI enables decision-making and control for autonomous vehicles, drones, and robotic assistants.

Key Applications :

- Self-driving cars
 - Drones
 - Assistive robots
- **Natural Language Processing (NLP) :** AI models process and generate human language in applications like translation, sentiment analysis, and virtual assistants.

Key Applications :

- Machine translation
 - Speech recognition
 - Chatbots and virtual assistants
- **Education and E-Learning :** AI supports personalized learning, intelligent tutoring systems, and automated grading.

Key Applications :

- Adaptive learning platforms
 - Automated grading systems
 - Student performance prediction
- **Smart Manufacturing and Industry 4.0** : AI is central to predictive maintenance, quality control, and process optimization in manufacturing.

Key Applications :

- Predictive maintenance
 - Quality control using computer vision
 - Process automation
- **Agriculture and Environmental Monitoring** : AI is applied to crop monitoring, precision agriculture, weather prediction, and environmental protection.

Key Applications :

- Precision agriculture
 - Crop disease detection
 - Automated irrigation
- **Cybersecurity** : AI enhances threat detection, anomaly detection, and security automation.

Key Applications :

- Intrusion detection systems
- Phishing detection
- User authentication

- **Smart Cities and Urban Planning** : AI helps optimize traffic, energy usage, waste management, and urban infrastructure.

Key Applications :

- Traffic flow prediction
- Energy consumption optimization
- Urban development simulation

- **Entertainment and Creative Arts** : AI is used for content generation, recommendation systems, and interactive storytelling.

Key Applications :

- Music and art generation
- Video game AI
- Recommendation engines (e.g., Netflix, Spotify)

3. Medical Image Processing :

3.1. Definition Medical Image Processing :

Image processing involves applying techniques and algorithms to analyze and enhance digital images by modifying properties such as clarity and contrast. This is achieved through signal processing methods or matrix manipulation [4]. Medical image processing is the first step in the analysis of medical images, which makes images more intuitive to improve the diagnosis efficiency [5].

3.2. Types of Medical Image :

3.2.1. Ultrasound image :

Is an effective technique, providing high-resolution images through the interaction of sound waves with tissues, balancing frequency and penetration depth for optimal medical diagnosis [6].

3.2.2. Magnetic resonance image MRI :

Uses the inherent magnetic properties of atomic nuclei to generate an image. Anatomical imaging uses hydrogen ions for the signal source but functional imaging uses

other ions such as carbon, oxygen, fluorine, sodium, and phosphorous (Driehuys, Nouls et al. 2008)[6].

3.2.3. Computer Tomography CT :

Clinical CT emits X-ray beams to generate two-dimensional images using up to 256 detectors, making it ideal for clinical use with limited rotation requirements [6].

3.2.4. X-ray :

Produces images by measuring the attenuation of X-ray through the body via a detector array [7].

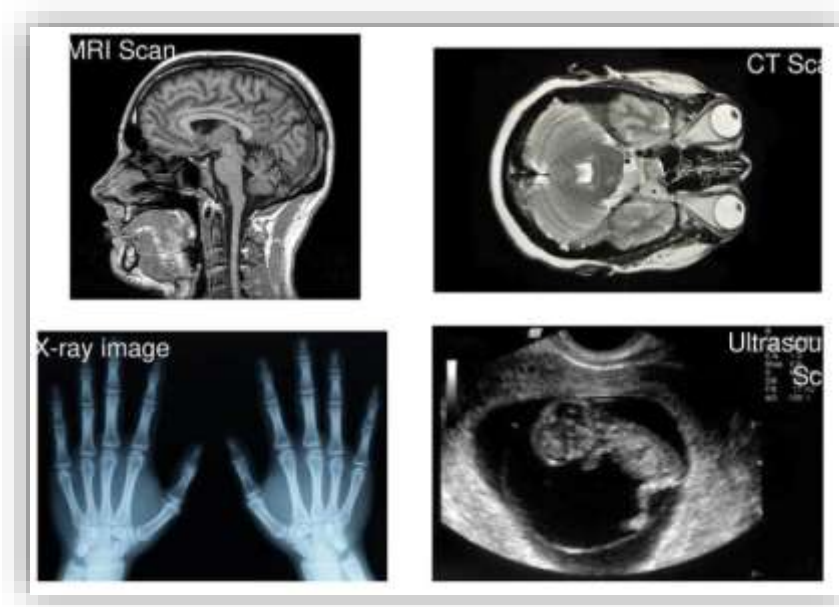


Figure I.2 : Types of Medical Image [8].

3.3. Medical Image Classification System :

3.3.1. Datasets : Challenges and Damages :

A dataset is a collection of related information that is typically organized in a standardized format. These datasets are used for data analysis, business intelligence, and training artificial intelligence (AI) models, among many other applications[9].

Datasets are fundamental to the development of artificial intelligence systems for medical image diagnosis. However, their use raises several technical and ethical challenges.

➤ Data Quality :

The quality of medical images is a determining factor for the effectiveness of machine learning models. Images can be affected by various types of noise, such as Gaussian noise, Poisson noise, or artifacts related to medical equipment [10]. These imperfections can compromise the model's ability to detect clinically significant anomalies. For example, in CT

scans, metallic artifacts can obscure critical regions of the image, making their analysis difficult [11].

Furthermore, the spatial resolution of images can vary depending on the imaging modality used (MRI, X-rays, etc.). Low resolution can lead to the loss of important information, limiting the accuracy of classification algorithms [12].

➤ **Class Imbalance:**

A major challenge lies in the imbalance of classes in medical datasets. Some pathologies are rare and underrepresented in databases, which can introduce bias into machine learning models. For instance, in lung cancer screening, malignant nodules represent a minority compared to benign nodules [13]. This imbalance can lead to poor generalization of the model, as it tends to favor the majority class.

To address this issue, techniques such as oversampling (e.g., SMOTE - Synthetic Minority Over-Sampling Technique) or undersampling can be used. Oversampling involves generating synthetic examples for the minority class, while undersampling reduces the size of the majority class to balance proportions [14].

➤ **Data Protection:**

The privacy of medical data is a major concern. Datasets must be anonymized to protect sensitive patient information while maintaining their value for research. However, anonymization must be carefully performed to prevent any leakage of identifiable information. Advanced techniques such as data masking or homomorphic encryption can be used to enhance security [15].

Moreover, sharing medical datasets between institutions raises ethical and legal questions. Initiatives like Federated Learning allow models to be trained without directly sharing raw data, thereby better respecting patient privacy [16].

3.3.2. Feature Extraction:

Feature extraction is a key step in medical image classification. It aims to transform images into representative numerical vectors that can be exploited by machine learning algorithms.

➤ Traditional Methods :

Before the advent of deep neural networks, traditional methods were widely used to extract features from medical images. Among these approaches are :

- **Histograms of Oriented Gradients (HOG):** This method captures local variations in brightness and color in an image, which is particularly useful for detecting specific anatomical structures [17].
- **Wavelet Transform :** Wavelets decompose an image into different spatial frequencies, facilitating the detection of textures or edges [18].
- **SIFT (Scale-Invariant Feature Transform) Descriptors :** This descriptor identifies interest points in an image and extracts their scale- and rotation-invariant features, ideal for organ segmentation applications [19].

These methods require human expertise to select relevant features, which can limit their effectiveness in complex cases.

➤ Deep Learning-Based Approaches :

Convolutional Neural Networks (CNNs) have revolutionized feature extraction by enabling an automatic and hierarchical approach. Unlike manual methods, CNNs learn features directly from raw data without explicit human intervention [20]. Here are some advantages of CNNs :

- **Hierarchical Representation :** Early layers of CNNs capture simple features (edges, angles), while deeper layers detect complex patterns (organ shapes, pathological anomalies).
- **Adaptability :** CNNs can be adapted to different types of medical images (X-rays, MRIs, CT scans) through flexible architectures like ResNet, DenseNet, or U-Net [21].

However, these models require large amounts of data to be trained effectively, which can be problematic in the medical field where datasets are often limited.

3.3.3. Classification and Decision Making:

Classification is the final step where extracted features are used to assign each image to a specific class (e.g., "normal" vs. "pathological"). Several approaches can be adopted for this task.

➤ Classical Algorithms:

Classical algorithms remain relevant in certain contexts, especially when datasets are small or when features are well-defined. Among these algorithms are:

- Support Vector Machines (SVM): SVMs are particularly effective for linearly separable problems. They construct a hyperplane that maximizes the margin between classes [22].
- Decision Trees: These algorithms recursively divide the feature space to create simple and interpretable decision rules [23].
- Random Forests: By combining multiple decision trees, random forests offer better robustness against noise and imperfect data [24].

➤ Deep Neural Networks:

Deep neural networks, particularly CNNs, often outperform classical methods in terms of accuracy. They are capable of capturing complex relationships between features and performing fine-grained classification [25].

These models generally require significant computational resources and large datasets to achieve their full potential.

3.3.4. Model Evaluation :

Evaluating model performance is essential to ensure their reliability and clinical applicability. This phase involves the use of appropriate metrics and rigorous validation techniques.

➤ Evaluation Metrics:

Several metrics are commonly used to evaluate classification models:

- **Accuracy:** Proportion of correctly classified examples. However, it can be misleading in cases of class imbalance.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \quad \mathbf{I.1}$$

The **accuracy** of a classification model is calculated using the following equation :

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad \text{I.2}$$

Where :

- ✓ **TP** = True Positives (correctly predicted positive cases)
- ✓ **TN** = True Negatives (correctly predicted negative cases)
- ✓ **FP** = False Positives (incorrectly predicted as positive)
- ✓ **FN** = False Negatives (incorrectly predicted as negative)

• **Sensitivity**: Model's ability to detect positive cases. Critical in medical diagnosis to minimize false negatives.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad \text{I.3}$$

- ✓ **TP** = True Positives (correctly predicted positives)
- ✓ **FN** = False Negatives (incorrectly predicted as negative)

• **Specificity**: Model's ability to identify negative cases. Important to avoid false positives.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \quad \text{I.4}$$

- ✓ **TN** = True Negatives (correctly predicted negatives)
- ✓ **FP** = False Positives (incorrectly predicted as positive)

• **F1 Score**: Harmonic mean between precision and sensitivity, useful for balancing these two criteria [26].

$$\text{F1 Score} = \frac{2 \cdot \text{Precision} \cdot \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} \quad \text{I.5}$$

Where:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad \text{I.6}$$

- ✓ Precision = Out of everything the model said was "tumor", how many were correct.
- ✓ Sensitivity = Out of all real tumors, how many the model found.

4. The Role of Artificial Intelligence in Medical Imaging Diagnosis :

AI technologies and algorithms have transformed disease diagnosis by providing healthcare professionals with accurate and efficient tools [27]. Owing to their ability to extract nuanced patterns from complex medical data, machine-learning techniques, particularly deep learning, have gained importance [27]. Convolutional neural networks (CNNs) have become the standard for image-based diagnoses such as tumour detection in radiological scans [28]. The fusion of AI with conventional medical imaging techniques has expedited disease diagnoses [27]. For instance, the AI-assisted analysis of retinal images aids in the early detection of diabetic retinopathy [29].

In addition, natural language processing (NLP) enables the rapid analysis of textual clinical records, offering insights for accurate diagnosis and patient care [30]. In radiology, AI algorithms have shown proficiency in interpreting medical images and assisting radiologists in the detection of various diseases. AI-powered systems can detect anomalies in X-rays, MRIs, and CT scans, resulting in faster and more accurate disease diagnosis [31,32].

Similarly, AI has made significant advances in pathology, revolutionising the field by speeding slide processing and enhancing disease identification. Research has highlighted the ability of AI to identify cellular and tissue anomalies, enabling pathologists to diagnose diseases with greater accuracy [33,34].

In dermatology, AI-powered tools such as deep learning algorithms can accurately identify skin cancer by analysing images, even rivalling the diagnostic acumen of dermatologists [27].

In one study, Haensle and colleagues demonstrated how AI algorithms can identify melanomas and other skin cancers by analysing images, thereby offering a supplementary diagnostic tool for Clinicians [32,35].

This accelerated data processing translates into faster diagnoses and timely interventions, potentially averting critical outcomes [27].

5. Conclusion:

Chapter 1 explains that AI helps machines think and learn like humans. In medicine, AI improves medical image processing. It helps doctors find diseases early and make better decisions, making diagnosis faster.

As future work, more research should focus on developing explainable AI models that can provide transparent reasoning behind their predictions. Additionally, integrating AI systems more effectively into clinical workflows and ensuring data privacy and ethical considerations will be essential for widespread adoption in medical practice.

Chapter II

Deep Learning And Convolutional Neural Network

1. Introduction :

Deep learning is a branch of artificial intelligence that has revolutionized data processing and intelligent decision-making. It relies on deep artificial neural networks, which mimic the way the human brain learns and extracts patterns from vast amounts of data.

In this chapter, we will explore the concept of deep learning and delve deeply into Convolutional Neural Networks (CNN), including their various layers and fundamental architecture, with a focus on how they are used for image classification and accurate content recognition.

2. Deep Learning :

2.1. Deep learning definition : a subfield of machine learning that structures algorithms in layers to create an “artificial neural network” that can autonomously learn and make intelligent decisions[36].

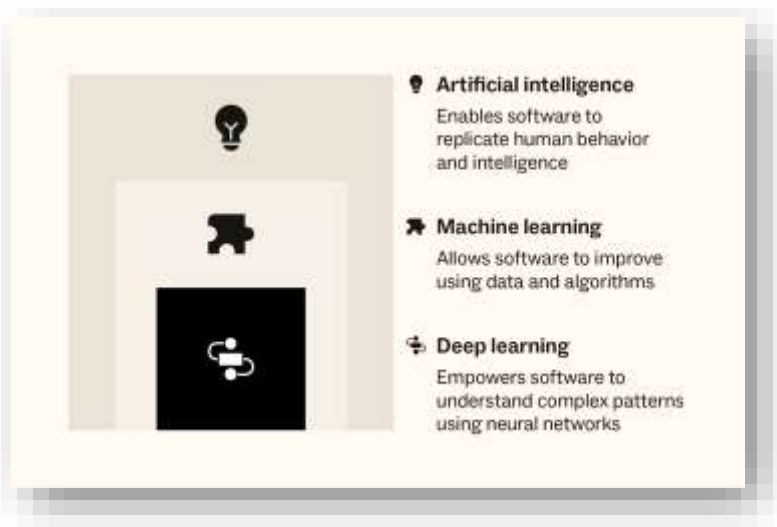


Figure II.1: The relation between AI, Machine learning, Neural networks and Deep learning [37].

2.2. How Does Deep Learning Work ?

Deep learning models are based on neural network architectures. Inspired by the human brain, a neural network consists of interconnected nodes or neurons in a layered structure that relate the inputs to the desired outputs [36]. The neurons between the input and output layers of a neural network are referred to as hidden layers. The term “deep” usually

refers to the number of hidden layers in the neural network. Deep learning models can have hundreds or even thousands of hidden layers [36].

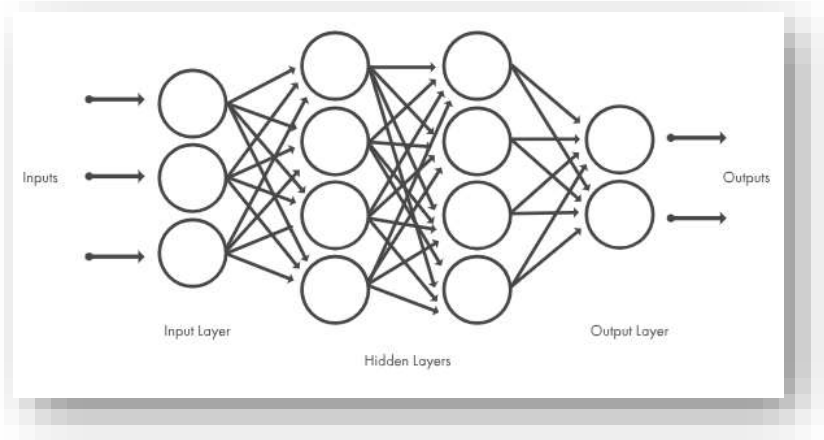


Figure II.2: Viewing a typical neural network architecture [36].

Deep learning models are trained by using large sets of labeled data and can often learn features directly from the data without the need for manual feature extraction. While the first artificial neural network was theorized in 1958, deep learning requires substantial computing power that was not available until the 2000s. Now, researchers have access to computing resources that make it possible to build and train networks with hundreds of connections and neurons [36]. High-performance GPUs have a parallel architecture that is efficient for deep learning. When combined with clusters or cloud computing, this enables development teams to reduce training time for a deep learning network from weeks to hours or less [36].

2.3. Types of Deep Learning Models:

Three types of deep learning models are convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer models [36].

CNNs: A CNN convolves learned features with input data, and uses 2D convolutional layers, making this architecture well suited for processing 2D data, such as images. The CNN works by extracting features directly from images. The relevant features are learned while the network trains on a collection of images. This automated feature extraction makes deep learning models highly accurate for image classification tasks. CNNs can also be used for classifying other types of data, such as time series and text [36].

RNNs: A recurrent neural network (RNN) is a network architecture for deep learning that predicts on time-series or sequential data. RNNs are particularly effective for working with sequential data that varies in length and solving problems such as natural signal classification, language processing, and video analysis. The long short-term memory (LSTM) network is a special type of RNN that is better in learning longer term dependencies than simple RNNs [36].

Transformers: Transformers are designed to track relationships in sequential data. They rely on a self-attention mechanism to capture global dependencies between input and output. They are often used for natural language processing and they are the basis for large language models (LLMs) such as BERT and ChatGP [36].

3. Convolution Neural Network :

3.1. Definition :

CNN Convolutional neural network is a special type of deep learning model designed to work with structured data like images. It is inspired by how the human visual system works and is used for tasks such as classifying images or making predictions. A CNN is made up of several basic layers that work step by step to process the input and give a final result. These main layers include convolutional layers (to detect features), activation function (to add flexibility), pooling layers (to reduce size), fully connected (to combine features), and the output layer (to make the final prediction) [38].

- ❖ Neural networks are a special kind of machine learning that works like a simplified version of the human brain. They help computers recognize patterns, make predictions, and sort information. They are made up of three main parts:
 - Input layer – Collects and organizes the data.
 - Hidden layers – Process and analyze the data step by step.
 - Output layer – Produces the final result based on what the network has learned[39].

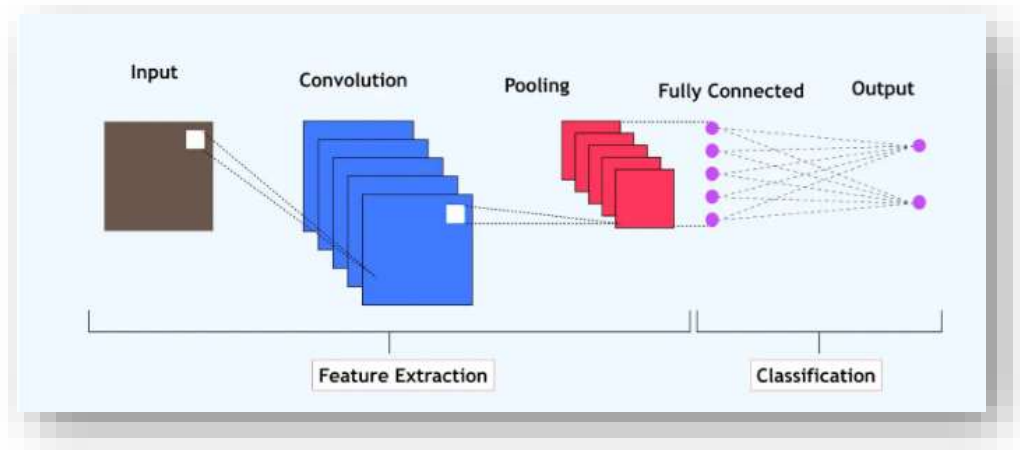


Figure II.3: The architecture of CNN [40]

In math, convolution is the operation of two functions to create a new one. In CNNs, the image is the first function, and the filter is the second [41].

3.2. Basic components of a CNN:

There are three main layers of a CNN consist of convolutional layers, ReLU activation layers, pooling layers, and fully connected layers [41]:

3.2.1. Convolutional layers:

A convolutional layer is the core building of a CNN. It works like a small window that moves across an image pixel by pixel, looking for important patterns to help recognize objects. We will perform some mathematical operations to produce a modified image with new pixel values [41].

The first convolutional layer scans the image in small parts using a filter (kernel). It processes each part separately and creates a new version of the image, called a **feature map**, which highlights important details [41].

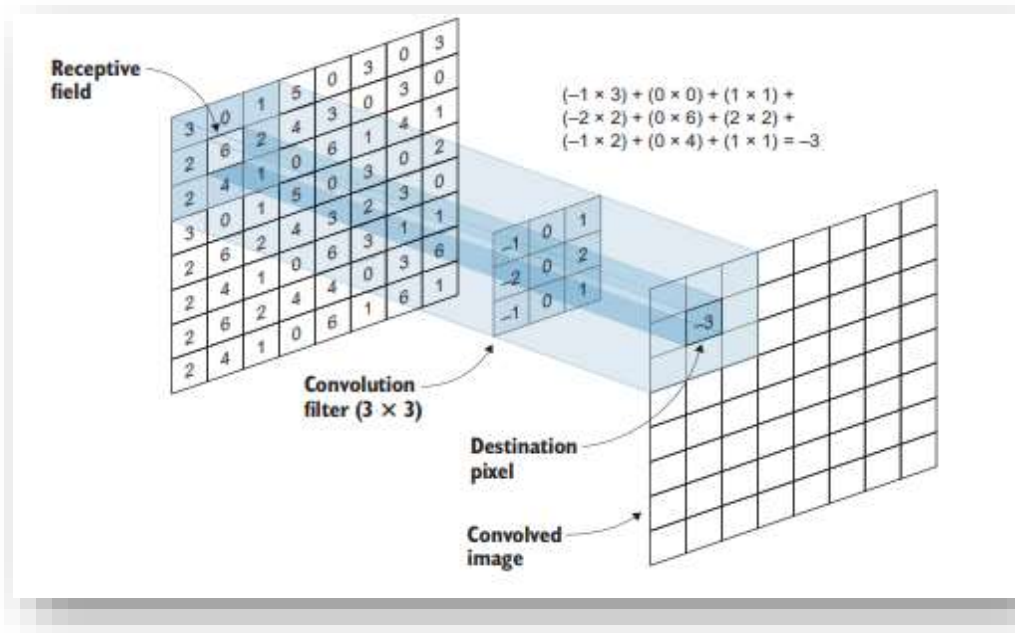


Figure II.4: A 3x3 convolutional filter is sliding over the input image [41].

Keeping this diagram in mind, here are some facts about convolution filters:

- The kernel slides over the original image pixel by pixel and does some math calculations to get the values of the new “convolved” image on the next layer.
- The area of the image that the filter convolves is called **the receptive field** in **Figure II.4**[41].

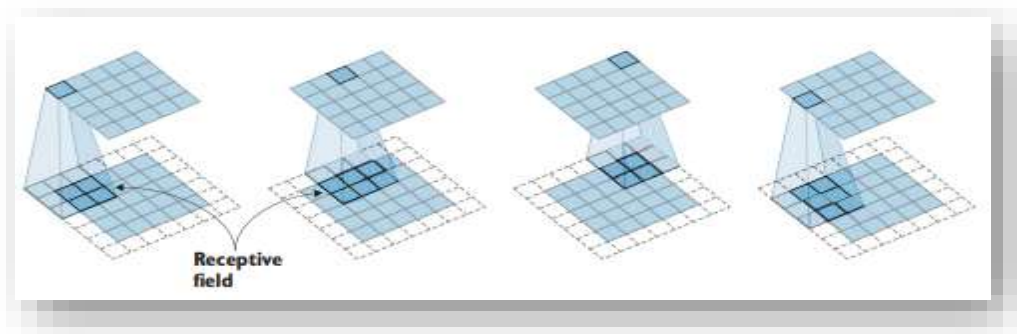


Figure II.5: The kernel slides over the original image pixel by pixel and calculates the convolved image on the next layer. The convolved area is called the receptive field [41].

What are the kernel values? In CNNs, the kernel values are like small filters that scan the image, these values start as random numbers, and the network learns the best values on its own during training. You don’t need to set them manually [41].

➤ **Convolutional operations:**

We multiply the input by the weights and sum them all together to get the weighted sum
Weighted

$$\text{sum} = x_1 \cdot w_1 + x_2 \cdot w_2 + x_3 \cdot w_3 + \dots + x_n \cdot w_n + b \quad \text{II.1}$$

x_1, x_2, \dots, x_n = These are the pixel values from a small section of the image.

w_1, w_2, \dots, w_n = These are the weights in the filter (filter values).

$+ b$ = This is the bias. It's just an extra number added at the end to help the result be more flexible [41].

In CNNs, the neurons and weights are structured in a matrix shape. So we multiply each pixel in the receptive field by the corresponding pixel in the convolution filter and sum them all together to get the value of the center pixel in the new image (figure II-5)[41].

$$(93 \times -1) + (139 \times 0) + (101 \times 1) + (26 \times -2) + (252 \times 0) + (196 \times 2) + (135 \times -1) + (240 \times 0) + (48 \times 1) = 243$$

The filter (or kernel) moves across the entire image, multiplying each pixel by the corresponding filter value. The results are then summed to produce a new image with updated pixel values. This processed image is known as a feature map or activation map [41].

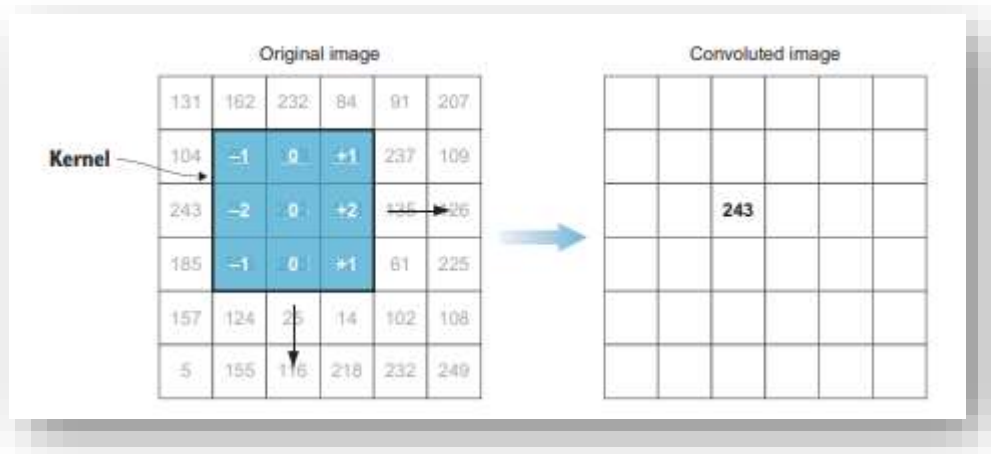


Figure II.6: Multiplying each pixel in the receptive field by the corresponding pixel in the convolution filter and summing them gives the value of the center pixel in the new image [41].

➤ **Strides and padding:**

These two settings together control the shape of the output of a convolutional layer. Let's see how [41] :

- Strides: determine how far the filter moves across the image each time. If the filter moves one pixel at a time, the stride is 1. If it moves two pixels at a time, the stride is 2. Larger strides (like 3 or more) are rare. Smaller strides (like 1) keep the output image size close to the original, while larger strides (like 2) reduce the output size. The exact size also depends on the padding setting, which affects how edges are handled.
- Padding: also known as zero-padding, adds extra zeros around the edges of an image. This helps keep the input and output sizes the same after applying a convolution. Padding is useful because, without it, the image would get smaller as we go deeper into the network. Keeping the size consistent allows us to build deeper CNNs without losing too much spatial information.

The purpose of using strides and padding in a CNN is to control how much detail from the image is passed to the next layer[41].

Later, we use a pooling layer (which we'll discuss next) to further reduce the image size and focus on important features. For now, just remember that strides and padding help determine how much of the original image is kept or ignored in each layer [41].

3.2.2. Activation function:

Activation function is a very important feature in a neural network. They help the network make smart decisions by changing numbers in a way that makes sense for what the network is learning. They also allow the network to handle more complex patterns and build deeper layers, which helps it learn better. There are different kinds, Sigmoid, Tan Hyperbolic and Rectified Linear Unit (ReLU), each one works a little differently [42].

But ReLU commonly used in deep learning models, especially in Convolutional Neural Networks (CNNs). The main advantage of ReLU is that it doesn't activate all the neurons at once, which makes the network more efficient and quicker than the other functions. This non-linear function takes an input value x and sets it to 0 if x is negative, and if x is positive, it keeps the value as it is. ReLU is defined as $f(x)=\max(0, x)$. It's faster and requires less computation time compared to other activation functions, making it ideal for CNNs [42].

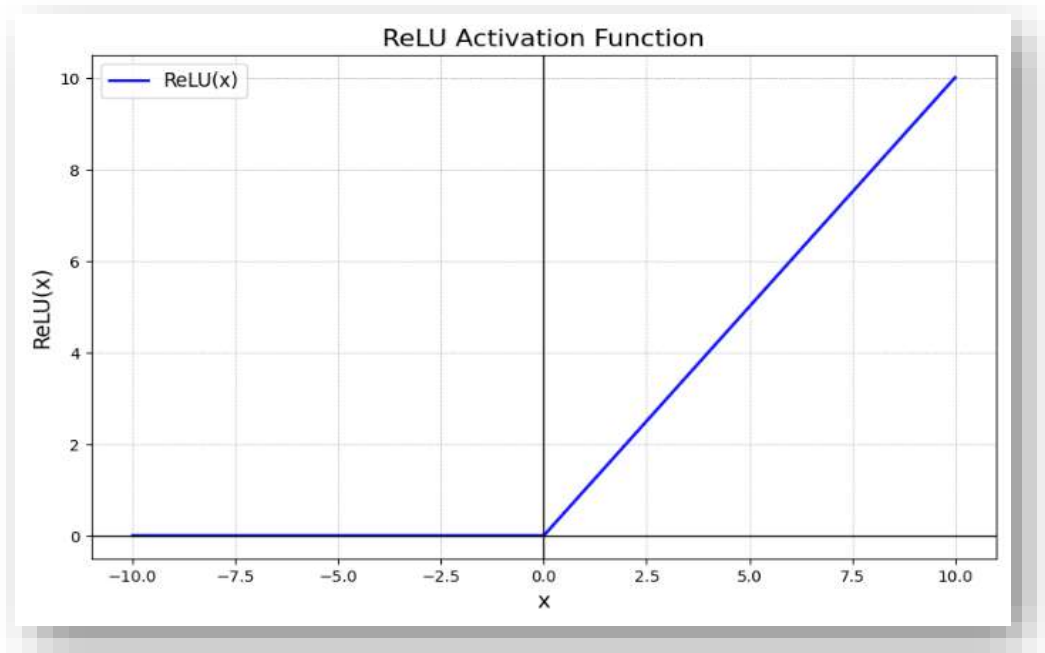


Figure II.7: ReLU Activation function [43]

3.2.3. Pooling layers:

Adding more convolutional layers makes the network deeper, which means it has more parameters (weights) to learn. The more layers we add, the more complex the calculations become, requiring more time and memory to process [41].

To manage this, we use **pooling layers**, which help reduce the size of the network by keeping only the most important information. Pooling works by summarizing regions of the image, using functions like 'max pooling' (taking the highest value) or 'average pooling' (taking the average). This reduces the number of parameters passed to the next layer, making the network more efficient while still preserving key features [41].

The pooling layer's main job is to shrink the feature maps created by the convolutional layer, reducing the number of parameters and making computations faster. To keep the network efficient, it's common to add a pooling layer after every one or two convolutional layers in a CNN [41].

➤ How pooling layers work:

There are 2 types of pooling layers : max pooling and average pooling. We will discuss max pooling first:

is a technique used to reduce the size of feature maps while keeping the most important information? It works by sliding a small window (or filter) over the image, just like a convolutional filter. However, unlike convolution, max pooling does not have weights or learn any values. Instead, for each region it covers, it simply selects the highest pixel value and discards the rest.

For example, if we use a 2×2 filter with a stride of 2, the window moves across the feature map, taking only the maximum value from each 2×2 section. This effectively reduces the image size from 4×4 to 2×2 , making the network more efficient while preserving the most significant features [41].

$$y = \max(x_1, x_2, x_3, x_4) \quad \text{II.2}$$

x_1, x_2, x_3, x_4 : are the 4 numbers (the pixels).

y : is the result (the biggest one).

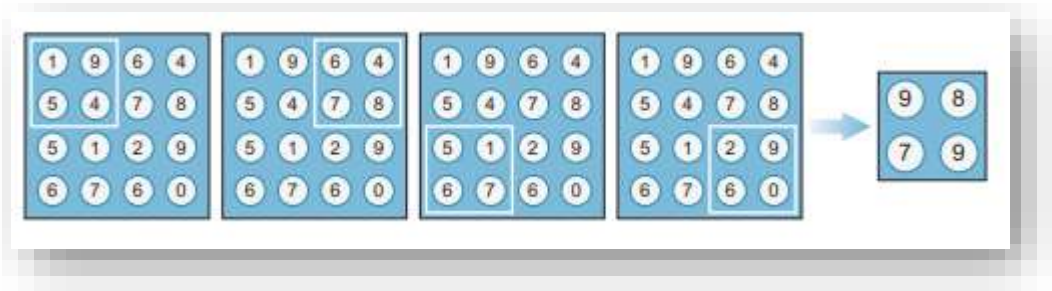


Figure II.8: A 2×2 pooling filter and strides of 2, reducing the feature map from 4×4 to 2×2 . [41]

When we apply max pooling to all the feature maps from a convolutional layer, we reduce their width and height but keep the same depth. This means that if the convolutional layer has three feature maps, the pooling layer will also produce three feature maps just smaller in size. Each feature map is processed individually using the pooling filter, which selects the most important values while discarding the rest. This helps make the network more efficient without losing essential details [41].

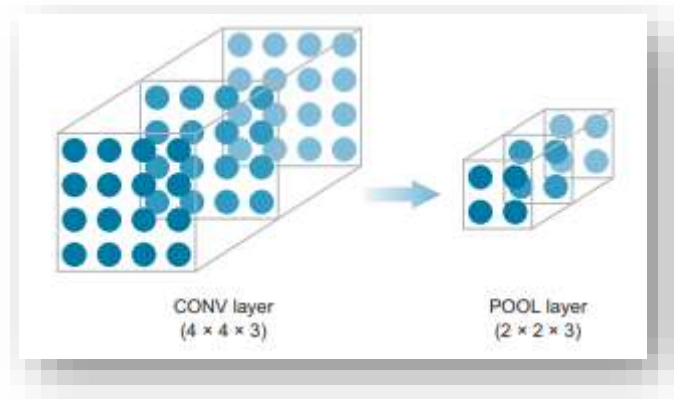


Figure II.9: If the convolutional layer has three feature maps, the pooling layer's output will have three smaller feature maps[41]

Average pooling is a more aggressive way to reduce the size of feature maps. Instead of using a sliding window, it takes the entire feature map and calculates the average of all its pixel values **Figure II.7**. This results in a single value for each feature map, effectively turning the 3D feature maps into a simple 1D vector **Figure II.9**[41].

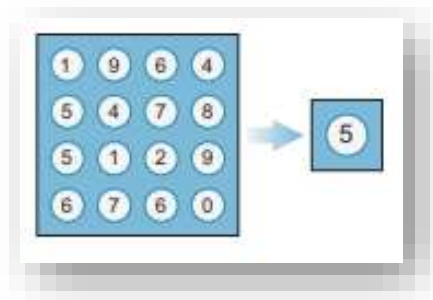


Figure II.10: average pooling calculates the average values of all the pixels in a feature map.[41]

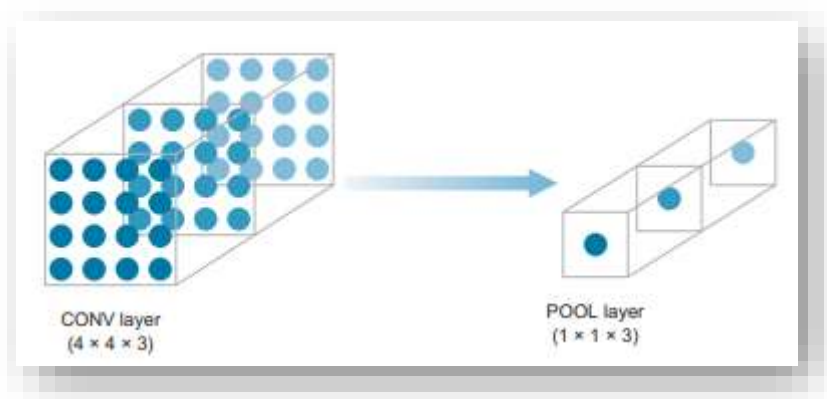


Figure II.11: Average pooling layer turns a 3D array into a vector.[41]

- Here's a simple example of an image produced by the pooling layer.



Figure II.12: Pooling layers reduce image resolution and keep the image's important features.[41]

3.2.4. Fully connected layers:

After multiple convolution and pooling layers, a CNN usually ends with fully connected layers. The output from the previous layers is flattened into a vector, which is then processed through several neural network layers. These fully connected layers are typically found at the end of the network. As shown in **Figure II.13**, a technique called dropout regularization can be applied to these layers to prevent overfitting. The final fully connected layer contains as many output neurons as the number of categories the model needs to classify[44].

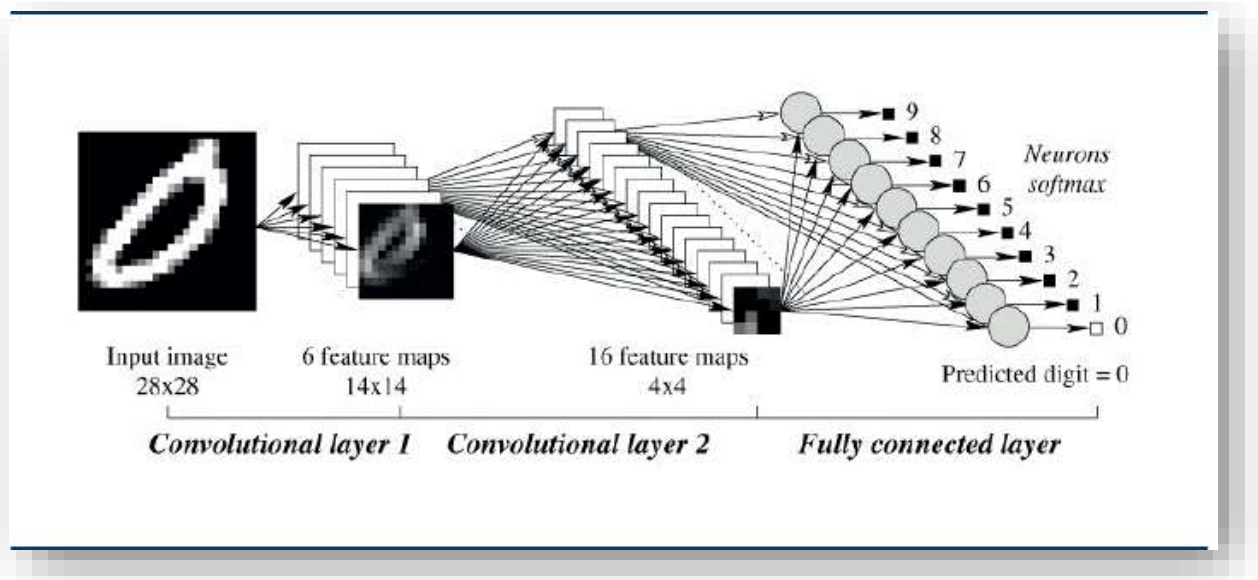


Figure II.13: Two convolutional layers followed by a fully connected layer [44].

4. Convolution Neural Network Architecture :

4.1. AlexNet :

This CNN model has eight layers : five convolutional layers for feature extraction and three fully connected layers for classification. The final fully connected layer outputs to a 1000-way SoftMax, which classifies images into 1000 categories. The first convolutional layer processes $224 \times 224 \times 3$ images using 96 filters of size $11 \times 11 \times 3$ with a stride of 4 pixels. The second layer applies 256 filters of size $5 \times 5 \times 48$ after normalization and pooling. The third, fourth, and fifth layers use 384 and 256 filters of size 3×3 , connected without pooling in between. Max-pooling follows the first, second, and fifth layers to reduce the image size, while ReLU activation is used in all layers to improve learning. The fully connected layers have 4096 neurons each, helping the model make final predictions. Additionally, the model runs on two GPUs, with certain layers interacting only within the same GPU. This architecture allows the model to efficiently extract important features and classify images accurately [45].

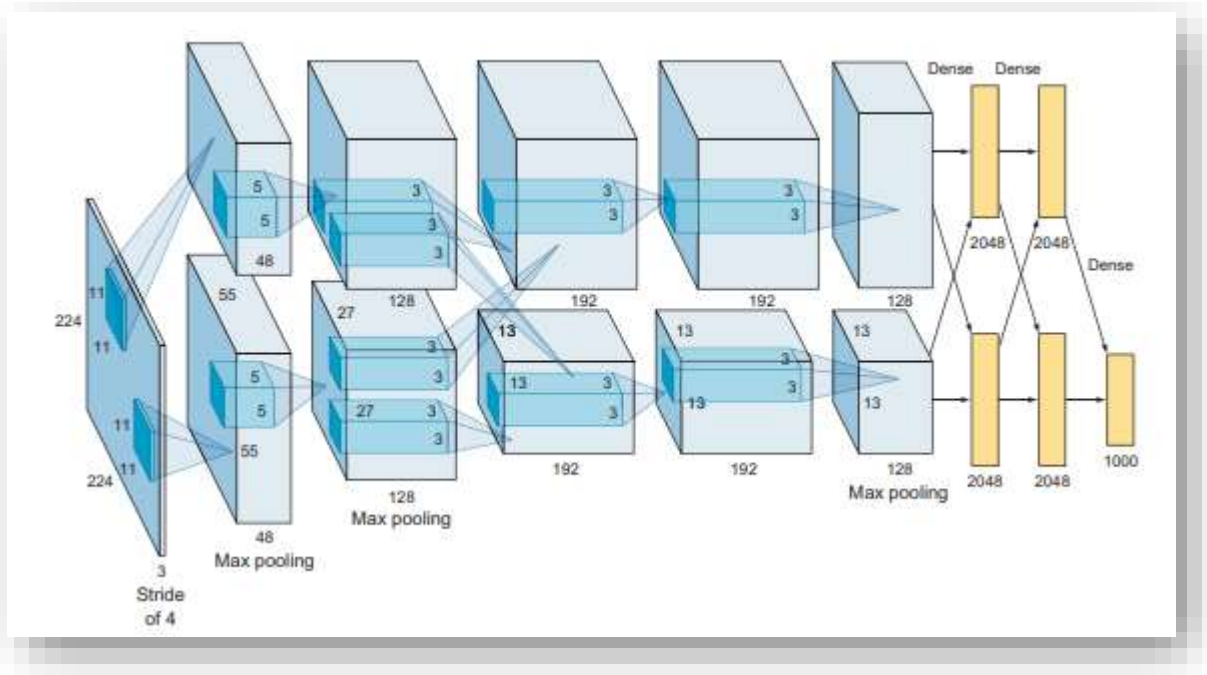


Figure II.14: Alex Net architecture [41]

4.2. VGGNet :

VGGNet, introduced in 2014 by Karen Simonyan and Andrew Zisserman, is a deep Convolutional Neural Network (CNN) designed for image classification. It takes 224×224 RGB images as input and applies small 3×3 convolution filters with a stride of 1 pixel and padding of 1 pixel to preserve spatial dimensions. Some configurations also use 1×1 filters for

additional transformations. Five max-pooling layers (2×2 window, stride 2) reduce image size while keeping key features. After convolution, three fully connected layers process the data, with the final softmax layer classifying 1000 categories. ReLU activation is used throughout, but Local Response Normalization (LRN) is excluded to save memory and computation time [46].



Figure II.15: VGGNet architecture [41].

4.3. GoogleNet :

The Inception architecture is designed to make convolutional networks more efficient by combining different filter sizes in the same layer. Instead of using just one filter size, it mixes 1×1 , 3×3 , and 5×5 convolutions, along with pooling, to capture both small and large patterns in an image [47].

Each Inception module groups related features together and processes them in parallel using these different filters. Smaller filters (1×1) handle local details, while larger filters (3×3 and 5×5) capture broader patterns. Pooling layers help keep important information while reducing size. These modules are stacked, and as they go deeper, the network focuses more on larger patterns. This design improves accuracy and efficiency compared to traditional CNNs [47].

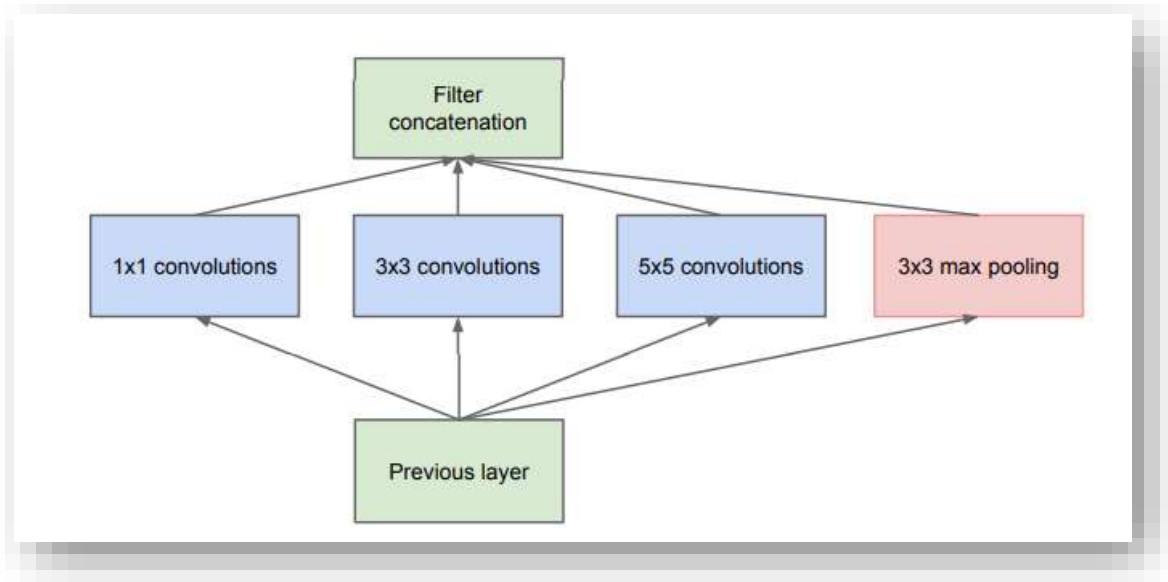


Figure II.16: Inception module, naive version [47]

5. Conclusion :

This chapter explored deep learning, with a particular focus on Convolutional Neural Networks (CNNs) and their crucial role in image classification. We began by explaining the fundamental concepts of deep learning, highlighting the significance of neural networks in this domain. CNNs, as a specialized type of neural network, have demonstrated remarkable effectiveness in processing images and extracting meaningful features, at futur work to choose an appropriate architecture and provide a diverse and sufficient dataset to ensure the model can generalize well and extract accurate, meaningful features from images.

Chapter III

**Modeling and Evaluating a CNN
Approach for Brain MRI Image
Classification**

1. Introduction :

Deep learning has become a powerful tool in medical image diagnosis, helping computers to recognize patterns in medical scans and assist doctors in making more accurate decisions. In this chapter, we explain how build brain tumor diagnosis using deep learning (CNN).

The chapter is divided into three main parts, each with a specific goal. In the first part, our goal was to design and train a basic CNN model using a small medical image dataset. Here, we focused on explaining the architecture of the network, how we set the training options, and what results we got. This part helped us understand how our model works.

In the second part, we aimed to improve the performance of our model by training it with a much larger dataset. This allowed us to test how the model responds to more data and better image variety.

The third part focused on testing the trained model with a real-world medical image database. The goal here was to see how well the system performs in a more realistic and practical setting. Showing that our model is strong enough for real medical applications.

We used MATLAB 2021 to develop and test the system, on a Windows 10 machine with 128 GB of RAM and Graphics Card (GPU) to handle the large data and training processes.

Overall, this chapter shows the full journey of building a medical image diagnosis system—from a simple model with limited data to a powerful and reliable tool ready for real testing.

2. Part one :

2.1.The System:

Figure III.1 illustrates the overall architecture of our proposed brain MRI classification system based on Convolutional Neural Networks (CNNs). The system is designed to automatically detect and classify brain tumors from MRI images.

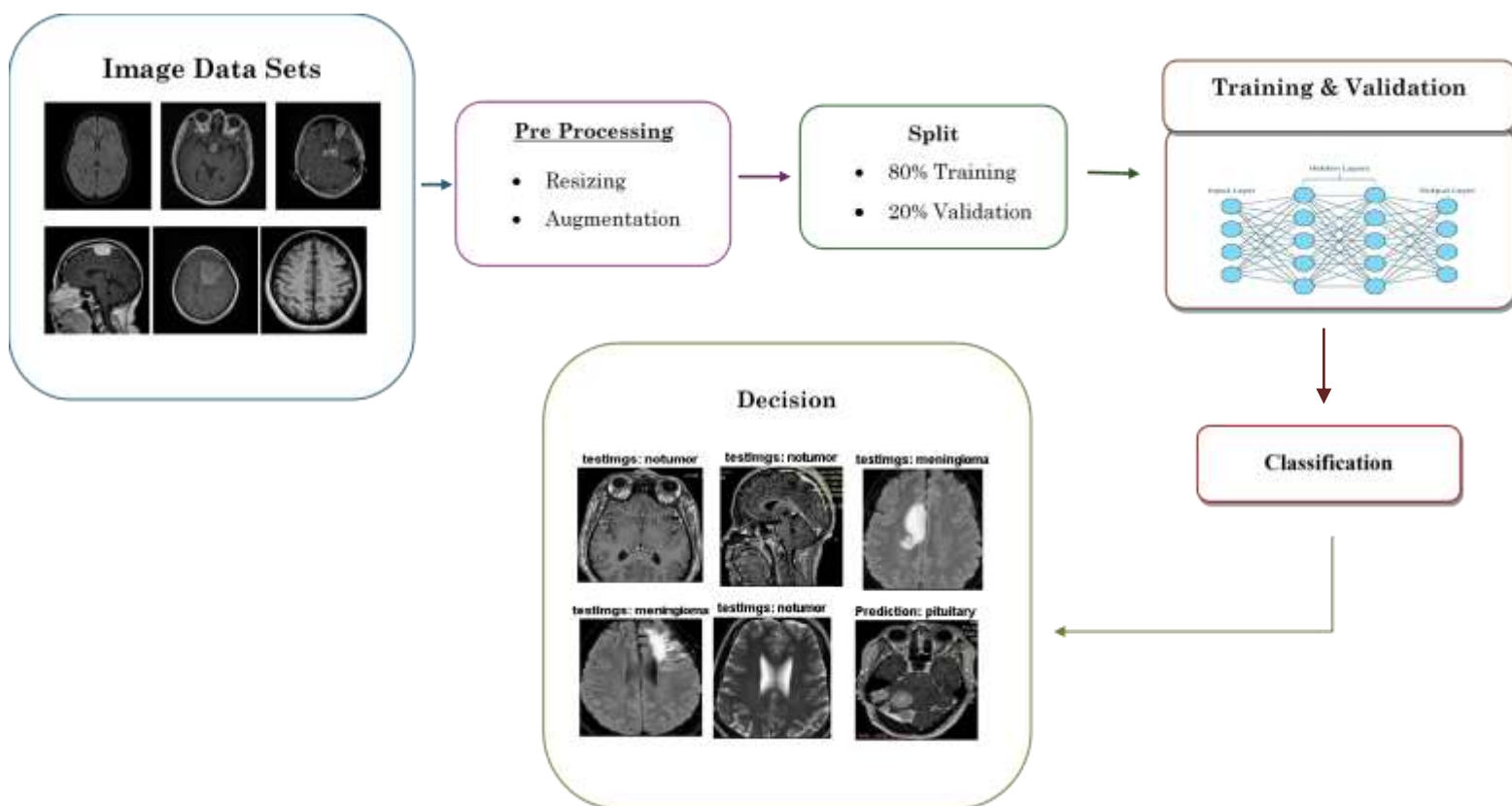


Figure III.1: Image classification System

The process starts brain MRI images, some showing healthy brains and others with tumors like glioma, meningioma, or pituitary. Before training, the images are cleaned up by resizing them to the same size and slightly changing them (like flipping or rotating) to help the system learn better. Then, the data is split—80% is used to teach the system (training), and 20% is used to check how well it's learning (validation). During training, a neural network learns to recognize patterns in the images to understand what kind of tumor is present. Once trained, the system can look at new images and decide if there's a tumor and what type it is. Finally, it gives a result that a doctor can review for diagnosis.

2.2.Data Base :

The **SARTAJ** dataset consists of 3,264 human brain MRI images, categorized into four classes : glioma tumor, meningioma tumor, pituitary tumor, and no tumor. The dataset is divided into 2,870 images for training and 394 images for testing. The training data is further split into two parts : 80% for training, where the images are used to teach the system how to recognize different patterns, and 20% for validation, which is used to assess how well the system is learning during the training process.

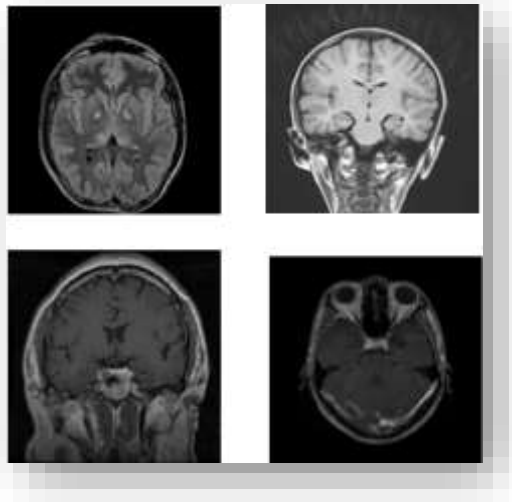


Figure III.2: The Dataset SARTAJ [48]

2.3.Data Augmentation :

Data Augmentation is a technique that expands a dataset by applying transformations like flipping, rotating, and scaling. It helps improve model performance by making it more robust and adaptable to variations in data.

2.4.Define CNN Architecture:

It is a good practice, to start with a basic model at first and then keep trying to improve it in every step. To further improve the Model, we need to:

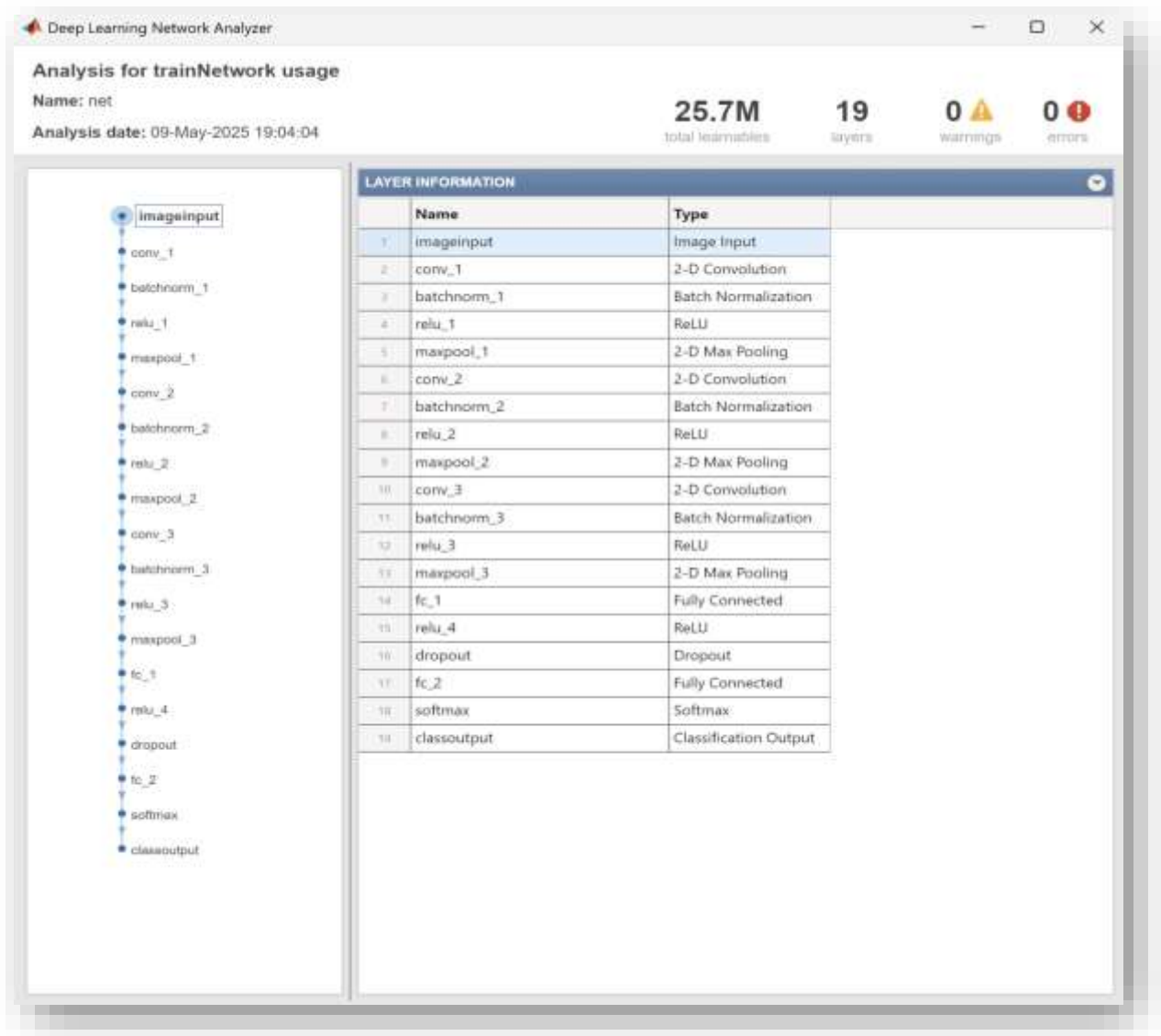
in our simulation we used the following 19 layers:

✚ Image Input Layer (224*224*3)

✚ **Convolution Layer:** Extracts features (edges, textures, shapes) from the input image

using filters.

- ✚ **Batch Normalization Layer:** is a layer in deep neural networks used to accelerate and improve training by normalizing the inputs of each layer, reducing internal covariate shift, and making the model more stable and efficient.
- ✚ **RELU Layer:** is an activation function used in neural networks. It replaces all negative input values with zero while keeping positive values unchanged. This operation helps speed up training and reduces the problem of vanishing gradients.
- ✚ **Max Pooling Layer:** is a type of pooling layer in Convolutional Neural Networks (CNNs) used to reduce the spatial dimensions (width and height) of feature maps while preserving the most important information.
- ✚ **Fully Connected Layer:** Combines extracted features to classify the image into a specific category.
- ✚ **Dropout Layer:** Reduces overfitting by randomly deactivating neurons during training.
- ✚ **SOFTMAX Layer:** Converts raw scores into probabilities for multi-class classification
- ✚ **Classification Layer:** Assigns the final class label based on the highest probability.



FigureIII.3: Training Layers

2.5. Training Options :

In our training we are going to manipulate different options like Optimization Algorithms (Adam, Sgdm), Epoch number, miniBatch size, number of convolution layer and filters size.

- ✚ **Optimization Algorithm** : An Optimization Algorithm is a technique used to adjust a model's parameters to minimize errors and improve its performance. It helps find the best values for weights and biases to enhance accuracy. Examples include **SGDM** and **Adam**.

- **SGDM (Stochastic Gradient Descent with Momentum):** Enhances standard gradient descent by adding momentum, which helps speed up learning and avoid local minima.
 - **Adam (Adaptive Moment Estimation) :** Combines the benefits of SGDM and RMSprop by adapting the learning rate for each parameter, making it highly effective in deep learning.
- ✚ **Initial Learn Rate :** The starting value that determines how fast the model updates during training. A small value makes training slower but more stable, while a large value speeds up training but may cause instability.
 - ✚ **Epochs :** The number of times the model goes through the entire dataset during training. More epochs can improve accuracy, but too many may lead to overfitting.
 - ✚ **Batch Size :** The number of samples passed to the model at once during training. Smaller batch sizes require less memory, while larger batch sizes speed up training but need more memory.
 - ✚ **Regularization :** Techniques used to prevent overfitting, such as L1 and L2 regularization, which help the model generalize better to new data.
 - ✚ **Validation Frequency :** The number of times the model's performance is evaluated on validation data during training. This helps monitor progress and prevent overfitting.

```

%% Training Options
options = trainingOptions('sgdm', ...
    'InitialLearnRate', 1e-5, ...
    'MaxEpochs', 50, ...
    'MiniBatchSize', 16, ...
    'L2Regularization', 0.001, ... % L2 weight decay parameter
    'ValidationData', augmentedTestImgs, ...
    'ValidationFrequency', 30, ...
    'Verbose', true, ...
    'Plots', 'training-progress');

```

FigureIII.4: Training options.

2.6.Results and Discussion :

At first, We change in the number of convolutional layers, filter sizes, number of epochs and minibatch size for improving the training in **Table III.1**

Table III.1: Effect of Network Architecture and Training Parameters on Classification Accuracy.

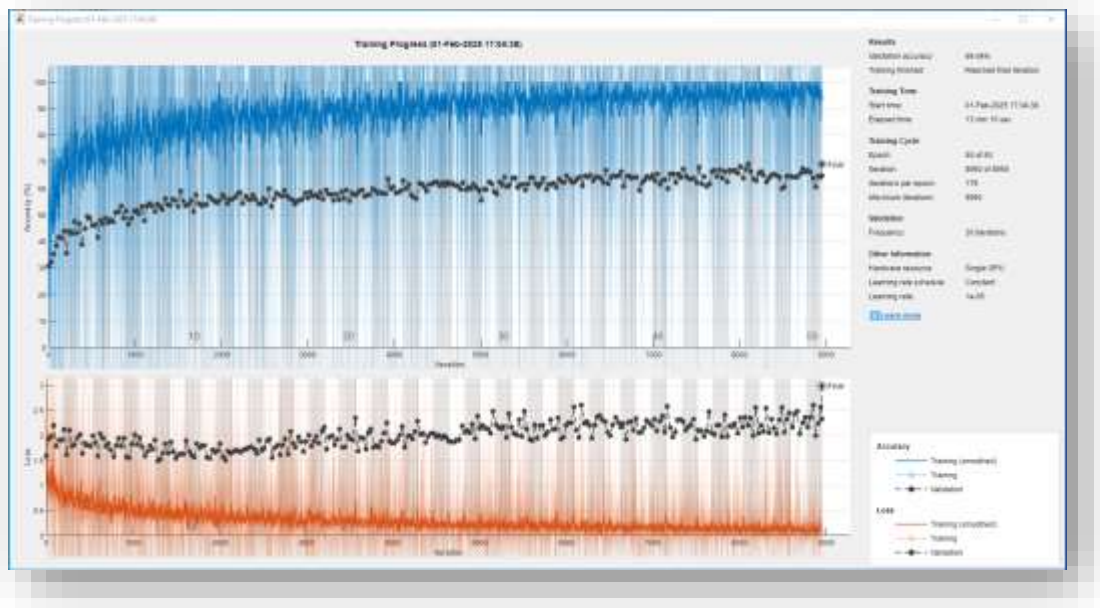
Number of Convolution layer	Filter Size	Number of Epochs	MiniBatch Size	Results
(64,128)	(3,3)	20	20	59,90%
(64,128)	(3,3)	20	32	56,85%
(64,128)	(3,3)	30	30	59,39%
(64,128)	(3,3)	50	16	66,75%
(64,128,256)	(6,6,6)	50	16	66,24%
(64,128,256)	(3,6,3)	50	16	69,04%
(64,128,256)	(3,3,3)	50	16	66,24%
(64,128,256)	(3,6,6)	50	16	67,77%
(64,128,256)	(6,3,3)	50	16	68,02%
(128,128)	(3,3)	50	16	64,72%

- ✓ Changes in the number of convolutional layers, filter sizes, number of epochs and minibatch size for improving the training in **Table III.1:**

First, using the optimization algorithm (SDGM), we fixed the number of convolutional layers at (64, 128) and the filter size at (3,3). Then, we started changing the number of epochs and the mini-batch size. We achieved the best result **66.75%** when the number of epochs was 50 and the mini-batch size was 16. After that, using the optimization algorithm(Adam),we fixed the number of epochs at 50 and the mini-batch size at 16, then we started changing the number of convolutional layers and the filter size. We achieved the best result **69.04%** when the number of convolutional layers was (64, 28, 256) and the filter size was (3, 6, 3).

After manipulating the training options, the number of convolutional layers, and the filter size, we have reached the best choices that achieve the best results :

- Number of convolution layers (64,128,256).
- Filter size (3,6,3).
- Number of Epochs = 50.
- Mini Batch size =16.



FigureIII.5: Performance of CNN Trained on a SARTAJ Dataset.

Comment:InFigureIII.5 illustrates the training and validation curves of the deep learning model over 50 training epochs. The results show that the training accuracy increased rapidly from the early stages, while the validation accuracy plateaued at **69.04%**, indicating that the model did not generalize well to unseen data. The loss curves show a gradual decrease in training loss, while the validation loss remained relatively high, suggesting the presence of overfitting. The Adam optimization algorithm was used, with a total of 8,950 iterations, and the training process lasted approximately 13 minutes. These results highlight the need to improve training configurations by increasing the amount of data to enhance the model's performance.

Then we set Changes in data augmentation for improving the training in **Table III.2** :

Table III.2 : Effects of Data Augmentation Variations on Classification Accuracy.

Rand Rotation	Rand X Reflection	Rand Y Reflection	Rand X Scale	Rand Y Scale	Results
[-10,10]	True	False	[-20,20]	[1,1]	48,98%
[-8,8]	True	True	[0.5,1]	[0.5,1]	54,06%
[0,200]	True	False	[0.9,1.1]	[0.9,1.1]	56,35%
[-8,8]	True	False	[0.9,1.4]	[0.9,1.4]	57,11%
[-60,80]	True	False	[0.9,1.1]	[0.9,1.1]	57,36%
[-10, 10]	True	False	[0.9, 1.1]	[0.9, 1.1]	69,04%

✓ Changes in data augmentation for improving the training in **Table III.2** :

Based on the results, we observed that using a single augmentation, such as random rotation, led to only a slight improvement in the model's performance. However, when combining multiple augmentations—like rotation, vertical flipping (along the Y-axis), and scaling along both the X and Y axes—the accuracy increased significantly. In fact, the best accuracy achieved was **69,04%** when these augmentations were applied together. Nevertheless, the accuracy remained relatively low and did not reach high levels such as 90%. This could be due to several reasons, such as the small or imbalanced size of the original dataset, the simplicity of the model architecture, or that the augmentations, although helpful, cannot fully compensate for other issues like noisy or low-quality images.

3. Part Two :

Following the initial experiment, where the model showed signs of overfitting—evidenced by a large gap between training and validation performance—this experiment was conducted to address this issue. In this phase, the network was trained using a **combined dataset** consisting of three publicly available MRI image databases : SARTAJ, Br35H, and Figshare.

3.1. Data base :

This dataset is a combination of the following three datasets : **figshare**, **SARTAJ** and **Br35H**. This dataset contains 7023 images of human brain MRI images which are

classified into 4 classes : glioma - meningioma - no tumor and pituitary. Divided into 5712 images for training and 1311 images for testing.

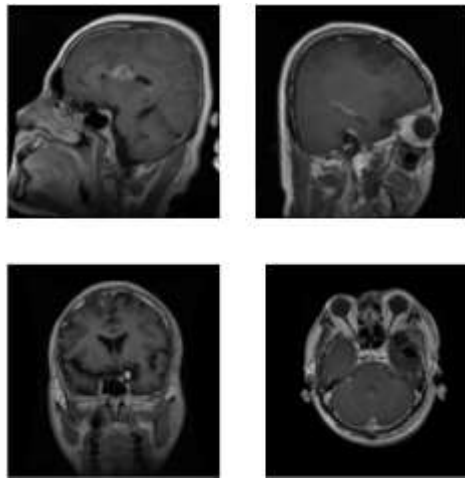


Figure III.6: The combinationDataset [48]

3.2.Results and Discussion :

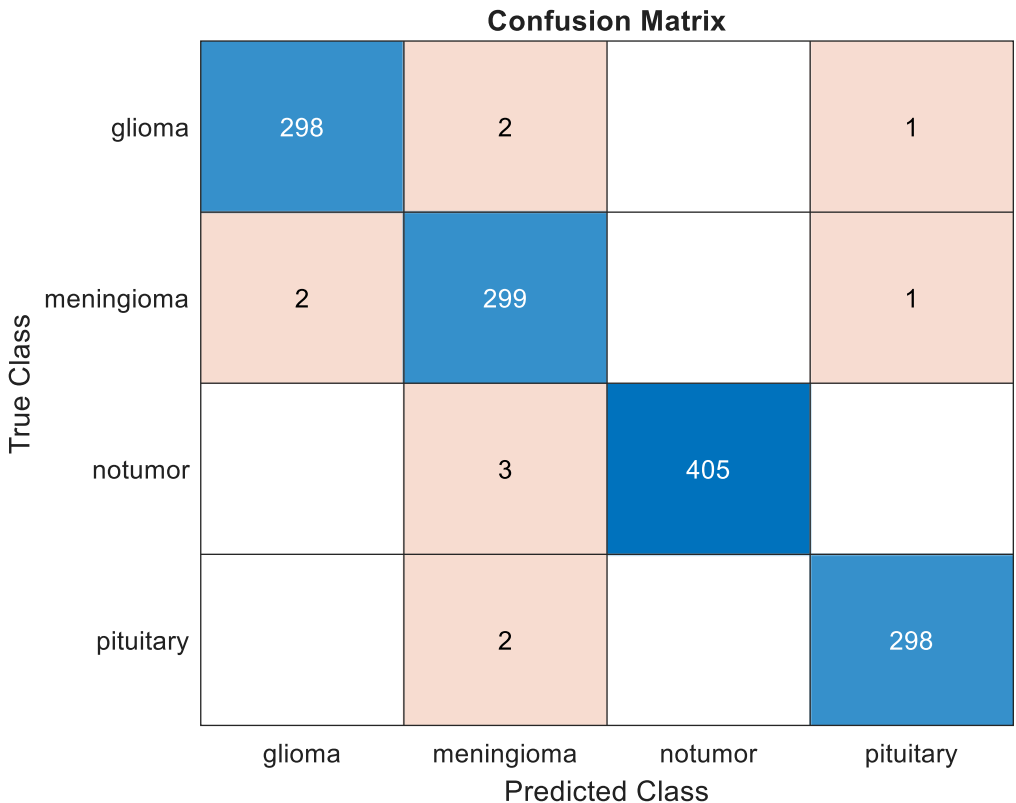
The parameters that achieved the best results in Experiment 1 were selected and reused in Experiment 2. These parameters include the optimization algorithm (Adam) number of epochs, and mini-batch size (16) and Filter size. In the following, we present the reported results in the **Table III.3**.

Table III.3: The Impact of Different Model Settings on Classification Accuracy.

Number of Convolution layer	Regularization	Dropout	Epoch	Results
(8,16,32)	Without L2	0,6	50	93,52%
(32,128,256)	With L2	0,3	50	94,6%
(32,128,256)	With L2	0,6	50	94,81%
(16,32,64)	Without L2	0,6	50	94,81%
(32,64,128)	Without L2	0,3	50	96,64%
(16,32,64)	Without L2	0,3	50	97,71%

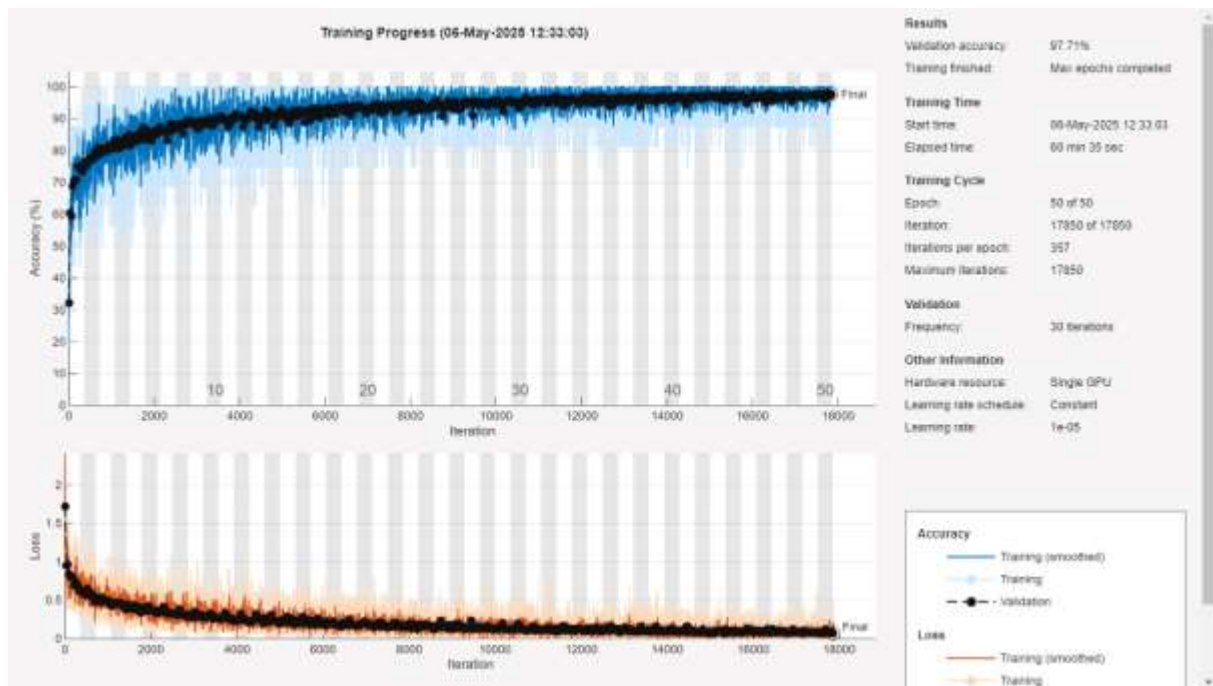
Comment: In **Table III.3** The results show that the best performance was achieved using the configuration (16, 32, 64) without L2 regularization and with a dropout rate of 0.3, reaching an accuracy of **97.71%**. It also indicates that using L2 regularization and varying dropout rates can improve performance in some cases, but not consistently. Selecting the right hyperparameters plays a critical role in enhancing the model’s accuracy.

In our case, the confusion matrix represents an analytical tool used to evaluate the performance of a tumor classification model in brain MRI images **FigureIII.7** :



FigureIII.7: Confusion Matrix for Tumor Classification on Brain MRI Images.

This confusion matrix **FigureIII.8** shows how well the system predicted brain tumor types during training. Most predictions are correct, especially for "no tumor" and "pituitary" cases, with only a few mistakes like confusing some meningioma cases as glioma. The high numbers along the diagonal mean the system is accurately identifying the correct tumor types.



FigureIII.8: Performance of CNN Trained on an SARTAJ, Figshare, and Br35H Dataset.

Discussion :

The training graph **FigureIII.8** shows how well our system learned to recognize brain MRI images over time. The top part shows **accuracy**, which means how many images the system got right. At the beginning, it made more mistakes, but as training continued, the accuracy went up and reached about **97.71%**, which is very good. This means the system learned well.

The bottom part shows **loss**, which tells us how much the system was "wrong" during training. A high loss means more errors, and a low loss means fewer errors. In our case, the loss started high but kept going down smoothly. This means the system kept getting better and making fewer mistakes.

Overall, the graph shows that the system trained well, learned to recognize the images correctly, and didn't just memorize them but understood how to handle new images too.

4. Part Three :

In this phase of our study, the primary objective was to validate the clinical relevance of our trained CNN model rather than to benchmark its performance using standard metrics. We aimed to evaluate the generalization ability of our trained CNN model in a real-world clinical setting. To do this, we collected brain MRI images from multiple hospitals, ensuring variability in acquisition conditions, equipment, and patient demographics. These images were not part of the training or validation datasets used in the previous phases.

We used this new set of clinical images exclusively for testing, simulating a real diagnostic environment. The model was applied directly to these unseen images to classify the presence or absence of brain tumors. To validate our results, we collaborated with experienced radiologists who reviewed the same MRI scans independently. Their diagnostic conclusions were then compared with the model's predictions to assess clinical relevance and reliability.

This step was crucial to verify the robustness and practical applicability of our system outside of controlled experimental datasets. The initial results showed a promising match between the model's output and expert radiological assessments, demonstrating the model's potential as a supportive diagnostic tool in clinical practice.

4.1.Data Base :

The images collection utilized in this study comprises 6000 medical MRI frame videos of brain tumors, collected from the " Centre de Lutte Contre le Cancer (CLCC) Bachir Rezgui " and " Clinique Ibn Hayane " in El Oued. These MRI scans encompass different imaging modalities, primarily including T1-, T2, FLAIR, DWI and sT1W-3D-FFEGD weighted sequences.

Each MRI scan was originally a video, and we extracted several images (frames) from it to cover different parts and angles of the brain. For example :

- Some videos gave about 250 images.
- Others gave around 45 images.

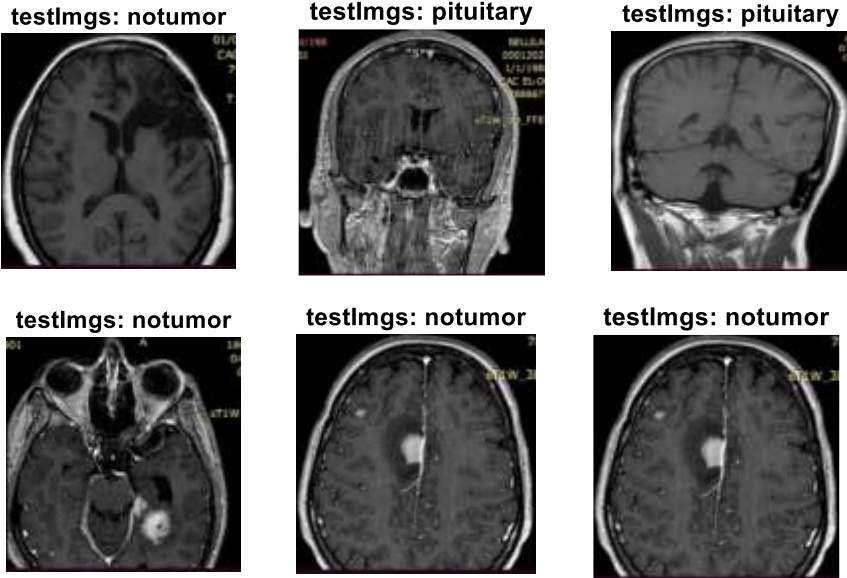
This variation in the number of images resulted from differences in video length and the extent of anatomical coverage during scanning. The diversity within the dataset enriched

the training process, enabling the model to learn from a broader range of patterns and improving its generalization capabilities when exposed to new, unseen data.

4.2.Result :

We processed brain MRI videos frame by frame by extracting individual frames, then applied preprocessing steps such as resizing, and cropping. Each processed frame was classified by the CNN model into tumor or no tumor categories.

The results revealed two main outcomes from the system's predictions : accurate classifications and misclassifications.



FigureIII.9: Images Illustrating Incorrect Classification Cases

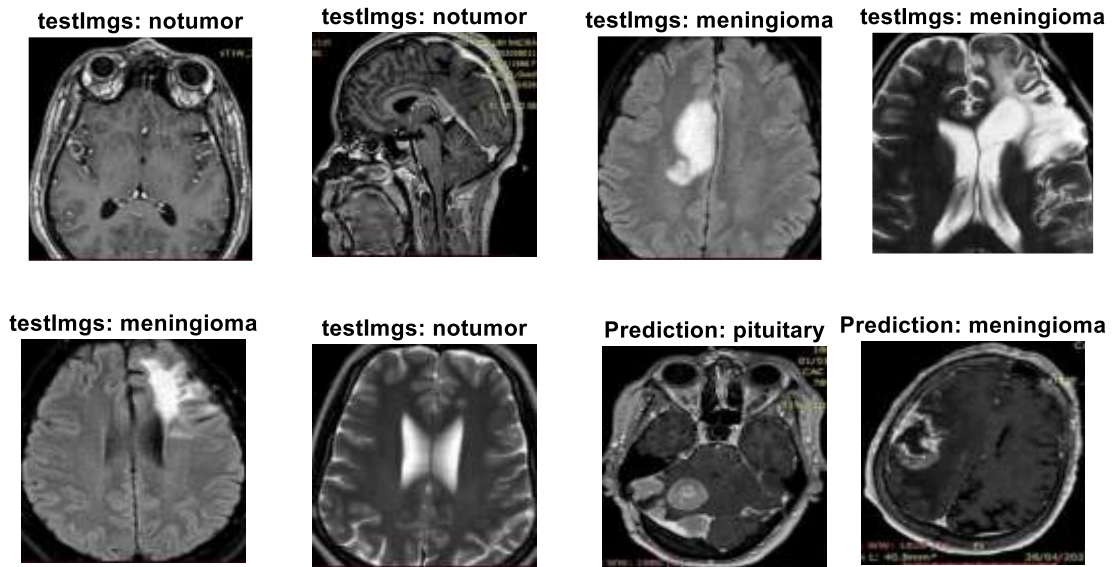


Figure III.10: Images Illustrating Correct Classification Cases

4.3. Discussion :

When we tested our system using real brain MRI images from a hospital, we found that it was able to correctly detect and classify some types of brain tumors. This shows that the system can work on real medical data—not just the training images. However, some predictions were still incorrect. These errors might be caused by low image quality, differences in how the images were taken, or tumor features the model didn’t learn well.

After showing our results to a radiologist, we discovered that some of the images in our dataset were not entirely correct. We also noticed that the system often made wrong predictions when the MRI images were taken from the back of the head. This may be because the system didn’t have enough properly labeled examples of that kind during training.

Overall, the results show that the system is promising and could be useful in medical settings, but it still needs improvement. A small or unbalanced training dataset may have limited its ability to handle new, different cases. Adding more data and training on a wider variety of images could help the system become more accurate and reliable in the future.

5. Conclusion :

This chapter described classification medical image of a CNN-based approach for medical image diagnosis. We first trained the network using a small database, allowing us to define the model architecture and training settings. We then expanded the training to a larger database, which improved the model's performance.

Finally, we tested the network on a real-world medical database using MATLAB 2021 and a high-capacity computing system. From these experiments, we observed that increasing the amount and variety of data significantly enhances the network's accuracy and stability. We also concluded that while the network shows good potential in real-world scenarios, further optimization is needed to fully meet clinical requirements.

As a recommendation, future work should focus on integrating domain-specific knowledge and exploring advanced data augmentation techniques to further boost diagnostic performance and robustness.

General Conclusion

This research has shed light on the transformative role that Artificial Intelligence, particularly deep learning, can play in the field of medical image diagnosis. With the rapid increase in the volume of medical data, the need for fast, accurate, and efficient diagnostic tools has become more pressing than ever. AI techniques—especially Convolutional Neural Networks (CNNs)—have demonstrated a high capability in accurately analyzing complex medical images.

This thesis was divided into three main chapters to provide a comprehensive understanding of the topic. The first chapter presented an overview of artificial intelligence, followed by an explanation of medical image processing, and then illustrated the role of AI in this domain. The second chapter focused on explaining how CNN layers work and explored some of their most well-known architectures. The third chapter tackled the practical aspect, which was divided into three parts: in the first part, a deep learning network architecture was designed and trained using a simple labeled dataset of MRI images, with a study of the impact of different training options, including optimization algorithms, on model performance. In the second part, a combined dataset was used to obtain better and more accurate results. Finally, the system was applied to real clinical MRI scans collected from local hospitals to evaluate its generalization in a practical setting.

The measured accuracy across different datasets confirms that CNN-based models have potential as supportive tools in medical diagnostics. While the system showed promising results, it also highlighted limitations, especially when applied to diverse real-world data. These findings suggest that further improvements—such as using larger and more balanced datasets—are necessary to reach clinically acceptable performance.

Overall, this work demonstrates that it is feasible to build a basic CNN system capable of classifying brain MRI images with reasonable accuracy, laying the foundation for future development in AI-assisted medical imaging.

This paved the way for more research and practical applications in hospitals and research centers, aiming to enhance the quality of healthcare for patients worldwide.

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Annex

Working Principle of Magnetic Resonance Imaging (MRI) :

Magnetic Resonance Imaging (MRI) is a non-invasive medical imaging technique used to obtain highly detailed and accurate images of internal organs and tissues, especially soft tissues such as the brain, spinal cord, and muscles.

1. Strong Magnetic Field :

The MRI machine contains a very strong magnet (typically between 1.5 and 3 Tesla). When the patient enters the scanner, this magnetic field causes the hydrogen nuclei (protons) in the body—mainly found in water and fat—to align in the same direction.

2. Radiofrequency Pulses (RF) :

The machine emits radiofrequency pulses at a specific frequency, which disturb the alignment of the protons and push them out of their equilibrium state. These pulses provide energy to the protons, putting them into an “excited” state.

3. Resonance and Signal Emission :

When the RF pulse is turned off, the protons return to their natural alignment within the magnetic field. During this relaxation process, they emit radiofrequency signals.

4. Signal Reception :

Special receiver coils in the MRI machine detect these emitted signals. The characteristics of the signals vary depending on the type and density of the tissue (e.g., brain, muscle, fat), allowing clear differentiation between them.

5. Image Processing :

A computer uses mathematical techniques (such as the Fast Fourier Transform) to analyze the signals and reconstruct them into detailed cross-sectional images. These slices can be combined to create a 3D image of the body if needed.

After the protons in the human body emit radiofrequency signals as they return to their natural alignment within the magnetic field, the MRI machine detects these signals. However, these signals do not directly form a visible image. Instead, they are complex

electrical signals that require mathematical processing and conversion in order to generate a clear and interpretable image.

➤ **How Does Image Reconstruction Work ?**

- **Data Acquisition :**

Signals emitted from different regions of the body are collected using specialized receiver coils.

- **Converting Data to Frequency Domain (Fourier Transform):**

A mathematical process called the **Fast Fourier Transform (FFT)** is applied. This process converts the signals from the time or wave domain into a frequency map that can be analyzed.

You can imagine this like listening to a piece of music and trying to identify the different instruments playing (piano, violin, drums) each frequency represents a different "component" of the image.

- **Determining the Signal Origin :**

By applying additional magnetic fields known as **magnetic gradients**, the system can determine the precise location from which each signal was emitted within the body—this is essential for spatial mapping.

- **Image Reconstruction :**

After identifying both the strength and location of each signal, the computer assembles this information into a 2D image (like a slice of the brain, for example). This process is repeated multiple times across different slices to form a 3D image if needed.

Advantages of MRI

- Does not use ionizing radiation (unlike X-rays or CT scans).
- Provides high contrast for soft tissues.
- Can image the body in multiple planes (axial, coronal, sagittal).

Main Applications

- Neurology : Imaging the brain to detect tumors, strokes, or multiple sclerosis.
- Muscles and Joints : Detecting ligament and cartilage injuries.
- Cardiology : Imaging the heart muscle and measuring ventricular volumes.
- Oncology : Detecting and monitoring cancers.

MRI sequences :

Such as **T1**, **T2**, **FLAIR**, **DWI**, and **T1W-3D-FFEGD** are specialized imaging techniques used to highlight different brain tissues and abnormalities. Each sequence provides unique contrast and detail to aid in accurate diagnosis.

- T1: Good for anatomical detail, fat appears bright.
- T2: Highlights fluid; useful for spotting edema and tumors.
- FLAIR: Like T2 but suppresses fluid to better show lesions near cerebrospinal fluid.
- DWI (Diffusion Weighted Imaging): Detects early stroke and tumor cellularity.
- T1W-3D-FFEGD: A high-resolution 3D T1-weighted sequence, often used for detailed brain structure imaging.

