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A Smart Platform for Management and Diagnosis of Multiple Sclerosis

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Abstract

Multiple Sclerosis (MS) represents one of the most prevalent neurological disorders globally. It is a chronic autoimmune condition affecting the central nervous system, characterized by the immune system attacking the myelin sheath protecting nerve fibers, thereby resulting in lesions within the brain and spinal cord. Magnetic Resonance Imaging (MRI), specifically the FLAIR sequence, serves as the gold standard diagnostic tool for detecting these lesions.

In this research, an intelligent platform was developed utilizing deep learning techniques to assist neurologists in the diagnosis and monitoring of Multiple Sclerosis via brain MRI analysis. The core architecture of the platform comprises a Convolutional Neural Network (CNN) trained from scratch to classify FLAIR images into two categories—MS and Healthy—while localizing suspicious regions through the Grad-CAM method.

The model was trained and validated on a dataset of FLAIR MRI images sourced from public repositories. Performance was evaluated using standard classification metrics to quantify the model's efficacy. The platform integrates this model into a comprehensive and intuitive environment designed to facilitate clinical image analysis, patient management, and disease longitudinal follow-up.

Keywords: Multiple Sclerosis, MRI, FLAIR, Deep Learning, CNN, Grad-CAM, Classification.

Résumé

La sclérose en plaques (SEP) constitue l'une des affections neurologiques les plus fréquentes à l'échelle mondiale. Il s'agit d'une pathologie auto-immune chronique affectant le système nerveux central : le système immunitaire s'attaque à la myéline protégeant les fibres nerveuses, entraînant ainsi l'apparition de lésions cérébrales et médullaires. L'imagerie par résonance magnétique (IRM), et plus particulièrement la séquence FLAIR, demeure l'outil de référence pour la détection de ces lésions.

Dans le cadre de ce travail, nous avons conçu une plateforme intelligente exploitant l'apprentissage profond (deep learning) afin d'assister les neurologues dans le diagnostic et le suivi de la sclérose en plaques à partir d'images IRM cérébrales. Le cœur de la plateforme est un réseau de neurones convolutif (CNN) entraîné à partir de zéro pour classer les images FLAIR en deux classes, SEP et sain, et pour localiser les régions suspectes à l'aide de la méthode Grad-CAM.

Le modèle a été entraîné et testé sur une base d'images IRM FLAIR collectées à partir de sources publiques. Les résultats obtenus ont été évalués à l'aide des métriques de classification habituelles afin de mesurer les performances du modèle. La plateforme intègre ce modèle dans un environnement complet et simple à utiliser, qui assiste le médecin dans l'analyse des images, la gestion des patients et le suivi de la maladie.

Mots clés : sclérose en plaques, IRM, FLAIR, apprentissage profond, CNN, Grad-CAM, classification.

ملخص:

التصلب المتعدد (Multiple Sclerosis) هو أحد أكثر الأمراض العصبية انتشارًا في العالم .وهو مرض مناعي ذاتي مزمن يصيب الجهاز العصبي المركزي، حيث يهاجم الجهاز المناعي غمد الميالين الذي يحمي الألياف العصبية، مما يؤدي إلى ظهور آفات في الدماغ والنخاع الشوكي .ويُعدّ التصوير بالرنين المغناطيسي(IRM) ، وخاصة تسلسلFLAIR ، الأداة المرجعية المستعملة للكشف عن هذه الآفات.

في هذا العمل، قمنا بتطوير منصة ذكية تعتمد على التعلم العميق لمساعدة أطباء الأعصاب في تشخيص ومتابعة مرض التصلب المتعدد انطلاقًا من صور الرنين المغناطيسي للدماغ .تعتمد المنصة على شبكة عصبية التفافية (CNN) تم تدريبها من الصفر لتصنيف صور FLAIR إلى فئتين :مصاب بالتصلب المتعدد وسليم، وتحديد المناطق المشبوهة باستخدام طريقة.Grad-CAM

تم تدريب النموذج واختباره على قاعدة بيانات من صور الرنين المغناطيسي من نوع FLAIR تم جمعها من مصادر عمومية .وقد تم تقييم النتائج المتحصل عليها باستخدام مقاييس التصنيف المعتادة لقياس أداء النموذج .وتدمج المنصة هذا النموذج في بيئة متكاملة وسهلة الاستعمال تساعد الطبيب في تحليل الصور وإدارة المرضى ومتابعة المرض.

الكلمات المفتاحية:

التصلب المتعدد، التصوير بالرنين المغناطيسي،FLAIR ، التعلم العميق، الشبكات العصبية الالتفافية، Grad-CAM التصنيف.

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List of Abbreviations

AI	Artificial Intelligence
AUC	Area Under the ROC Curve
BN	Batch Normalization
BPMN	Business Process Model and Notation
CE	Conformité Européenne (European Conformity marking)
CIS	Clinically Isolated Syndrome
CNN	Convolutional Neural Network
DL	Deep Learning
EDSS	Expanded Disability Status Scale
FDA	Food and Drug Administration (U.S.)
FLAIR	Fluid-Attenuated Inversion Recovery
FN	False Negative
FP	False Positive
Grad-CAM	Gradient-weighted Class Activation Mapping
IRM	Imagerie par Résonance Magnétique (French: MRI)
JSON	JavaScript Object Notation
MCD	Modèle Conceptuel de Données (Conceptual Data Model)
ML	Machine Learning
MLD	Modèle Logique de Données (Logical Data Model)
MR	Magnetic Resonance
MRI	Magnetic Resonance Imaging
MS	Multiple Sclerosis
PACS	Picture Archiving and Communication System
PDF	Portable Document Format
PNG	Portable Network Graphics
PPMS	Primary-Progressive Multiple Sclerosis

ReLU	Rectified Linear Unit
ResNet	Residual Network
RGB	Red, Green, Blue (colour channels)
ROC	Receiver Operating Characteristic
RRMS	Relapsing-Remitting Multiple Sclerosis
SEP	Sclérose en Plaques (French: Multiple Sclerosis)
SPMS	Secondary-Progressive Multiple Sclerosis
TN	True Negative
TP	True Positive
UML	Unified Modeling Language
VGG	Visual Geometry Group (CNN architecture)

General Overview

Introduction

The central nervous system governs movement, perception, cognition, and the coordination of nearly every function in the body. Any disease that disturbs it therefore carries heavy personal and clinical consequences. Multiple Sclerosis (MS) is among the most common of these disorders: a chronic autoimmune disease in which the immune system attacks the myelin that insulates nerve fibers in the brain and spinal cord, leaving inflammatory lesions that interrupt the transmission of neural signals. It effects ranging from visual disturbance and fatigue to impaired coordination and loss of mobility vary widely from one patient to another and evolve unpredictably over time. Although no cure currently exists, early and accurate diagnosis, together with continuous monitoring, plays a decisive role in slowing the progression of the disease and preserving patient's quality of life.

Problematic

Magnetic Resonance Imaging (MRI) has become the corner stone of MS diagnosis and follow-up, as it reveals demyelinating lesions with a sensitivity no other imaging technique can match. Howeverthe interpretation of MRI scans remains a demanding task: it is time-consuming, requires considerable expertise, and is subject to variability between observers. As the volume of medical imaging continues to grow, there is an increasing need for intelligent tools capable of supporting clinicians by making the analysis of MRI data faster, more consistent, and more reproducible. In this context AI and deep learning in particular has emerged as a powerful approach for the automatic analysis of medical images.

Objectives

The present work proposes an intelligent medical platform designed to assist neurologists in the diagnosis and monitoring of patients affected by MS . At the core of the platform is a Convolutional Neural Network (CNN) trained on FLAIR brain MRI images to automatically detect the presence of MS and to localize the regions suspected of containing lesions. Rather than producing a diagnosis in isolation, the model's probability output is presented to the clinisian alongside contextual refrence to established diagnostic frameworks such as the McDonald criteria, supporting a structured and interpretable reading of the result rather than computing a criteria-based diagnosis. The platform further integrates patient management and monitoring within a single environment, allowing doctors to organize medical data, follow the evolution of the disease over time, and support their decisions with objective, reproducible information.

The principal objective of this work is therefore to contribute to the analysis of Multiple Sclerosis through deep learning applied to brain MRI. More specifically, the work aims to design and develop a complete assistive platform that automates the detection and localization of MS-related lesions, presents results in a form that is clear and clinically meaningful, and centralizes the information required for effective patient follow-up.

It is important to emphasize that MRI alone is not sufficient to establish a definitive diagnosis of Multiple Sclerosis, which relies on the combination of medical imaging, clinical evaluation, biological testing, and patient history. The proposed system does not seek to replace the neurologist's judgment, but rather to offer a reliable second-reading tool that highlights regions of interest, quantifies the model's confidence, and leaves the final clinical decision in the hands of the doctor.

This thesis is organized as follows. The first chapter presents the medical and technical background of the study, introducing Multiple Sclerosis and the role of MRI in its diagnosis. The second chapter is devoted to the theoretical foundations of machine learning and deep learning, with particular attention to convolutional neural networks and the techniques used in this work. The third chapter describes the modeling and design of the proposed platform, detailing its actors, functionalities, architecture, and data organization through UML. The last chapter which is dedicated to the implementation and Mylinecare platform. Finally, a general conclusion summarizes the main contributions of this work and outlines perspectives for future development.

CHAPTER I:
MEDICAL AND TECHNICAL BACKGROUND

Part 1: Multiple Sclerosis (MS)

I.1.1 Introduction

The central nervous system, composed of the brain and spinal cord, plays a fundamental role in human cognition, movement, and overall bodily control. Consequently, any disorder affecting this system can have significant consequences on a patient's quality of life. Multiple Sclerosis (MS) is one of the most prevalent neurological diseases impacting the central nervous system. It is characterized by inflammatory and demyelinating lesions that disrupt normal neural function. [1] Diagnosing and monitoring MS remains a challenging task for clinicians due to the variability of lesion appearance and disease progression.

In recent decades, Magnetic Resonance Imaging (MRI) has become an essential tool for the detection and follow-up of MS lesions, offering high sensitivity to pathological changes in brain tissue. [2] However, the interpretation of MRI scans is often time-consuming and subject to inter-observer variability. [2]

In this context, Artificial Intelligence (AI), particularly deep learning, has emerged as a promising approach for the automatic analysis of medical images. AI-based methods have demonstrated strong potential in assisting clinicians by improving the accuracy, consistency, and efficiency of lesion detection and segmentation on MRI images. [3]

The aim of this chapter is to provide the medical and technological background necessary for this work. It begins with an overview of Multiple Sclerosis, including its causes, forms, and clinical manifestations. Subsequently, the principles of MRI and its role in MS diagnosis are discussed, along with the characteristics of MS lesions on MRI scans. Finally, existing research on AI-based MS lesion detection is reviewed to highlight current approaches, challenges, and limitations.

I.1.2 Medical definition

Multiple sclerosis (MS) is a chronic neurological disorder. It’s an autoimmune disorder, meaning that in MS, the immune system which normally protects us from viruses, bacteria, and other threats mistakenly attacks healthy cells. MS symptoms usually begin in young adults, between ages 20 and 40. [1]

MS affects people differently. A small number of people with MS will have mild symptoms with little disability, but others will experience worsening symptoms that will lead to increased disability over time. Most people with MS have short periods of symptoms that resolve fully or partially after they appear. These periods are followed by long stretches without noticeable symptoms. Most people with MS have a normal life expectancy. [1]

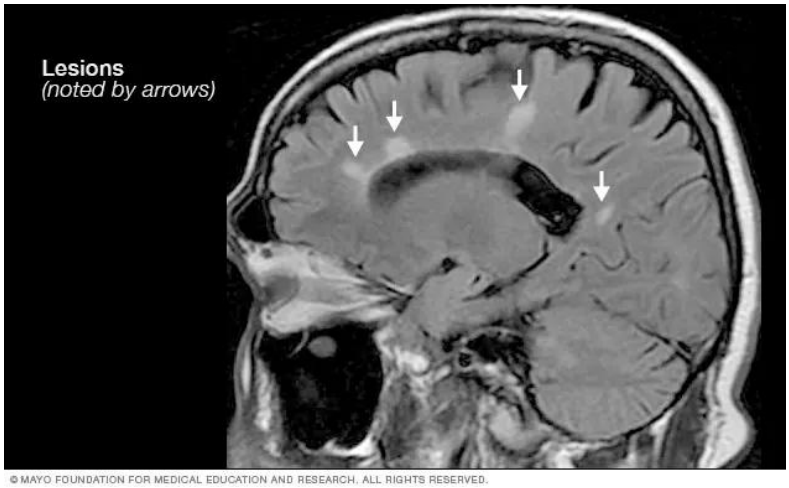
In MS, the immune system attacks myelin in the central nervous system. Myelin is a mixture of protein and fatty acids that makes up the protective cover (known as the myelin sheath) that coats

nerve fibers (axons). Myelin is what gives the brain's white matter its whitish appearance and helps with communication between neurons. The central nervous system is made up of the brain and the spinal cord. [1]

In addition to causing damage to the myelin sheath, MS also damages the nerve cell bodies, which are found in the brain's gray matter, as well as the axons themselves. As the disease progresses, the outermost layer of the brain, called the cerebral cortex, shrinks. This process is known as cortical atrophy. The way that cortical atrophy happens in MS may connect it with some neurological degenerative disorders. [1]

Sclerosis is a medical term for the distinctive areas of scar-like tissue (also called plaques or lesions) that result from the attack on myelin by the immune system. These areas are visible on an MRI (magnetic resonance imaging) scan. The patches of scar-like tissue can be as small as the head of a pin or as large as a golf ball. [1]

The symptoms of MS depend on the severity of the attacks as well as the location and size of the plaques.



FigureI.1: MRI multiple sclerosis lesions

I.1.3 Types of Multiple Sclerosis (MS):

The course of MS is different for each person, which makes it difficult to predict how a person will do with the disease. While many different courses or progressions of MS have been used over the years, these are changing as the scientific and medical community better understands different ways the disease can progress. [4]

Currently, the five courses used to describe MS are:

- Clinically Isolated Syndrome (CIS): This is characterized by a single episode of symptoms (also called an "attack,""exacerbation," or "relapse") followed by complete or near-complete recovery. MRI and other tests, such as a lumbar puncture (spinal tap) or visual evoked potentials, may show "silent" damage in other places in the central nervous system. If this damage is identified, it could allow a full diagnosis of MS even after a single attack.
- Relapsing-Remitting MS (RRMS): This form is characterized by recurrent attacks with total or partial recovery. The periods of disease inactivity between MS attacks are referred to as remission. Weeks, months, or even years may pass before another attack happens. Treatment with disease-modifying therapies can reduce the frequency of attacks or eliminate them entirely. Most people with MS are initially diagnosed with this form.
- Secondary-Progressive MS (SPMS): In some cases, relapsing-remitting MS can gradually evolve into secondary-progressive MS. Attacks become less frequent but may still happen, and people gradually develop worsening symptoms with deteriorated functioning over time. Secondary-progressive MS with attacks is called "active," whereas secondary-progressive MS without attacks is called "non-relapsing." Disease-modifying therapy for relapsing-remitting MS can delay and sometimes prevent secondary progressive MS, but the transition can happen even with treatment.
- Primary-progressive MS(PPMS): This course of MS is less common and has progressively worsening symptoms from the beginning, with no noticeable acute attacks. But there may be temporary or minor relief from symptoms.
- Radiologically isolated syndrome: This is the rarest course of MS where a person has abnormal MRI results that look like MS, but doesn’t have MS symptoms. MS symptoms (attacks or progression) may happen in the future.

I.1.4 Symptoms of MS

Multiple sclerosis symptoms vary depending on the person. Symptoms may change over the course of the disease depending on which nerve fibers are affected. [1]

Common symptoms:

- Vision problems, such as double vision or optic neuritis (inflammation of the optic nerve), which causes pain with eye movement and vision loss.
- Muscle weakness, often in the arms and legs, and muscle stiffness with painful muscle spasms.
- Tingling, numbness, or pain in the arms, legs, trunk, or face.

- Clumsiness, especially difficulty staying balanced when walking.
- Bladder control problems.
- Intermittent or constant dizziness.
- Fatigue.
- Slurred speech.
- Troubles with memory, thinking and understanding information.
- Mood swings.

I.1.5 Causes of MS

The cause of multiple sclerosis is not known. It's considered an immune-mediated disease in which the body's immune system attacks its own tissues. In MS, the immune system attacks and destroys the fatty substance that coats and protects nerve fibers in the brain and spinal cord. This fatty substance is called myelin. It can be compared to the insulation coating on electrical wires. When the protective myelin is damaged and the nerve fiber is exposed, the messages traveling along that nerve fiber may be slowed or blocked. It isn't clear why MS develops in some people and not others. A combination of genetics and environmental factors may increase the risk of MS. [1]

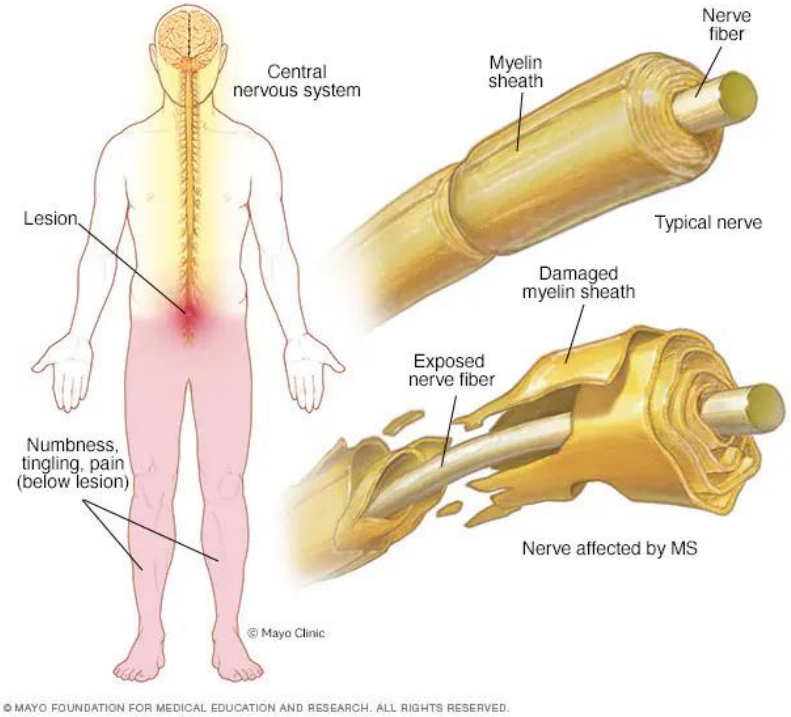


Figure I.2: nerve tissue damaged

I.1.6 Treatments for MS attacks

During an MS attack, treatment mainly aims to reduce inflammation and limit damage to the nervous system. [5] Common treatments are:

- **Corticosteroids:** These medicines reduce nerve inflammation. For MS, the corticosteroids used are oral prednisone and intravenous methylprednisolone. Side effects may include insomnia, increased blood pressure, increased blood glucose levels, mood swings and fluid retention.
- **Plasma exchange:** This treatment involves removing the liquid part of your blood, called plasma, and separating it from your blood cells. The blood cells are then mixed with a protein solution called albumin and put back into your body. Plasma exchange may be used if your symptoms are new, severe and haven't responded to steroids. Plasma exchange also is known as plasmapheresis.

Part 2: MRI based diagnosis

I.2.1 Magnetic resonance imaging (MRI):

An MRI (magnetic resonance imaging) scan is a painless test that produces very clear images of the organs and structures inside your body. MRI uses a large magnet, radio waves, and a computer to produce these detailed images. Because MRI doesn't use X-rays or other radiation, it is the imaging test of choice when patients require frequent imaging for diagnosis or treatment monitoring, especially of the brain. [7]

MRI is particularly valuable in neurological imaging because of its superior contrast resolution between different types of soft tissues. In the context of Multiple Sclerosis, MRI allows the visualization of demyelinating lesions in the brain and spinal cord. For this reason, MRI has become the gold standard imaging technique for the diagnosis, monitoring, and follow-up of Multiple Sclerosis. [2]

I.2.2 Types of MRI Scanners:

There are two basic types of MRI machines that all private MRI scans use:

- **Closed MRI:**

Design-wise, a closed MRI scanner is a narrow, cylindrical machine with a 60 cm bore diameter. These scanners usually come with a strength up to 3.0 Tesla. As far as commercial MRIs go, that’s the ultimate strength an MRI can produce.

A 1.5-T magnet possesses a magnetic strength that is 30,000 times greater than that of the Earth's magnetic field, whereas a 3-T magnet boasts a strength that is 60,000 times higher. [7] Due to the clarity and precision of images, medical professionals have an unobstructed view of the internal organs and can clearly set a diagnosis for a variety of illnesses.

Figure I.3: closed MRI

- **Open MRI:**Designed with patient comfort in mind, open MRI scanners deviate from the traditional tunnel design. These scanners off a more spacious and accommodating environment, making them suitable for individuals who find closed bore scanners unsettling. These MRI scanners differ from the rest due to the option to open on all four enclosing sides. The feature allows for more airflow and ventilation, but, at the same time, the image quality delivered is significantly less.

FigureI.4: open MRI

I.2.3 The main components of MRI:

An MRI system consists of four major components:

- **Main magnet formed by superconducting coils.**
- **Gradient coils.**
- **Radiofrequency (RF) coils.**
- **Computer systems.**

Each component has safety considerations. Unless carefully controlled, the MRI machine's strong static magnetic field could turn a ferromagnetic object into a harmful projectile or cause vertigo and headache. [7]

I.2.4 MRI sequences

An MRI sequence is a number of radiofrequency pulses and gradients that result in a set of images with a particular appearance. [7]

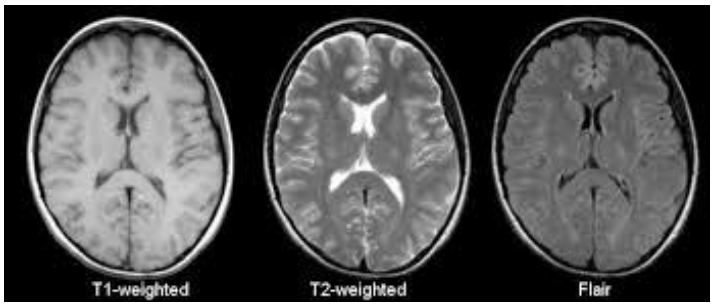


Figure I.5 : MRI sequences.

Among the most commonly used sequences in neurological imaging are:

- **T1-weighted imaging (T1):**

T1-weighted sequences provide high anatomical detail and clear visualization of brain structures. They are particularly useful for assessing tissues integrity and structural abnormalities. These sequences produce high-contrast images of tissues with different water and fat content. In T1-weighted images, fatty tissues are bright, while areas that contain a lot of water are dark. [7]

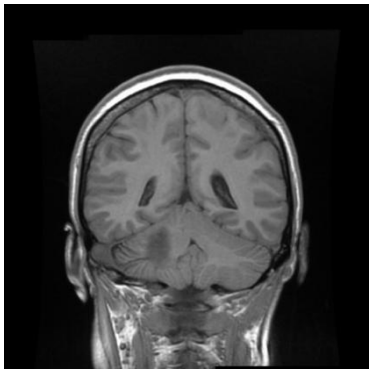


Figure I.6: T1-weighted

- **T2-weighted imaging (T2):**

T2-weighted imaging is highly sensitive to water content and inflammatory changes. These sequences produce images in which areas with a lot of water are bright and fatty tissues are dark. They are particularly useful in detecting pathologies such as edema or tumors. This sequence is widely used to detect the total lesion burden in MS patients. [2]

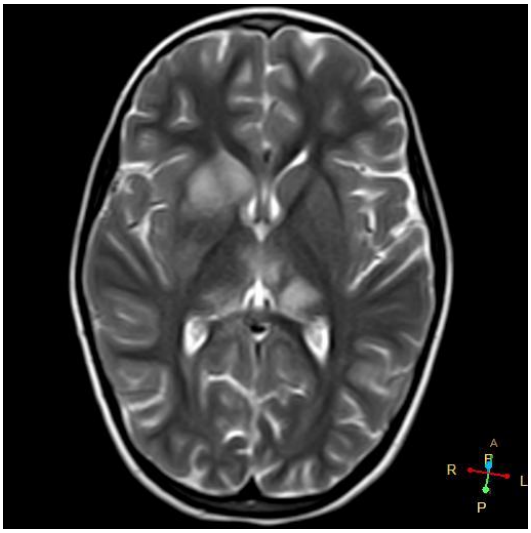


Figure I.7: T2-weighted

- **Fluid-Attenuated Inversion Recovery (FLAIR):**

Fluid-Attenuated Inversion Recovery is a special type of T2-weighted sequence that suppresses the cerebrospinal fluid signal, which allows for better visualization of certain pathological changes in the brain. It is considered one of the most important sequences for MS lesion detection and evaluation. [2]

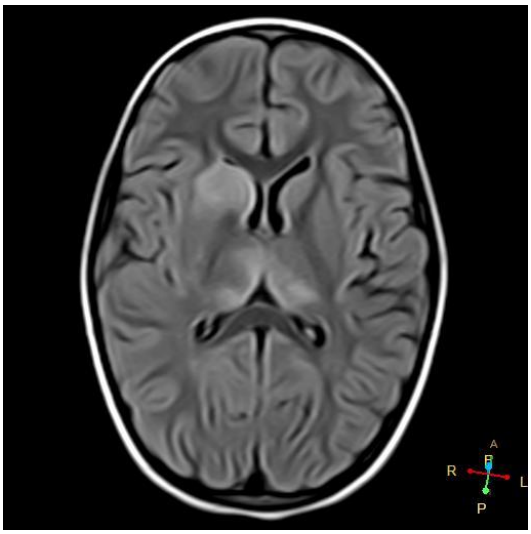


Figure I.8: FLAIR

I.2.5 MR images of MS patients:

MS activity appears on an MRI scan as either bright or dark spots. Typical MS lesions tend to be oval or frame shaped. MS lesions can appear in both the brain's white matter and gray matter. Healthcare professionals may use a chemical contrast dye called gadolinium to improve the brightness of MRI scan images. [2]

MS lesions can show white matter inflammation, demyelination, and scarring, or sclerosis. Scans can let healthcare professionals know when lesions are new and growing and potentially how damaging they are to the brain. [2]

An MRI scan can reveal several things about a person's MS, including:

- **if there is a relapse in MS**
- **if the MS is active without worsening**
- **if the MS is stable without activity**
- **if there is new active inflammation**
- **if there is no evidence of activity [2]**

I.2.6 Advantages of MRI in MS:

MRI has also shaped how we monitor and treat MS. It is used to build a picture of how someone's MS is changing over time. This can help to decide if a treatment is working. Research has highlighted the benefits of regular MRI scans to monitor MS and inform treatment decisions. The frequency of MRI follow-up varies depending on several factors, including disease subtype, clinical activity, treatment regimen, and individual patient characteristics. [2]

Therefore, decisions regarding the timing and regularity of MRI scans should be made collaboratively between the patient and healthcare professionals, based on clinical guidelines and personalized medical evaluation.

I.2.7 Limitations of MRI in MS:

Despite its high sensitivity and its central role in the diagnosis of Multiple Sclerosis, MRI presents several limitations. Although it is fully capable of detecting visible demyelinating lesions within the central nervous system, it does not visualize all existing pathological changes at the microscopic level (such as normal-appearing white matter damage).

Some lesions, particularly in the early stages of the disease, may remain undetected due to spatial resolution constraints. Furthermore, MRI findings are not entirely specific to MS, as similar white matter abnormalities can appear in other neurological conditions such as vascular diseases, migraines, or inflammatory disorders. [2]

For these reasons, MRI alone is insufficient to definitively confirm the diagnosis of MS and must be interpreted in combination with clinical evaluation, patient history, and established diagnostic criteria (such as the McDonald criteria). [6]

I.2.8 Conclusion

This chapter provided the medical and technological foundations necessary for understanding the context of this work. In its first part, we examined Multiple Sclerosis as a chronic autoimmune disease of the central nervous system, in which the immune system attacks the myelin sheath and causes the demyelinating lesions responsible for disrupted neural communication. We described the main forms of the disease, its varied clinical manifestations, its underlying causes and risk factors, as well as the therapeutic approaches used to reduce relapse severity and slow its progression. These elements highlighted both the complexity of the disease and the difficulty of diagnosing and monitoring it, given the variability of lesion appearance and disease evolution from one patient to another.

The second part focused on the central role of Magnetic Resonance Imaging in addressing these challenges. We introduced the technical principles of MRI, the different types of scanners, and the main sequences used in neurological imaging particularly T1-weighted, T2-weighted, and FLAIR each providing complementary information for the visualization of demyelinating lesions. We showed how MRI supports established diagnostic criteria by demonstrating lesion dissemination in space and time, and how it enables long term disease monitoring, treatment evaluation, and therapeutic decision making. At the same time, we discussed the limitations of MRI including its inability to detect certain microscopic changes, the imperfect correlation between imaging findings and clinical symptoms, and the fact that MRI abnormalities are not entirely specific to MS and must be interpreted alongside clinical assessment.

Taken together, these two parts establish a clear picture: Multiple Sclerosis is a complex neurological disease whose diagnosis and follow-up rely heavily on medical imaging, and MRI remains the gold standard modality for this purpose. However, the manual interpretation of MRI scans is time consuming and subject to inter observer variability. This observation motivates the central contribution of this work the development of automated, artificial intelligence-based methods for the detection and analysis of MS lesions which will be addressed in the following chapters.

CHAPTER II:
MACHINE LEARNING AND DEEP LEARNING

II.1Introduction

The previous chapter established the medical and imaging foundations of this work, showing how Multiple Sclerosis is diagnosed and monitored through MRI, and why the interpretation of these images remains a demanding and time-consuming task. It is in response to this challenge that Artificial Intelligence has become a central tool in modern medical imaging.

This chapter introduces the theoretical foundations on which the intelligent component of the proposed platform is built. It follows a progressive approach, moving from the broadest concept toward the most specific one. It begins with Artificial Intelligence as a general field, then narrows to Machine Learning, the family of methods that allow systems to learn from data rather than from explicitly programmed rules. The discussion then focuses on Deep Learning, and in particular on Convolutional Neural Networks (CNNs), which have become the reference approach for the automatic analysis of medical images.

Beyond explaining how these models work, the chapter also addresses two aspects that are essential in a medical context: the explainability of the model's decisions, introduced through the Grad-CAM technique, and the evaluation metrics used to measure the reliability of a classification model. Together, these notions provide the conceptual framework needed to understand the design and functioning of the AI module described in the following chapters.

II.2Artificial Intelligence

Artificial Intelligence is the branch of computer science concerned with the design of systems capable of performing tasks that normally require human intelligence, such as reasoning, perception, decision-making, and language understanding [8]. Since its emergence as a formal discipline in the mid-twentieth century, AI has evolved from systems based on explicitly programmed rules toward systems that are able to learn and adapt from experience.

Traditional, rule-based AI relies on knowledge manually encoded by human experts in the form of logical rules. While effective for well-defined problems, this approach becomes impractical for tasks such as image interpretation, where the relevant patterns are too numerous, too subtle, or too variable to be described explicitly. Medical imaging is a representative example: the visual characteristics that distinguish a pathological region from healthy tissue cannot be captured by a finite set of handwritten rules.

This limitation motivated the rise of data-driven approaches, in which the system infers the rules directly from examples. Within this paradigm, Machine Learning and, more recently, Deep Learning have produced remarkable results in the automatic analysis of medical images, achieving performance comparable to that of human experts in several diagnostic tasks [9], [3]. The remainder of this chapter focuses on these learning-based methods, which form the technical basis of the proposed platform.

II.3 Machine Learning

II.3.1 Definition and principles

Machine Learning (ML) is a subfield of Artificial Intelligence that enables computer systems to learn from data and improve their performance on a given task without being explicitly

programmed for it. The term was introduced by Arthur Samuel in 1959, who described it as the field of study that gives computers the ability to learn without being explicitly programmed [10]. A more formal definition was later proposed by Tom Mitchell, who stated that a program learns from experience with respect to a task and a performance measure if its performance on the task, as measured by that measure, improves with experience [11].

In practice, a machine learning model is exposed to a set of examples and progressively adjusts its internal parameters in order to capture the underlying patterns in the data. Once trained, the model can generalize this knowledge to new, previously unseen examples. This ability to generalize rather than simply memorize, is the central goal of machine learning.

II.3.2 Types of Machine Learning

Machine learning methods are generally divided into three main categories according to the nature of the data and the learning signal available [12].

- Supervised learning is the most widely used category, particularly in medical applications. The model is trained on a dataset in which each example is associated with a known label provided by an expert. The objective is to learn the relationship between the input data and the corresponding label so that the model can predict the label of new inputs. Supervised tasks are further divided into classification, where the output is a discrete category (for example, MS or Healthy), and regression, where the output is a continuous value. The model developed in this work belongs to the supervised classification category.

- Unsupervised learning works with data that has no labels. Instead of predicting a known output, the model seeks to discover hidden structures within the data, for example by grouping similar examples together (clustering) or by reducing the number of variables while preserving the essential information (dimensionality reduction).

- Reinforcement learning follows a different principle, in which an agent learns to make decisions by interacting with an environment. The agent receives rewards or penalties according to its actions and gradually adjusts its behaviors to maximize the cumulative reward over time. This category is mainly used in domains such as robotics and game playing.

II.3.3 Limitations of classical Machine Learning on images

Although classical machine learning algorithms perform well on structured, tabular data, they face important limitations when applied directly to images. These algorithms generally cannot operate on raw pixels they require a preliminary stage of feature extraction, in which a human expert manually designs the descriptors that the model will use, such as edges, textures, or shapes.

This process, known as feature engineering, is time-consuming, requires domain expertise, and is difficult to transfer from one problem to another.

Moreover, an image contains a very large number of pixels, which leads to a high-dimensional input space. Classical models struggle to handle this dimensionality efficiently and tend to lose the spatial relationships between neighboring pixels, which are essential for recognizing visual patterns. These limitations explain the reason behind why classical machine learning has been largely replaced in image analysis as well as by deep learning methods capable of learning the relevant features automatically.

II.4 Deep Learning

II.4.1 From Machine Learning to Deep Learning

Deep Learning is a subfield of machine learning based on artificial neural networks composed of many successive layers. Its defining characteristic is the ability to learn the relevant features directly from raw data, without the need for manual feature engineering [9]. Rather than relying on descriptors designed by a human expert, a deep network discovers, layer after layer, an increasingly abstract representation of the input. This property, known as representation learning, is the main reason for the success of deep learning in image analysis [13].

The relationship between these fields is hierarchical: deep learning is a subset of machine learning, which is itself a subset of artificial intelligence. Deep learning therefore does not replace machine learning but represents its most powerful branch for problems involving complex, high-dimensional data such as images, audio, and natural language.

II.4.2 Artificial neural networks

Artificial neural networks are computational models loosely inspired by the organization of biological neurons in the brain. Their fundamental unit is the artificial neuron, which receives several inputs, multiplies each by an associated weight, adds a bias term, and passes the result through an activation function that introduces non-linearity. The weights and biases are the parameters that the network adjusts during training.

Neurons are organized into layers: an input layer that receives the data, one or more hidden layers that progressively transform it, and an output layer that produces the final prediction. When every neuron in a layer is connected to every neuron in the next, the structure is called a fully connected or dense layer. A network with a sufficient number of hidden layers is referred to as a deep neural network, which gives deep learning its name.

II.5 Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are a category of deep neural networks specifically designed to process data with a grid-like structure, such as images. Introduced in their modern form by LeCun et al. for handwritten digit recognition [14], they have since become the standard architecture for almost all computer vision tasks, including medical image classification.

Following this work, deeper architectures such as VGG [15] and ResNet [16] progressively improved performance and established design patterns that are still widely used today. Unlike fully connected networks, CNNs preserve the spatial structure of the image and drastically reduce the number of parameters through two key ideas: local connectivity and weight sharing. A typical CNN is built from a succession of convolutional, activation, and pooling layers, followed by one or more fully connected layers that produce the final prediction.

II.5.1 Convolution and filters

The convolutional layer is the core building block of a CNN. It applies small matrices of weights, called filters or kernels, that slide across the entire image. At each position, the filter computes a weighted sum of the pixels it covers, producing a single value; the collection of these values forms a feature map that indicates where in the image a particular pattern is present.

Because the same filter is applied across the whole image, the number of parameters remains small regardless of the image size, and the network becomes able to detect a given pattern wherever it appears. By stacking several convolutional layers, the network learns a hierarchy of features: early filters respond to simple structures such as edges, while deeper filters respond to increasingly complex and abstract patterns relevant to the task.

II.5.2 Pooling layers

Pooling layers are used to progressively reduce the spatial dimensions of the feature maps, which decreases the computational cost and the number of parameters while retaining the most important information. The most common form, max pooling, divides the feature map into small regions and keeps only the maximum value of each region. In addition to compressing the representation, pooling makes the network more robust to small translations of the patterns within the image.

II.5.3 Activation functions

Activation functions introduce the non-linearity that allows neural networks to model complex relationships; without them, a deep network would behave like a single linear transformation. The most widely used activation function in modern CNNs is the Rectified Linear Unit (ReLU), which replaces negative values by zero and keeps positive values unchanged [17]. ReLU is computationally efficient and helps mitigate the vanishing-gradient problem encountered with older functions.

At the output of the network, a different activation function is used according to the task. For binary classification, the sigmoid function is applied; it maps the output to a value between 0 and 1, which can be interpreted as the probability of belonging to the positive class. For multi-class problems, the soft-max function is used instead.

II.5.4 Batch Normalization

Batch Normalization is a technique that normalizes the inputs of each layer so that they maintain a stable distribution during training [18]. By doing so, it allows the use of higher learning rates, accelerates convergence, and makes the training process more stable. It also has a mild regularizing effect. Batch Normalization is typically inserted after a convolutional layer and before the activation function.

II.5.5 Dropout and regularization

One of the main difficulties in training deep networks is overfitting, which occurs when the model learns the training data too closely, including its noise, and consequently fails to generalize to new data. This risk is particularly high in medical applications, where annotated datasets are often limited in size.

Several regularization techniques are used to address this problem. Dropout randomly deactivates a fraction of the neurons during each training step, forcing the network to learn redundant and more robust representations [19]. Other common strategies include weight regularization, which penalizes

excessively large weights, and data augmentation, which artificially increases the diversity of the training set by applying transformations such as rotations or flips to the images.

II.5.6 Fully connected layers and classification:

After the convolutional and pooling layers have extracted a compact set of high-level features, these features are passed to one or more fully connected layers that perform the final decision. The multidimensional feature maps are first transformed into a vector, either by flattening them or, more efficiently, by applying a global average pooling operation that averages each feature map into a single value.

This vector is then processed by dense layers, and the last layer produces the prediction. In the case of binary classification, this final layer contains a single neuron with a sigmoid activation, whose output represents the probability that the input image belongs to the positive class.

II.5.7 Image classification vs. segmentation

It is important to distinguish between two related but fundamentally different tasks in medical image analysis: classification and segmentation. In classification, the network assigns a single label to the entire image, for example indicating whether or not it contains signs of Multiple Sclerosis. In segmentation, the network instead assigns a label to every individual pixel, producing a detailed mask that delineates the exact contour of each lesion. Segmentation architectures, such as the U-Net [20] and Fully Convolutional Networks [21], are trained on pixel-level annotations.

This distinction is essential for the present work. The proposed model performs binary classification: it determines whether an MRI slice is healthy or affected by Multiple Sclerosis, and produces a probability score. The visual localization of the suspected regions is obtained afterwards, through an explainability technique applied to the trained classifier, and not through a segmentation network. This approach, presented in the next section, highlights the areas that most influenced the model's decision without requiring pixel-level annotations.

II.6 Explainability with Grad-CAM

Deep neural networks are often described as black boxes because the reasoning behind their predictions is not directly accessible. In a medical context, where decisions can have serious consequences, this lack of transparency is a major obstacle to clinical adoption. A physician needs to understand not only what the model predicts, but also on what visual evidence the prediction is based. This requirement has given rise to the field of explainable artificial intelligence.

Gradient-weighted Class Activation Mapping (Grad-CAM) is one of the most widely used explainability techniques for convolutional neural networks [22]. It produces a heatmap that highlights the regions of the input image that contributed most to a given prediction.Explainability methods have been applied to CNN-based MS diagnosis to make predictions interpretable [40]. To do so, Grad-CAM computes the gradients of the predicted class with respect to the feature maps of the last convolutional layer, uses these gradients as importance weights, and combines the feature maps accordingly. The resulting map is then superimposed on the original image.

A crucial point is that Grad-CAM is a post-hoc method: it is applied after the model has been trained and does not modify the network or its prediction. It provides a localization of the regions of interest rather than a precise segmentation of the lesions. In the proposed platform, Grad-CAM is used to highlight the brain regions suspected of containing Multiple Sclerosis lesions, thereby making the model's output interpretable and visually verifiable by the clinician.

II.7 Evaluation Metrics

Once a model has been trained, its performance must be assessed objectively using quantitative metrics. The choice of metrics is particularly important in medical applications, where different types of errors do not carry the same consequences. This section presents the metrics used to evaluate a binary classification model.

II.7.1 Confusion matrix

The confusion matrix is the starting point for evaluating a classification model. It compares the predictions of the model with the true labels and organizes the results into four categories: true positives (correctly identified positive cases), true negatives (correctly identified negative cases), false positives (negative cases incorrectly classified as positive), and false negatives (positive cases incorrectly classified as negative).

In a medical diagnostic context, false negatives are especially critical, since failing to detect a real pathology may delay treatment. The confusion matrix makes these errors explicit and serves as the basis for computing the metrics described below.

II.7.2 Accuracy, precision, recall, and F1-score

Accuracy is the proportion of correct predictions among all predictions, defined as (TP + TN) / (TP + TN + FP + FN). Although intuitive, accuracy can be misleading when the classes are imbalanced, as a model may achieve a high score simply by predicting the majority class [23].

Precision measures the proportion of correct predictions among the cases predicted as positive, defined as TP / (TP + FP); it indicates how reliable a positive prediction is. Recall, also called sensitivity, measures the proportion of actual positive cases that the model correctly identifies, defined as TP / (TP + FN); it is especially important in diagnosis, where missing a positive case is costly.

Precision and recall are often in tension, as increasing one tends to decrease the other. The F1-score combines them into a single value by computing their harmonic mean, defined as 2 × (precision × recall) / (precision + recall). It provides a balanced measure of performance, particularly useful when the classes are imbalanced.

II.7.3 ROC curve and AUC

The Receiver Operating Characteristic (ROC) curve provides a global view of a classifier's behavior by plotting the true positive rate against the false positive rate for all possible decision

thresholds [24]. A model that classifies perfectly produces a curve that reaches the top-left corner, while a model that performs no better than chance follows the diagonal.

The Area Under the Curve (AUC) summarizes the ROC curve into a single number between 0 and 1, where 1 corresponds to a perfect classifier and 0.5 to random guessing. Because it is independent of any particular decision threshold, the AUC is a robust and widely used indicator of the overall discriminative ability of a classification model.

II.8 Conclusion

This chapter has presented the theoretical foundations of the methods used in this work, progressing from the general field of Artificial Intelligence to the specific tools employed in the proposed platform. It showed how Machine Learning enables systems to learn from data, why Deep Learning overcomes the limitations of classical methods on images, and how Convolutional Neural Networks are able to learn hierarchical visual features and perform image classification.

The chapter also introduced two notions that are essential in a medical context: the Grad-CAM technique, which makes the model's decisions interpretable by localizing the regions of interest, and the evaluation metrics that allow its reliability to be assessed objectively. The distinction between classification and segmentation was clarified, situating the proposed approach as a classification model complemented by post-hoc localization rather than a segmentation system.

Together, these concepts constitute the conceptual framework required for the design and implementation of the intelligent module of the platform. The following chapter builds upon this foundation to present the modelling and design of the proposed system.

CHAPTER III:
STATE OF THE ART

III.1 Introduction

The development of an intelligent platform for Multiple Sclerosis (MS) cannot be undertaken in isolation from the existing technological. Over the past decade, several software platforms and applications have been proposed to assist clinicians in the analysis of brain Magnetic Resonance Imaging (MRI) and in the monitoring of MS patients. These range from regulatory-approved commercial platforms integrated into hospital radiology workflows, to cloud-based systems and open-source tools. This chapter reviews five representative systems that share objectives similar to those of the proposed platform, MyelineCare. For each, the underlying logic (the artificial-intelligence method employed) and the data used to build it are described, and a comparison is then drawn to highlight the distinctive contribution of MyelineCare.

III.2 Existing systems for MS diagnosis and mangment:

III.2.1 icobrain ms (icometrix):

Icobrain ms, developed by icometrix (Leuven, Belgium), is one of the most widely adopted and clinically validated commercial solutions for MS imaging. It is a clinical platform, complemented by a patient application and clinician portal (icompanion) for symptom and treatment monitoring [27], [29].

Logic: icobrain ms relies on deep-learning convolutional neural networks that automatically detect, segment and quantify white-matter hyperintensities on FLAIR/T2 sequences images and hypointensities on T1 images, while also measuring brain atrophy; it reports lesion distribution according to the McDonald criteria and tracks lesion evolution between examinations [27], [28].
Dataset: the models are trained and validated on large proprietary, multi-centre clinical MRI datasets that are not publicly released, with clinical validation reported in several reviewed studies [28].

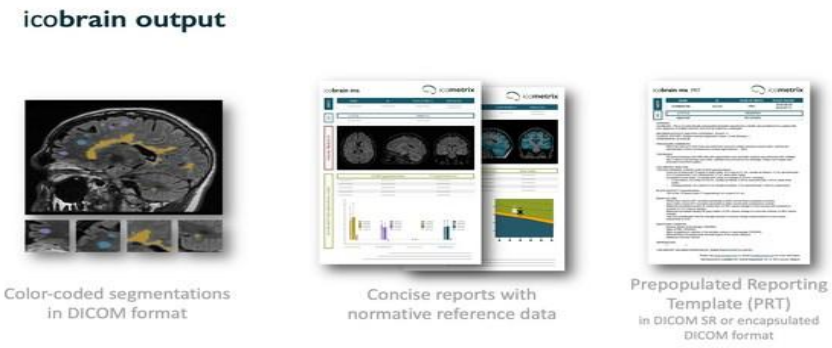


Figure III.1: icobrain https://www.icometrix.com/multiple-sclerosis

III.2.2 Pixy.Neuro.MS(pixyl)

Pixyl.Neuro.MS, developed by Pixyl (Grenoble, France), is a CE-marked and FDA-cleared software-as-a-service solution with an integrated viewer, dedicated to the automatic analysis of brain MRI in MS [30], [31].

Logic: it uses a deep-learning (U-Net-style convolutional) model to segment and characterise lesions, quantify lesion count and volume per anatomical region, and classify lesions according to their longitudinal evolution as stable, enlarging or new; prior and current examinations are co-registered and a structured report is generated automatically in a few minutes [31].

Dataset: training relies on proprietary clinical data, and the tool has been evaluated in independent clinical studies, including cohorts of patients with clinically isolated syndrome [32]. Like icobrain ms, it is designed as an analysis engine that augments the radiologist's workflow rather than as a standalone patient-management platform.

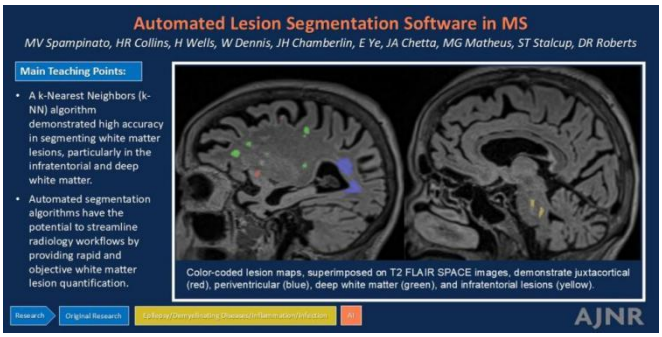


Figure 4.2.2:Pixy.neuro.MS https://www.gleamer.ai/copilot/pixyl-neuro-ms

III.2.3 QMENTA

QMENTA (Boston, USA / Barcelona, Spain) is a cloud-based neuroimaging platform that, based on the systems reviewed, most closely resembles an integrated management environment: it combines a cloud PACS, a data uploader, dashboards, central review and reporting in a single system [33], [34]. **Logic:** rather than a single model, QMENTA hosts a catalogue of AI biomarker algorithms including deep-learning white-matter lesion segmentation and atrophy-quantification tools (e.g., FreeSurfer, SIENAX) orchestrated within one cloud workflow [33].

Dataset: the platform processes the user's own securely uploaded, multi-site imaging and clinical data; its algorithms are trained on a variety of research datasets, and the platform has served as the central hub for large MS data-sharing initiatives [34]. Its focus is on imaging data management and research/clinical-trial workflows rather than day-to-day clinical patient management.

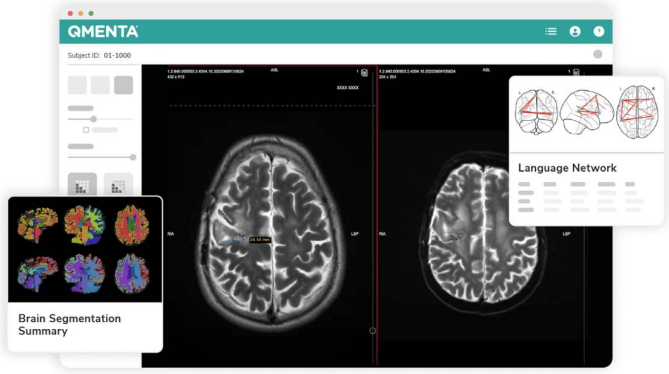


Figure 4.2.3: Qmenta https://www.qmenta.com/

III.2.4 mdbrain(mediaire)

Mdbrain, developed by Mediaire GmbH (Berlin, Germany), is a certified, PACS-integrated AI module that supports MS diagnostics by producing two quantitative reports: a lesion report and a volumetry report [35], [36].

Logic: it uses a deep convolutional neural network based on the U-Net architecture to automatically segment MS lesions from FLAIR images and to segment tissue classes and brain regions from three-dimensional T1-weighted images, then quantifies lesion load and brain volumes against a normative reference population [35].

Dataset: the lesion-segmentation network was trained on 280 expert-annotated FLAIR scans and tested on a separate set of 30 expert-annotated FLAIRs, while the volumetry model was trained on a large, heterogeneous set of more than one thousand T1-weighted datasets [35], [36].

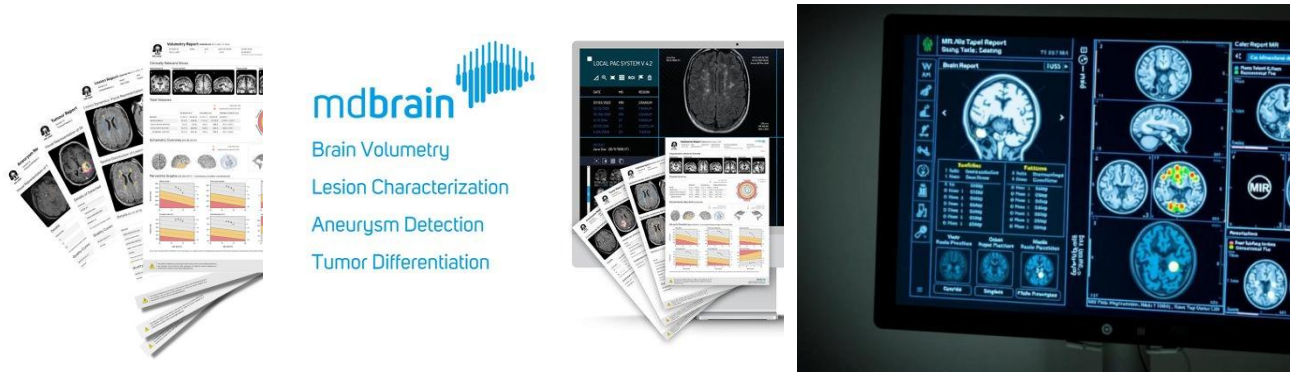


Figure4.2.4: mdbrain https://mediaire.ai/en/lesion-characterization/

III.3 Comparative analysis

The following table summerises the 4 systems and compares them with MylineCare platform across four points: the AI logic employed, the dataset used the type and availbility of the system and the presence of a patient mangment layer.

System	AI logic	Dataset	Availability	patient management
icobrain ms	Deep-learning CNN: lesion segmentation + brain volumetry; McDonald-criteria distribution	Proprietary multi-centre clinical MRI (not public)	Commercial, FDA / CE	Partial (engine + icompanion app)
Pixyl.Neuro. MS	Deep-learning (U-Net-style) segmentation + longitudinal lesion classification (new/enlarging/stable)	Proprietary clinical data; clinical-study validation	Commercial, FDA / CE	No
QMENTA	Cloud platform hosting a catalogue of AI biomarker algorithms (DL lesion segmentation, atrophy)	User-uploaded multi-site data; varied research datasets	Commercial cloud platform	Partial (data management, no clinical mangment)
mdbrain	Deep CNN (U-Net): FLAIR lesion segmentation + T1 tissue/region volumetry	280 annotated FLAIRs (lesions); 1000+ T1 sets (volumetry)	Commercial, CE	No

Table 4.1: comparison of existing systems

III.4 Positioning of the proposed platform MylineCare:

The reviewed systems fall into: commercial products such as icobrain ms, Pixyl.Neuro.MS and mdbrain offer mature, regulatory-approved and clinically validated lesion segmentation and volumetric quantification, but they are designed primarily as analysis engines that plug into existing hospital radiology infrastructure and are subject to licensing costs; QMENTA adds a powerful cloud data-management layer but remains oriented toward research and clinical-trial workflows.

MyelineCare is positioned to address a gap that none of these systems fully covers. It is conceived not as an isolated analysis engine but as an integrated, web-based platform that unifies, within a single environment, clinician authentication, structured patient records, multi-scan imaging sessions, an artificial-intelligence decision-support module, the recording of lesion findings, report preparation, longitudinal patient follow-up and administrative supervision.

Its artificial-intelligence logic also differs from that of the reviewed systems. Whereas most of them perform segmentation of three-dimensional, multi-sequence volumes [20] which requires manually annotated lesion masks and substantial computational resources MyelineCare employs a

lightweight custom CNN that classifies two-dimensional FLAIR slices and then localises the relevant regions a posteriori using Grad-CAM [22]. This approach does not require voxel-level ground-truth masks, is far less demanding in data and computation, and produces interpretable heatmaps that indicate the regions driving each decision.

This design choice entails a deliberate trade-off that must be stated clearly. Because it relies on classification rather than on segmentation[38], MyelineCare does not generate voxel-precise lesion masks or quantitative volumetric measures such as total lesion volume or brain atrophy, which validated engines like icobrain ms, Pixyl.Neuro.MS and mdbrain provide. The objective of MyelineCare is therefore not to replace such certified quantification tools, but to offer accessible clinical decision support coupled with end-to-end patient management in a single, low-barrier platform suited to settings where certified commercial solutions may be costly or unavailable. In this sense, the proposed platform is complementary to existing systems while offering an integration and accessibility profile that distinguishes it from all five reviewed solutions.

III.5 Conclusion

This chapter reviewed four representative platforms and tools sharing objectives similar to those of MyelineCare, describing the logic and dataset behind each and comparing them with the proposed system. The analysis showed that current solutions specialise either in clinically validated lesion segmentation and quantification, in cloud-based imaging data management, or in reproducible research-oriented analysis, while generally lacking an integrated environment for everyday patient management. By combining an interpretable, lightweight artificial-intelligence module based on FLAIR-slice classification and Grad-CAM localisation with a complete patient-management layer, MyelineCare occupies a distinctive position in this landscape. Having situated the platform within the state of the art, the following chapter presents the implementation and user interfases of the proposed system in detail

CHAPTER IV:
MODELING & DESIGN

IV.1 Introduction

The design and modeling phase represent a fundamental step in the development of any intelligent healthcare system. After analyzing the medical context and existing research, it becomes necessary to define how the proposed platform will be structured and how its different components will interact. This chapter aims to present the conceptual and technical design of the proposed intelligent platform dedicated to supporting doctors in the management and diagnosis of Multiple Sclerosis patients.

Special attention is given to system modeling, including the identification of actors, functional requirements, system architecture, and data organization. The integration of artificial intelligence within the platform is also described, highlighting how MRI images can be processed to assist clinicians in detecting MS lesions. Through these design choices, the platform seeks to provide an efficient, reliable, and user-friendly environment that facilitates medical decision-making and patient monitoring.

IV.2 Project presentation

This project aims to develop an intelligent medical platform designed to assist healthcare professionals in the diagnosis and monitoring of patients affected by Multiple Sclerosis. The proposed system relies primarily on the analysis of MRI images combined with advanced artificial intelligence techniques to support the detection of MS lesions and provide clinically relevant information to doctors.

In addition to diagnostic assistance, the platform enables continuous monitoring of patients' health status by organizing medical data, imaging results, and follow-up information within a unified environment. It offers a set of integrated features intended to improve the efficiency of medical workflows, facilitate patient management, and enhance decision-making processes.

Special attention is given to usability and system maintainability by providing an intuitive user interface and a structured architecture that allows easy data management and future system evolution. Through this approach, the platform seeks to improve both the user experience of medical staff and the overall quality of patient care while supporting the integration of artificial intelligence into clinical practice.

IV.3 Identification of system actors

The proposed intelligent platform involves several actors that interact with the system in order to ensure proper functionality and efficient medical workflow management. Each actor plays a specific role within the platform:

- **Doctor:**

  Identification:
  The Doctor is the primary user of the system and represents medical professionals such as neurologists who interact directly with the platform.

  Role:
  The Doctor is responsible for managing patient information, uploading MRI images, and using the AI module to assist in detecting Multiple Sclerosis lesions.

Additionally, the doctor analyzes the results provided by the system, generates medical reports, and monitors the patient's health progression over time. This actor plays a central role in decision-making and clinical validation.

- **Administrator:**

Identification:
The Administrator is a system management actor responsible for supervising and maintaining the platform.

Role:
The Administrator ensures the proper functioning of the system by managing user accounts, monitoring system performance, and handling maintenance operations. This includes detecting and resolving technical issues, updating system configurations, and ensuring data integrity and security. The administrator guarantees system reliability and continuous availability.

- **Artificial Intelligence Module (MylineVision - system actor)**

Identification:
The AI System is an internal system actor that represents the artificial intelligence module integrated into the platform.

Role:
The AI System is responsible for processing MRI images, classifying scans for the presence of Multiple Sclerosis, and localizing suspected lesion regions, generating analytical results such as a prediction (confidence) score and approximate lesion regions. It supports the doctor by providing automated and accurate analysis, thus enhancing the diagnostic process and reducing manual workload.

IV.4Analysis and conception:

IV.4.1 UML Modeling

Unified Modeling Language (UML) is a standardized modeling language that emerged from the unification of several object-oriented design methods. It is used to represent, in a clear and structured manner, both the static structure and the dynamic behavior of a system, independently of any programming language or implementation technology. [25] UML provides a graphical approach that helps designers visualize, analyze, and organize complex software systems before the development phase.

In the context of this project, UML modeling plays an essential role in the conceptualization of the proposed intelligent medical platform dedicated to Multiple Sclerosis management and diagnosis support. Through graphical representations, UML allows the identification of system actors, the definition of functional requirements, and the description of interactions between platform components, including the integration of the artificial intelligence module responsible for MRI lesion detection.

Different UML diagrams are used to describe complementary aspects of the system. Use case diagrams illustrate user interactions and system functionalities, class diagrams define the structural

organization of data and system entities, while sequence diagrams represent the dynamic exchange of information during critical processes such as lesion detection and tracking patient medical progress. These models facilitate a better understanding of the platform architecture, ensure coherence between system components, and reduce design complexity.

Therefore, the adoption of UML in this work provides a methodological framework that supports requirements analysis, system design, and future implementation. It enables a precise and structured representation of the proposed solution, ensuring that both medical and technical requirements are clearly defined before development begins.

IV.4.1.1 Use case diagram

The use case diagram represents the functional view of the proposed AI-based system for Multiple Sclerosis (MS) monitoring and lesion detection. It describes how different actors interact with the platform and the services provided by the system. In this project, actors are: the **Doctor**, **Administrator** and **MylineVision** the AI system, collaborate to perform tasks including lesion detection from MRI images, patient progress tracking, and system management. This diagram helps identify system boundaries, user goals, and main functionalities during the requirements analysis phase.

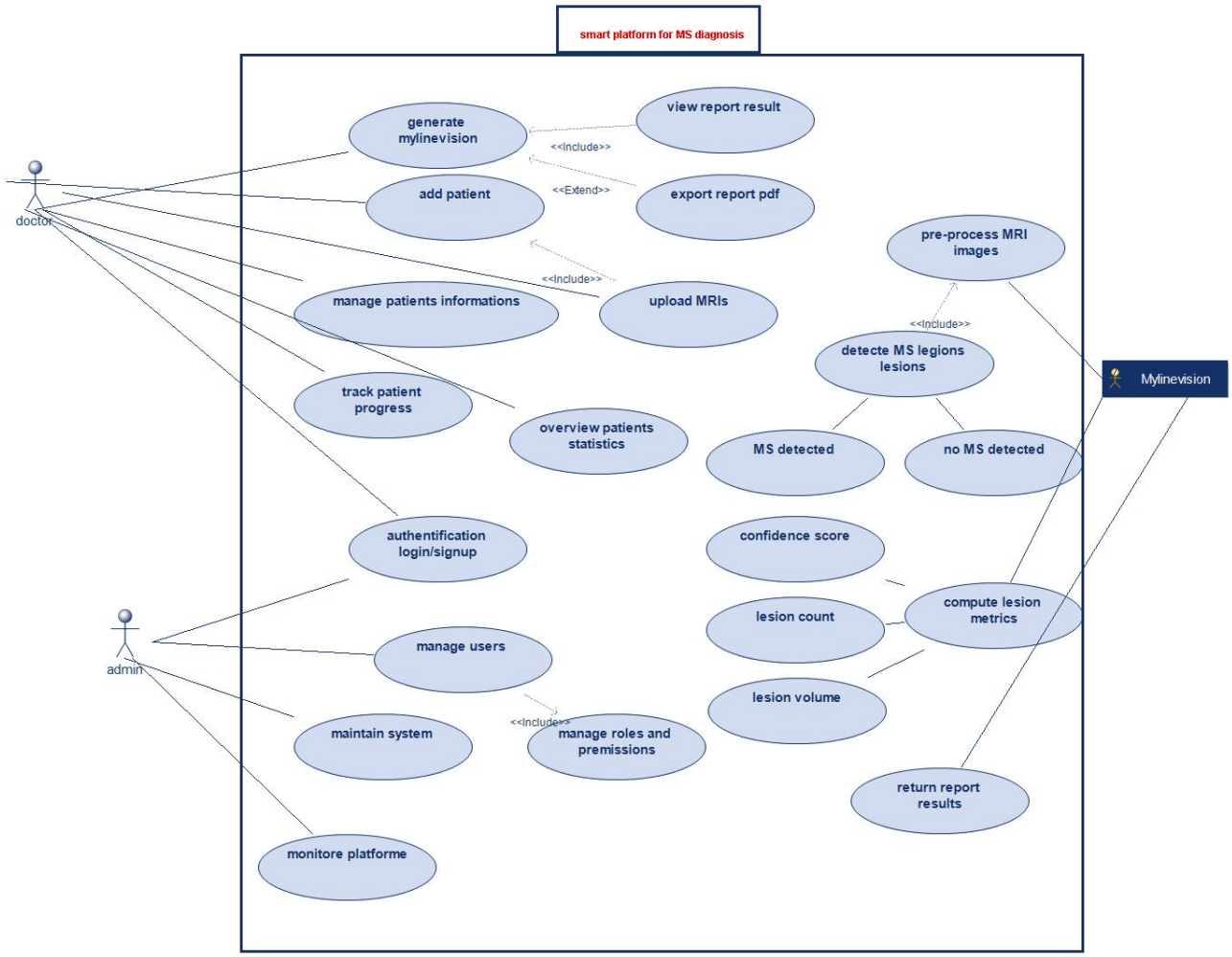


Figure IV.1: use case diagram

Use cases description:

Doctor: primary actor

1. Authentication (Login / Sign up)

Description: This use case lets users access the platform. A new doctor creates an account by providing personal and professional information, which the system validates and stores securely; a registered user logs in with their credentials and is directed to the dashboard matching their role.

Actor: Doctor, Administrator

Precondition: For sign up, the user is not yet registered; for login, the user already has an account.

Postcondition: A new account is created and/or the user is authenticated and connected.

2. Add patient

Description: The doctor creates a new patient record by entering personal and clinical identification data. The system validates and stores it in the database.

Precondition: Doctor is logged in.

Postcondition: A new patient is registered in the system.

3. Manage patient information

Description: The doctor views and updates existing patient data, including personal details and medical history.

Precondition: Doctor is logged in and the patient exists.

Postcondition: Patient data is updated or retrieved.

4. Upload MRIs

Description: The doctor uploads one or more MRI scans of a patient. The images are stored and prepared for analysis by MyelineVision.

Precondition: Doctor is logged in and the patient exists.

Postcondition: MRI scans are stored and ready for processing.

5. Generate MyelineVision analysis

Description: The doctor launches the MyelineVision module on a patient's uploaded MRI(s). This triggers the AI pipeline (pre-processing, classification and localization, metric computation, and return of results) and produces the analysis used for the report. («Include» View report result.)

Actor: Doctor (supported by MyelineVision)

Precondition: At least one MRI scan is uploaded for the patient.

Postcondition: An AI analysis is generated and available for review.

6. View report result

Description: The doctor visualizes the analysis the Grad-CAM overlay highlighting the suspected lesion regions on the MRI, the computed metrics (lesion count, approximate lesion area, confidence score), and the MS / no-MS conclusion.

Precondition: A MyelineVision analysis has been generated.

Postcondition: Results are displayed to the doctor.

7. Export report (PDF):

Description: The doctor exports the displayed report as a PDF for archiving or sharing. This is an optional extension of viewing the report. («Extend» View report result.)

Precondition: A report result is displayed.

Postcondition: A PDF version of the report is generated and saved.

8. Track patient progress:

Description: The doctor monitors the evolution of a patient's condition over time by comparing historical MRI analyses and metrics.

Precondition: The patient has at least one prior analysis on record.

Postcondition: The patient's progression is displayed.

9. Overview patient statistics:

Description: The doctor consults aggregated statistics across their patients (e.g., number of patients, detected cases, lesion trends) through a summary dashboard.

Precondition: Doctor is logged in.

Postcondition: A statistical overview is displayed.

MyelineVision (secondary / AI actor):

10. Pre-process MRI images:

Description: MyelineVision prepares the uploaded MRI through normalization, formatting, and resizing so the data matches the model's input requirements. («Included» by Detect MS lesions.)

Precondition: An MRI scan has been uploaded.

Postcondition: The image is ready for lesion detection.

11. Detect MS lesions:

Description: MyelineVision analyzes the pre-processed MRI to classify them for MS and localize suspected lesion regions using a trained CNN. The process ends in one of two outcomes MS detected (suspected lesion regions localized) or no MS detected (no suspicious regions found). («Include» Pre-process MRI images.)

Precondition: The MRI image has been pre-processed.

Postcondition: scan is classified and suspected lesion regions are localized. Out come (MS detected / No MS detected) is produced.

12. Compute lesion metrics:

Description: From the localized regions MyelineVision computes the quantitative metrics describing the lesion load the number of suspected lesion regions (lesion count), their approximate area, and a confidence score for the prediction.

Precondition: Lesions have been detected and localized.

Postcondition: Lesion count, approximate lesion area, and confidence score are available.

13. Return report results:

Description: MyelineVision sends the complete analysis back to the platform the Grad-CAM overlay highlighting the suspected lesion regions, the computed metrics, and the MS / no-MS conclusion so the doctor can review it.

Precondition: Detection and metric computation are complete.

Postcondition: Results are stored in the system and available to the doctor.

Administrator: primary actor

14. Manage users:

Description: The administrator creates, updates, or deletes user accounts and assigns their roles. («Include» Manage roles and permissions.)

Precondition: Administrator is authenticated.

Postcondition: User accounts are updated.

15. Manage roles and permissions:

Description: The administrator defines and assigns access rights per role, controlling which features each user can reach. («Included» by Manage users.)

Precondition: Administrator is authenticated.

Postcondition: Roles and permissions are updated.

16. Monitor platform:

Description: The administrator supervises system performance, usage statistics, and overall health to ensure smooth operation.

Precondition: System is running.

Postcondition: Platform status is displayed.

17. Maintain system:

Description: The administrator performs maintenance tasks such as updating configurations, fixing issues, and ensuring data integrity and security.

Precondition: Administrator has access.

Postcondition: System is updated and maintained.

These use cases collectively define the functional scope of the system and illustrate the interaction between the Doctor, the Administrator, and the MyelineVision AI module, ensuring efficient diagnosis and monitoring of Multiple Sclerosis

IV.4.1.2 Class diagram:

The class diagram represents the structural aspect of the system by modeling the main classes involved, their attributes, and the relationships that connect them. It provides a detailed view of the internal organization of the MS monitoring platform, including core entities such as patients, doctors, MRI scans, lesion detection results, medical reports, and system management components. This diagram helps define how information is stored, manipulated, and exchanged within the application. Furthermore, it plays an essential role in bridging the conceptual design and the technical implementation, as it guides both database modeling and software development by ensuring consistency between system requirements and data structure.

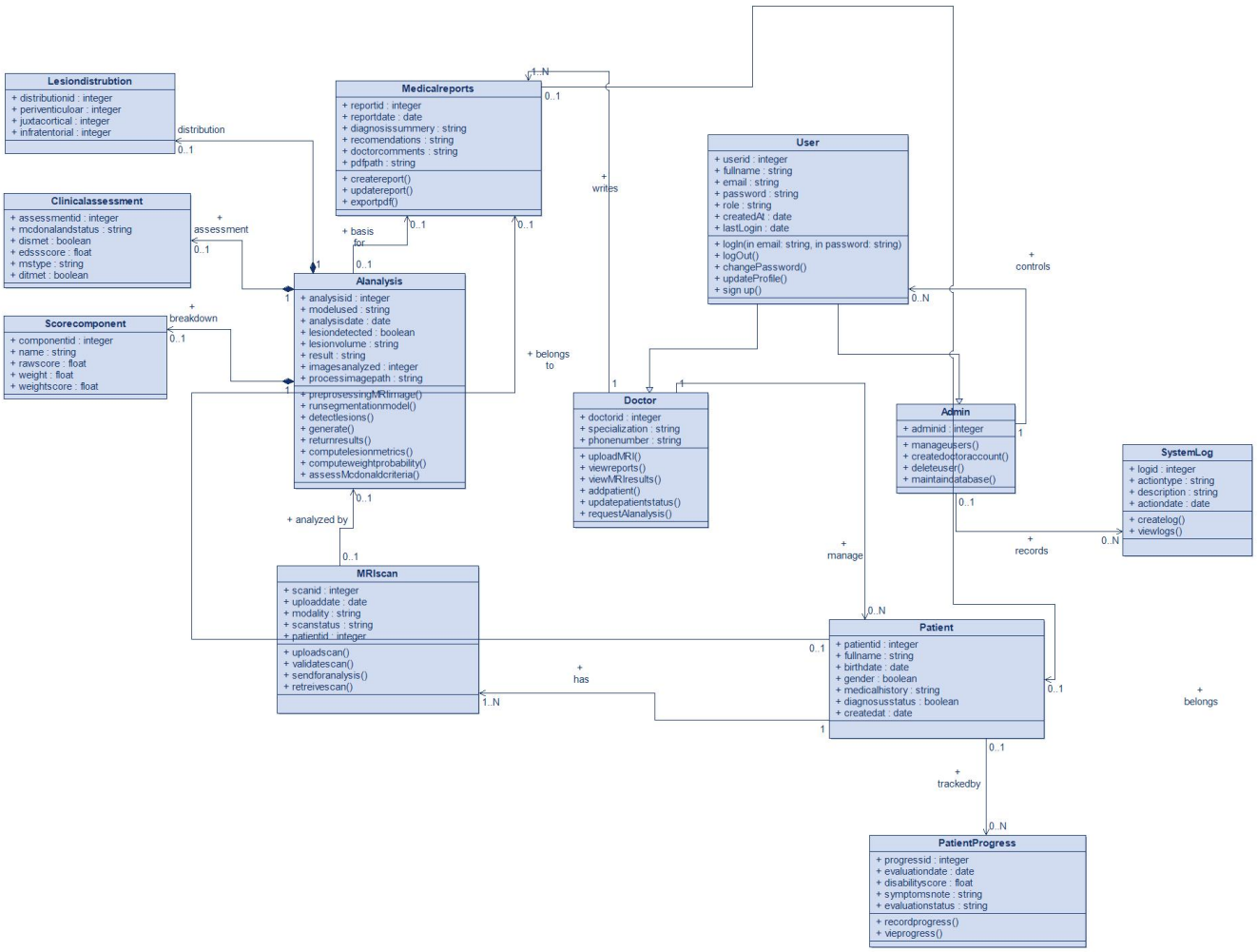
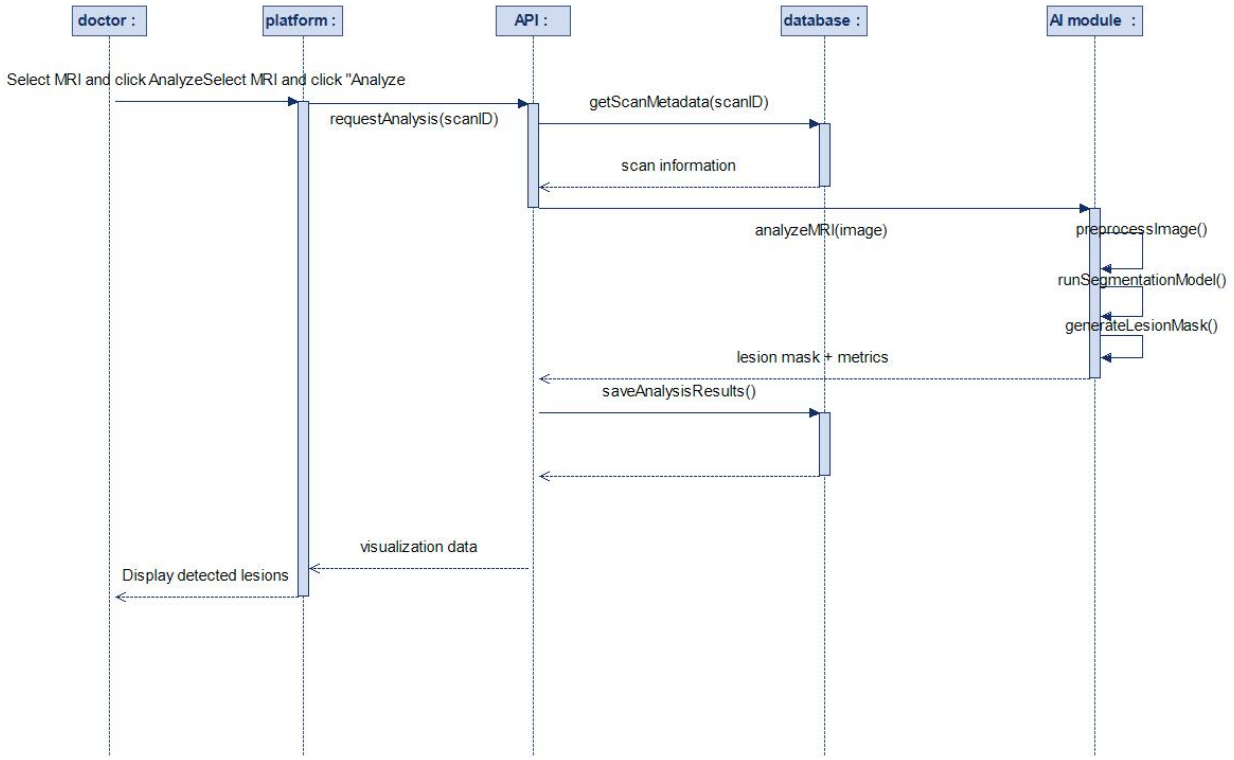


Figure IV.2: Class diagram of the MS diagnosis platform

At its center, the AIanalysis class handles the AI process (preprocessing, lesion detection, probability scoring, McDonald criteria) and is detailed by three components: LesionDistribution, ClinicalAssessment and ScoreComponent. Each analysis produces a MedicalReports object created by the doctor. The abstract Userclass is specialized into Doctor and Admin: the doctor uploads MRI scans, requests analyses and manages patients, while the admin manages accounts and logs events in SystemLog. Finally, each Patient is linked to one or more MRIscan objects and tracked over time through PatientProgress.

IV.4.1.3 Sequence diagram

Use case: Lesion detection



FigureIV.1: sequence diagram

This sequence diagram illustrates the interaction between the doctor, the platform, and the artificial intelligence module during the MS lesion detection process. The system retrieves the MRI image, sends it to the AI module for processing, then stores and displays the results.

Use case: Track patient progress

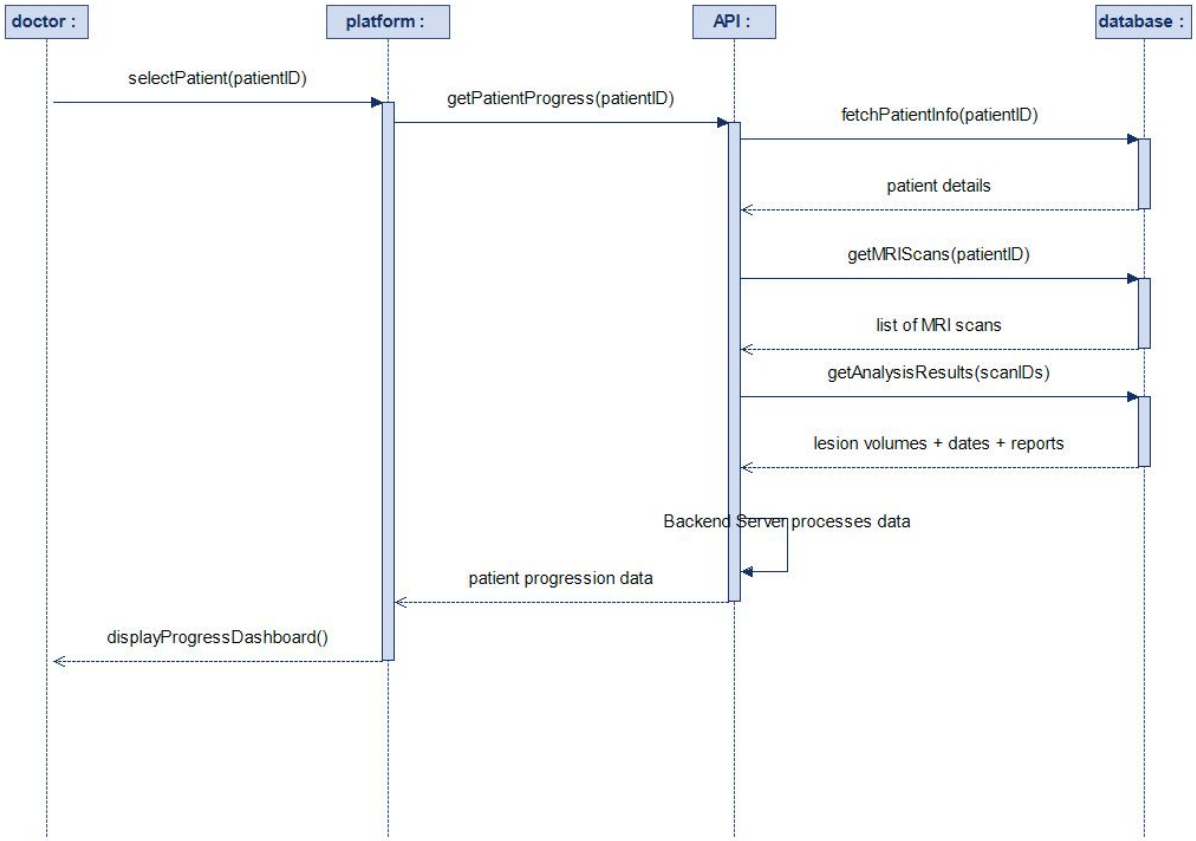
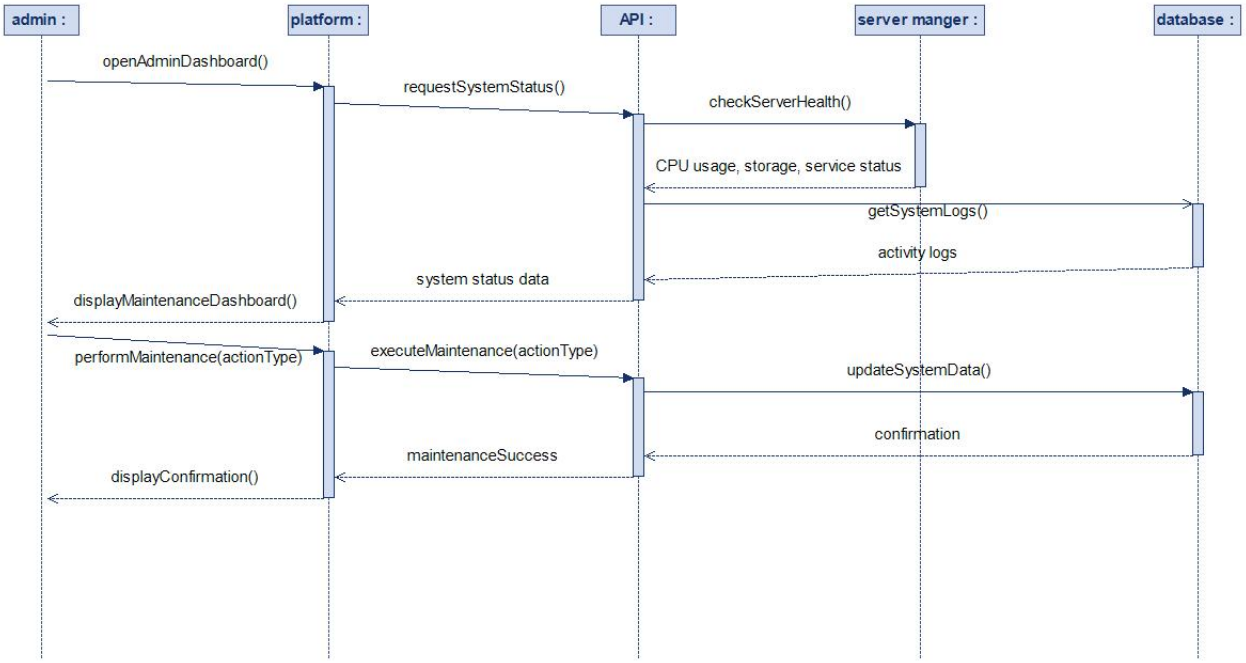


Figure IV.2: sequence diagram

This sequence diagram illustrates the patient progress tracking, which relies on historical MRI analyses and AI-generated metrics, enabling doctors to evaluate disease evolution and support clinical decision-making.

Use case: Maintain system

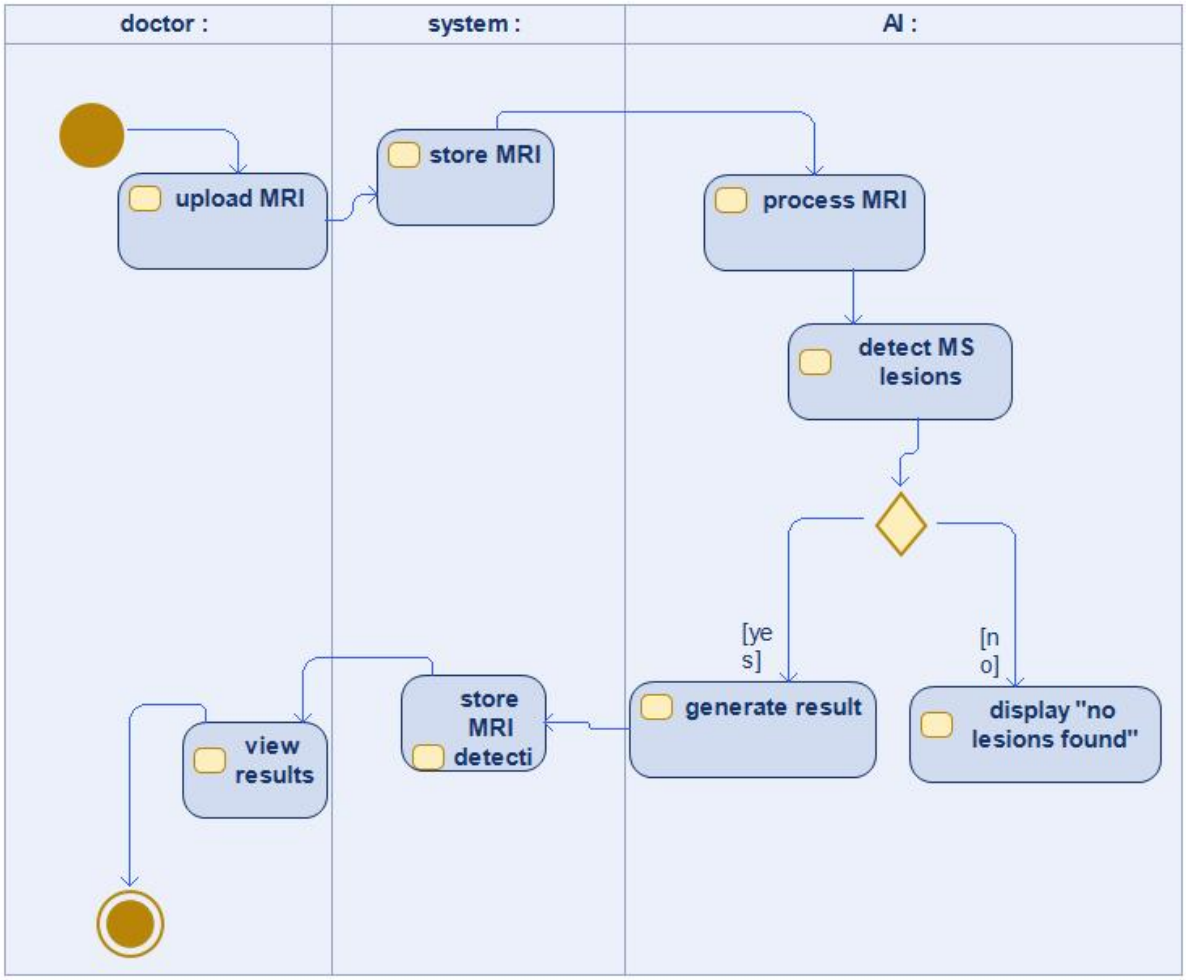


FigureIV.3: Sequence diagram

This sequence diagram illustrates the interaction between the administrator and the system during maintenance operations. The administrator monitors platform status and performs management actions through the backend server, ensuring system reliability, data integrity, and continuous availability. The administrator does not interact directly with the AI module – only with the backend server

IV.4.1.4 Activity diagram:

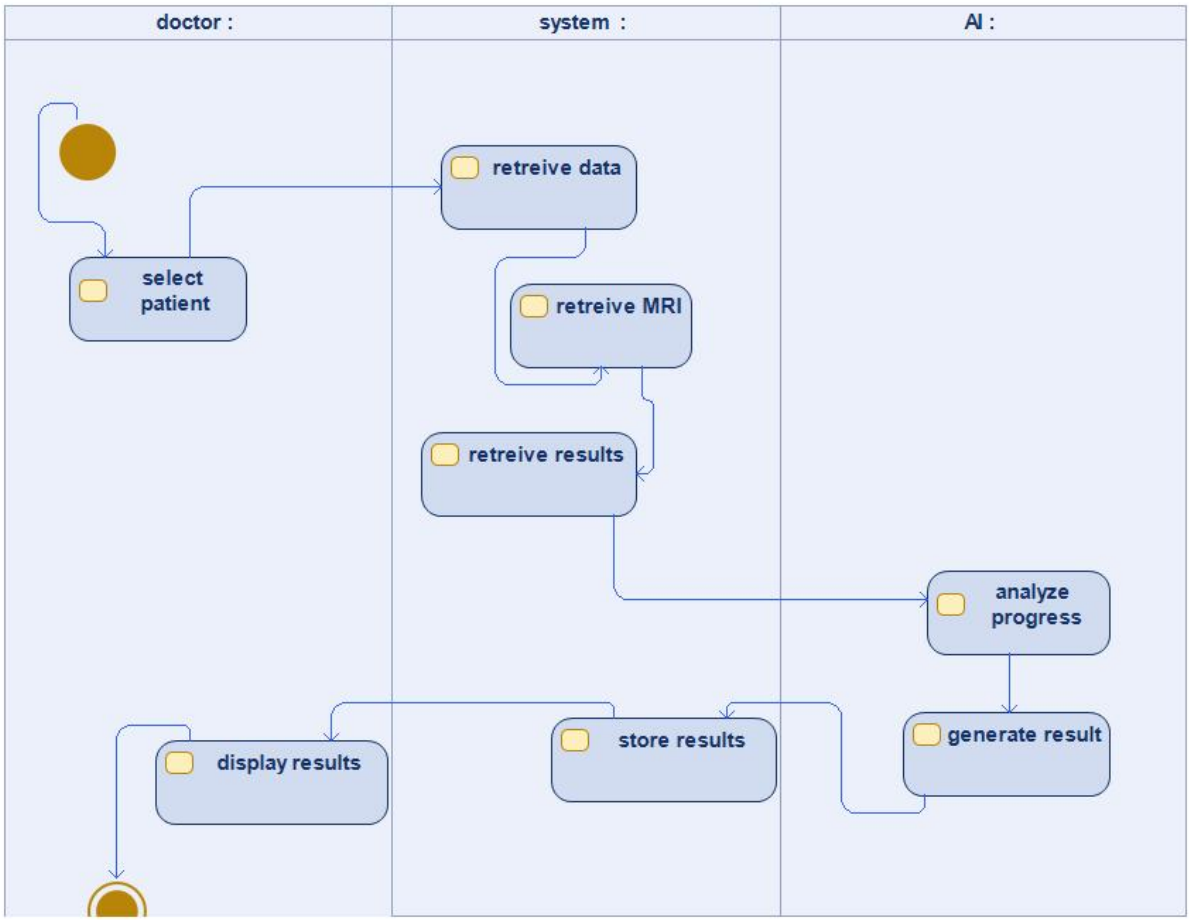
MRI analysis process :



FigureIV.1: activity diagram

The activity diagram illustrates the workflow of the MRI analysis process within the system. It describes the sequence of operations starting from MRI upload to lesion detection and result visualization. This representation highlights the interaction between the user and the AI system in a structured and sequential manner.

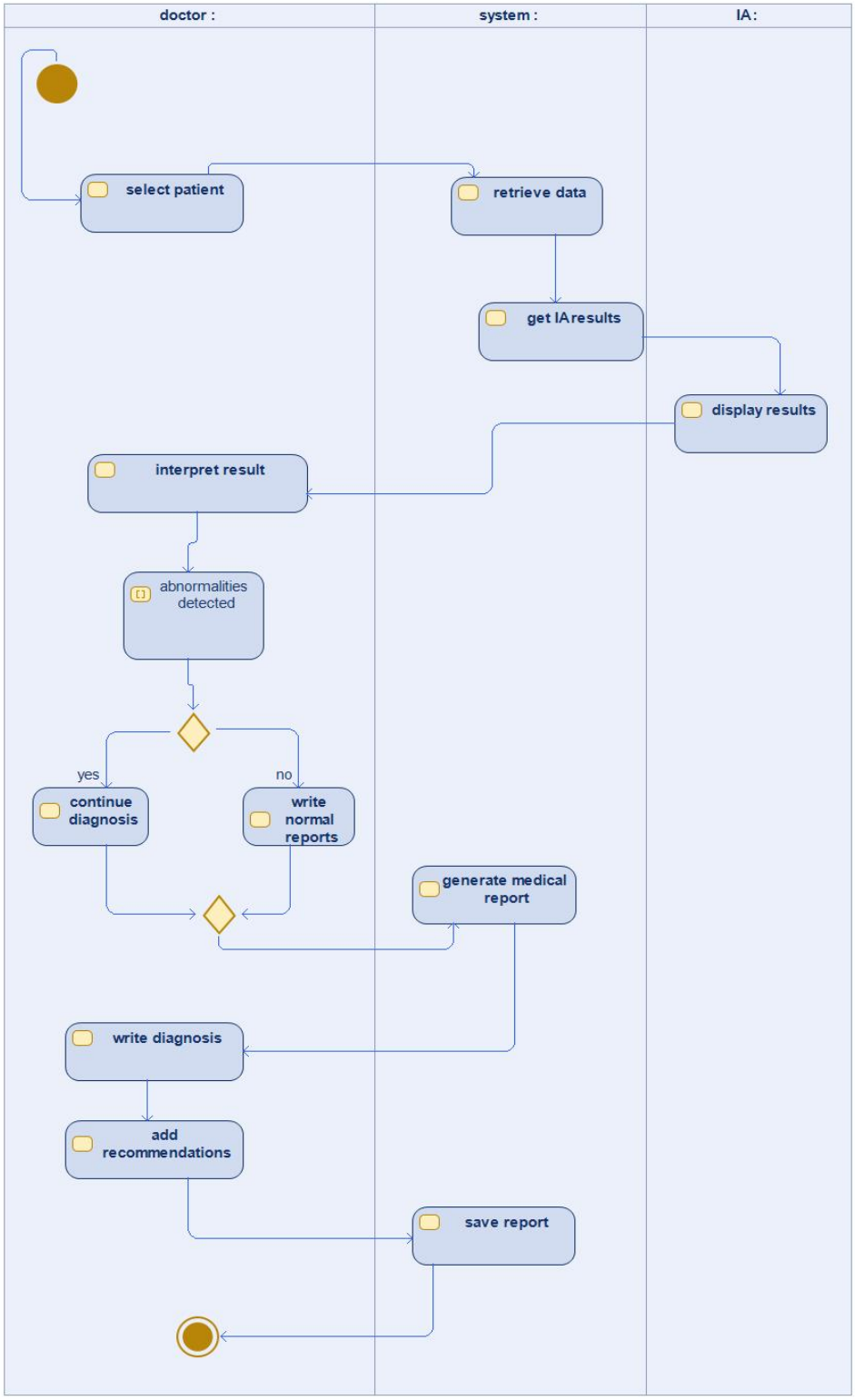
Track patient progress:



FigureIV.2: activity diagram

The activity diagram illustrates the workflow of tracking a patient's health progression within the platform. It shows how the system retrieves historical MRI data and AI analysis results to evaluate disease evolution. This process enables doctors to monitor changes over time and support clinical decision-ma

Generate reports:



FigureIV.3: activity diagram

The activity diagram illustrates the process of generating a medical report within the platform. It shows how the doctor interprets AI-generated MRI analysis results and combines them with clinical expertise to produce a structured diagnosis and recommendations. The system then generates and stores the report, ensuring traceability and accessibility for future patient monitoring.

IV.4.1.5 Object diagram

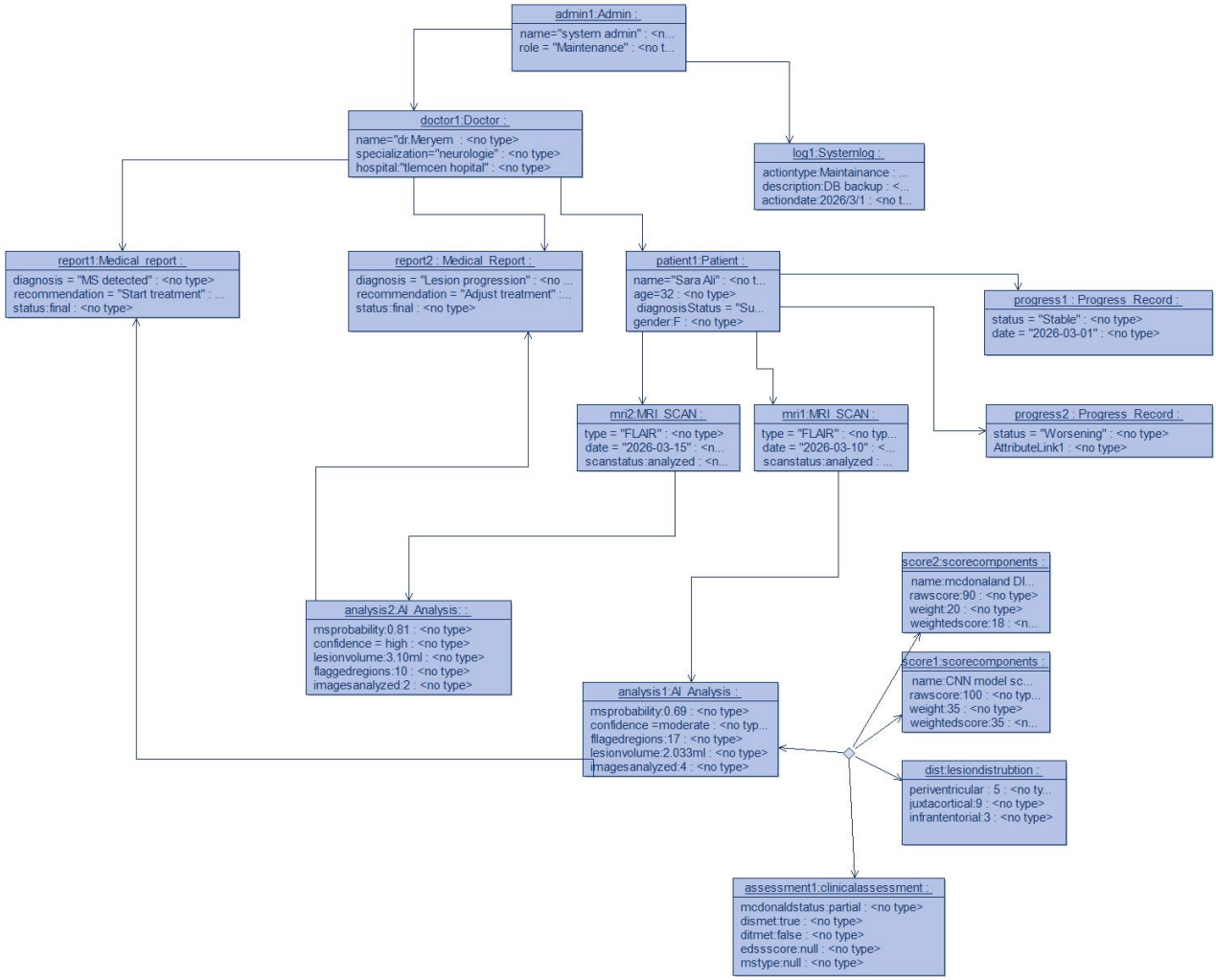


Figure IV. 5: object diagram

The object diagram represents a global instance of the proposed platform, illustrating how different system components interact in a real scenario. It includes a doctor managing a patient with multiple MRI scans analyzed by the AI module, generating medical reports and tracking disease progression over time. This diagram highlights the dynamic relationships between system entities and provides a concrete view of how the platform supports diagnosis and patient monitoring.

IV.4.1.6 State machine diagram:

MRI scan lifecycle

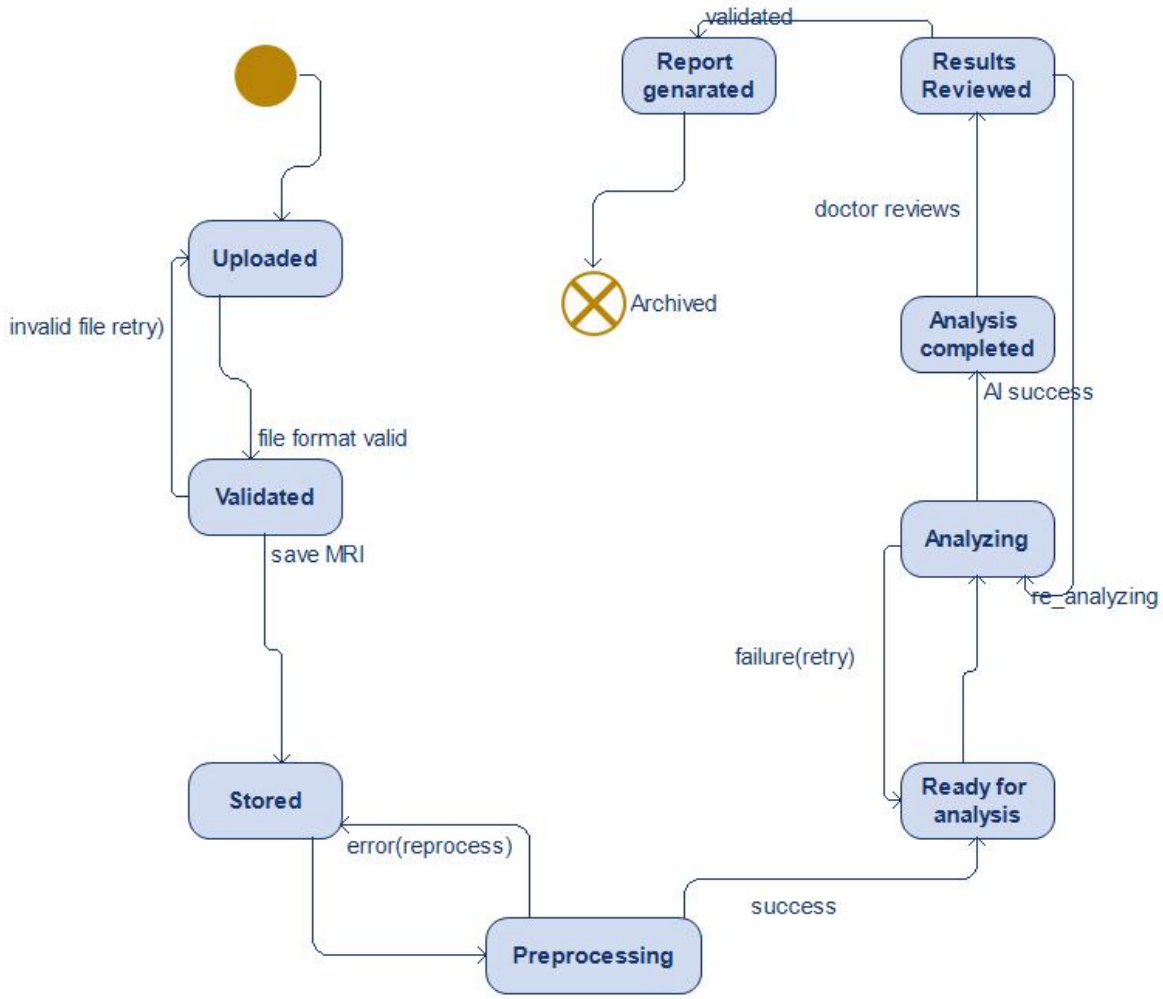


Figure IV.1: state machine diagram

This state machine diagram represents the complete lifecycle of an MRI scan within the platform. It describes the different states the MRI data passes through, starting from upload and validation, through preprocessing and AI-based lesion detection, to medical review and report generation. The diagram also integrates error handling and reprocessing mechanisms, ensuring robustness and reliability of the diagnostic workflow.

Patient health evolution

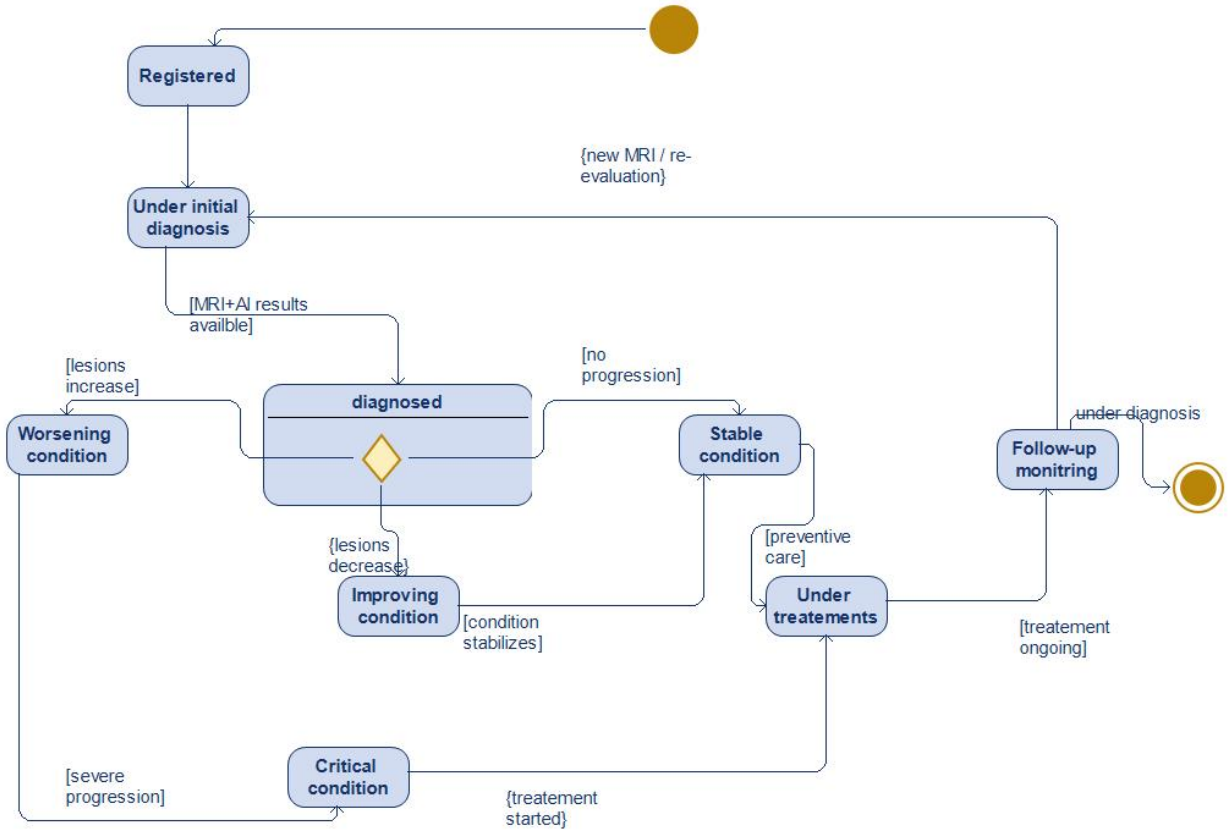


Figure IV.2: state machine diagram

This state machine diagram illustrates the dynamic evolution of a patient's health status within the platform. Based on MRI data and AI-assisted analysis, the patient transitions between different clinical states such as stable, improving, or worsening condition. The model incorporates treatment phases and continuous follow-up, allowing iterative reassessment through new MRI scans. This representation supports long-term monitoring and enhances clinical decision-making.

System monitoring

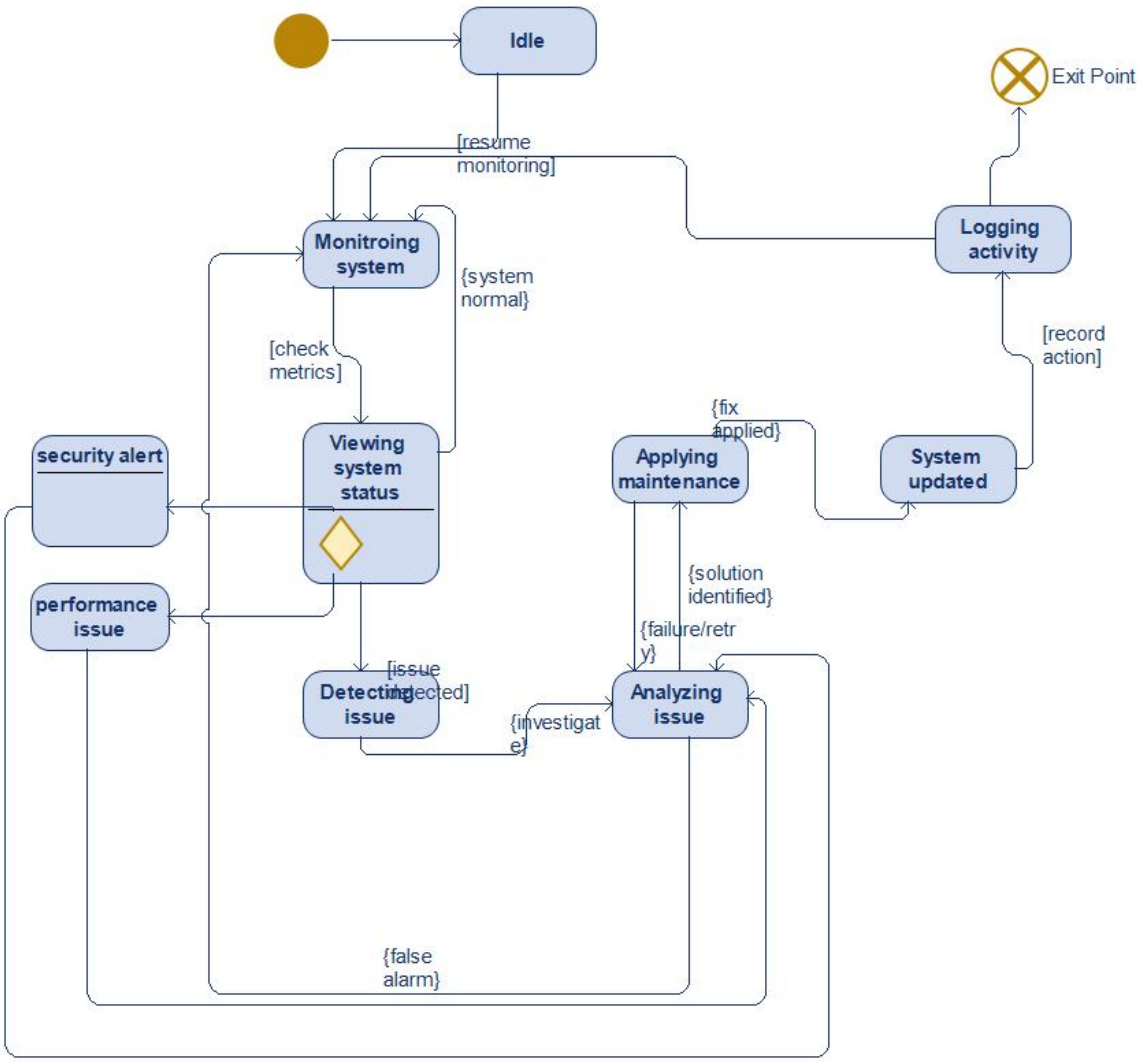
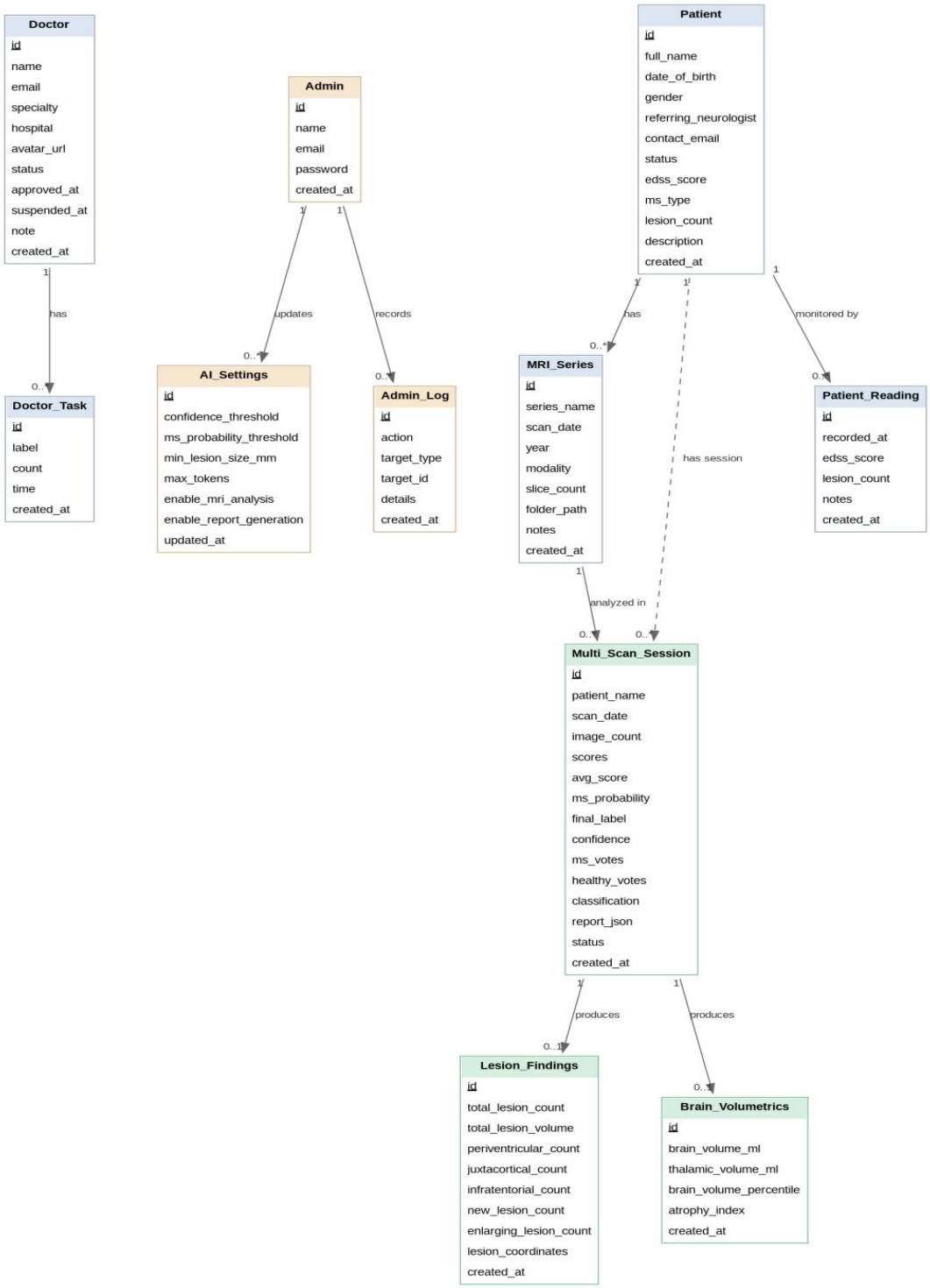


Figure IV.3: State machine diagram

This state machine diagram represents the behavior of the administrator during system monitoring and maintenance. It illustrates how the administrator continuously supervises system status, detects potential issues, analyzes their causes, and applies corrective actions. The process ensures system reliability, performance, and security, while maintaining a log of all administrative activities for traceability.

IV.4.2 Conceptual Data Model (MCD)

The MCD gives an independent view of the platform's data, describing its main entities, their attributes, and the associations connecting them. It models relationships through cardinalities rather than foreign keys, and constitutes the conceptual basis from which the logical data model is derived.



FigureIV.7: MCD diagram

IV.4.3 Logical Data Model (MLD)

The MLD represents the logical transformation of the class diagram into a relational schema. Each class becomes a database table, attributes become columns, and associations are implemented using foreign keys to ensure data integrity and consistency.

- Doctor(doctor_id, name, email, specialty, hospital, avatar_url, status, approved_at, suspended_at, note, created_at)
- Admin(admin_id, name, email, password, created_at)
- Patient(patient_id, full_name, date_of_birth, gender, referring_neurologist, contact_email, status, edss_score, ms_type, lesion_count, description, created_at)
- MRI_Series(MRI_series_id, series_name, scan_date, year, modality, slice_count, folder_path, notes, created_at, #patient_id)
- Multi_Scan_Session(session_id, patient_name, scan_date, image_count, scores, avg_score, ms_probability, final_label, confidence, ms_votes, healthy_votes, classification, report_json, status, created_at, #patient_id, #MRI_series_id)
- Lesion_Findings(lesion_id, total_lesion_count, total_lesion_volume, periventricular_count, juxtacortical_count, infratentorial_count, new_lesion_count, enlarging_lesion_count, lesion_coordinates, created_at, #session_id)
- Brain_Volumetrics(brain_id, brain_volume_ml, thalamic_volume_ml, brain_volume_percentile, atrophy_index, created_at, #session_id)
- Patient_Reading(readings_id, recorded_at, edss_score, lesion_count, notes, created_at, #patient_id)
- Doctor_Task(tasks_id, label, count, time, created_at, #doctor_id)
- AI_Settings(AI_id, confidence_threshold, ms_probability_threshold, min_lesion_size_mm, max_tokens, enable_mri_analysis, enable_report_generation, updated_at, #admin_id)
- Admin_Log(admin_log_id, action, target_type, target_id, details, created_at, #admin_id)

It should be noted that the analysis tables combine two types of information. The prediction outputs (ms_probability, confidence, final_label) and the approximate lesion localization (lesion_count, lesion_coordinates, total_lesion_area) are produced automatically by the MyelineVision module. However the anatomical lesion distribution (periventricular, juxtacortical, and infratentorial counts), the longitudinal indicators (new and enlarging lesion counts), and the volumetric measures are clinical fields entered or validated by the doctor; they are stored in the same schema to provide a complete clinical picture but are not computed by the CNN itself.

IV.5 Conclusion

This chapter has presented the modeling and design phase of the proposed intelligent medical platform, which represents a fundamental step before system implementation. Through a structured analysis approach, the functional and technical aspects of the platform were clearly identified and translated into conceptual models that describe how the system operates and how its different components interact. The use of UML modeling allowed a precise visualization of the system's architecture, and dynamic behaviors, ensuring a coherent understanding of the platform's objectives and features.

The use case diagrams helped define the interactions between the main actors and the system services, while the class diagram described the internal organization of data and the relationships

between core entities such as patients, MRI examinations, AI analysis results, and medical reports. In addition, sequence diagrams illustrated the workflow of critical processes, including lesion detection using artificial intelligence and patient progress tracking. The database design derived from these models ensured a logical and consistent data structure capable of supporting future system scalability and maintenance.

Overall, this modeling and design phase establishes a solid foundation for the next stages of development. By defining a clear architecture and well-structured system components, the project reduces implementation risks and guarantees that the intelligent platform will effectively support medical professionals in diagnosing multiple sclerosis lesions and monitoring patient health progression in an efficient, reliable, and user-friendly environment.

CHAPTER V: IMPLEMENTATION

V.1 Introduction

After the conceptual and structural design of the platform presented in the previous chapter, this chapter is dedicated to the practical realization of the proposed system. It describes how the theoretical models and design choices were transformed into a functional intelligent platform for Multiple Sclerosis (MS) detection and patient management. The objective is to demonstrate the technical feasibility of the solution by detailing every step of its construction, from the preparation of the medical imaging data to the deployment of the complete platform used by clinicians and mostly doctors.

V.2 Development environment and tools:

The platform was developed entirely on a local workstation, the deep learning model and its data pipeline were implemented in python and executed in visual studio code environment. The main libraries and technologies used are summarized below:

- **Python 3.11:** the programming language used for the artificial intelligence engine, the data

pipeline, and the backend logic.

- **TensorFlow 2.18 / Keras:** the deep learning framework used to build, train, save, and

serve the convolutional neural network .

- **NumPy 2.0:** used for numerical array manipulation and the construction of the image

tensors fed to the network.

- **scikit-learn:** used to compute the evaluation metrics (confusion matrix, precision, recall,

F1-score) and to derive the balanced class weights .

- **Pillow / Keras image utilities:** the image-loading utilities of Keras were used to read, resize, and normalize the MRI images.
- **Supabase (PostgreSQL):** the backend database, used to store patient records, multi-scan-sessions, lesion findings, brain volumetrics, and the AI analysis reports, which are persisted in a structured JSON format.
- **Visual Studio Code:** the integrated development environment used for coding, debugging, and running the training and inference scripts locally.
- **React (frontend):** the entire user-facing interface of the MyelineCare platform authentication, dashboard, patient management, MRI upload, and result visualization was developed using the React framework.
- **Voice assistant:** a voice assistant is integrated into the dashboard, allowing the doctor to interact with the platform vocally, which improves accessibility and speeds up navigation during clinical use.

V.3 Dataset

The dataset used in this work is composed of two dimensional brain MRI slices acquired in the FLAIR sequence. As discussed in the first chapter , FLAIRE is the reference sequence for the detection of demylinating MS lesions. The image are stored in PNG format and organized in two classes: images of MS diagnosed patients(class MS) and images of healthy subject(class healthy).

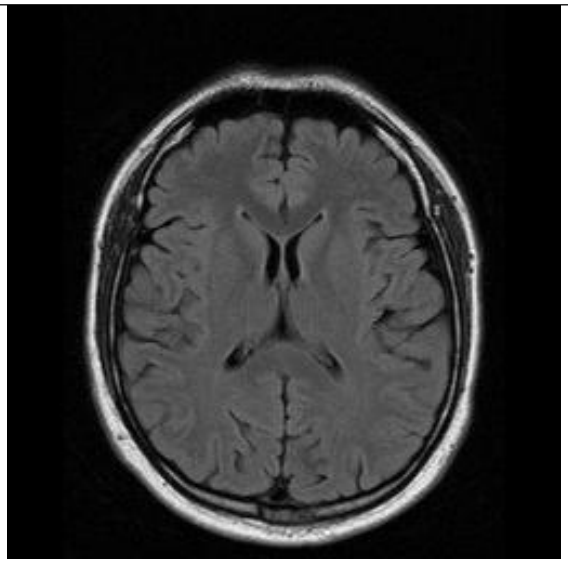
To gather a sufficient number of examples for both classes, the images were assembled from three publicly available sources. The MS images were obtained from the Kaggle "Brain MRI – Multiple Sclerosis Dataset", while the healthy control images were collected from the Kaggle "Normal Brain MRI Dataset" and from the NIMH Healthy Research Volunteer Datasets hosted on the OpenNeuro repository. All the collected images were converted to a common FLAIR grayscale format, resized to a uniform resolution, and reorganized into a single train/test structure, and the training set was further enriched through data augmentation.

The data is organized on disk into a hierarchical folder structure separating the training and testing subsets, each of which is further divided into the two diagnostic classes (train/MS, train/Healthy, test/MS, test/Healthy). This pre-defined partition is loaded directly by the data-loading module of the project. The overall composition of the datasets is presented in the table below.

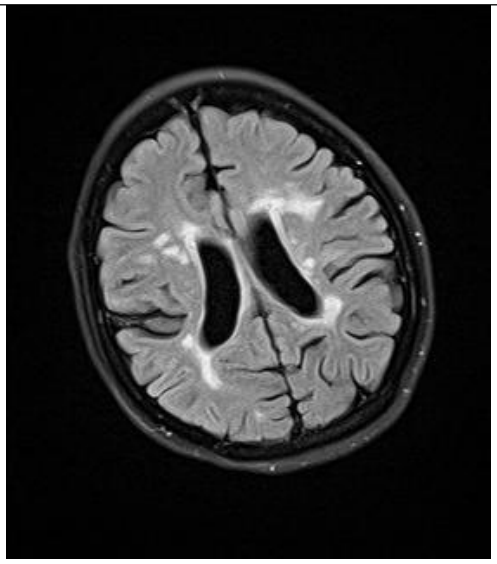
Subset	MS	Healthy	Total
Training set	3,220	3,293	6,513
Testing set	878	762	1,640
Total	**4,098**	**4,055**	**8,153**

Table V.1 Composition of the FLAIRE MRI datasets.

The dataset therefore contains **6,513 images** of training set (approximately 80%) and **1.640 images** for testing(approximately 20%). The distribution between the two classes is nearly balanced, both at the global level and within each subset, which is an important property for training a reliable binary classifier and for obtaining meaningful evaluation metrics.



Healthy flaire MRI image



MS flaire MRI image

Figure V.1: Representative FLAIR MRI samples from the MS and Healthy classes.

V.4 Data preprocessing

Before being presented to the convolutional neural network, every image undergoes a preprocessing stage whose role is to standardize the input and to improve the generalization capacity of the model. The preprocessing pipeline is strictly identical during training and during inference, which guarantees the consistency of the predictions made by the deployed platform.

V.4.1 Image standardization:

Each MRI image is processed through the following operations:

- **Grayscale conversion:** each image is loaded as a single-channel image, since the structural information contained in a FLAIR slice is fully described by intensity values and does not require colour channels.
- **Re-sizing:** all images are resized to a fixed resolution of 128 × 128 pixels, in order to provide a uniform input size to the network and to keep the computational cost compatible with local training.
- **Normalization:** the pixel intensities, originally ranging from 0 to 255, are divided by 255 so that all values lie in the [0, 1] interval. This scaling stabilizes and accelerates the training process.
- **Tensor shaping:** a channel dimension is added so that each image is represented as a tensor of shape (128, 128, 1), which corresponds exactly to the input layer of the network.

V.4.2 Data augmentation

To increase the diversity of training dataset and to reduce the risk of overfitting, a data augmentation strategy adapted to brain MRI was applied on the training set. Each training image is randomly transformed on the fly during training using the following geometric transformations where the transformations were intentionally kept moderate ,since aggressive deformations could mess with diagnostic content of the MRI and alter the signature of the lesions:

- **Rotation:** random rotations of up to 10 degrees.
- **Translation:** random horizontal and vertical shifts of up to 5% of the image dimensions.
- **Zoom:** random zoom of up to 5%.
- **Horizontal flip:** horizontal mirroring, justified by the approximate left–right symmetry of brain anatomy.
- **Fill mode:** the "reflect" mode is used to fill the empty pixels created by the geometric transformations, avoiding the introduction of artificial black borders.

V.4.3 class balancing

Although the datasets is almost balanced, balanced class weights were computed automatically from the training labels and supplied to the model during training. This mechanism slightly increases the contribution of the minority class to the loss function, ensuring that the network does not become biased toward either of the two diagnostic categories.

V.5 Implementation of the the Deep Learning algorithm

The core of the intelligent engine, named MyelineVision is a CNN trained to perform a binary classification of FLAIR MRI slices into the MS and healthy categories. It is important to mention that the model performs classification and lesion localization, not pixel level segmentation:the engine predicts whether an image contains signs of MS through the mechanism described later and indicates the regions that motivated this decision.

V.5.1 Design Strategy

The engine was designed and trained entirely from scratch rather than relying on transfer learning from models pretrained on natural images. This choice is motivated by the specific nature of the data. Models pre-trained on large natural-image collections expect three-channel RGB photographs with a particular intensity distribution, whereas the data used here consists of single-channel grayscale MRI scaled to the [0, 1] interval. Feeding grayscale medical images into such pre-trained weights introduces a domain mismatch that, in preliminary experiments, kept the accuracy close to chance level. A compact architecture trained directly on the FLAIR data, in contrast, learns the relevant MRI texture and lesion patterns directly, trains efficiently on a local machine, and yields far more reliable behaviour for this task.

V.5.2 Network architecture

The proposed architecture is based on a compact VGG-inspired design. It consists of four sequential convolutional blocks with increasing depth, followed by a classification stage. Each convolutional block contains two convolutional layers using 3 × 3 filters. These layers are followed by batch normalization and ReLU activation to improve learning stability and introduce non-linearity. A max-pooling layer is then applied to reduce the spatial dimensions, along with spatial dropout to help prevent overfitting.

The number of filters increases progressively across the blocks, starting from 32, then 64, 128, and finally 256 filters. This gradual increase allows the model to capture simple visual patterns in the early layers and learn more complex and abstract features from MRI images in deeper layers.After the convolutional feature extraction phase, a global average pooling layer is used to transform the extracted feature maps into a compact 256-dimensional feature representation. This layer also supports model interpretability, as it maintains the relationship between the learned features and their spatial locations in the input image, which is useful for the Grad-CAM visualization method.

The extracted representation is then passed through a fully connected layer containing 128 neurons, followed by batch normalization, ReLU activation, and a dropout rate of 0.45 to improve generalization.

Finally, the output layer contains a single neuron with a sigmoid activation function, providing the probability that the input MRI image belongs to the Multiple Sclerosisclass.

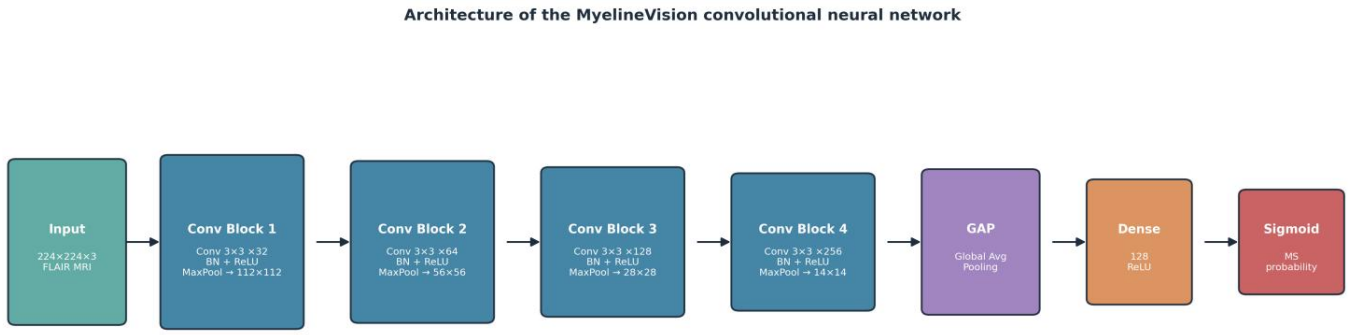


Figure V.2: Architecture of MyilineVision CNN

The complete structure of the nework is summarized in the following table

Layer (block)	Output shape	Parameters
Input (FLAIR slice)	128 × 128 × 1	0
Block 1 — 2× Conv(32) + BN + Pool	64 × 64 × 32	~9.8 K
Block 2 — 2× Conv(64) + BN + Pool	32 × 32 × 64	~55 K
Block 3 — 2× Conv(128) + BN + Pool	16 × 16 × 128	~222 K
Block 4 — 2× Conv(256) + BN + Pool	8 × 8 × 256	~886 K
Global Average Pooling	256	0
Dense + BN + Dropout(0.45)	128	~33 K
Output (sigmoid)	1	129
Total trainable parameters		**1,205,793**

Table V.2: layer by layer summary of the network.

The network contains approximately 1.2 million trainable parameters, which make the training on a standard local machine realisble while staying clear enough to capture the patterns of MS lesions on FLAIR images.

V.6 choice of parameters and training configuration:

The training of the network was by a set of carefully chosen hyper-parameters and control mechanisms whose purpose is to obtain a model that converges reliably and generalizes well. The main training parameters are described below:

- **Optimizer:** the Adam optimizer was used with an initial learning rate of 1×10^{-3}. Adam combines the advantages of adaptive learning rates and momentum, which makes it well suited to training deep networks efficiently [1].
- **Loss function:** the binary cross-entropy loss was used, as it is the standard objective for two-class classification problems with a sigmoid output.

- **Batch size:** a batch size of 32 images was used as a compromise between gradient stability and memory consumption.
- **Epochs:** training was configured for up to 80 epochs, with early stopping monitoring the validation performance so that training stops automatically once the model ceases to improve.
- **Monitored metrics:** during training the accuracy, the area under the ROC curve (AUC), the precision, and the recall were monitored, providing a complete view of the learning behaviour beyond raw accuracy.

Three callback mechanisms were used to control and optimize the training process:

- **Model checkpointing:** the model weights are automatically saved each time the validation AUC reaches a new maximum, so that the best version of the model is preserved regardless of later fluctuations.
- **Early stopping:** training is interrupted if the validation AUC does not improve for twelve consecutive epochs, and the best weights are restored. This prevents overfitting and avoids unnecessary computation.
- **Adaptive learning rate:** the learning rate is reduced by half whenever the validation loss stagnates for several epochs, allowing the optimizer to refine the solution as it approaches a minimum.

V.7 Results and evaluation

The model was evaluated on an independent test set of 1,640 FLAIR images that were never used during training. The evaluation relies on the standard classification metrics: accuracy, precision, recall, F1-score, and the area under the ROC curve. The results obtained are reported in the table below.

Metric	Value (test set)
Accuracy	99.94%
Precision (MS)	1.00
Recall / Sensitivity (MS)	0.999
F1-score	1.00
Area under ROC curve (AUC)	1.00
Loss (binary cross-entropy)	0.0043

Table V.3: performance of the model on independent test set.

V.7.1Confusion Matrix:

The confusion matrix summarises the model's predictions on the 1,640-image test set. Of the 762 healthy cases, all 762 were classified correctly, and of the 878 MS cases, 877 were correctly identified, leaving a single false negative and no false positives. The absence of false positives means the model never raised a false MS alarm on a healthy scan, while the only error one MS slice predicted as healthy occurs at the default 0.50 decision threshold. Since the false-negative rate is the most clinically sensitive quantity in a screening context, this result corresponds to a very high sensitivity for the MS class.

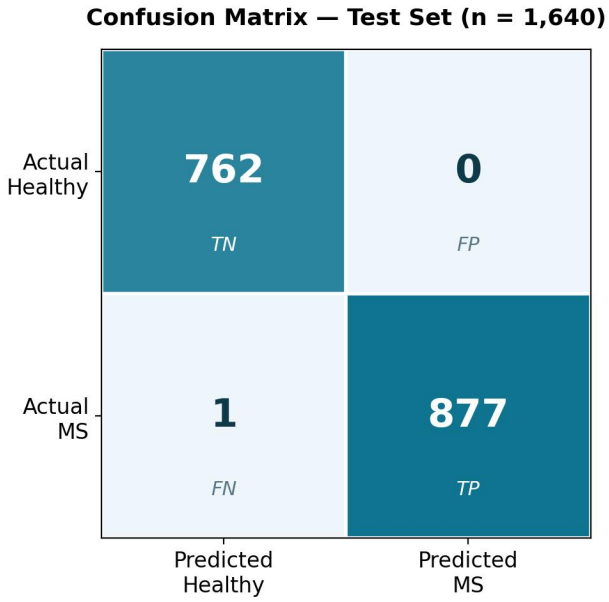
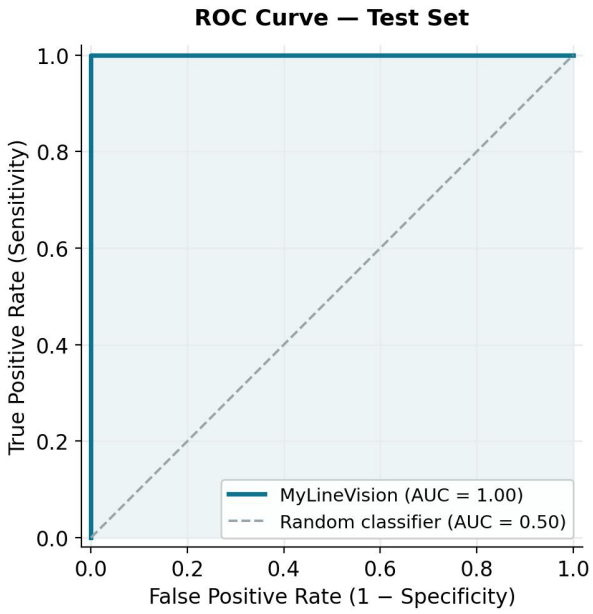


Figure V.7.1:confusion matrix

V.7.2 ROC curve:

The ROC curve plots the true positive rate against the false positive rate as the decision threshold varies. The curve rises immediately to the top-left corner and yields an area under the curve (AUC) of 1.00, indicating that every MS image received a higher predicted probability than every healthy image the two classes are perfectly separable on this dataset. It should be noted that an AUC of 1.00 describes the model's ranking ability across all thresholds, whereas the single false negative noted above appears only at the fixed 0.50 threshold and disappears at a slightly lower operating point. As discussed in the following section, such perfect separation should be interpreted with cautions, since it may partly reflect differences between the data sources rather than disease-specific features alone.



FigureV.7.2: ROC curve.

V.8 Discussion of Results

- ✓ The obtained results show very high performance, with an accuracy of 99.94% and an AUC of 1.00. These results indicate that the model successfully learned to differentiate between MS and healthy cases in the available datasets obtained. However, such high performance should be interpreted carefully and does not necessarily represent real clinical accuracy.Two main factors must be considered. First, the datasets was collected from different sources due to the lack of MRI images of MS [39]. As a result, the model may learn source-related differences, such as image intensity, resolution, or preprocessing variations, instead of only detecting disease-related features. This can lead to overly optimistic results.

- ✓ Second, the data split was performed at the image slice level. Since multiple slices can come from the same patient, similar images may appear in both training and testing sets, reducing the independence of the evaluation and causing possible data leakage.
- ✓ These limitations do not invalidate the results. They show that the model performs well on the available data, while further improvements and datasets evaluation is needed before considering clinical or hospital use. In this project, the model is designed as an assistance tool for neurologists rather than an autonomous diagnostic system.
- ✓ For future improvements, the evaluation can be strengthened by using patient-level data splitting, applying data harmonization techniques, and testing the model on an independent external datasets. These steps would provide a more reliable measure of the model's ability to generalize to real clinical conditions.

V.9 Usage of Grad-Cam

From a medical context the prediction given by a model is only useful if the clinicians or doctor can understand and trust the reasoning behind it, therefor a probability score alone won't be enough . for this reason,the platform integrates a mechanism based on Grad-CAM.

Grad-CAM exploits the information contained in the last convolutional layer of the network, just before the global average pooling operation. It computes the gradient of the predicted class with respect to the feature maps of this layer, and uses these gradients to weight the feature maps according to their importance for the decision. The result is a coarse heat map that highlights the regions of the MRI that contributed most strongly to the prediction. This heat map is then resized to the original image dimensions and overlaid on the FLAIR slice, producing an interpretable visualization in which the suspicious regions appear as warm-coloured areas.

Although we must mention that this localization is explainbility output and not a segmentation:Grad-CAM indicates approximately where the network focused its attention, allowing the clinician to verify that the decision is based on plausible anatomical regions, but it does not delineate the precise contour of each lesion. In the platform, this mechanism transforms the binary decision into an interpretable result, reinforcing the confidence of the neurologist in the system.

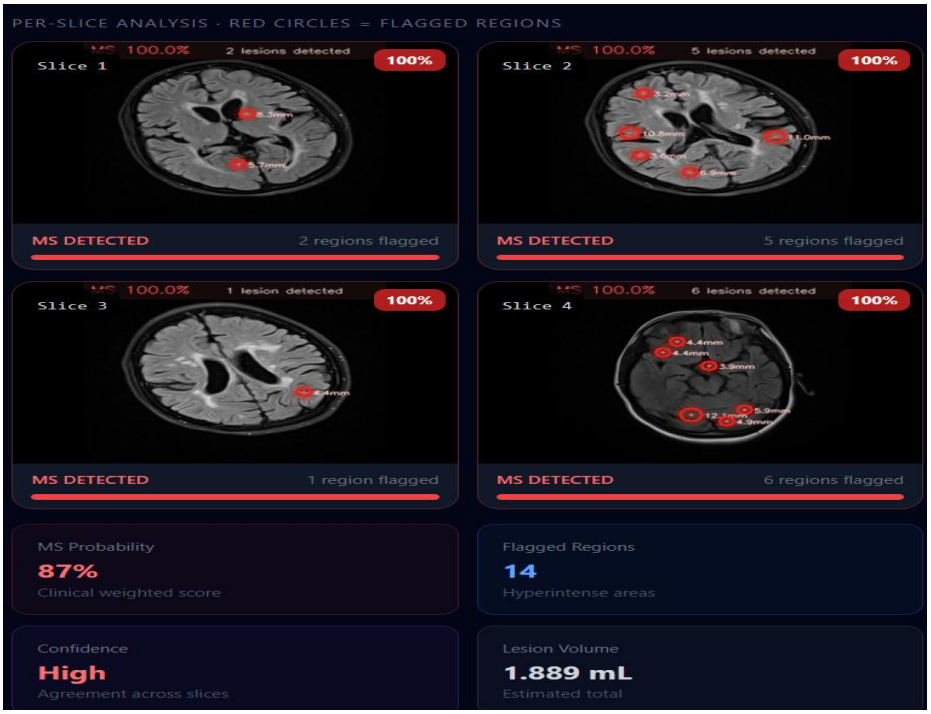


Figure V.3: Grad-CAM lesion detection

V.10 Presentation of the platform

Plus the AI engine the project also add a complete management web platform named MylineCare designed to be used as a management and diagnosis platform for the doctors and clinicians as well surrounded with the functionalities needed to smooth and secure patient diagnosis process.

All clinical and analytical data are stored in a Supabase backend, and each AI analysis is persisted in a structured JSON report. The following figures present the main screens of the platform, accompanied by a brief description of each.

V.10.1 Authentification

The entry point of the platform is the authentication interface, which secures access to the medical data. A registered doctor logs in with personal credentials, or signs in if they'll have no account after which the admin approves their access to the personalized dashboard. This mechanism guarantees that sensitive patient information is only accessible to authorized doctors and their own patients.

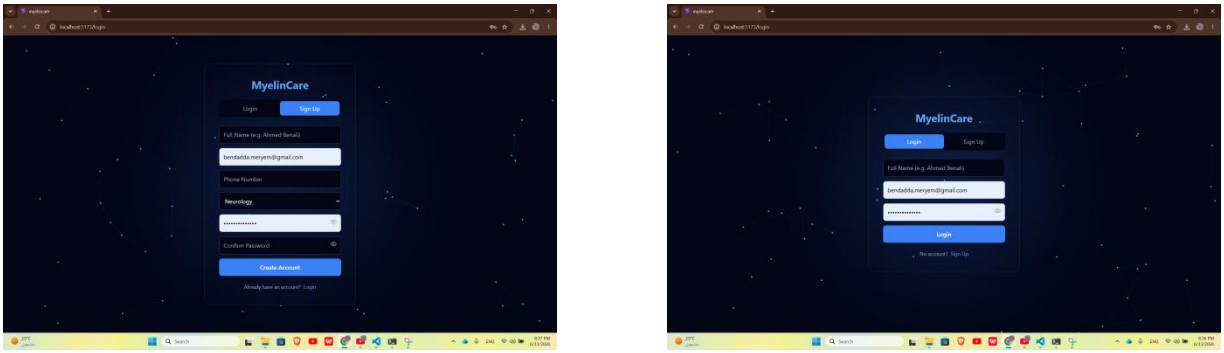


Figure V.4 Authentication interfase.

V.10.2 Doctor dashboard:

After the log in or sign up the doctor will reaches out to the main dashboard ,which gives a global overview of the patients information.It also integrates a voice assistant, allowing the doctor to interact with the platform vocally and improving the accessibility of the interface during clinical use.

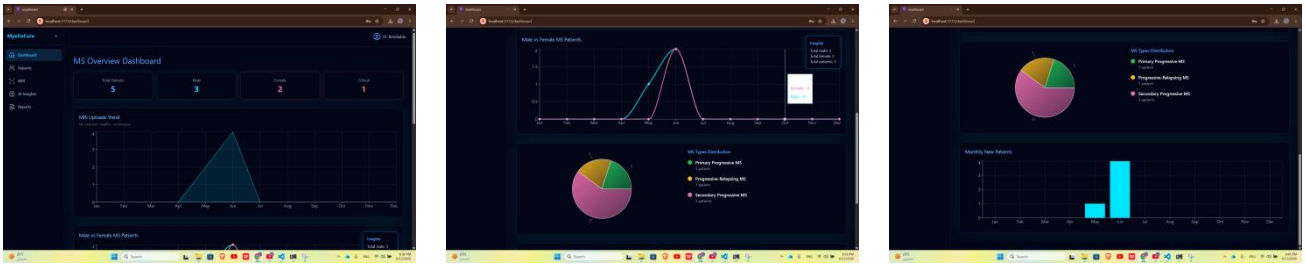


Figure V.5 Main dashboard doctor.

V.10.3 Patient management

The platform allows to create and mange patient files recording their personal information, medical history and the diagnosis information associated for each patients.

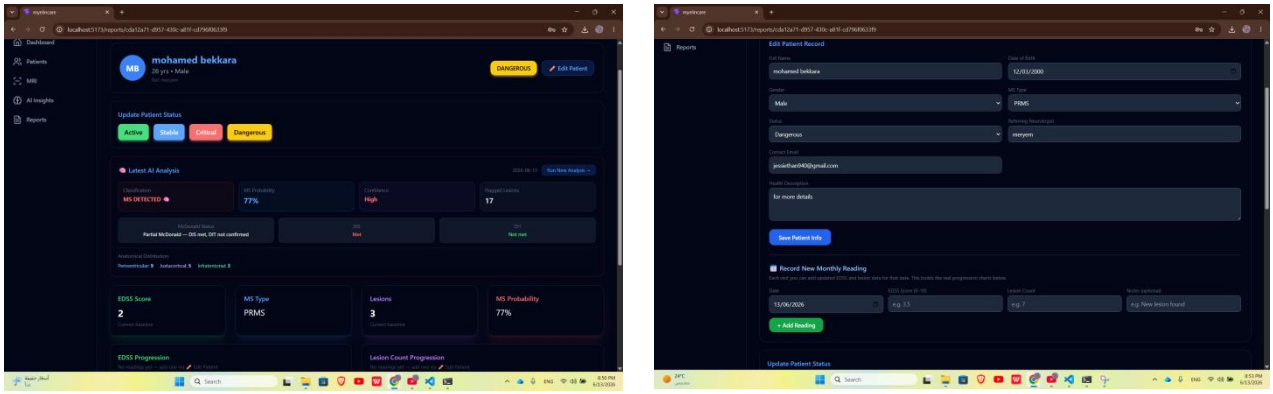


Figure V.6 Patient management interface.

V.10.4 MRI uploads

From a file of a patient the doctor can upload one or several MRI images as needed to store them in the medical folder of the patient .

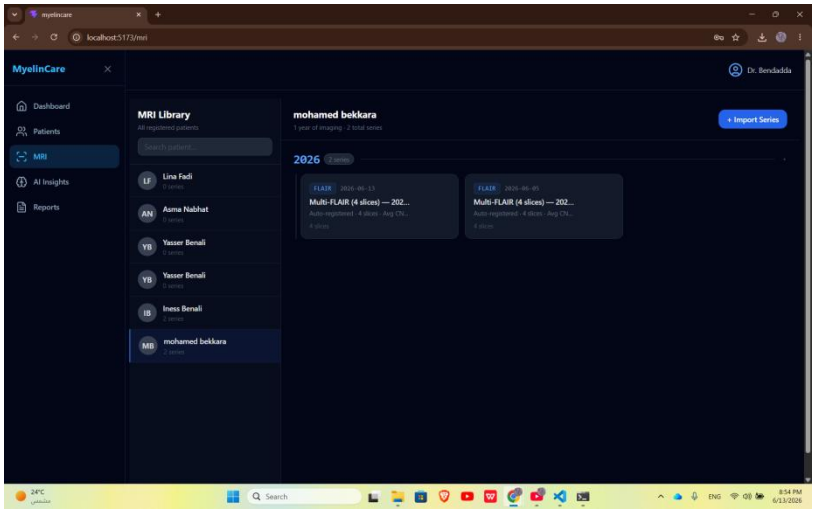


Figure V.7:MRI uploads interfase.

V.10.5 AI Analysis

The platform stores the images and submit them to the MylineVision engine which applies the preprossing pipeline and runs the trained network. The analysis return for each image the probability of the MS presence and the regions highlighted by the Grad-CAM mechanism.

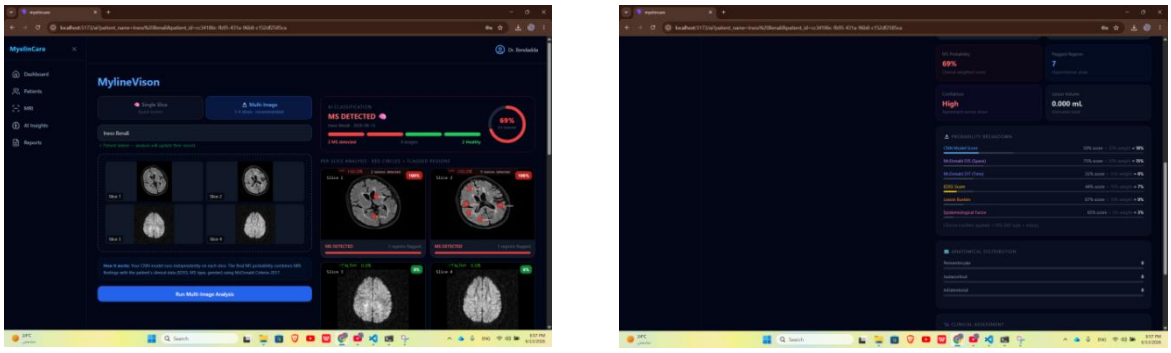
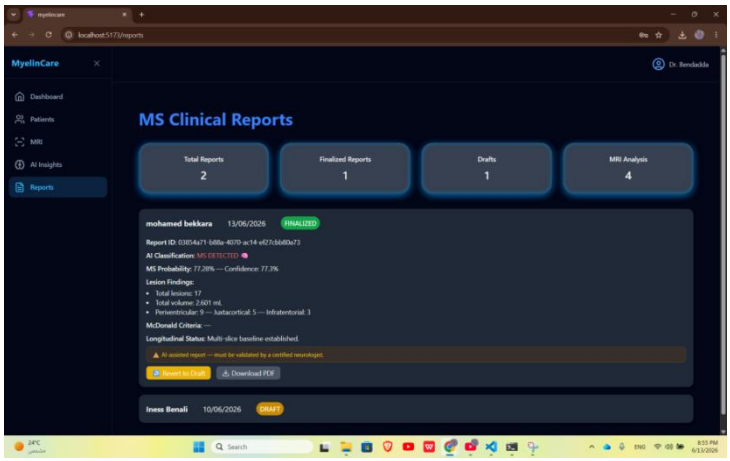


Figure:V.8:Myline vision interfase

V.10.6 Report interfase:

The platform enables the doctor to generate a structured medical report and to follow the evaluation of the patient over time This longitudinal monitoring is essential in Multiple Sclerosis, a

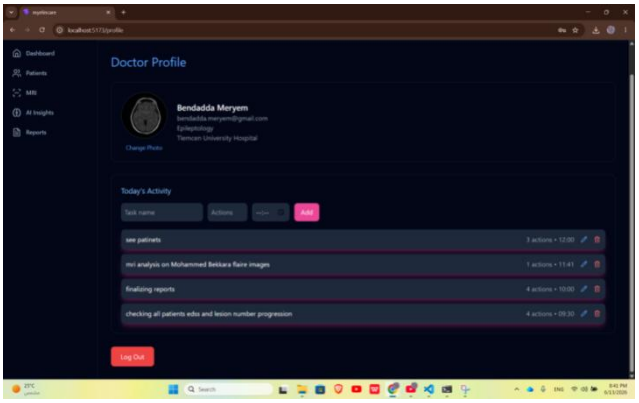
disease whose management relies on tracking the appearance of new lesions and the progression of the patient's condition.



FigureV.9:report interfase.

V.10.7 Doctor profile

The platform has an accessible user friendly interface for the doctor’s information and a helpful task note manger for the doctor to keep track of his tasks with their main information.



FigureV.10:doctor profile interfase.

V.10.8 Administrator log in

As well as the doctor, the admin must enter and have their log in information verified.

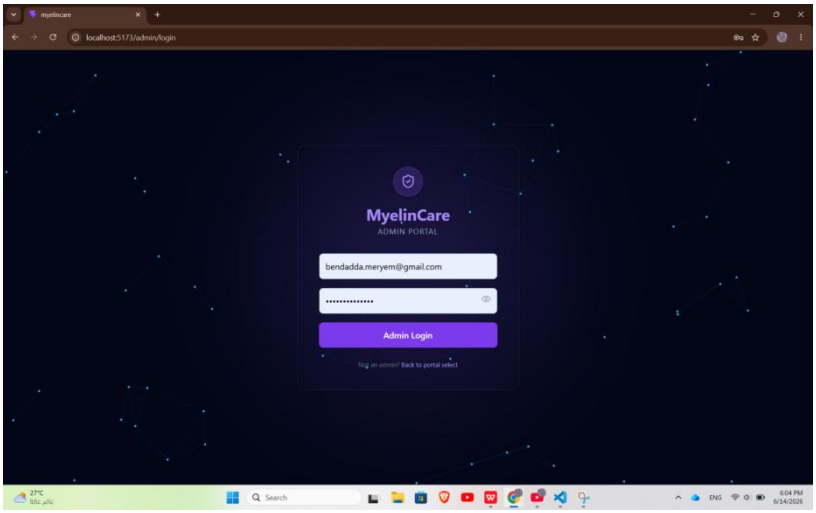
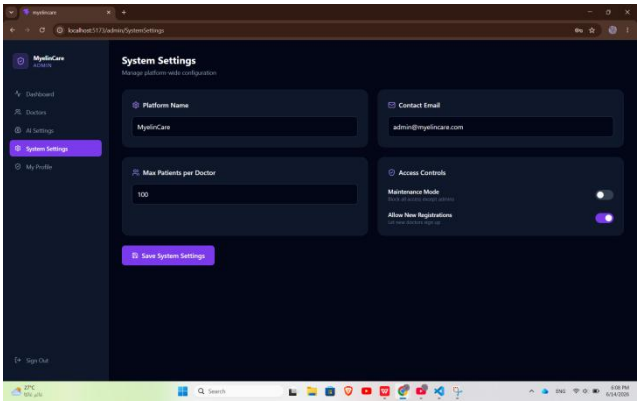


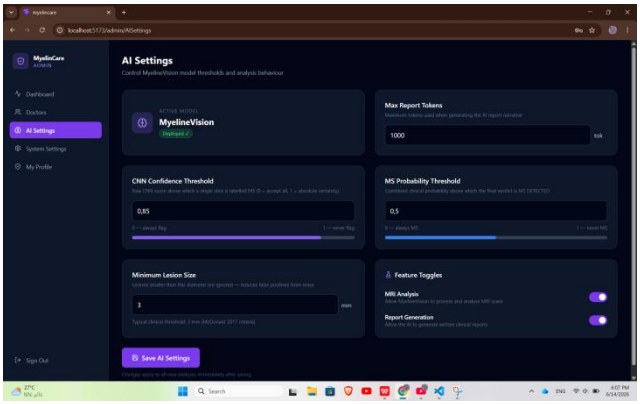
Figure V.11: admin log in interfase

V.10.9 System monitoring and maintenance

In addition to managing users, the administrator supervises the overall health and activity of the platform. The administration space provides an overview of the system status and usage, allows the configuration of the parameters of the artificial intelligence module (such as the analysis settings stored in the AI_settings table), and keeps a traceable record of every administrative action performed on the platform through an activity log (admin_logs).

This monitoring and maintenance capability ensures the reliability, the security, and the continuous availability of the system over time, and supports the long-term evolution of the platform.





FigureV.12: System and mylineVision settings interfaces.

V.11 Future perspectives

Regardless that the platform contains functional and coherent solution,at the same time it opens diverse directions for improvements .these perspective concern at the first place the data and its validation,the deep learning model itself and the clinical integration of the platform.The model

could be improved to recognize the different types of MS, to work directly on 3D MRI volumes, and to add a segmentation step that measures the size of the lesions.

Finally, the platform could be connected to hospital systems and deployed in a secure way, so that it can be used by doctors in real conditions.these perspectives outline a clear road-map for transforming the present prototype into a robust, clinically validated, and fully integrated decision-support tool for the diagnosis and the monitoring of Multiple Sclerosis.

V.12 Conclusion

This chapter has described the concrete implementation of the proposed intelligent platform for the detection of Multiple Sclerosis and the management of patients. Starting from a datasets ,followed by the design and training of a compact convolutional neural network of approximately 1.2 million parameters, trained from scratch to perform a binary classification of the images and to localize the lesion regions through Grad-CAM.

The model achieved very high performance on the available test set, and these results were discussed clearly, identifying the diversity of sources nature of the data and the slice-level partitions well as the lack of datasets concerning MS all of that will be considered as factors that must be considered when interpreting the metrics. The chapter also presented the complete MyelineCare platform through its main interfaces, demonstrating how the artificial intelligence engine is integrated into a usable maintainable clinical tool covering authentication, patient management, MRI analysis, explainable results, report generation, and longitudinal follow-up.

Together, these elements demonstrate the technical feasibility of the proposed solution and its capacity to assist neurologists in the diagnosis and monitoring of Multiple Sclerosis, while remaining a decision-support tool placed under the responsibility of professional neurologict.

Business Model Canvas

BMC

Project Overview

MyelineCare is an intelligent medical platform that supports neurologists and radiologists in the diagnosis and long-term monitoring of Multiple Sclerosis (MS). The platform analyzes brain MRI images (FLAIR sequences) using a custom deep-learning model that classifies each slice and flags those likely to contain MS lesions. The regions the model relies on are then highlighted through Grad-CAM heatmaps, giving the physician a transparent visual explanation of where to look. The platform does not segment lesions and does not replace medical judgement: every result is a decision-support signal that the clinician validates.

Around this AI core, MyelineCare provides complete patient management — patient records, MRI sessions, detected findings, longitudinal follow-up across successive scans, and structured report generation — within a single, secure environment. The platform is launched with a deliberate one-year free-access phase whose purpose is to gather locally representative, ethically collected MRI data, continuously improve the model's accuracy, and build clinical trust before any paid subscription is introduced. This document presents the Business Model Canvas of the project, block by block.

1. Value Proposition

a. What problems do we solve for our clients?

In a context where MS diagnosis and follow-up rely heavily on MRI, and where neurology and neuroradiology expertise is scarce — especially outside major Algerian cities — our solution addresses concrete clinical challenges:

- *MRI interpretation for MS is time-consuming and subject to inter-observer variability: two specialists may read the same FLAIR scan differently.*
- *Specialists are scarce and overloaded, leading to long delays before a patient's scan is read.*
- *MS is a lifelong disease requiring repeated MRI follow-up; tracking lesion changes across many scans over years, by hand, is tedious and error-prone.*
- *Patient records, imaging, and follow-up data are scattered across paper files and disconnected systems, making longitudinal monitoring difficult.*
- *Junior doctors and general radiology centers lack a reproducible, objective second reading to support their judgement.*

b. What needs of our clients do our products and services satisfy?

- ***Fast, reproducible screening:*** *the AI classifies FLAIR MRI slices and flags those likely to contain MS lesions in seconds.*
- ***Visual explanation:*** *Grad-CAM heatmaps highlight the regions the model relied on, so the physician sees where to look — assistance, not a black box.*
- ***Centralized patient management:*** *a single environment for patient files, MRI sessions, findings, and follow-up.*
- ***Longitudinal monitoring:*** *comparison of results across successive scans to support assessment of disease evolution over time.*
- ***Documentation:*** *structured medical report generation.*

- ***Clinician in control:*** *every AI output is a decision-support signal that the doctor validates; the platform never replaces medical judgement.*

c. How is our offer different from that of our competitors?

Direct competitors

International AI neuroimaging tools (e.g., icometrix icobrain, QMENTA, Quibim) provide advanced MS analytics but show several limits in the Algerian context:

- *They are priced for high-income healthcare systems and are out of reach for most public hospitals here.*
- *They are built around heavy 3D volumetric and segmentation pipelines that require standardized acquisition and infrastructure not always available locally.*
- *They offer analysis modules but rarely an integrated, simple patient-management workflow adapted to local practice.*
- *They are not adapted to local language, data-governance rules, and budget realities.*

Indirect competitors

- *Purely manual interpretation by radiologists: slower, subjective, and dependent on specialist availability.*
- *Generic PACS / record systems with no AI assistance and no automated longitudinal tracking.*

Why MyelineCare stands out

- *Locally developed and affordable, designed for the realities of Algerian hospitals and clinics.*
- *Combines AI-assisted lesion detection and localization with full patient management in one platform.*
- *Doctor-in-the-loop by design: transparent Grad-CAM explanations and mandatory clinical validation.*
- *A data-driven improvement model (free first year) that makes the system progressively more accurate on locally representative data.*

d. What is our unique value proposition?

MyelineCare is the first locally developed, affordable, and explainable AI-assisted platform for Multiple Sclerosis in Algeria that unites three things competitors keep separate: rapid lesion detection and localization on FLAIR MRI, transparent visual explanations that keep the neurologist in control, and complete longitudinal patient management. By launching with a one-year free-access phase, the platform continuously learns from locally representative, ethically collected MRI data — becoming more accurate and more relevant to the Algerian medical context than any imported solution.

2. Customer Segments

a. Who are our main clients?

- ***Neurologists and (neuro)radiologists*** *— the front-line users who read MRIs and follow MS patients.*

b. What different segments of clients do we target?

- *Public university hospital centers (CHU) and public hospitals with neurology / radiology departments.*
- *Private neurology clinics and private medical imaging centers as the first client .*
- *Medical research teams and academic laboratories studying MS (longer-term segment).*

c. What are the specific needs of each segment?

Public hospitals & CHU

- *High patient volume and limited specialist time — need efficiency and reproducibility.*
- *Tight budgets — need affordable, locally supported tools.*
- *Teaching role — value transparent, explainable AI for training junior staff.*

Private clinics & imaging centers

- *Faster turnaround and a differentiating, premium service for patients.*
- *Professional reports and a smooth, integrated workflow.*

Research teams

- *Structured, anonymized, longitudinal datasets and reproducible analysis (with ethics approval).*

d. How can we categorize our clients into distinct groups?

1) By role / mission

- *Diagnostic and clinical actors (neurologists, radiologists) — use the AI and management tools daily.*
- *Management actors (hospital / clinic administrators) — manage accounts, users, and oversight.*
- *Research actors — use anonymized data and analytics.*

2) By access level

- *Doctors: full clinical access (upload MRI, run AI analysis, view results, manage patients, generate reports).*
- *Administrators: system management (users, configuration, logs, monitoring).*

3) By usage frequency

- *Daily users: active neurology / radiology departments with continuous patient flow.*
- *Periodic users: smaller clinics using the platform for specific cases or second opinions.*

3. Customer Relationships

a. What type of relationship does each segment expect from us?

Medical clients expect trust, reliability, confidentiality, and competent support. Because this is a clinical decision-support tool, credibility and clinical safety matter most. We adopt a proactive "push" approach: we go to hospital neurology and radiology departments to present the platform and propose collaboration centered on clinical value. To build a durable relationship, we offer:

- *A one-year free-access phase with full features for partner hospitals and clinics.*
- *Personalized onboarding and training for medical staff throughout the trial.*

This establishes trust from the start through transparency, ease of integration, and demonstrated clinical usefulness.

b. How do we currently maintain relationships with our clients?

- ***Continuous improvement:*** *the model and platform are updated regularly; clinician feedback and newly collected data feed measurable accuracy gains.*
- ***Training after each major update:*** *short remote or on-site sessions so staff adopt new features smoothly.*
- ***Responsive technical support:*** *phone, email, and in-platform messaging to resolve issues quickly.*
- ***Regular follow-up with partner institutions:*** *ongoing dialogue with department heads to align the platform with real clinical needs.*

c. How can we improve or personalize our interactions with our clients?

- ***In-platform help assistant / chatbot*** *for common questions and step-by-step guidance.*
- ***Quarterly webinars*** *to gather clinician feedback and present new features and validation results.*
- ***Integrated feedback system*** *(short surveys, contextual ratings) so clinicians can flag false positives / negatives, directly improving the model.*

4. Channels

a. Through which channels do our clients want to be reached?

Our clients — hospital department heads, clinic directors, and radiologists — prefer professional, direct, and personalized contact. Our communication therefore relies on:

- ***Targeted professional emails*** *to department heads and clinic directors, presenting the solution and offering free trial access.*
- ***Meeting requests*** *(in person or by video) for live demonstrations and discussion of collaboration.*
- ***On-site visits*** *to hospitals and imaging centers for live demos and training.*
- ***A dedicated phone line and a professional web portal*** *with detailed information on the solution.*

b. Which channels are most effective for each segment?

A direct, on-the-ground, personalized strategy works best with medical institutions:

- *On-site demonstrations and training at hospitals and clinics build the strongest trust and credibility.*
- *Presence at neurology and radiology conferences and congresses to reach many specialists at once and build reputation.*
- *A professional web portal with use cases, validation evidence, and documentation.*
- *Personalized email to decision-makers to initiate formal contact.*
- *Word of mouth within the medical community, which is decisive for adoption in healthcare.*

c. How can we integrate channels to improve the client experience?

- ***Coordinated follow-up:*** *after an email or call, an on-site demo is scheduled; afterwards the client receives a personalized follow-up email with portal access, documentation, and a demo recap.*
- ***Centralized client information:*** *all interactions (emails, calls, visits, training) are logged in an internal CRM so the team keeps a clear, continuous view of each institution.*

5. Key Partnerships

a. Who are our key partners?

- ***University hospital centers and public hospitals*** *(e.g., CHU Tlemcen): clinical validation, pilot deployment, and access to ethically sourced, anonymized MRI data.*
- ***Private imaging / radiology centers:*** *additional data and deployment sites.*
- ***Neurology and radiology departments and medical societies:*** *clinical credibility and reach.*
- ***University research laboratories*** *(computer science and medicine): continuous model development and independent validation.*
- ***Ministry of Health and health authorities:*** *regulatory support and a path to national scaling.*
- ***Research ethics committees / review boards:*** *ensuring lawful, consented, anonymized data collection.*
- ***Cloud / hosting and backend providers:*** *secure infrastructure for the data and the platform.*

b. Which partnerships help us reduce costs, access new resources, or improve our value proposition?

- *Hospital partnerships give access to real, locally representative MRI data and clinical expertise — the core ingredient for accuracy — without the prohibitive cost of buying datasets.*
- *University laboratories provide research capacity and student talent, reducing R&D costs.*
- *Public-institution backing reduces customer-acquisition friction and lends credibility that few competitors can match.*

c. How can we align our interests with those of our partners?

1) Identify common goals

Better and faster MS diagnosis, reduced specialist workload, training value for teaching hospitals, and the advancement of local medical research are shared objectives that create a solid strategic alignment.

2) Create mutual value

- ***For hospitals:*** *a free, useful decision-support tool during the trial, reduced reading time, and reproducibility.*
- ***For doctors:*** *a transparent assistant that supports — never replaces — their judgement.*
- ***For research partners:*** *structured, anonymized, longitudinal data (with ethics approval) for studies.*
- ***For us:*** *representative data, clinical validation, and credibility.*

3) Transparent communication

- *Share regular updates on progress, technical advances, and validation results.*
- *Actively listen to clinicians' concerns and suggestions.*
- *Demonstrate a strong long-term commitment built on trust, confidentiality, and continuous collaboration.*

6. Key Activities

a. What are the main actions we must take to deliver our value proposition?

- *Continuous development and retraining of the AI model on newly collected, annotated MRI data to improve accuracy.*
- *Ethical MRI data collection, anonymization, and clinical annotation in partnership with hospitals.*
- *Development and maintenance of the platform (patient management, MRI sessions, results, reports, security).*
- *Clinical validation: measuring performance with neurologists and documenting results for credibility.*
- *Training and support for medical staff.*
- *Ensuring data security, confidentiality, and regulatory / ethical compliance.*

b. What are the essential operations for our company? (Deployment roadmap)

Phase 1 — Free pilot (Year 1)

Deploy the platform free of charge in partner hospitals and clinics. Collect clinician feedback and locally representative MRI data, fix issues, improve accuracy, and build clinical evidence and trust. This deliberate “free-first” strategy mirrors how leading AI tools (such as conversational-AI assistants) grew: by offering free access to gather data and adoption before monetizing.

Phase 2 — Progressive regional expansion

Roll out to more institutions across regions, prioritizing high-volume neurology centers. Each deployment includes training and technical adjustment. Paid subscriptions begin as accuracy and clinical evidence mature.

Phase 3 — National generalization

Once validated, extend the platform across the country, integrate it into routine clinical workflows, and ensure long-term maintenance, support, and continuous model improvement.

c. Which activities create the most value for our clients?

- *AI-assisted detection and localization of suspected MS lesions on FLAIR MRI in seconds.*

- *Transparent Grad-CAM explanations that keep clinicians in control.*
- *Longitudinal tracking of findings across successive MRI sessions.*
- *Structured report generation.*
- *Continuous accuracy improvement driven by locally collected data.*
- *Training and responsive support for medical teams.*

7. Key Resources

a. What are our essential material, immaterial, and human assets?

1) Material assets

- *Secure servers / cloud infrastructure for storing and processing medical data (PostgreSQL / Supabase backend).*
- *A GPU-equipped workstation or server for training and updating the AI model.*
- *Development equipment and high-speed connectivity.*

2) Immaterial assets

- *The trained MS-detection model and the Grad-CAM localization pipeline (core intellectual property).*
- *The growing, ethically collected, locally representative MRI dataset — the platform's most defensible long-term asset.*
- *Clinical partnership agreements and validation results.*
- *Ethics / data-governance approvals and the compliance framework.*

3) Human resources

- *AI / Machine-Learning engineer(s).*
- *Software developer(s).*
- *Medical advisor(s) — neurologist / radiologist for clinical guidance and annotation.*
- *Trainers, support staff, and project coordination.*

b. What tools, technologies, or partnerships do we need to succeed?

- *A deep-learning stack (Python / Keras) for the custom CNN and the Grad-CAM localization.*
- *Secure cloud hosting with a PostgreSQL / Supabase backend and automated backups.*
- *A modern web stack for the platform interface.*
- *Clinical partnerships for data and validation, and collaboration with ethics committees.*

c. What are the main competitive advantages of our resources?

- ***The data flywheel:*** *free access → more locally representative MRI data → higher accuracy → stronger adoption and credibility → more data. This compounding advantage is hard for imported tools to replicate locally.*
- ***Local development and affordability.***
- ***Integrated diagnosis support and patient management*** *in a single platform.*
- ***Clinical co-development with neurologists,*** *giving real-world relevance and trust.*
- ***Transparent, explainable AI (Grad-CAM),*** *increasingly demanded in medical AI.*

8. Cost Structure

a. What are the fixed and variable costs of our economic model?

1) Fixed costs — human resources (monthly, illustrative)

Human resource	Salary (DA)	Number	Monthly amount (DA)
AI / Machine-Learning engineer	120 000	1	120 000
Web / software developer	100 000	1	100 000
Medical advisor (part-time)	60 000	1	60 000
Total	-	-	**280 000 DA**

1.2) Fixed costs — technical resources (illustrative)

Element	Price (DA)
GPU workstation / server & equipment (one-time)	250 000
Secure cloud hosting & PostgreSQL/Supabase backend (monthly)	25 000
Web hosting & domain (monthly)	10 000
Office rent (monthly)	25 000
Total recurring (monthly, excl. one-time hardware)	**60 000 DA**

2) Variable costs

- *Travel for hospital and clinic outreach, demonstrations, and training.*
- *Data annotation (radiologist time to label scans).*
- *Compute for periodic model retraining.*
- *Participation in medical conferences and marketing.*

b. What are the most important costs for our company?

- *AI talent and compute for training and retraining the model.*
- *Clinical data acquisition and expert annotation.*
- *Regulatory / ethical compliance and data security.*
- *Secure cloud infrastructure.*

c. How can we reduce costs or improve the efficiency of our operations?

- *Share infrastructure and data-collection effort with partner hospitals and university labs (mutualize resources).*
- *Use student and research collaborations for annotation and development.*
- *Negotiate volume cloud / hosting contracts.*
- *Offer online training modules (videos, interactive guides) to limit travel and logistics.*
- *Automate the retraining pipeline to reduce engineering overhead.*

9. Revenue

a. What products or services are our clients willing to pay for? (after the free year)

- ***Platform access*** *(SaaS subscription / license) for AI-assisted MS lesion detection, localization, patient management, and longitudinal tracking.*
- ***Premium tier:*** *advanced analytics, larger storage, priority support, and multi-user departments.*
- ***Reporting features*** *and documentation tools.*
- ***Training and continuous technical support packages.***
- ***Customization / integration*** *with existing hospital systems (PACS, record systems).*
- ***(Future, with ethics approval)*** *anonymized, aggregated insights for research.*

b. What are the different ways we can generate revenue?

- *Annual institutional subscriptions / licenses (hospitals, clinics, imaging centers).*
- *Per-department or per-seat licensing for larger institutions.*
- *Tiered plans (standard / premium).*
- *Paid training and premium support.*
- *Customization and integration services.*

> **Strategic note on the free first year:** Year 1 is intentionally free. The goal is data, accuracy, clinical evidence, and trust — not immediate revenue. Like leading AI products that grew by offering free access first, MyelineVision captures early adoption and builds an irreplaceable, locally representative MRI dataset, then converts validated and satisfied institutions into paying subscribers from Year 2 onward. The free phase is not a cost center but the engine of the platform's long-term accuracy and defensibility.

c. What is our pricing model? (illustrative, from Year 2)

Client type	Year 1	Monthly (from Y2)	Annual (from Y2)
Public hospital / CHU (department license)	**Free**	-	300 000 DA
Private clinic / imaging center	**Free**	35 000 DA	350 000 DA
Premium support & analytics add-	-	-	+150 000 DA

Client type	Year 1	Monthly (from Y2)	Annual (from Y2)
on			

The figures above are illustrative and intended to be adjusted to market study and partner agreements. All MRI data used to improve the model during and after the free phase is collected with patient consent, fully anonymized, and approved by the relevant research ethics committee.

Summary of Chapters

This document is organized into five chapters. The following sections provide a concise overview of the all the chapters.

Chapter 1 : Medical and Technical Background

This chapter establishes the medical and technological foundations on which the entire project rests. It first introduces Multiple Sclerosis as a chronic autoimmune disease of the central nervous system, in which the immune system mistakenly attacks the myelin sheath surrounding nerve fibers, producing demyelinating lesions (or plaques) that slow or block the transmission of neural signals. The chapter describes the principal forms of the disease clinically isolated syndrome, relapsing-remitting, secondary-progressive and primary-progressive MS along with its highly variable clinical manifestations, its underlying causes and risk factors, and the therapeutic strategies used to reduce relapse severity and slow progression. Together, these elements highlight both the complexity of the disease and the difficulty of diagnosing and monitoring it, given how much lesion appearance and disease evolution differ from one patient to another.

The second part of the chapter focuses on Magnetic Resonance Imaging, the reference modality for detecting demyelinating lesions and for confirming the dissemination of the disease in space and time. It explains the physical principles of MRI, the difference between closed and open scanners, and the main acquisition sequences (T1-weighted, T2-weighted and FLAIR), emphasizing why FLAIR is particularly suited to revealing MS lesions. The chapter concludes that, although MRI is the gold standard for diagnosis and follow-up, the manual interpretation of these images is time-consuming and subject to inter-observer variability a limitation that directly motivates the development of automated, artificial-intelligence-based methods, which form the central contribution of this work.

Chapter 2 : Machine Learning and Deep Learning

This chapter presents the theoretical foundations of the intelligent component of the platform, following a progressive structure that moves from the broadest concept to the most specific. It begins with Artificial Intelligence as a general discipline, then narrows to Machine Learning, explaining how systems can learn from data rather than from explicitly programmed rules. It defines the main categories of learning supervised, unsupervised and reinforcement situates the proposed model within supervised classification, and analyzes the limitations of classical machine learning when applied directly to images, where manual feature engineering and high dimensionality become major obstacles.

The chapter then introduces Deep Learning and, in particular, Convolutional Neural Networks, which overcome these limitations by learning relevant features automatically. It details the essential building blocks of a CNN convolution and filters, pooling, activation functions such as ReLU, batch normalization, dropout and other regularization techniques, and fully connected layers and clarifies the fundamental distinction between image classification and segmentation, situating the proposed approach as a classifier complemented by post-hoc localization.

Finally, the chapter addresses two notions that are essential in a medical context: explainability, introduced through the Grad-CAM technique that makes the model's decisions visually interpretable, and the evaluation metrics (confusion matrix, accuracy, precision, recall, F1-score, ROC curve and AUC) used to assess the reliability of a classification model. Together, these concepts constitute the conceptual framework needed to understand the design and functioning of the AI module.

Chapter 3: State of the Art

This chapter situates the proposed platform within the existing technological landscape by reviewing representative software systems that pursue objectives similar to those of MyLineCare. It examines a set of well-established solutions icoBrain, Pixyl.Neuro.MS, QMENTA and mdbrain ranging from regulatory-approved commercial platforms integrated into hospital radiology workflows to cloud-based systems and research-oriented tools. For each, the chapter describes the underlying artificial-intelligence logic and the data used to build it, before drawing a structured comparison across these systems.

The analysis shows that current solutions tend to specialize in a single dimension: clinically validated lesion segmentation and quantification, cloud-based imaging data management, or reproducible research analysis. While each excels in its own domain, they generally lack an integrated environment that combines automated analysis with everyday patient management. By bringing together an interpretable and lightweight AI module based on FLAIR-slice classification and Grad-CAM localization with a complete patient-management layer, MyLineCare occupies a distinctive position in this landscape. Having clarified this contribution, the chapter prepares the transition to the implementation of the proposed system.

Chapter 4: Modeling and Design

This chapter presents the conceptual and technical design of the platform, a fundamental step between the analysis of the medical context and the actual implementation. Using the Unified Modeling Language, it first identifies the system's actors and functionalities, then translates the requirements into a coherent set of models that describe both the structure and the behavior of the system. The use case diagram defines the boundaries of the system and the interactions of doctors and administrators with its main functions, while the class diagram captures the static structure the core entities, their attributes and operations, and the associations of composition, inheritance and multiplicity that connect them.

The dynamic behavior of the platform is then modeled through sequence diagrams, activity diagrams, an object diagram and state machine diagrams, which describe how the principal processes such as MRI analysis, patient follow-up and report generation unfold over time and how key objects evolve through their different states. Finally, the chapter derives the conceptual and logical data models (MCD and MLD), which organize the persistent data into a relational schema based on tables, attributes and foreign keys.

This modeling provides a precise and consistent vision of the platform's architecture and ensures continuity between the conceptual design, the database structure and the software development carried out in the following chapters.

Chapter 5 :I mplementation

This chapter describes the concrete realization of the platform, demonstrating the technical feasibility of the solution from data preparation to deployment. It begins with the dataset, composed of two-dimensional brain MRI slices acquired in the FLAIR sequence and organized into two classes, MS and Healthy. On this basis, a compact convolutional neural network of approximately 1.2 million parameters named MylineVision was designed and trained from scratch to perform binary classification of the images and to localize the suspected lesion regions through Grad-CAM. The chapter details the network architecture, the training configuration and the performance obtained on an independent test set, while honestly discussing the factors that must be considered when interpreting these metrics, such as the diversity of data sources and the limited availability of MS datasets.

Beyond the AI engine, the chapter presents the complete MyLineCare management platform through its main interfaces: authentication, the doctor's dashboard, patient management, MRI upload, the MylineVision analysis screen, report generation, the doctor profile, and the administrative and settings modules. All clinical and analytical data are stored in a Supabase backend, and each analysis is persisted as a structured report. Overall, the chapter shows how the artificial-intelligence model is integrated into a usable and maintainable clinical tool that covers authentication, patient management, explainable MRI analysis, report generation and longitudinal follow-up, transforming the conceptual design into a functional decision-support system for clinicians.

General conclusion

Multiple Sclerosis is a serious disease that affects the central nervous system and is not always easy to diagnose. MRI plays a big role in detecting the lesions caused by this disease, but reading these images takes time and depends a lot on the experience of the doctor. The goal of this work was to use deep learning to help neurologists in this task, and to make the diagnosis and the follow-up of patients easier.

To reach this goal, we first studied the medical side of the disease and the role of MRI in its detection. Then we presented the main ideas of machine learning and deep learning, and especially convolutional neural networks, which are well suited for image analysis. After that, we designed and built our platform, MyelineCare, with its AI engine MyelineVision. This engine is a CNN that we trained from scratch to classify FLAIR images into two classes, MS and Healthy, and to show the suspicious regions using Grad-CAM.

The model gave very good results on the test set. Still, we tried to stay honest about these results: the images came from different sources, which can make the task easier than it really is, so the results should be confirmed later on a larger and more controlled datasets. It is also important to say that our platform is only a tool to help the doctor, and not to replace the doctor, because the final decision always belongs to the neurologist.

In the end, this project allowed us to bring together the medical field and artificial intelligence, and to build a complete and usable platform. We learned a lot during this work, on the technical side as well as on the medical side. The platform can still be improved in the future, for example by working on 3D images, by adding lesion segmentation, or by testing it in real conditions with doctors. We hope that this work can be a small step toward a better use of artificial intelligence in the medical field.

Contributions and Limitations:

This work contributes a complete, interpretable and deployable decision-support platform for Multiple Sclerosis, rather than an isolated classification model. It integrates a compact convolutional neural network of about 1.2 million parameters trained entirely from scratch on FLAIR slices into a usable clinical environment built on a React frontend, a FastAPI backend and a Supabase database.

Around this engine, the platform provides the functionalities of a realistic clinical workflow: role-based authentication, patient management, MRI upload and analysis, Grad-CAM visual explanations, a probability score presented alongside McDonald_criteria context, report generation, longitudinal follow-up, a voice assistant and an administration module. By adding a lightweight, explainable classifier with a full management layer and framing the tool as a decision aid rather than a diagnostic replacement, MyLineCare is distinguished from the more specialised platforms reviewed in the state of the art. Its main contribution is therefore the demonstration of the technical feasibility of such an integrated, interpretable system, together with a working prototype that can serve as a foundation for clinically validated future development.

The project also has clear limitations that must be stated honestly, the most important concerning the data. There is currently no large, public, unified FLAIR dataset containing both MS and healthy brains acquired under a common protocol, so the dataset had to be assembled from several heterogeneous sources the MS images from one collection and the healthy controls from others. As a result, the two classes differ not only in the presence of disease but also in scanner, intensity, resolution and preprocessing, which means the near-perfect results obtained (accuracy 99.94%, AUC 1.00) most likely reflect the model's ability to distinguish the *origin* of the images rather than true MS-specific features.

These metrics should therefore be read as evidence that the training pipeline functions correctly, not as a measure of real clinical accuracy. Related limitations follow from the same constraint: the data consists of 2D slices rather than 3D volumes, the labels are image-level rather than lesion-level, the train/test split is performed at the slice level (risking leakage if slices of the same patient fall in both subsets), and the system was never validated on prospective clinical cases.

These limitations define the natural direction of future work: validating the model on single-source or domain-harmonised data, enforcing a strict patient-level train/test separation, testing on external and prospectively collected cases with clinicians, and extending the analysis toward volumetric, lesion-annotated data. In summary, the value of this project lies in the design and implementation of a coherent, explainable and fully integrated MS support platform, and in the transparent analysis of its current diagnostic limitations an honest assessment that is itself an essential step toward responsible medical artificial intelligence.

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