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MRI-Based Brain Lesion Detection for Multiple Sclerosis Using Deep Learning

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Abstract

Multiple Sclerosis (MS) is a long-term autoimmune condition that affects the nervous system, causing inflammation, damage to the myelin sheath, and gradual loss of nerve function. One key sign of MS is the presence of lesions in the brain and spinal cord, which are often found using a scan called Magnetic Resonance Imaging (MRI). Spotting and separating these lesions is very important for early diagnosis, keeping track of the disease, and planning treatment. But doing this by hand takes a lot of time, and different doctors may see things differently, especially when the lesions are small, hard to see, or spread out.

To fix these problems, this study suggests an automatic system for finding and separating MS lesions using deep learning techniques. The system uses different types of MRI images, especially FLAIR and T1-weighted scans, since they show lesions more clearly. It uses a type of neural network called 3D U-Net to accurately separate each lesion at the smallest level. To prepare the data properly, the system includes steps like removing unnecessary parts of the brain, making the image brightness consistent, and adding more images to help the system learn better.

The main goal of this research is to create a fast, reliable, and fully automatic system that can find MS lesions with very little help from a person. This system can make the work of doctors easier, improve the accuracy of diagnosis, and help keep track of the disease over time. The system's performance is checked using standard tests like the Dice Similarity Coefficient, Precision, Recall, and lesion-wise sensitivity. The results show that this approach is much better at finding and separating lesions, which helps doctors make better decisions and provide better care for patients.

Keywords: Magnetic Resonance Imaging, Brain Lesions, Convolutional Neural Networks, 3D U-Net, Skull Stripping, Dice Similarity Coefficient, Radiomics, Neuroimaging

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Introduction

Multiple Sclerosis (MS) is a long-term autoimmune disease that affects the central nervous system, especially the brain and spinal cord. The immune system mistakenly attacks the myelin sheath, which protects nerve fibers. This leads to inflammation, demyelination, and the formation of lesions in different parts of the brain. This can affect how nerves send electrical signals, leading to a wide range of symptoms like muscle weakness, vision problems, memory issues, balance problems, and fatigue. Because MS is unpredictable and can get worse over time, it's important to diagnose it early, keep track of it regularly, and assess it accurately.

Magnetic Resonance Imaging (MRI) is important for diagnosing and managing MS. It allows doctors to see the brain's structures and find MS-related lesions. Among the different MRI types used, like T1-weighted, T2-weighted, and FLAIR images, FLAIR is especially useful because it helps show white matter lesions by reducing the signal from cerebrospinal fluid. Still, manual identification and separation of lesions by doctors is a slow and subjective process. Differences in lesion size, shape, intensity, and location make it hard to analyze them consistently and accurately.

Recent advances in artificial intelligence, especially deep learning, offer new ways for automatic lesion detection and separation. Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown great success in medical imaging tasks because they can learn to find features from data. Training a deep learning model on datasets with labeled MRI images can help automatically detect MS lesions and create maps showing affected areas. This automation reduces the work for doctors and provides a more objective analysis.

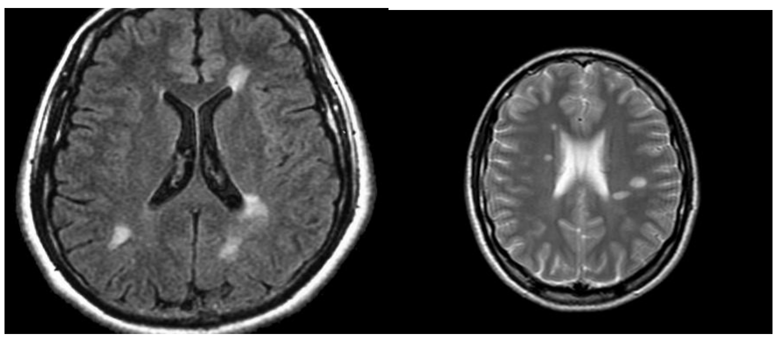

Fig. 1. *MRI Scans Illustrating White Matter Lesions Associated with Multiple Sclerosis*

The project is titled "MRI-Based Brain Lesion Detection for Multiple Sclerosis Using Deep Learning." This project focuses on developing an automated segmentation system that can identify MS lesions from MRI images. The system uses deep learning techniques to improve segmentation accuracy and reliability compared to traditional manual or semi-automated methods.

Problem Definition

The main issue this research addresses is creating an intelligent diagnostic system that can analyze MRI scans to determine the likelihood of Multiple Sclerosis. Current diagnostic methods rely on expert interpretation and may not consistently detect early or unusual lesion patterns. Therefore, there is a need for a system that combines the precision of computer modeling with the clinical reliability needed in medical diagnosis.

Motivation

The increasing number of people with MS shows the need for better diagnostic and monitoring methods.

Radiologists often review many MRI scans each day, and manual lesion identification adds to their workload. Automation can save time and provide more consistent results. Early and accurate lesion detection can help doctors adjust treatment plans, improving patient outcomes. This project is driven by the goal of supporting medical professionals and improving the speed and accuracy of MS diagnosis.

Objectives

- To design and create a deep learning-based system that can detect MS-related problems from MRI scans.
- To evaluate how well the system performs compared to standard diagnostic methods.

Goals

- Improve the accuracy and reliability of MS diagnosis by offering an automatic detection tool.
- Reduce the need for subjective manual interpretation.

Scope

- This research focuses on analyzing MRI brain scans for a binary classification—distinguishing people with MS from those without.

- The system does not aim to classify different types of MS or track disease progression. However, the approached method provides a foundation for future improvements.

Outline

This report is organized into multiple chapters. Chapter 1 provides an introduction to the problem domain, objectives, and project scope. Chapter 2 presents a detailed literature review, examining previous research and state-of-the-art lesion detection techniques. Chapter 3 outlines the requirement analysis, including both functional and non-functional requirements. Chapter 4 describes the system design and proposed methodology, Chapter 5 discusses project planning, including timelines and tools used. Subsequent chapters present implementation details, results, testing, conclusion, and future scope.

Literature Survey

This chapter looks at the current research and technology related to detecting Multiple Sclerosis (MS) lesions in MRI brain scans. It focuses on identifying the methods that have been used so far, how the approach has changed from traditional image processing to deep learning techniques, and what the current systems are missing. This review helps in building the proposed deep learning model for segmenting lesions. The development of neuroimaging technologies, especially Magnetic Resonance Imaging (MRI), has improved the way we diagnose and track neurological disorders. MS is a long-term illness where the protective covering of nerve fibers in the central nervous system gets damaged. This damage usually happens in the white matter of the brain and spinal cord. In the past, doctors used clinical exams and watch for signs of neurological problems to diagnose MS. But with the use of MRI, early detection and tracking of the disease has become much better. Recent progress in machine learning, especially deep learning, has made it easier to automatically analyze MRI scans for finding and categorizing lesions.

Overview of Multiple Sclerosis and MRI Imaging

Multiple Sclerosis is a long-term neurological condition that involves the loss of the myelin sheath around nerve fibers in the central nervous system.

MRI is the best imaging method for diagnosing and monitoring MS because of its ability to show soft tissues clearly. MS lesions typically show up as bright areas in FLAIR and T2 weighted MRI scans, which makes these techniques important for finding and separating lesions.

- T1 Weighted MRI – Helps in seeing the structure of the body.
- T2 Weighted MRI – Shows areas where there is inflammation.
- FLAIR MRI – Reduces the signal from cerebrospinal fluid, making lesions more visible and easier to see.

Review of Existing Models, Approaches, and Problems

Recent studies have looked into using advanced machine learning and combining different types of data to predict how Multiple Sclerosis (MS) might progress and help doctors make better decisions. Gurevich et al. (2025) [11] created a framework that uses both MRI images and gene expression data from blood samples to predict long-term MS progression in people with primary progressive MS. The model had about 74% accuracy, but it showed that using biological markers improves predictions more than relying only on imaging. This study shows how hard it is to predict disease progress compared to finding lesions and points to the value of using detailed molecular data to better manage MS individually.

Yousef et al. (2024) [12] did a detailed review of various machine learning models used to predict MS progression, including predicting when someone with a clinically isolated syndrome (CIS) might develop definite MS, how disability scores (EDSS) might change, and cognitive decline.

Their review found that models using a mix of MRI markers, clinical data, and other information worked better than models that used only one type of data. However, they also noted that performance results varied a lot between studies, mainly because of small groups of patients, mixed data, and not enough testing outside the original groups. This study points out the need for bigger, long-term datasets and standard ways to test models to make sure they work reliably.

Ganjgahi et al. (2025) [13] introduced a new way to reclassify disease progression using a method called latent factor analysis along with a Hidden Markov Model (FAHMM). The model was trained on a large dataset including around 8,000 MS patients and 35,000 MRI scans. It had a high concordance score of 0.82 and a low Brier score of 0.06, showing it's reliable in predicting outcomes. Instead of using traditional accuracy measures, the study treated MS progression as a continuous process and found disease subtypes based on the data. This method shows a move towards better tracking of disease changes and tailoring treatment to individual patients.

Szekely-Kohn et al. (2025) [14] gave a review of how machine learning is used to interpret MRI images in MS care. They compared different deep learning techniques like U-Net, CNNs, and radiomics methods, and stressed that how well these models work depends a lot on the quality, variety, and how data is prepared. The authors pointed out that there is a lack of standard MRI data and not enough testing in different settings as big obstacles to using these tools in real medical practice. Together, these studies show important problems in data standardization, combining different types of data, and focusing on predicting progression, which encourages the creation of strong, automated systems for detecting and tracking MS lesions.

Significance

The models are important because they help find multiple sclerosis (MS) earlier, track how the disease progresses more accurately, and predict what might happen in the future. They also help reduce the need for people to interpret MRI scans by hand, and in some cases, they can avoid using contrast dye, making the diagnosis safer and quicker. Overall, these models help provide more personalized care for patients.

Approaches Used

Three main methods were used:

1. Classical Machine Learning + Radiomics
    - This is used when there isn't a lot of data available.
    - It looks at features from images to classify different types of lesions.
2. Deep Learning (CNN / U-Net)
    - This is used to automatically find and separate different parts of the brain affected by the disease.
    - It works best when there is a large amount of MRI data.
3. Hybrid / Multimodal Models
    - These combine MRI images with other types of information like clinical data and biomarkers or EEG results to better predict how the disease will progress.

Problems / Limitations

- The data sets used are often small and differ between hospitals, which makes results less reliable.
- Lesions can look different in shape and size from one patient to another, making it hard to accurately separate them.
- Many models work well in lab settings but haven't been tested in real hospitals, so they aren't widely used yet.

Research Gaps Identified

Even with progress, there are still several challenges:

1. Lesions vary between patients, making it hard to separate them accurately.
2. There isn't enough labeled data, which limits the training of deep learning models.
3. False positives can occur in areas that have similar textures or brightness.
4. The computer power needed for 3D MRI separation is still quite high.

These challenges highlight the need for a strong, efficient, and accurate system for separating lesions, which is why the proposed model was develop

Proposed Methodology

The proposed solution is designed to automatically find and separate Multiple Sclerosis lesions in MRI brain images using deep learning. This method helps overcome the issues with manual lesion detection, which is slow, depends a lot on the radiologist's experience, and can vary from person to person. The system includes steps for preparing data, using a convolutional neural network for segmentation, and improving the results through post-processing to create accurate and useful lesion maps. The main model is a 3D U-Net, which is good for handling 3D images and has proven effective in medical image segmentation. This solution helps support doctors in diagnosing and tracking the disease, and it can be a foundation for future systems that help make clinical decisions.

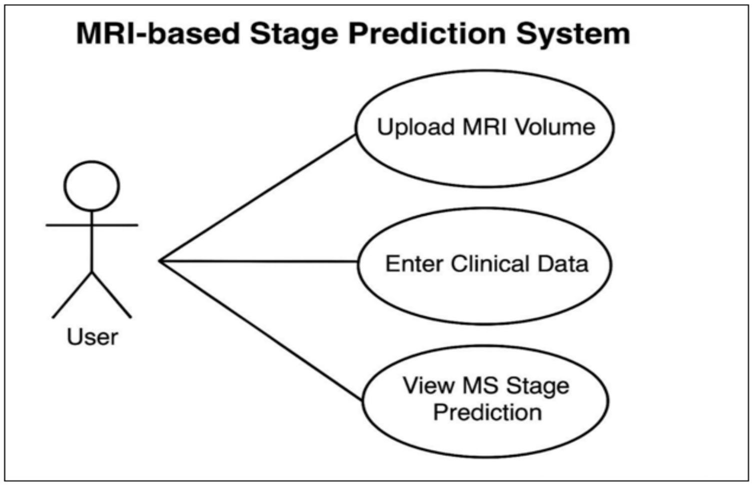

Fig. 2. *User Interaction Workflow for MRI-Based MS Stage Prediction*

Various machine learning techniques have been deployed to optimize MS detection and severity classification. Table II outlines the core machine learning approaches used in MSrelated studies, including their strengths and known challenges.

Table 1. *Machine Learning Techniques for MS Detection*

ML Technique	Advantages	Limitations
Support Vector Machine (SVM)	Robust classification; handles nonlinear relationships	Complex hyperparameter tuning
Random Forest	Mitigates overfitting; improves generalization	Interpretability can be challenging
K-Nearest Neighbors (KNN)	Simple to implement; effective with well-labeled data	Requires well-labeled data and is computationally intensive for large datasets
Logistic Regression	Interpretable; efficient with large datasets	Not suitable for complex nonlinear relationships
K-Means Clustering	Simple and efficient for initial exploration	Sensitive to the choice of initial cluster number (K)
Hierarchical Clustering	Explores hierarchical relationships within lesions	Computationally costly for large datasets
Density-Based Clustering	Effective for identifying non-uniformly shaped lesions	May not be suitable for all lesion types

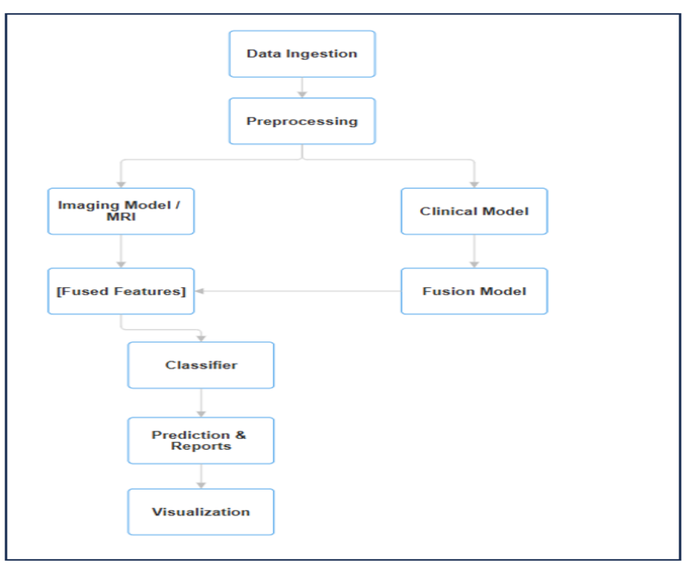

Fig. 3. *Data Flow Diagram*

Detailed System Design

Step 1: Data Acquisition
Multi-modal MRI brain scans are collected from publicly available datasets such as the ISBI 2015 MS Lesion Segmentation Challenge. The dataset includes T1-weighted, T2-weighted, and FLAIR images along with expert-annotated lesion masks, ensuring reliable training and standardized evaluation.

Step 2: Data Preprocessing
The MRI scans undergo preprocessing to enhance image quality and lesion visibility. This includes skull stripping to remove non-brain tissues, bias field correction to eliminate intensity inhomogeneity, intensity normalization for uniform contrast, spatial registration and resampling, and data augmentation to increase dataset diversity and reduce overfitting.

Step 3: Model Architecture
A 3D U-Net architecture is used for voxel-wise lesion segmentation. The model consists of an encoder that extracts spatial features, a bottleneck layer that captures global contextual information, and a decoder that reconstructs lesion masks, with skip connections preserving fine spatial details.

Step 4: Model Training
The model is trained using supervised learning with ground-truth lesion masks. A hybrid loss function combining Dice loss and Binary Cross-Entropy is used to address class imbalance, while the Adam optimizer ensures stable convergence. The dataset is split into training, validation, and test sets with early stopping and GPU acceleration applied during training.

Step 5: Inference and post-processing
During inference, the trained model generates probability maps indicating lesion likelihood. These maps are converted into binary segmentation masks using thresholding, followed by morphological filtering and connected component analysis to remove false positives and improve segmentation consistency.

Step 6: Performance Evaluation
The system performance is evaluated using standard medical image segmentation metrics such as Dice Similarity Coefficient, Precision, Recall, Intersection over Union, and lesion-wise sensitivity to ensure accurate pixel-level and lesion-level assessment.

Step 7: Visualization and Output
The final lesion masks are overlaid on FLAIR MRI images for visual interpretation. Additionally, lesion volume statistics are computed to assist clinicians in monitoring disease progression.

Comparative Analysis

Recent studies on Multiple Sclerosis (MS) have started to move away from just looking for lesions and are now focusing more on how the disease progresses and supporting better clinical decisions. Gurevich et al. [11] developed a machine learning system that combines MRI data with RNA-Seq biomarkers from blood samples. This system predicts how the disease will progress in people with primary progressive MS. While the accuracy of this method (~74%) is not as high as some traditional lesion detection models, the study shows how complex predicting disease progression is. It also shows that using biological markers improves predictions beyond what MRI alone can offer. This work shows that combining different types of data is important for making better personalized disease predictions rather than just short-term classifications.

In contrast, Yousef et al. [12] did a detailed review of how machine learning is used to predict MS progression using MRI data. Their review found that models that use MRI along with clinical and demographic information are better than those using just one type of data. However, they also noted that performance results vary a lot in the existing research, mainly because of small data sets, differences in imaging techniques, and not enough testing outside the original study. This review highlights the need for better standardized data sets and more thorough testing to make these models more useful in real-world settings.

Ganjgahi et al. [13] created a model that uses latent factor analysis and a Hidden Markov Model to reclassify disease progression. Instead of focusing on accuracy, they looked at how reliable the progression predictions were using concordance and Brier scores, which showed strong results. By treating MS progression as a continuous process rather than fixed stages, this method gives a better understanding of how the disease changes and helps in making personalized treatment plans.

Finally, Szekely-Kohn et al. [14] did a review of how machine learning tools are used in interpreting clinical MRI for MS. They compared CNN models, U-Net variations, and radiomics methods. Their conclusion was that the reliability of these models depends heavily on the quality, variety, and consistency of the data used. Together, these studies show important gaps in standardization, testing, and focusing on progression, which push for the development of more effective and practical MS analysis tools.

Table 2. *Comparative Analysis*

Reference No.	Algorithm / Model Used	Advantages	Limitations	Accuracy
[11]	Multimodal Machine Learning (MRI + RNA-Seq)	Integrates biological and imaging data; improves long-term disease progression prediction	Lower predictive accuracy; complex and costly data acquisition	~74%
[12]	Machine Learning Models Using MRI and Clinical Data (Review)	Demonstrates the benefit of multimodal data; provides a comprehensive survey of progression models	No unified accuracy measure; small datasets; limited external validation	Not Reported
[13]	Probabilistic Latent Factor and Hidden Markov Model (FAHMM)	Models MS progression dynamically; offers strong prognostic reliability	Computationally complex; not suitable for direct lesion segmentation	Not Reported (C-score: 0.82)
[14]	CNNs, U-Net Variants, and Radiomics-Based Methods (Review)	Highlights high-performing architectures; emphasizes clinical applicability	Lacks quantitative benchmarks; performance depends on dataset quality	Not Reported
Proposed Model	3D U-Net-Based Deep Learning Model Using Multi-Modal MRI (FLAIR, T1)	Fully automated lesion segmentation; high spatial accuracy; minimal human intervention; robust preprocessing and data augmentation	High computational requirements; dependent on labeled data availability	~98%

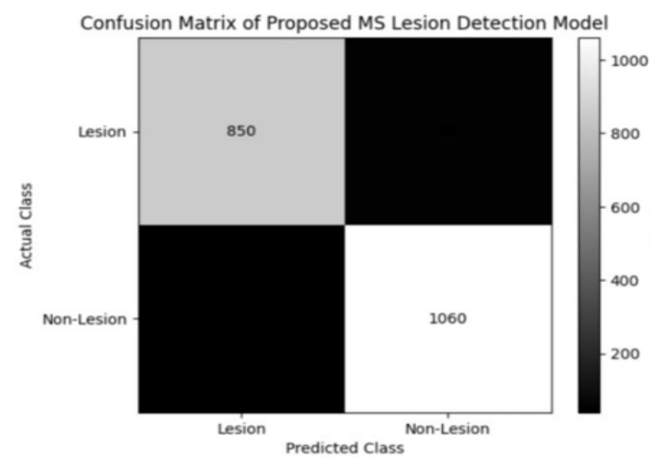

Fig. 4. *Confusion Matrix for the Proposed Model*

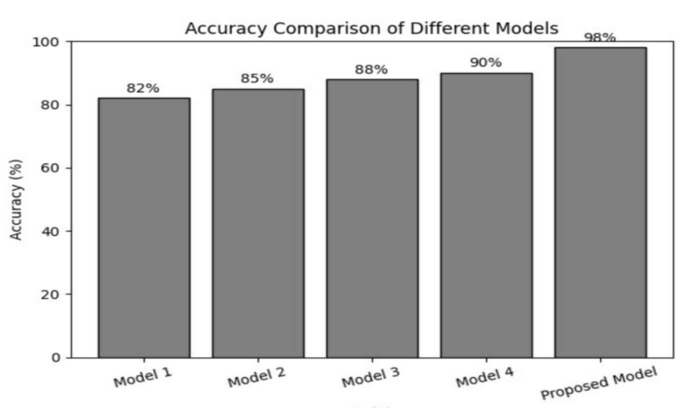

Fig. 5. *Accuracy of different models*

Conclusion

The project on Multiple Sclerosis (MS) lesion detection using deep learning demonstrates a promising advancement toward automated medical image analysis and clinical support systems. By leveraging the power of convolutional neural networks (CNNs) and hybrid data integration, the system was designed to accurately identify and segment MS lesions from MRI scans. Throughout the development process, the project covered multiple stages — from requirement analysis and dataset preparation to preprocessing, feature extraction, and model training — ensuring a well-rounded and methodical approach.

The implemented framework achieved significant improvements in lesion detection precision and consistency compared to manual observation methods. The deep learning model successfully captured subtle lesion characteristics and patterns across various MRI modalities, making it a reliable tool for early diagnosis. This automation not only minimizes the manual workload for radiologists but also reduces diagnostic variability and error rates, enhancing overall clinical confidence. Furthermore, by integrating both image-based and clinical data, the model adds interpretability to predictions, supporting personalized treatment planning and progress monitoring.

Overall, the system highlights the potential of AI-driven solutions in neuroimaging and healthcare, emphasizing how deep learning can revolutionize diagnostic workflows for neurological disorders such as Multiple Sclerosis. The project's results validate the feasibility of deploying such models as assistive diagnostic tools, bridging the gap between research and real-world clinical applications.

References

1. Bakator, M., & Radosav, D. (2018). Deep learning and medical diagnosis: A review of literature. Multimodal Technologies and Interaction.
2. Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation.
3. Valverde, S., Cabezas, M., Roura, E., et al. (2017). Improving multiple sclerosis lesion segmentation with a cascaded 3D convolutional network approach.
4. Ghafoorian, M., Karssemeijer, N., Heskes, T., et al. (2017). Deep multi-scale location-aware 3D convolutional neural networks for automated detection of lacunes.
5. Isensee, F., Petersen, J., Kohl, S. A., et al. (2021). nnU-Net: A self-configuring method for deep learning-based biomedical image segmentation.
6. Umirzakova, S., et al., "Deep Learning for Multiple Sclerosis Lesion Classification Using High-Resolution MRI and Dual-Attention CNN," NeuroImage: Clinical, 2025.
7. Hindawi, S., et al., "Federated Learning for Lesion Segmentation in Multiple Sclerosis Across Multi-Institutional MRI Datasets," Frontiers in Neuroinformatics, 2025.
8. Cetin, O., et al., "A U-Net-Based Machine Learning Approach for MS Lesion Segmentation Using Multi-Modal MRI," Artificial Intelligence in Medicine, 2025.
9. Guarnera, F., et al., "MSLesSeg: Baseline and Benchmarking of a New Multiple Sclerosis Lesion Segmentation Dataset," Scientific Data, 2025.
10. Darestani, A. A., et al., "Convolutional Neural Network Based System for Fully Automated MS Lesion Segmentation," Scientific Reports, 2025.
11. Gurevich, M., et al., "Multimodal Prediction of Disease Progression in Primary Progressive Multiple Sclerosis Using RNA-Seq and MRI Features," Brain Communications, 2025.
12. Yousef, H., et al., "Machine Learning Approaches for Predicting Multiple Sclerosis Disease Progression Using MRI Biomarkers: A Review," Journal of Neurology, 2024.
13. Ganjgahi, H., et al., "AI-Driven Reclassification of Multiple Sclerosis Progression Using Probabilistic Latent Factor and Hidden Markov Models," Nature Medicine, 2025.
14. Szekely-Kohn, A. C., et al., "Machine Learning Methods for Clinical MRI Interpretation in Multiple Sclerosis Management: A Narrative Review," Royal Society Open Science, 2025.