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Detection of Multiple Sclerosis Lesions in MR Images Based on Convolutional Neural Networks

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Abstract:
Multiple Sclerosis (MS) is a chronic autoimmune disease that affects the central nervous system and can lead to neurological disabilities. Early and accurate diagnosis plays a key role in managing its long-term effects. This study proposes a novel model based on convolutional neural networks (CNN) for identifying MS lesions in MRI images.
This study used an MRI dataset from 60 individuals divided into training, validation, and test sets. The preprocessing included removing initial slices and applying data augmentation (random rotations) to increase the number of training images to 1080. A customized CNN architecture was designed to learn the features related to MS lesions. The model's performance was evaluated using accuracy, sensitivity, and specificity metrics on validation and test data. The CNN performance was also compared with two machine learning algorithms: decision tree and support vector machine.
The proposed CNN model showed promising performance in detecting MS lesions. It achieved an accuracy of 99% during training and 96.44% during validation, demonstrating its ability to generalize to new data. The test accuracy was 92.6%, with sensitivity and specificity reported as 84% and 95%, respectively. Compared to other methods, the CNN outperformed the support vector machine (accuracy 85%, sensitivity 82.61%, specificity 98%) and the decision tree (accuracy 98%, sensitivity 95%, specificity 83.72%), highlighting its high capability in detecting MS lesions.
This research successfully demonstrates the capability of convolutional neural networks (CNN) in the accurate and automated detection of MS lesions in MRI images, achieving a test accuracy of 92.6%. The superior performance of CNN compared to traditional machine learning methods offers a promising approach for improving diagnostic accuracy, reducing reliance on human factors, and accelerating therapeutic interventions. The development of such tools can assist clinical specialists, enhance diagnostic efficiency, and facilitate better patient management. In the future, it is recommended to focus on improving CNN architecture, utilizing broader datasets, and exploring its application in different types of MS and disease progression monitoring.

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1. Introduction

Multiple sclerosis (MS) is a chronic autoimmune disease of the central nervous system (CNS) that has become a significant concern with increased life expectancy and improvements in public health. This disease, which is more prevalent among women and typically affects young individuals between the ages of 20 and 40, leads to the destruction of the myelin sheath surrounding nerve cells (axons), resulting in various neurological disorders and disabilities [1]. Despite notable advancements in diagnosis and treatment over recent decades, MS remains one of the leading causes of non-traumatic disability in adults worldwide. Its rising prevalence brings with it widespread social and economic consequences. The exact causes of this

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disease are still not fully understood; however, complex interactions between genetic predispositions and environmental factors, such as low vitamin D levels, smoking, childhood obesity, and infection with the Epstein-Barr virus, are believed to play a significant role in its onset [2, 3]. Early and reliable diagnosis of MS, especially in its initial stages and through non-invasive methods, is crucial for reducing serious complications and the risk of mortality, particularly in older individuals [4]. This research addresses a fundamental medical need: developing low-cost and non-invasive diagnostic methods. MRI has become a key tool for visualizing MS lesions, which indicate damage to the myelin sheath in the brain and spinal cord. The introduction of MRI in the 1980s revolutionized MS diagnosis by enabling live visualization of lesions and monitoring the progression of the disease [5].

This study uses convolutional neural networks (CNNs) to automate and accurately diagnose MS using brain and spinal cord MRI images. This research includes collecting MRI data from MS patients and healthy individuals, preprocessing the images to enhance quality, designing and training a CNN model to detect MS-related patterns, extracting relevant features using the trained model, and finally classifying the images into healthy and MS categories.

This research aims to demonstrate that CNNs can reduce dependence on human interpretation, minimize errors, enable timely diagnosis, monitor disease progression, and ultimately contribute to improving therapeutic strategies and personalized medical approaches for MS patients.

2. Research Background

Today, the science of image processing plays a significant role in aiding physicians and surgeons in diagnosis, treatment, and planning, enhancing accuracy in many medical procedures [6]. Interpreting MRI images for diagnosing multiple sclerosis (MS) is time-consuming and may vary among specialists. For this reason, numerous studies have investigated artificial intelligence, especially deep learning and convolutional neural networks (CNNs), to achieve more automated and accurate disease diagnoses [7-9]. In a study by Cole et al. [10], deep CNNs were proposed as a superior method to traditional visual analysis for extracting relevant features from MRI data in MS diagnosis. The study included 319 individuals who had available brain MRI sequences for image analysis and clinical assessment within six months after an MS attack. Layer-wise Relevance Propagation (LRP) was used to analyze the model's decision-making process to generate attention maps. The analysis of these maps revealed that the temporal lobe and cerebellum played a significant role in the CNN model's decisions. The model achieved an accuracy of 79%, and its effectiveness was confirmed by applying it to an independent external group without retraining, where it reached an accuracy of 71%. The results showed that CNNs are capable of identifying key anatomical features correlated with MS-related disability progression. Cracchiani et al. [11] also examined microstructural differences between progressive MS and relapsing-remitting MS using diffusion MRI and structural T1 MRI. They extracted features related to water diffusion in brain tissue, trained CNN models on this data, and identified brain regions with the highest contribution to classification using heatmaps. The results indicated differences in gray matter texture between the two MS types. The LRP method was also used to explain the most influential imaging components in subtype differentiation, helping uncover hidden information and enhancing the understanding of the disease's various forms. Filippi et al. [12] also highlighted the significant evolution of MRI diagnostic criteria for MS, including the 2017 McDonald criteria, which improved the sensitivity and accuracy of early diagnosis for the clinically isolated syndrome. While emphasizing the clinical efficiency of these criteria, they also pointed out the need to identify new biomarkers to improve diagnostic specificity and reduce the risk of misdiagnosis. Despite their high potential, indicators such as the central vein sign and chronic active lesions require further validation and standardization before clinical implementation. Nonetheless, there remains a strong emphasis on the need for up-to-date research on the clinical application of AI in MRI analysis for MS patients.

In a review study, Moazami et al. [13] categorized the main applications of machine learning using MRI data in multiple sclerosis (MS) into four areas: automated MS diagnosis, disease progression prediction, differentiation of various MS stages, and distinguishing MS from similar disorders. In automated diagnosis, SVM models using features extracted from MRI images achieved a high accuracy of over 89% in distinguishing MS patients from healthy individuals. Transfer learning in CNNs outperformed deep networks and random forest algorithms for predicting disease progression in forecasting disease conversion within the next two years. Regarding the differentiation of MS stages, studies utilized metabolic features and lesion locations combined with LDA and SVM algorithms to classify MS subtypes. Moreover, in the differential diagnosis between MS and neuromyelitis optica spectrum disorder (NMOSD), CNNs and transfer learning achieved 71% and 75% accuracy rates. The ability of these models to directly extract meaningful information from images and overcome data limitations through transfer learning represents a significant advantage in this field. Beyond lesion detection and disease prognosis, artificial intelligence has also been used to enhance the quality of MRI images. Leomora et al. [14] emphasized that high-resolution MRI imaging can offer a more accurate view of MS lesions. They utilized a novel deep learning-based image reconstruction technique (DLR) that reduces noise and sharp artifacts while preserving edges, thereby increasing the diagnostic value of thin 2D slices. A comparison between DLR-processed T2 images (1 mm slice thickness) and conventional MRI (5 mm slice thickness) in 42 MS patients showed a significantly higher number of detected lesions in the processed images. The whole-brain lesion detection process using DLR took about 7 minutes, an acceptable time frame for automated analysis. Additionally, Mani et al. [15] proposed a deep learning-based autoencoder model to enhance the quality of brain MRI sequences. Using a 2.5D approach, this model took a

set of low-resolution MRI slices as input and generated high-resolution outputs by leveraging information from neighboring slices. The model was trained on randomly degraded scans to minimize the L1 loss function between the reconstructed and original high-resolution images. This research demonstrates the ongoing efforts to improve the quality of base data for further analysis in MS-related studies.

In another approach focusing on the automatic segmentation of lesions, Fenteo et al. [16] aimed to reduce user interaction and the time required for this task by leveraging deep learning, particularly CNNs. They noted that although various CNN architectures are commonly used, detailed justifications for their selection are often lacking. Therefore, they explored the impact of simplifications and modifications in architectural design. As a result, they developed a lightweight and competitive architecture named "U-net" with only about 30,000 parameters. Experimental results on FLAIR MRI images showed that despite its low parameter count, this model achieved satisfactory performance in automatically segmenting MS lesions and reduced the need for human intervention. Despite the central role of brain MRI in diagnosing MS, research has also explored other imaging modalities and biomarkers. Ortiz et al. [17], while addressing the limitations of relying solely on brain lesions or atrophy for MS diagnosis, emphasized the importance of identifying new biomarkers. In a study aimed at detecting novel biomarkers for the early diagnosis of MS, spectral-domain optical coherence tomography (OCT) and artificial intelligence were employed. This study included 79 patients with relapsing-remitting MS and 69 age-matched healthy individuals. Retinal thickness in both eyes and inter-eye differences were analyzed. The results showed that the most significant changes in retinal thickness and inter-eye differences occurred in the ganglion cell, inner plexiform, and inner retinal layers. Using these structural differences as input, a two-layer convolutional neural network achieved an accuracy of 92%, a sensitivity of 87%, and a specificity of 82%. These findings suggest that analyzing the structure of retinal nerve layers using OCT can contribute to diagnostic criteria for MS.

3. Research Method

Deep learning is an evolution of machine learning that involves algorithms learning from data to perform tasks without explicit programming. Traditional machine learning methods are less effective than deep learning techniques because they require a large amount of data to deliver significant results. Deep learning models use a layered network architecture known as an artificial neural network [18].

Convolutional neural networks (CNNs) are robust neural networks widely used in various image-processing tasks. These networks consist of convolution and pooling layers that extract relevant features from the input image [19, 20]. The input to such a network can be an MRI image. The input layer sends the image to the first hidden layer, where filters are applied to the image. Each filter extracts specific features from the image, such as edges or textures. The output of the first hidden layer is passed to the next hidden layer, where more filters are applied to extract higher-level features. This process is repeated through several hidden layers until it reaches the final hidden layer, producing a feature set passed to the output layer. The output layer provides a probability distribution across the number of classes. The network then decides based on the class with the highest probability. The filter weights in each layer are learned through backpropagation, which adjusts the weights to reduce the error between the predicted and actual output [9, 21].

3.1. Dataset

The dataset utilized in this study, sourced from the public Mendeley Data repository consists of brain MRI scans from 60 individuals, including 30 patients clinically diagnosed with Multiple Sclerosis (MS) and 30 age- and sex-matched healthy controls, encompassing both male and female subjects. The MS subset exhibits a variety of lesion characteristics, spanning different types, sizes (ranging from 3 to 15 mm), and anatomical locations (primarily periventricular, cortical, and spinal cord regions), which contributes to the model's potential for generalization across heterogeneous disease presentations. However, the relatively small sample size and absence of longitudinal imaging data represent inherent limitations that may constrain the model's broader applicability as further discussed in the conclusion. Each patient's MRI includes 23 slices, totaling 1,280 samples after preprocessing, divided into 769 training samples, 253 validation samples, and 258 test samples. Figure 2 illustrates two sample images with MS lesions.

3.1.1. Data Augmentation and Preprocessing

To ensure consistency and enhance the quality of the MRI dataset for training the convolutional neural network (CNN), a series of preprocessing steps were applied. All MRI slices were resized to a uniform resolution of 64×64 pixels using bicubic interpolation to maintain spatial consistency while preserving computational efficiency. Slices containing less than 5% gray or white matter content, identified through pixel intensity thresholding, were excluded to focus on regions relevant to MS lesion detection. Intensity normalization was performed using z-score normalization (mean = 0, standard deviation = 1) to standardize pixel intensities across FLAIR MRI sequences, which had a slice thickness of 1 mm to ensure high resolution for lesion identification. To augment the training dataset and improve model robustness, data augmentation techniques were applied exclusively during the training phase, increasing the number of training samples from 769 to 3,845. These techniques included random rotations (±15 degrees), horizontal flipping, and intensity scaling (±10%). These augmentation methods were not applied to validation or test datasets to avoid introducing bias during evaluation.

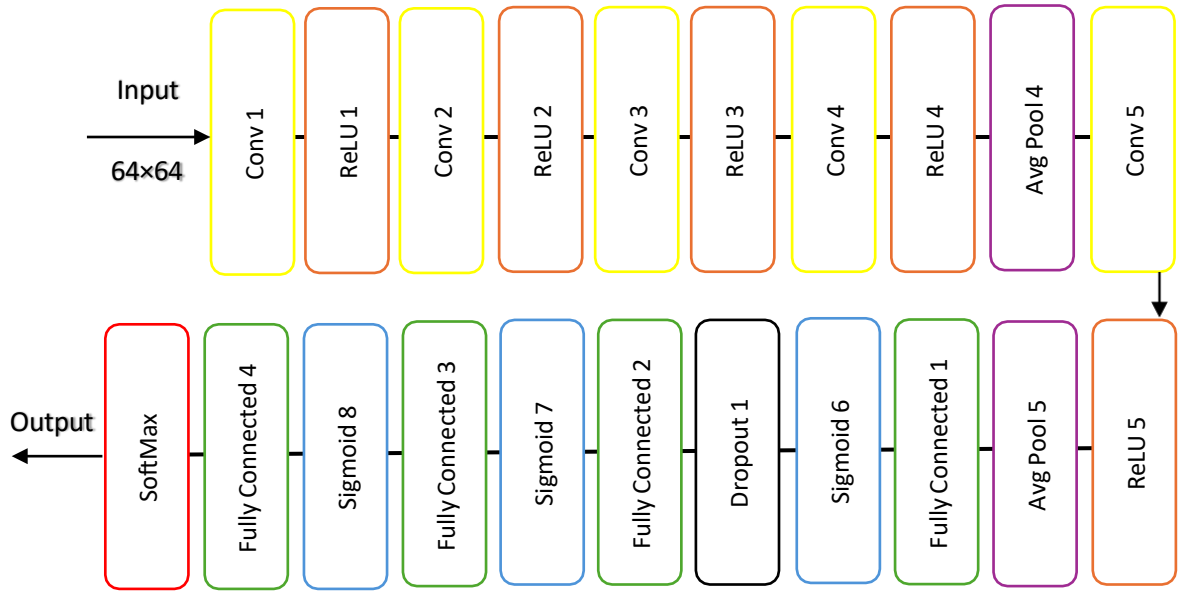

Figure 1. Architecture of the proposed convolutional neural network

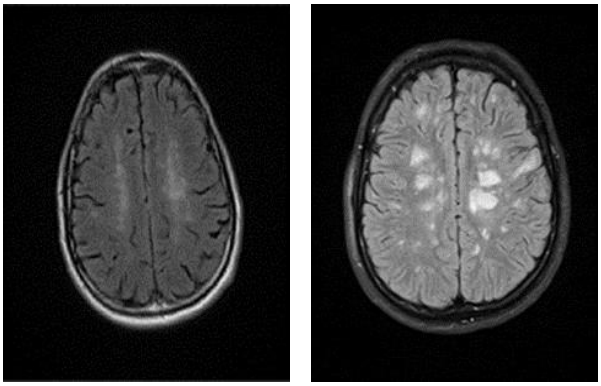

Figure 2. Multiple Sclerosis Lesion in Dataset Images

3.1.2. Training data

This dataset is used to train the model. The model learns to identify patterns and relationships between features and labels from this data. It forms the largest portion of the data. The model learns directly from this data and adjusts its internal weights and parameters accordingly. The quality and diversity of the training data have a direct impact on the model's final performance.

3.1.3. Validation data

This dataset is used to tune model parameters and prevent overfitting. It is not used to train the model but to evaluate its performance on unseen data after training. Based on the performance of this set, hyperparameter optimization, such as learning rate, number of layers, etc., is performed. Poor performance on validation data indicates overfitting or underfitting of the model. The model's performance is assessed on data it has not previously seen.

3.1.4. Test data

This dataset is used to tune model parameters and prevent overfitting. It is not used to train the model but to evaluate its performance on unseen data after training. Based on the performance on this set, hyperparameter optimization, such as learning rate, number of layers, etc., is performed. Poor performance on validation data indicates overfitting or underfitting of the model. The model's performance is assessed on data it has not previously seen.

3.2. Architecture of the proposed method and training of the convolutional neural network

Figure 2 shows the sequence of different layers of the proposed CNN.

1. Input Layer: The input data (images) are fed into the network in this layer.

2. Convolutional Layers (Conv Layers): The convolutional layer is one of the most important components of convolutional neural networks and plays a key role in extracting features from the input image. In this layer, learnable filters, which are small matrices, are used. These filters slide over the input image and examine small patches at each position. At each location, the filter overlays a small window of the image. It performs the dot product (element-wise multiplication) operation between the filter values and those inside that window.

Ultimately, the output of the convolutional layer is a set of feature maps, each corresponding to a specific feature in the image. These feature maps represent various characteristics of the input image.

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3. Activation Layers (ReLU Layers): After each convolutional layer, a ReLU layer introduces non-linearity into the model, allowing the network to learn more complex features.

Without a nonlinear activation function, the network would only learn linear combinations of inputs, which limits its power and accuracy in solving complex problems. ReLU sets negative values to zero and keeps positive values unchanged. Mathematically, if x is the input, the ReLU output is:

4. Pooling Layers: This layer aims to reduce the spatial dimensions of the feature maps produced by the convolutional layer. This layer operates on each feature map individually and typically reduces its size by selecting the maximum or average value from small regions of the map. This work used the averaging method, leading to improved accuracy and sensitivity. Additionally, this layer helps the network become more robust to small shifts in the input image, meaning that if small parts of the image are displaced, it won't significantly affect the network's output.

$$f(x) = max(0, x) \quad (1)$$

5. Fully Connected Layers: These layers convert the extracted features into the final output. In these layers, all neurons are connected to the neurons in the previous layer.

6. Sigmoid Function: This function limits the output to a range between 0 and 1 and is commonly used in problems requiring probabilities (e.g., binary classification). The sigmoid function is defined as follows:

$$f(x) = \frac{1}{1 + e^{-x}} \quad (2)$$

7. Dropout Layer: This technique is commonly used to prevent overfitting. The dropout layer randomly deactivates a portion of the neurons from the previous layer at each training step. This means the selected neurons do not send any information to the subsequent layers during that step. This random removal of neurons prevents the network from relying on a specific path or set of neurons, encouraging it to learn more general and robust features.

8. Final Softmax Layer: This layer is used for classification tasks. Its output provides probability values for each class. The Softmax function is used for multi-class problems in the network's output layer. This function transforms the output values into a probability distribution between 0 and 1, such that the sum of all outputs equals 1.

This study designed a task-specific shallow CNN architecture rather than employing more complex and widely used models such as ResNet or U-Net. This decision was primarily informed by the dataset's relatively limited size and the classification task's binary nature. While powerful, Deep architectures like ResNet generally demand larger datasets to achieve stable generalization and mitigate overfitting risks. Similarly, U-Net is predominantly tailored for image segmentation tasks and may not offer clear advantages in binary classification scenarios. By contrast, our custom architecture provides a balanced trade-off between model complexity and performance, with a significantly reduced parameter count, making it more suitable for effective training on small-scale medical imaging datasets.

4. Finding analysis

4.1. Assessment Criteria

In statistical analyses, accuracy, sensitivity, and specificity are three important indicators for evaluating the results of a binary classification. When data can be divided into two groups—positive and negative—the accuracy of an experiment that categorizes data into these two classes can be measured and described using the sensitivity and specificity metrics.

True Positive (TP): When a case under examination has MS and is correctly diagnosed with MS.

False Negative (FN): When a case has MS but is incorrectly diagnosed as healthy.

True Negative (TN): When a case does not have MS and is correctly diagnosed as not having MS.

False Positive (FP): When a case does not have MS but is incorrectly diagnosed as having MS.

Mathematically, sensitivity is the ratio of true positives to the sum of true positives and false negatives.

$$Sensitivity = \frac{TP}{TP + FN} \tag{3}$$

TP stands for True Positive, and FN stands for False Negative. Similarly, specificity (or true negative rate) is calculated as the ratio of true negatives to the sum of true negatives and false positives.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{4}$$

TN refers to True Negative, and FP refers to False Positive.

In addition to the two aforementioned metrics, accuracy percentage is one of the most well-known components for evaluating binary or multi-class classification results. Accuracy indicates the classifier's overall performance in correctly identifying the classes of different data within the system. This metric is calculated by dividing the total number of correct classifications by the sum of correct and incorrect classifications across all classes.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FN} + \text{FP}} \tag{5}$$

Figure 3 shows the training process of the network, and finally, the test accuracy is determined. Based on our data, 96.4% of the labels predicted by the model match the actual test data labels. This study used the ADAM optimization algorithm to optimize the model and achieve faster convergence. The learning rate was set to a fixed value of 0.0001. The training process of the proposed model was carried out with a maximum of 20 epochs, and in total, it took 65 minutes.

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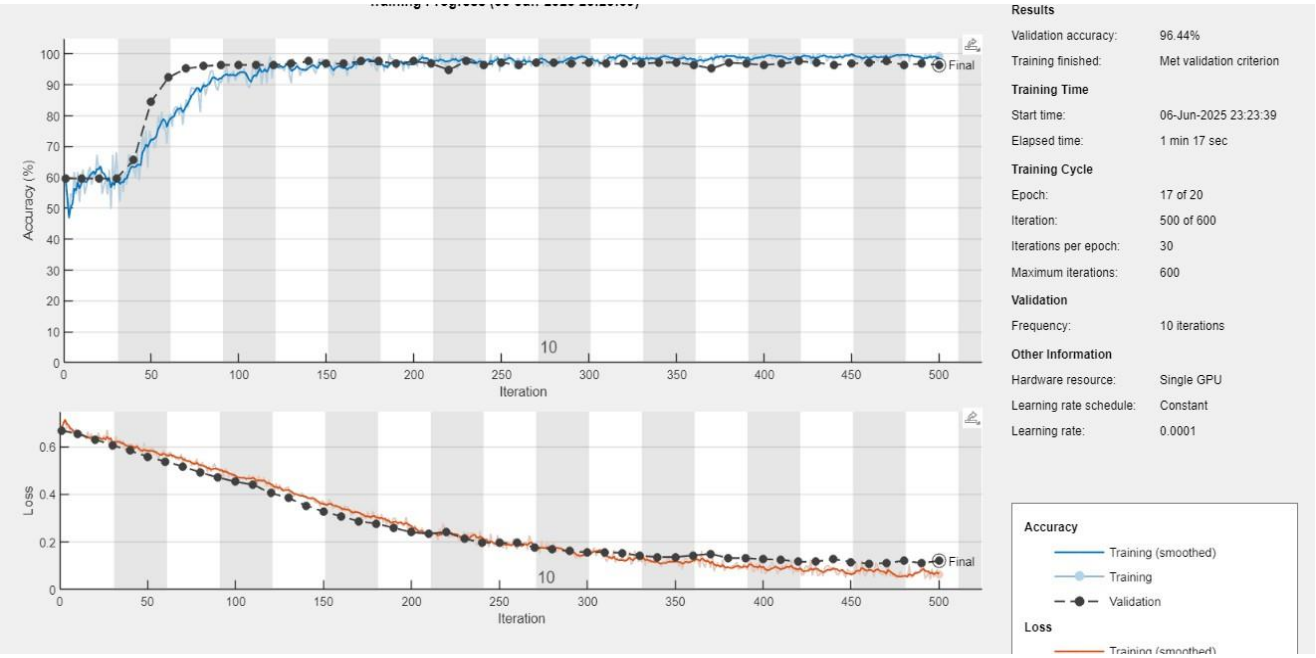

Figure 3.Training Process of the Proposed Convolutional Network

4.2. Results

4.2.1. Results with Training Data

Figure 4 shows the confusion matrices related to the training data. According to Figure 3, the model performs exceptionally well during the training phase. The accuracy for both classes (MS and Non-MS) is above 99%, indicating that the model has effectively learned the patterns in the MRI images. The model's performance on the training data is nearly perfect. However, such high accuracy and very low error may be a sign of overfitting, meaning that the model might have memorized specific details of the training data rather than learning general patterns, which could reduce its ability to generalize to new data.

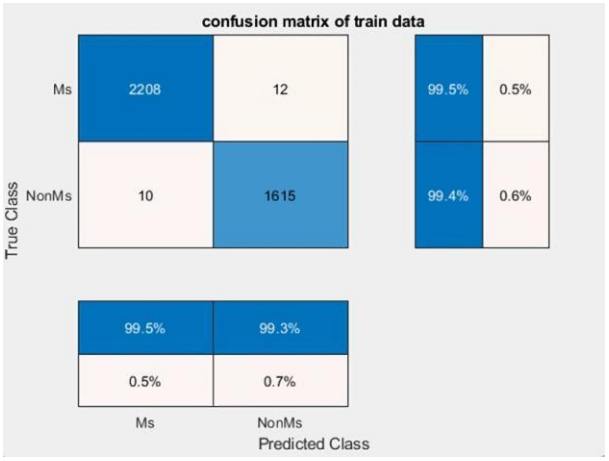

Figure 4. Confusion Matrix of the Training Data

4.2.2. Results with Validation Data

In Figure 5, the confusion matrices related to the validation data are shown, and the model's performance on data not used during the training process is evaluated. An accuracy of 95.4% was recorded for the MS class and 98% for the Non-MS class. This drop in accuracy compared to the training data is expected and indicates that the model is generalizing to new data. However, the presence of errors in identifying MS patients (false negatives) is noteworthy, as failing to diagnose patients correctly can have serious clinical consequences.

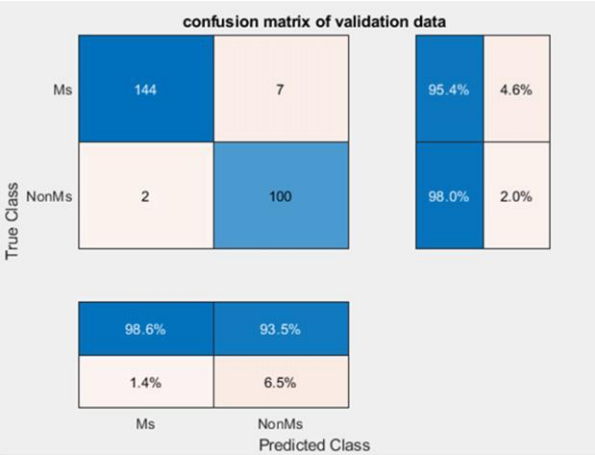

Figure 5. Confusion Matrix of the Validation Data

4.2.3. Results with Test Data

Figure 6 evaluates the model's performance on previously unseen data. The model performs well on the test data, with an accuracy of 94.9% for detecting MS and 98.3% for non-MS. These results indicate the model's good generalization capability; however, similar to the validation phase, the issue of many false negatives (FN) persists.

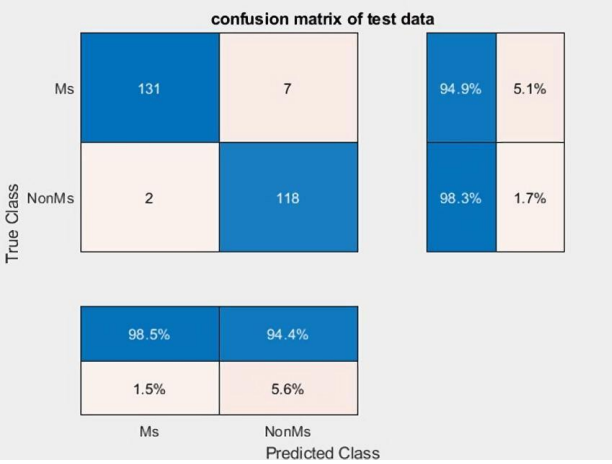

Figure 6. Confusion Matrix of the Test Data

4.3. Comparison of Results with Other Classifiers

As shown in Figure 7, the convolutional neural network (CNN) has been compared with different classifiers, such as Decision Trees and SVM. The sensitivity of the CNN, Decision Tree, and SVM are 0.95, 0.8261, and 0.84, respectively. The specificity of the CNN, Decision Tree, and SVM are 0.98, 0.85, and 0.99, respectively. The accuracy of the CNN, Decision Tree, and SVM are 0.96, 0.8372, and 0.8813, respectively.

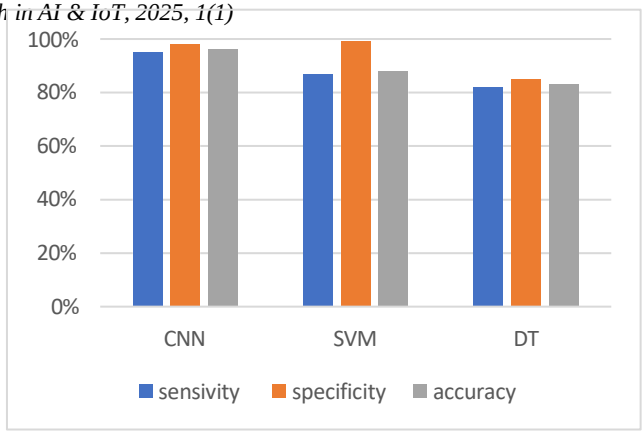

Figure 7. Quantitative Comparison of the Results of Different Classifiers with the Proposed Method

5. Conclusion

In this study, the application of convolutional neural networks (CNNs) for the automatic and timely detection of multiple sclerosis (MS) lesions was investigated using magnetic resonance imaging (MRI). MS is identified as a demyelinating disorder of the central nervous system, disrupting nerve signal transmission. It includes several types, with the relapsing-progressive form being the most common. MRI images play a crucial role in diagnosing MS as they allow for visualizing disease-related lesions.

This research aimed to develop and evaluate a CNN model for accurately identifying MS lesions in MRI images. The model's ultimate goal is to improve the accuracy of MS diagnosis and assist specialists, particularly neurologists and radiologists, in making faster and more precise clinical decisions.

The performance of the proposed CNN model was evaluated in three phases: training, validation, and testing, using a dataset of MRI images from 60 individuals (both MS patients and healthy controls). The model achieved high accuracy in detecting MS cases, with reported accuracies of 92.9% in training, 92.1% in validation, and 92.6% in testing. Additionally, the model's accuracy in identifying non-MS cases across the stages was 79.7%, 75.9%, and 76.9%, respectively. These results indicate the model's capability to learn and distinguish between MRI images of MS patients and healthy individuals.

The proposed CNN model's success demonstrates its high potential as an accurate and efficient tool for detecting MS lesions in MRI scans. Utilizing such an automated approach can assist physicians in the early diagnosis of MS, significantly improving treatment outcomes and disease management.

Despite the promising results, the study highlights several challenges, notably the visual similarity between MS lesions and some unrelated findings in MRI images, which may lead to misclassifications, particularly in identifying non-MS cases, necessitating future research to employ attention mechanisms to help the model focus on key image features and hybrid models to improve overall accuracy and stability. The development and refinement of such AI-based tools provide a promising outlook for supporting clinicians

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in the rapid and accurate diagnosis of MS, potentially leading to significant improvements in patient care and clinical processes, while future research should address current challenges and implement the suggested solutions to design more reliable and practical systems for clinical MS diagnosis. Although the dataset includes a diverse set of lesion types and patient profiles, future work could benefit from expanding the dataset size and incorporating longitudinal MRI data, which would allow for more comprehensive training and evaluation across different stages of MS and improve the model's applicability in clinical settings.

6. Statements & Declarations

6.1. Acknowledgments

This research is part of a Master's thesis titled "Detection of Multiple Sclerosis Lesions in MRI Images Based on Convolutional Neural Networks", completed in the year 1403 (2024–2025), and was carried out with the support of Shomal University, Amol, Iran. Additionally, to improve and enhance the coherence of the text structure, large language models such as ChatGPT (GPT-4o) and Grok (Grok 3) were used in the introduction and conclusion sections solely for literary editing and rewriting of certain sentences.

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