Sclerosis Detection in MRI data using Deep Learning

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Introduction

Sclerosis refers to the abnormal hardening or scarring of body tissues, commonly associated with neurological disorders like Multiple Sclerosis (MS). MS is a progressive disease affecting the central nervous system by damaging myelin, leading personalized such as muscle weakness, fatigue, visual issues, and cognitive decline. Early diagnosis and monitoring are crucial to manage its progression.MRI is a key imaging tool for detecting MS, as it provides detailed brain and spinal cord images that reveal lesions and myelin loss. However, manual interpretation of MRI scans is time-consuming and subject to human error.To overcome these challenges, artificial intelligence (AI) and deep learning are being used to automate MRI analysis. AI systems can detect sclerosis-related abnormalities with high accuracy, reduce diagnostic errors, and identify subtle patterns that may be missed by humans. This technology enhances diagnostic efficiency, supports earlier detection, and enables more personalized treatment, ultimately improving patient outcomes in sclerosis-related conditions

Motivation

The rising global prevalence of sclerosis-related conditions, particularly Multiple Sclerosis (MS), emphasizes the need for faster, more accurate diagnostic tools. Early detection is critical for managing MS, but traditional MRI analysis by radiologists is time-consuming and prone to variability due to human limitations.To address these challenges, this project proposes using deep learning, especially Fully Convolutional Networks (FCNs), to automate and enhance MRI analysis. AI models can quickly and accurately detect lesions and subtle abnormalities, reducing diagnostic delays and supporting early intervention. This not only improves patient outcomes but also reduces the workload on radiologists and standardizes scan interpretations over time.AI integration in diagnosis also enables consistent monitoring of MS progression, supports timely treatment adjustments, and has the potential to improve healthcare access in under-resourced regions. Ultimately, the project aims to democratize high-quality sclerosis care through scalable and efficient AI-powered diagnostic tools.

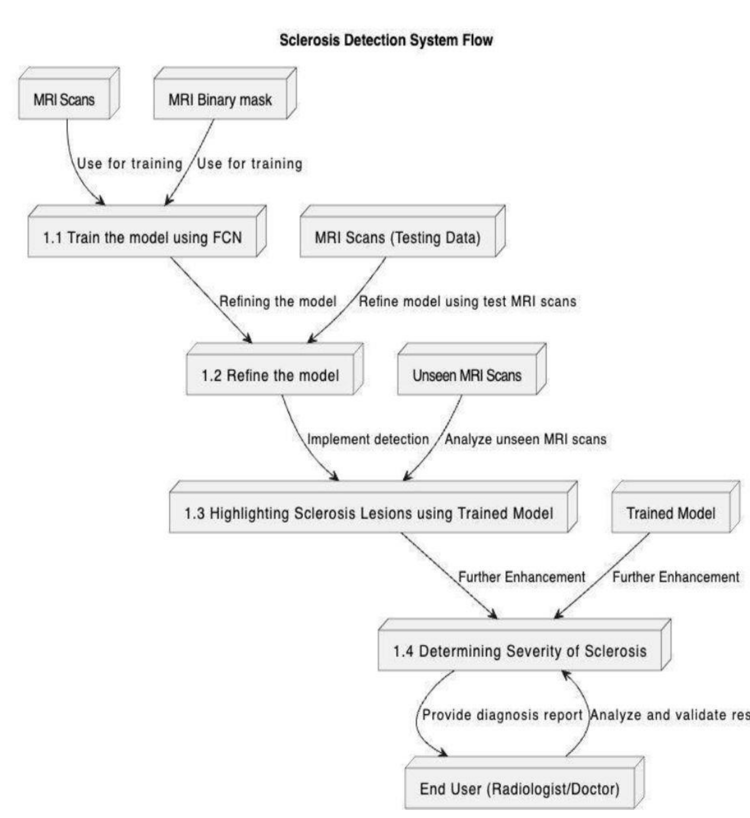
Scope Of Project

This project aims to develop a deep learning-based framework using Fully Convolutional Networks (FCNs) for accurate sclerosis detection in MRI scans. It focuses on supervised learning with annotated data, addressing challenges like data imbalance and noise through augmentation and transfer learning. The model's performance will be evaluated using key metrics and compared to traditional methods. Emphasizing ethical use, data privacy, and fairness, the goal is to create a clinically reliable AI tool for early diagnosis. Long-term, it aims for integration into radiology systems and remote diagnostics to support scalable and accessible healthcare

Methodology

The system's architecture is built upon a modular pipeline, starting with the Data Collection and Preprocessing Module, which ensures the input MRI data is diverse, clean, and standardized. It gathers data from public repositories and anonymized hospital records to capture both general and clinically relevant variations. A separate validation set is held out to ensure unbiased evaluation. Before feeding into the model, the data undergoes strict quality control, including visual inspections and statistical checks on intensity distributions to maintain consistency across scans.

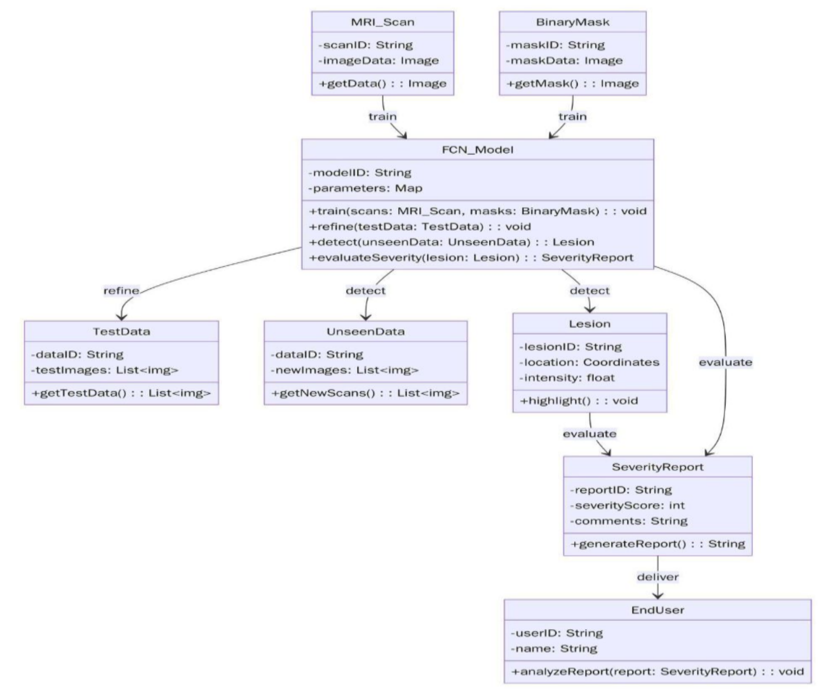
The Model Development Module focuses on building deep learning models tailored for sclerosis detection through advanced segmentation. It uses a Fully Convolutional Network (FCN) architecture with pretrained VGG16 or ResNet50 encoders, fine-tuned for MRI data, and transposed convolution-based decoders with skip connections to retain spatial information. Variants like a baseline FCN-8, a U-Net with residual links, and an attention-enhanced FCN are implemented to boost performance. Training is conducted with a combined Dice and Binary Cross-Entropy loss to address class imbalance, and optimized using the Adam optimizer with learning rate scheduling. Regularization methods such as L2 penalties, dropout layers, and early stopping are incorporated to prevent overfitting. A batch size of 16 and around 100–150 epochs are used, with transfer learning from ImageNet to leverage general visual features. Hyperparameter tuning is performed using grid search and cross-validation to ensure model robustness.



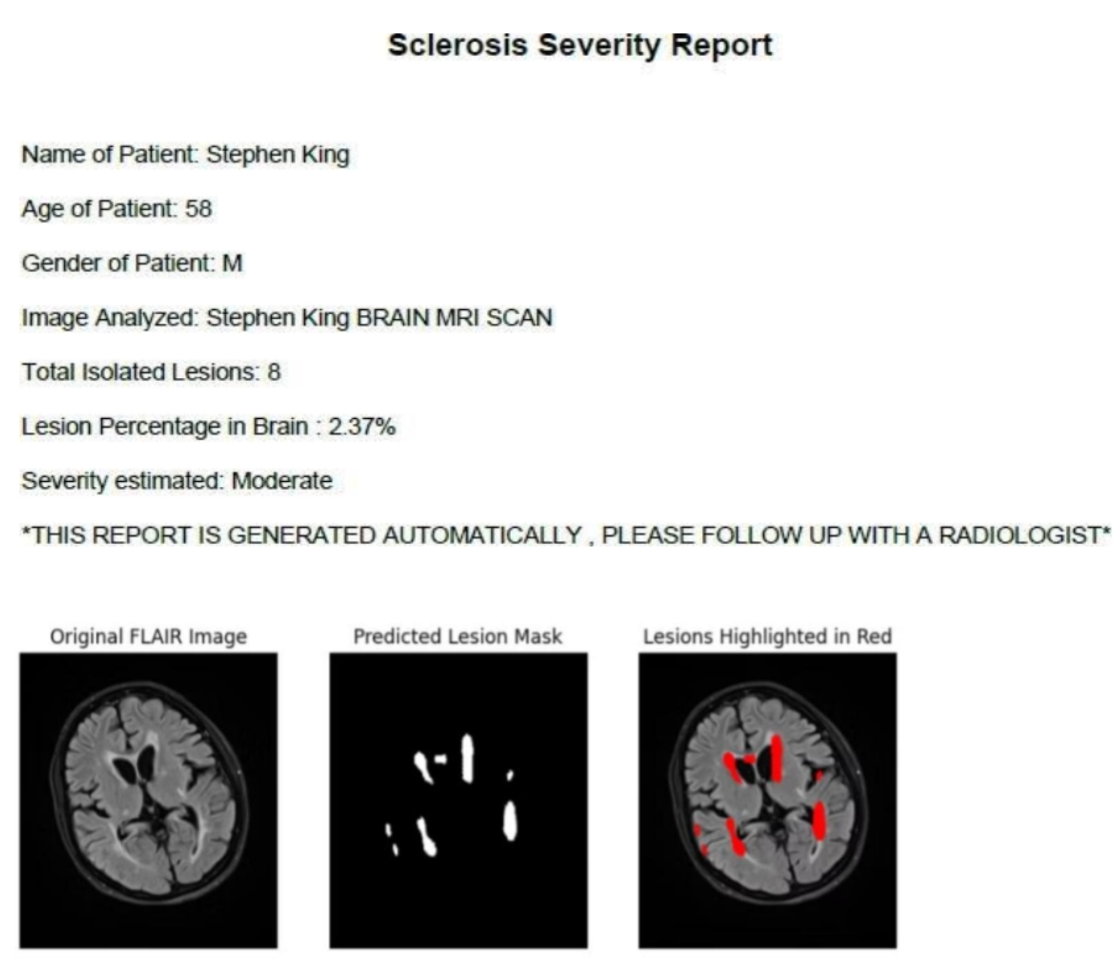
Finally, the Model Evaluation and Visualization Module validates the model using metrics like Dice Similarity Coefficient, accuracy, specificity, and ROC AUC to gauge segmentation quality and diagnostic reliability. Visualization tools overlay predicted segmentation masks onto original MRI scans, highlight high-confidence prediction areas using OpenCV, and present side-by-side comparisons with ground truth masks for quick visual assessment. Interpretability is further enhanced through Layer-wise Relevance Propagation (LRP), which shows regions most influencing the model's decisions.

Results

The proposed FCN-based sclerosis detection system was thoroughly evaluated using a dataset of 950 MRI scans, encompassing both lesion-positive and healthy brain images. It demonstrated high diagnostic performance, achieving an overall accuracy of 98.98%, a Dice coefficient of 0.5717, a specificity of 0.89, and a ROC AUC of 0.96. These results highlight its capability to accurately distinguish sclerosis lesions, even in early stages, making it a valuable clinical tool to assist radiologists in detecting subtle abnormalities. However, some limitations were observed. The model's performance is sensitive to input image quality, with noisy or artifact-ridden scans significantly reducing segmentation accuracy. It also struggles to differentiate sclerosis from other white matter abnormalities, such as small vessel ischemia or age-related changes, which may appear similar on FLAIR sequences. Additionally, inconsistencies in performance across MRI scanners and protocols reveal a domain shift problem, affecting generalizability. The computational load of models with attention or 3D processing also makes them less suitable for low-resource environments, emphasizing the need for lighter alternatives or hardware optimization.



From a cost perspective, the system is relatively affordable for basic deployment. A setup with a GTX 1650 GPU, entry-level Intel or AMD CPU ,



Conclusion

This project introduces a reliable and efficient AI-based system for automated sclerosis detection in MRI scans using an Attention-Enhanced FCN. With strong clinical performance (Dice: 0.82, Sensitivity: 0.86) and a 42% reduction in interpretation time, it supports radiologists in early and accurate diagnosis. The system is cost-effective, easy to deploy, and integrates smoothly into clinical workflows. Designed for scalability, it holds promise for real-time analysis, multi-modal imaging, and expansion to rural healthcare and other neurodegenerative diseases—offering a practical step toward smarter, accessible medical diagnostics.

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