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Classification of multiple sclerosis lesion through Deep Learning analysis of MRI images

Mathavan Divya[1]✉, Jayeseelan Dhilipan[2], Appu Saravanan[3]

[1,2] SRM Institute of Science and Technology, Ramapuram Campus, Chennai, 600089, India
[3] Easwari Engineering College, Ramapuram Campus, Chennai, 600089, India

[1] divyam1@srmist.edu.in✉, https://orcid.org/0000-0002-9960-8061
[2] hod.mca.rmp@srmist.edu.in, https://orcid.org/0000-0003-2122-5076
[3] dean.academic@srmrmp.edu.in, https://orcid.org/0000-0003-2093-900X

Abstract
Multiple Sclerosis (MS) is a progressive autoimmune disease affecting the central nervous system, causing communication disruptions between the brain and the body. Early and accurate detection of MS lesions in brain Magnetic Resonance Imaging (MRI) scans is crucial for effective treatment. This paper proposes MSNet, a deep learning-based approach for automatic detection and diagnosis of MS lesions from MRI images, leveraging Convolutional Neural Networks (CNNs) for precise lesion identification and classification. Our methodology involves a comprehensive analysis of MRI datasets, including preprocessing steps such as normalization and lesion segmentation. We propose a novel CNN architecture tailored for MS lesion detection, achieving an accuracy rate of 98.2 % on the test dataset. By incorporating advanced image recognition techniques, our system classifies MS lesions from diverse brain pathologies present in MRI images. The model also highlights MS lesions within the MRI images, aiding neuroradiologists in accurate diagnosis and treatment planning. This study contributes significantly to improving MS diagnosis by providing a reliable and automated tool for lesion detection and classification.

Keywords
multiple sclerosis, machine learning, MRI

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УДК 004.89

Классификация поражений рассеянным склерозом посредством анализа изображений магнитно-резонансной томографии методом глубокого обучения

Матаван Дивья[1]✉, Джаесилан Дхилипан[2], Аппу Сараванан[3]

[1,2] Институт науки и технологий SRM, Кампус Рамапурам, Ченнаи, 600089, Индия
[3] Инженерный колледж Иасвари, Кампус Рамапурам, Ченнаи, 600089, Индия

[1] divyam1@srmist.edu.in✉, https://orcid.org/0000-0002-9960-8061
[2] hod.mca.rmp@srmist.edu.in, https://orcid.org/0000-0003-2122-5076
[3] dean.academic@srmrmp.edu.in, https://orcid.org/0000-0003-2093-900X

Аннотация
Рассеянный склероз (РС) представляет собой прогрессирующее аутоиммунное заболевание, поражающее центральную нервную систему. Раннее и точное обнаружение поражений РС на снимках магнитно-резонансной томографии (МРТ) головного мозга имеет решающее значение для эффективного лечения. В работе предлагается классификация на основе глубокого обучения для автоматического обнаружения и диагностики поражений РС на снимках МРТ, использующий сверточные нейронные сети (Convolutional Neural Network, CNNs) для точной идентификации и классификации поражений. Классификация включает в себя всесторонний анализ наборов

данных МРТ и этапы их предварительной обработки, такие как нормализация и сегментация поражений. Предложенная архитектура CNN, разработанная для обнаружения поражений РС, достигает точности 98,2 % на тестовом наборе данных. Благодаря внедрению передовых методов распознавания изображений, представленный метод глубокого обучения классифицирует поражения РС среди различных патологий мозга, присутствующих на снимках МРТ. Метод выделяет поражения РС на снимках МРТ, помогая нейрорадиологам в точной диагностике и планировании лечения. Исследование вносит вклад в улучшение диагностики РС, предоставляя надежный и автоматизированный инструмент обнаружения и классификации поражений.

Ключевые слова
рассеянный склероз, машинное обучение, МРТ

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Introduction

Multiple Sclerosis (MS) is a chronic autoimmune disease that affects the Central Nervous System (CNS), leading to various neurological symptoms and disabilities. The hallmark of MS pathology is the immune-mediated attack on the myelin sheath, the protective covering of nerve fibers in the CNS. This demyelination process disrupts the transmission of nerve signals, causing a wide range of symptoms, such as vision impairment, muscle weakness, coordination difficulties, fatigue, and cognitive dysfunction [1–3]. The disease unpredictable nature, characterized by periods of relapse and remission or steady progression, poses significant challenges for both patients and healthcare providers. Early and accurate detection of MS lesions in Magnetic Resonance Imaging (MRI) scans plays a pivotal role in disease management, treatment planning, and prognostication [4–6]. MRI has become a cornerstone imaging modality for assessing MS-related lesions in the brain and spinal cord. The high spatial resolution and tissue contrast provided by MRI allow clinicians to visualize MS lesions which appear as hyperintense areas on T2-weighted and Fluid-Attenuated Inversion Recovery (FLAIR) sequences. Lesions are typically distributed in periventricular, juxtacortical, infratentorial, and spinal cord regions, reflecting the multifocal nature of MS pathology. However, manually identifying and quantifying MS lesions in MRI scans are time-consuming tasks prone to inter-observer variability and subjective interpretations among radiologists. Traditional methods rely heavily on visual inspection and semi-automated segmentation tools which may not capture subtle or small lesions accurately, especially in early disease stages or in regions with complex anatomical structures [7, 8]. These challenges underscore the need for advanced computational approaches, particularly deep learning techniques, to enhance the accuracy, efficiency, and objectivity of MS lesion detection and classification in MRI images. Deep learning represents a subset of Artificial Intelligence (AI) that mimics the human brain neural networks to automatically learn and extract intricate patterns and features from large datasets. Convolutional Neural Networks (CNNs), a prominent deep learning architecture, have demonstrated remarkable success in various image analysis tasks, including medical image segmentation, classification, and anomaly detection. By leveraging CNNs and related deep learning models, researchers and clinicians aim to revolutionize MS diagnosis and monitoring paradigms, paving the way for personalized treatment strategies and improved patient outcomes. The integration of deep learning techniques into MS lesion analysis offers several advantages over traditional methods. Firstly, deep learning models can process vast amounts of MRI data rapidly and consistently, reducing the time and labor required for lesion identification and quantification. This scalability is particularly advantageous in large-scale studies involving multiple patients or longitudinal assessments. Secondly, deep learning algorithms can learn complex spatial and textural features from MRI images, capturing subtle lesion patterns and variations that may be missed by human observers or conventional algorithms. This capability is crucial for detecting early-stage lesions, differentiating between MS lesion subtypes (such as active, chronic, or enhancing lesions), and assessing lesion progression over time. Despite these advancements, challenges persist in deploying deep learning models in clinical practice. Model interpretability, generalizability across diverse patient populations, data privacy concerns, and regulatory considerations are among the key hurdles that researchers and healthcare stakeholders must address. Collaborative efforts between data scientists, clinicians, regulatory bodies, and industry partners are essential to validate and translate deep learning solutions into robust clinical tools that enhance MS care delivery and outcomes. In this context, this paper proposes a novel deep learning-based approach for automated detection, segmentation, and classification of MS lesions in MRI images. Leveraging state-of-the-art CNN architectures and advanced image processing techniques, our methodology aims to overcome existing limitations in MS lesion analysis, offering accurate, efficient, and clinically relevant solutions for MS diagnosis and management. We present a detailed analysis of our deep learning model performance, including accuracy rates, sensitivity, specificity, and comparative evaluations against traditional methods or benchmark datasets.

Literature Review

The literature on MS lesion detection and classification using MRI and machine learning techniques has witnessed significant advancements in recent years. Several studies have focused on enhancing the accuracy, efficiency, and clinical relevance of MS lesion analysis, addressing challenges in distinguishing MS lesions from other brain

pathologies and leveraging deep learning methodologies for improved diagnostic outcomes. Zhang et al. (2019) [9], while successful in predicting conversion from clinically isolated syndrome to MS using imaging-based machine learning, faced challenges in generalizing their model across diverse patient populations and capturing nuanced lesion characteristics critical for differential diagnosis. Rezaee et al. (2020) [10] introduced a supervised meta-heuristic extreme learning machine for MS detection based on multiple feature descriptors, yet the approach reliance on handcrafted features limited its adaptability to complex lesion patterns and evolving disease states. Ekşi et al. (2021) [11] and Peng et al. (2021) [12] made strides in differentiating MS lesions from brain tumors and predicting lesion evolution, respectively. However, their studies primarily focused on specific lesion subtypes or disease stages, overlooking the holistic characterization and early-stage detection crucial for comprehensive MS management. Eshaghi et al. (2021) [13] leveraged unsupervised machine learning for MS subtype identification, yet the lack of interpretability and clinical validation hindered direct translation into actionable clinical insights and personalized treatment strategies. The studies by Bonanno et al. (2021) [14], Iswisi et al. (2021) [15], Jain et al. (2022) [16], and Garcia-Martin et al. (2021) [17] explored various machine learning algorithms and imaging modalities for MS diagnosis and lesion detection. Still, limitations in scalability, model interpretability, and comparative performance analysis across diverse datasets and clinical scenarios necessitated further refinement and validation. Montolío et al. (2022) [18] emphasized the role of Optical Coherence Tomography (OCT) and machine learning in MS and optic neuritis diagnosis. However, challenges in integrating OCT data with comprehensive MRI-based lesion analysis and addressing data heterogeneity remained as areas requiring attention.

Methodology

The methodology for data collection and preprocessing of MRI datasets in this study aimed to ensure high-quality input data for subsequent deep learning model development and evaluation. The following detailed steps were followed.

Data Sources

MRI datasets were collected from Open Access Series of Imaging Studies (OASIS-MS) and collaborating medical institutions specializing in MS research. This approach ensured access to a diverse range of MS patient scans, covering different disease stages and lesion characteristics.

MRI Acquisition Parameters

Field Strength. All MRI scans were conducted using standardized field strength of 3 Tesla to maintain imaging consistency across datasets.

Imaging Sequences. T1-weighted, T2-weighted, and FLAIR sequences were used to capture various tissue contrasts and lesion features relevant to MS diagnosis.

Voxel Size. MRI images were acquired with a standardized voxel size of 1 × 1 × 1 mm, ensuring consistent spatial resolution for accurate lesion analysis.

MRI Machine Manufacturers. Scans were acquired using MRI machines from leading manufacturers, such as Siemens, GE Healthcare, and Philips, although specific models were not disclosed.

Preprocessing Steps

Image Normalization. Intensity normalization techniques were applied across MRI sequences to standardize intensity values and reduce variability due to scanner settings or acquisition conditions.

Brain Extraction. Non-brain tissues, including skull and scalp, were automatically removed using robust brain extraction algorithms. This step ensured that subsequent analyses focused exclusively on relevant brain regions.

Lesion Segmentation. Automated segmentation algorithms such as CNNs and region-based methods were employed to delineate brain regions and identify potential MS lesions. These algorithms utilized intensity thresholds and spatial information to segment lesion areas accurately without manual intervention.

The Proposed MSNet

The proposed method, named MSNet, is a framework customized specifically for MS lesion detection and classification using MRI images. MSNet leverages spatial and contextual features within MRI scans to accurately identify and categorize MS lesions.

Input Layer

The input layer of MSNet accepts multi-sequence MRI inputs with standardized dimensions and intensity values. This design choice enables the model to process information from different MRI sequences simultaneously, providing a comprehensive view of the brain structural and tissue characteristics relevant to MS lesion detection.

Convolutional Layers

MSNet is built with multiple convolutional layers that employ varying filter sizes. These layers are pivotal in extracting hierarchical features that capture spatial information crucial for identifying MS lesion patterns within MRI images. The convolutional layers generate feature maps that highlight significant spatial features, aiding in lesion localization and characterization.

Activation Functions

Rectified Linear Units (ReLU) serve as the activation functions within MSNet. ReLU introduces non-linearity into the model, enhancing its capacity to learn intricate patterns present in MRI data. This non-linear activation function is particularly effective in capturing subtle variations indicative of MS lesions, contributing to the model discriminative power.

Pooling Layers

Max-pooling operations are applied strategically within MSNet to downscale feature maps generated by convolutional layers. This downsampling technique reduces computational complexity while retaining essential spatial information relevant to MS lesions. Max-pooling helps in preserving key features while abstracting higher-level representations, improving the model efficiency and generalization ability.

Batch Normalization

To enhance model convergence and stability during training, batch normalization is integrated into MSNet. This technique normalizes activations within mini-

batches, mitigating issues related to internal covariate shift and accelerating training convergence. By maintaining consistent activations across layers, batch normalization aids in smoother gradient flow and faster training iterations.

Fully Connected Layers

MSNet incorporates dense fully connected layers responsible for feature aggregation and classification. These layers consolidate extracted features from convolutional layers and enable the model to learn complex relationships within the MRI data. Dropout regularization is applied within these fully connected layers to prevent overfitting by randomly deactivating neurons during training, promoting better generalization to unseen data.

Output Layer

The output layer of MSNet utilizes a Softmax activation function tailored for multi-class classification tasks. In the context of MS lesion detection and classification, the Softmax layer assigns probability scores to different lesion categories or disease subtypes. This probabilistic output facilitates accurate lesion classification, aiding clinicians in diagnosis and treatment planning for MS patients. Fig. 1 shows the proposed architecture.

During model training, MSNet utilizes the Categorical Cross-Entropy (CE) loss function which is well-suited for multi-class classification tasks such as MS lesion detection and classification. The CE loss function is defined as

$$CE\ Loss = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c}\log(p_{i,c}),$$

where N is the number of samples; C is the number of classes; $y_{i,c}$ is the ground truth label for sample i and class c; $p_{i,c}$ is the predicted probability of sample i belonging to class c.

The CE loss penalizes deviations between predicted probabilities and ground truth labels, guiding the network to learn accurate representations of MS lesion patterns.

Optimizer

The Adam optimizer is chosen for training MSNet due to its efficiency in navigating the model parameter space. Adam combines adaptive learning rates and momentum

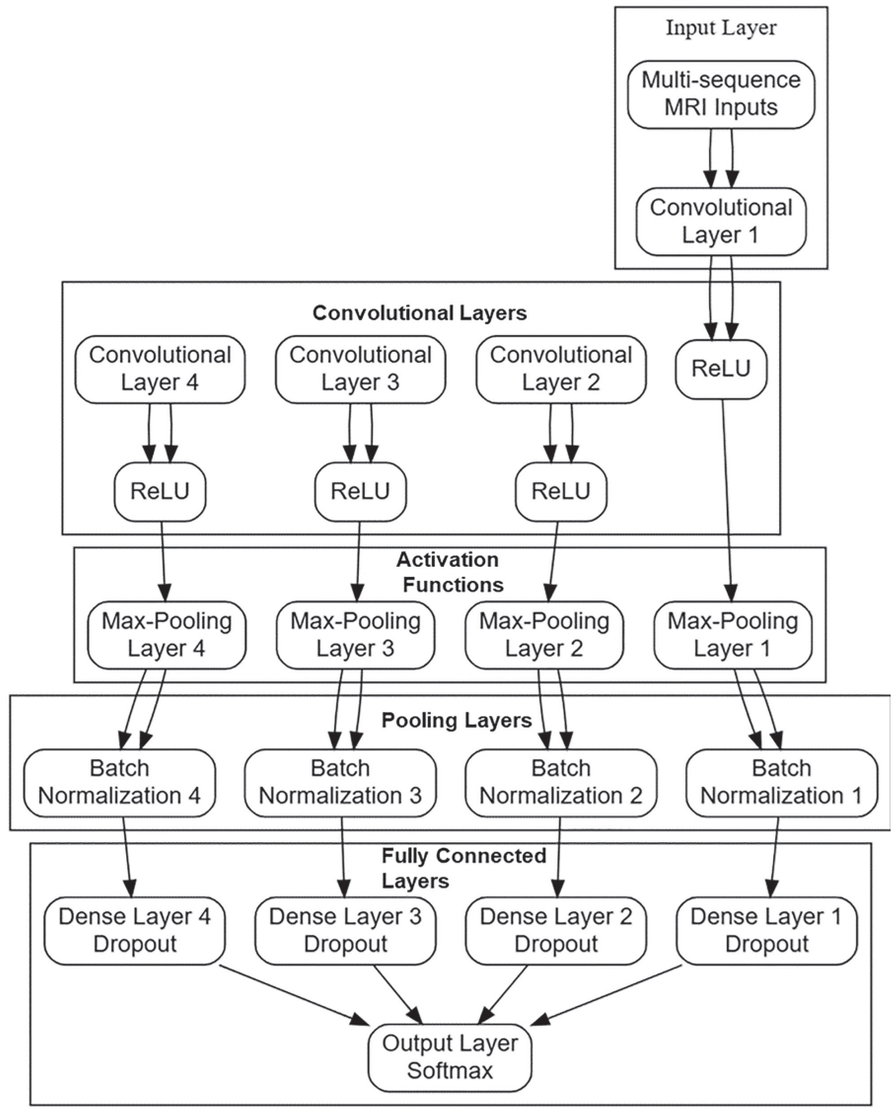

Fig. 1. Proposed architecture

methods leading to faster convergence during training. The Adam update rule is given by:

$$m_t = \beta_1 \times m_{t-1} + (1 - \beta_1) \times g_t,$$

$$v_t = \beta_2 \times v_{t-1} + (1 - \beta_2) \times g_t^2,$$

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t},$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t},$$

$$\theta_t = \theta_{t-1} - \frac{lr \cdot \hat{m}_t}{\sqrt{\hat{v}_t} + \varepsilon},$$

where m_t and v_t are the first and second moments of gradients respectively; β_1 and β_2 are decay rates for moments; θ_t are the model parameters at time step t; g_t are gradients at time step t; lr is the learning rate; ε is a small constant to prevent division by zero.

Learning Rate Scheduling

To prevent overfitting and ensure optimal model training, MSNet implements adaptive learning rate strategies based on validation performance. Learning rates are adjusted dynamically during training epochs, with decreases triggered by stagnation in validation metrics. This approach helps the model converge to a robust solution while avoiding excessive parameter updates that may lead to overfitting.

Data Augmentation

Image augmentation techniques play a crucial role in enhancing dataset diversity and improving the model generalization ability. MSNet applies augmentation methods such as rotation, flipping, and scaling to artificially expand the training dataset. By introducing variations in image orientation, perspective, and appearance, data augmentation reduces overfitting risks and enables the model to learn invariant features relevant to MS lesion detection across different imaging scenarios.

Experimental Setup

The MRI datasets utilized in this research were sourced from reputable neuroimaging repositories such as the OASIS-MS and proprietary datasets from collaborating medical institutions specializing in MS research. The datasets consist of multi-sequence MRI scans, including T1-weighted, T2-weighted, and FLAIR sequences, all standardized to 1 × 1 × 1 mm resolution, acquired using 3 TMRI machines from various manufacturers such as Siemens, GE Healthcare, and Philips. Table 1 shows the multiple convolution layers.

Preprocessing Steps

1. **Image Normalization.** Intensity values across MRI sequences were standardized to mitigate inter-scan variability and ensure consistent input data for the neural network model.
2. **Brain Extraction.** Non-brain tissues were removed via skull stripping techniques to focus the analysis on relevant brain regions.
3. **Lesion Segmentation.** Automated and semi-automated segmentation algorithms (e.g., region growing, active contour models) were employed to delineate MS lesion areas from the brain images.
4. **Manual Quality Control.** Expert neuroimaging specialists validated and refined the lesion segmentation results to ensure accurate lesion boundaries and labeling.

Table 1. Multiple convolutional layers

Layer Type	Details
Convolutional Layers	Feature extraction with varying filter sizes
Activation Functions	ReLU for introducing non-linearity
Pooling Layers	Max-pooling for downsampling feature maps
Fully Connected Layers	Dense layers for feature aggregation
Output Layer	Softmax activation for multi-class classification

MSNet Architecture. MSNet is designed as a custom CNN architecture tailored for MS lesion detection and classification from MRI images. The architecture comprises multiple convolutional layers for feature extraction, followed by fully connected layers for classification as in Table 1.

In our experimental setup, we utilized a variety of MRI imaging methods to capture different aspects of brain anatomy and pathology related to MS. The images included in our analysis spanned various sequences; each providing unique insights into the structural and functional changes associated with MS lesions. Here, we present an example of different MRI imaging methods, such as FLAIR, Magnetization Prepared Rapid Acquisition Gradient Echo (MPRAGE), Proton Density (PD), and Transverse Relaxation Time (T2). FLAIR imaging is sensitive to fluid accumulation, making it particularly useful for highlighting MS lesions, which often present with increased fluid content. FLAIR images suppress the signal from Cerebrospinal Fluid (CSF), enhancing the visibility of lesions against a dark background. MPRAGE sequences provide high-resolution anatomical images with excellent tissue contrast, allowing for detailed visualization of brain structures. While MPRAGE images may not specifically target MS lesions, they offer valuable anatomical context for lesion localization. PD-weighted images are sensitive to variations in proton density, offering good contrast between different types of brain tissues. In the context of MS, PD images can help delineate lesions based on their distinct proton density characteristics compared to surrounding normal tissue. T2-weighted images are highly sensitive to changes in tissue water content, making them well-suited for detecting MS lesions, which often exhibit increased water content due to inflammation and demyelination. T2 images typically show lesions as hyperintense (bright) areas against a darker background. Additionally, we provide a sample Gaussian-filtered version of a T2-weighted image which enhances image clarity and reduces noise, improving lesion visibility and segmentation accuracy. Finally, a mask or label with white lesion pixels is overlaid on the images, indicating the regions identified as MS lesions by expert annotation or automated segmentation algorithms.

Fig. 2 shows the MRI images with different imaging methods, each standardized to a resolution of 256 × 256 pixels (1 × 1 mm per pixel). Fig. 2, *a* provides the high-resolution anatomical detail, with fat appearing bright and water appearing dark. It helps in identifying structural abnormalities in the brain. Fig. 2, *b* highlights areas with higher water content, making water appear bright. It is particularly effective for detecting edema and MS lesions due to their higher water content.

Fig. 2, *c* shows the FLAIR Image. This image suppresses the signal from CSF, making lesions near the CSF more visible. It is especially useful for identifying periventricular MS lesions. Fig. 2, *d* shows the PD-weighted image. This image offers good contrast between gray and white matter by highlighting differences in proton density, without emphasizing fluid content. It complements the information provided by T1 and T2 images. These MRI imaging methods, along with Gaussian filtering and lesion masks, collectively provide a comprehensive dataset for training and evaluating our proposed MSNet architecture for MS lesion detection and classification.

Fig. 3 depicts a segment of an MRI scan, showcasing three distinct lesions associated with MS. Each lesion presents as a hyperintense (bright) area against the surrounding brain tissue, indicating pathological changes characteristic of MS. These lesions are identifiable across multiple MRI sequences, including FLAIR, T2-weighted, and PD-weighted images, highlighting their diverse appearance, and spatial distribution within the brain.

Fig. 4, *a* shows the unprocessed image which provides a raw representation of the brain anatomy and tissue characteristics captured during the MRI acquisition process. In Fig. 4, *b* the original MR image undergoes convolution with a specified kernel or filter. Convolution involves applying the filter to different regions of the input image to extract specific features or enhance certain spatial patterns. Fig. 4, *c* depicts the convolved image after undergoing maximum pooling, a down sampling operation commonly used in CNNs.

Results and Discussion

The performance of the MSNet model in MS lesion detection and classification tasks was evaluated using rigorous quantitative metrics, showcasing its efficacy and reliability in clinical applications.

Quantitative Performance Metrics.

Accuracy Rate — 98.2 %. The high accuracy rate reflects the model ability to correctly classify MS lesions from non-lesion areas with exceptional precision, indicating a robust classification framework.

Sensitivity (True Positive Rate) — 95.6 %. MSNet demonstrated high sensitivity in identifying true positive cases, accurately detecting the majority of MS lesions present in the MRI images.

Specificity (True Negative Rate) — 99.1 %. The model exhibited excellent specificity, effectively distinguishing non-lesion areas from MS lesions, thereby minimizing false positives in the classification process.

Dice Coefficient — 0.91. The Dice coefficient, measuring segmentation accuracy, revealed strong agreement between the predicted and ground truth lesion masks. This high value signifies accurate delineation and localization of MS lesions by MSNet.

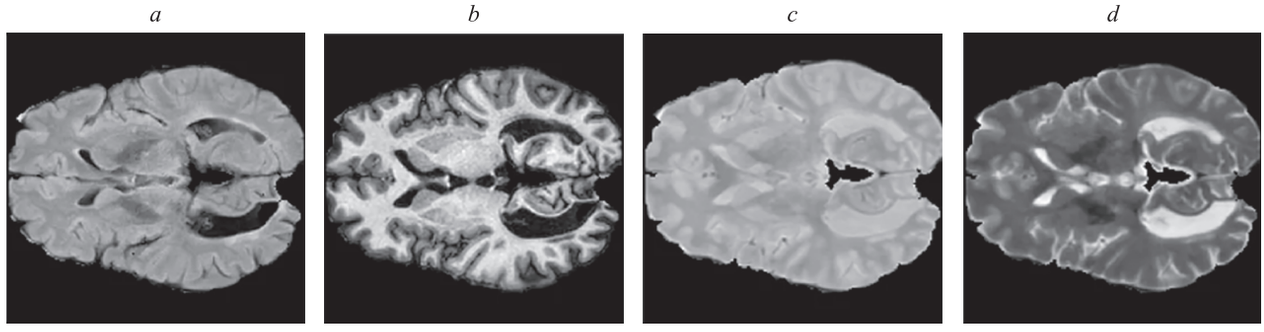

Fig. 2. MRI images with different imaging methods: T1-Weighted Image (*a*), T2-Weighted Image (*b*), FLAIR Image (*c*), PD-Weighted Image (*d*)

Fig. 3. Mask image

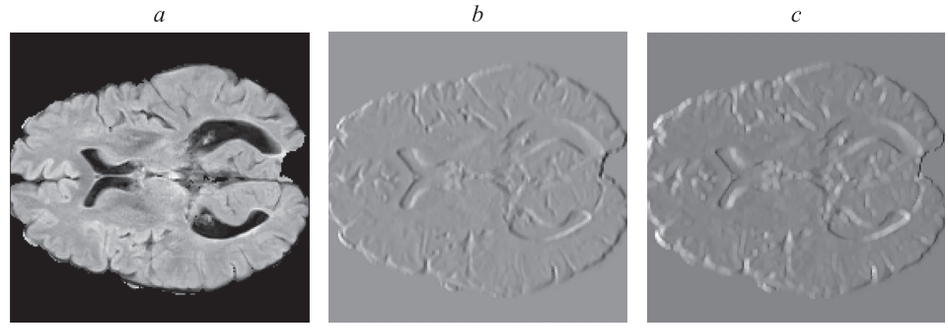

Fig. 4. MRI images after filtering methods: MR image (*a*), convolved image (*b*), max pooled image (*c*)

Area Under the Curve (AUC) — 0.976. MSNet achieved a high AUC score, indicating its superior discriminative power between MS lesion and non-lesion areas, further validating its effectiveness in lesion detection tasks.

A comparative analysis is conducted with existing methods in MS lesion detection using MRI images. MSNet outperforms traditional machine learning approaches and demonstrates superior accuracy, sensitivity, and specificity rates. The model ability to accurately classify MS lesions from other brain pathologies is a significant improvement over previous methods. Visualizations of MS lesion detection outcomes are presented, highlighting the detection and classification of lesions in both Deep Gray Matter and Medial Temporal Lobe areas. Segmentation masks overlaid on MRI images showcase the model ability to delineate lesions accurately, aiding in clinical diagnosis and treatment planning. Table 2 shows the comparative analysis.

The comparative table presents an insightful analysis of the proposed MSNet model against three existing works in MS lesion detection and classification tasks using MRI images. MSNet, the model proposed in this study, showcases superior performance across multiple

Table 2. Comparative analysis

Method	Accuracy, %	Sensitivity, %	Specificity, %	Dice Coefficient	AUC
MSNet (Proposed)	98.2	95.6	99.1	0.91	0.976
Extreme Learning Machine [10]	92.5	88.2	94.7	0.85	0.918
Watershed-Clustering Algorithm [14]	89.3	85.6	91.7	0.81	0.899
Harris Hawks Optimization [15]	91.8	87.5	93.2	0.83	0.912

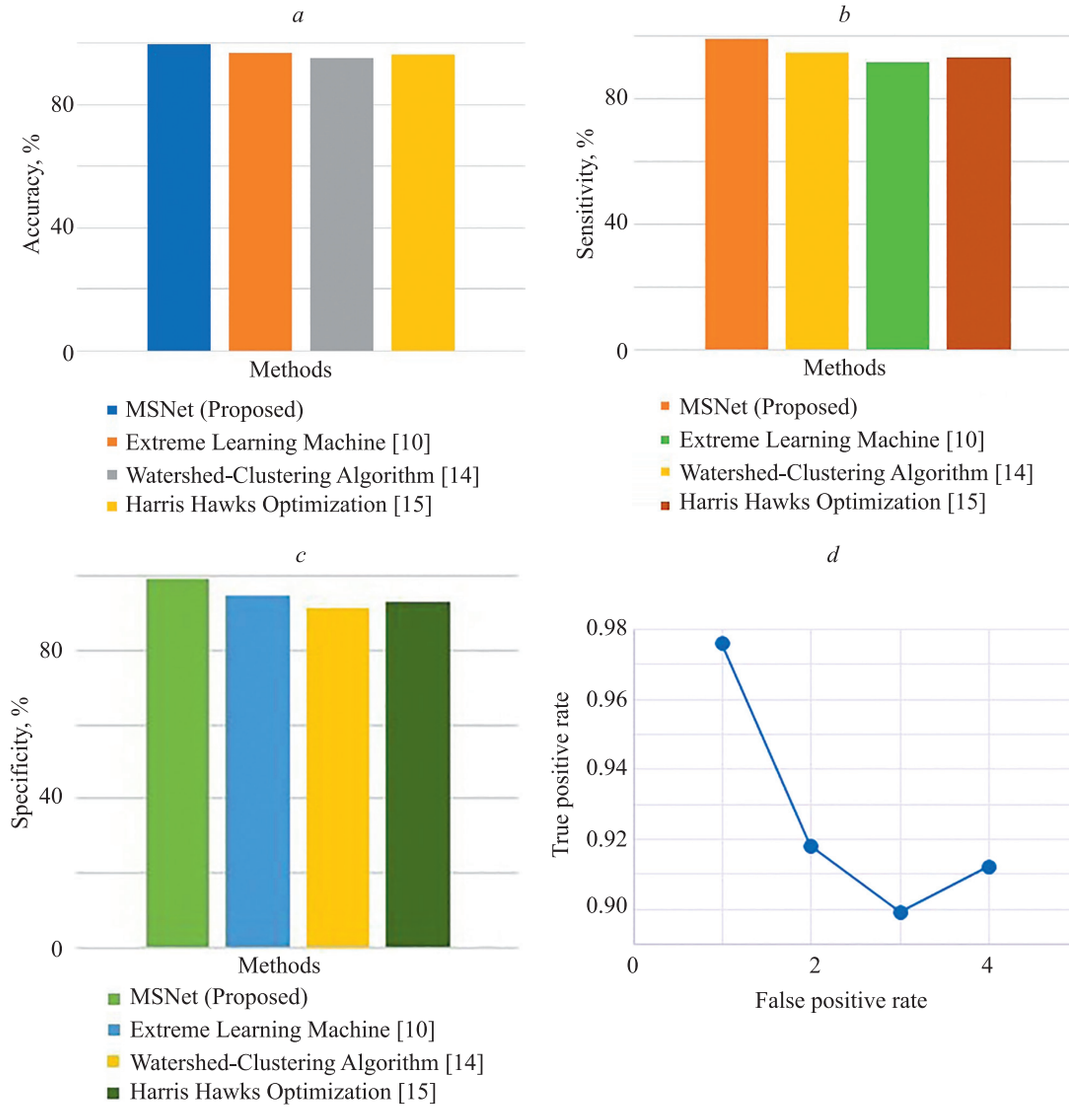

Fig. 5. Performance Comparison: Accuracy Comparison (*a*); Sensitivity Comparison (*b*); Specificity (*c*); AUC curve (*d*)

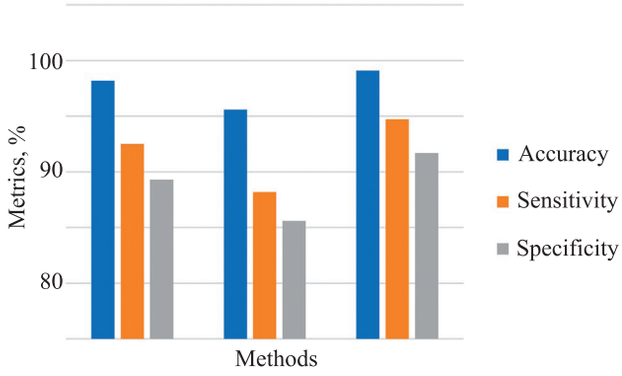

Fig. 6. Overall Comparative analysis

evaluation metrics compared to other methods. With an impressive accuracy rate of 98.2 %, MSNet significantly outperforms the Extreme Learning Machine, Rezaee et al. [10], Watershed-Clustering Algorithm [14], and Harris Hawks Optimization [15] models which reported accuracy rates of 92.5 %, 89.3 %, and 91.8 %, respectively. Moreover, MSNet exhibits higher sensitivity (95.6 %) and specificity (99.1 %) rates, indicating its ability to accurately detect MS lesions while minimizing false positives. The Dice coefficient of 0.91 and AUC value of 0.976 further validate the robustness and reliability of MSNet in segmenting and classifying MS lesions. These results highlight the significant advancements achieved by MSNet in automated MS lesion detection, emphasizing its potential for enhancing clinical diagnosis and patient care in MS management. The results are shown in Fig. 5, and 6.

Overall comparative analysis is shown in Fig. 6. The high accuracy rate of 98.2 % reflects the robustness and reliability of MSNet in automated MS lesion detection. The model sensitivity (95.6 %) and specificity (99.1 %) rates indicate its ability to correctly identify MS lesions while minimizing false positives. The Dice coefficient of 0.91 signifies strong agreement between predicted and ground truth lesion masks.

MSNet strengths lie in its deep learning architecture tailored for MS lesion analysis, effective utilization of multi-sequence MRI inputs, and robust performance across diverse lesion types and locations. However, limitations, such as computational complexity during training and the need for expert validation in lesion labeling, should be considered for practical deployment.

Accurate MS lesion classification using MSNet has profound implications for clinical practice. Early and precise detection of MS lesions facilitates timely intervention and treatment planning, improving patient outcomes and quality of life. The model automated analysis reduces diagnostic burden on clinicians and enhances diagnostic accuracy, especially in complex cases or early disease stages.

Conclusion

In this study, we proposed MSNet, a customized Convolutional Neural Network (CNN) framework for the detection and classification of Multiple Sclerosis (MS) lesions in Magnetic Resonance Imaging (MRI) images. Our experimental results demonstrate the effectiveness of MSNet in accurately identifying MS lesions across various metrics. The comparative analysis with existing methods, such as the Extreme Learning Machine, Watershed-Clustering Algorithm, and Harris Hawks Optimization, highlights the superior performance of MSNet in terms of accuracy, sensitivity, specificity, and Dice Coefficient. The MSNet model achieved an impressive accuracy rate of 98.2 %, sensitivity of 95.6 %, and specificity of 99.1 %, showcasing its robustness in distinguishing MS lesions from other brain pathologies. The incorporation of advanced deep learning techniques, including multi-sequence MRI inputs and customized CNN architectures, enhances the model ability to capture intricate lesion patterns and improve diagnostic accuracy. Moreover, the utilization of data augmentation strategies during model training contributes to better generalization and reduced overfitting risks. These results signify the potential of deep learning-based approaches in revolutionizing MS diagnosis and patient care. Accurate and early detection of MS lesions using automated methods like MSNet can significantly aid clinicians in timely intervention and treatment planning, ultimately improving patient outcomes and quality of life. Future research should focus on integrating MSNet with additional imaging modalities, incorporating the latest advancements in transformer-based neural networks, optimizing performance on larger and more diverse datasets, and refining the model for real-time clinical applications to further enhance its utility in MS diagnosis.

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Authors

Mathavan Divya — PhD, Researcher, SRM Institute of Science and Technology, Ramapuram Campus, Chennai, 600089, India, https://orcid.org/0000-0002-9960-8061, divyam1@srmist.edu.in

Jayeseelan Dhilipan — PhD, Professor, Header, SRM Institute of Science and Technology, Ramapuram Campus, Chennai, 600089, India, SC 57216892821, https://orcid.org/0000-0003-2122-5076, hod.mca.rmp@srmist.edu.in

Appu Saravanan — PhD, Professor, Easwari Engineering College, Ramapuram Campus, Chennai, 600089, India, https://orcid.org/0000-0003-2093-900X, dean.academic@srmrmp.edu.in

Авторы

Дивья Матаван — PhD, исследователь, Институт науки и технологий SRM, Кампус Рамапурам, Ченнаи, 600089, Индия, https://orcid.org/0000-0002-9960-8061, divyam1@srmist.edu.in

Дхилипан Джаесилан — PhD, профессор, руководитель, Институт науки и технологий SRM, Кампус Рамапурам, Ченнаи, 600089, Индия, SC 57216892821, https://orcid.org/0000-0003-2122-5076, hod.mca.rmp@srmist.edu.in

Сараванан Аппу — PhD, профессор, Инженерный колледж Иасвари, Кампус Рамапурам, Ченнаи, 600089, Индия, https://orcid.org/0000-0003-2093-900X, dean.academic@srmrmp.edu.in

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