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MS Identification in Brain Magnetic Resonance Images Using Wavelet Transfer Learning

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Abstract

Multiple Sclerosis (MS) is one of the most important diseases of the central nervous system. This disease causes small lesions detectable in Magnetic Resonance Imaging (MRI) images of the patient's brain. Because of the small size of the lesions, their distribution, and their similarity to some other diseases, the MS diagnosis can be difficult for specialists and may be mistaken. In this paper, we presented a new method based on deep learning for the automatic classification of MRI images. The proposed method is a combinational architecture from transfer learning and wavelet transform (WT). First, WT was applied to the input MRI image, and its four output sub-bands are used as the input of four fine-tuning networks based on EfficientNet-B3. Transfer learning networks perform feature extraction on all four sub-bands. Then, their outputs are combined, and the result is classified by a fully connected neural network. Due to the feature of WT to extract local features, it was possible to highlight the lesions in the images and subsequently classify it with higher accuracy and precision. Various criteria have been used to evaluate the proposed method. The results of the experiments show that the Values of accuracy, precision, sensitivity, and specificity are 98.91%, 99.20%, 99.20%, and 98.33%, respectively.

Keywords: Multiple Sclerosis (MS); Deep Learning; Transfer Learning; Wavelet; Magnetic Resonance Imaging (MRI)

1.Introduction

Multiple Sclerosis is the most common chronic inflammation of the central nervous system (CNS). The disease destroys the protective sheath of the nerve cells and over time causes degraded masses known as plaques [1, 2]. Cellular damage to the brain or spinal cord has various side effects such as impaired vision, weakness of the limbs, loss of balance, muscle spasms, sensory and speech problems, impaired body systems, and learning disorder for the patient.

To diagnose MS, clinical symptoms of suspected MS are first examined. MRI images are then used for definitive diagnosis. These images show the location and number of lesions in the white matter portion of the brain, which is an essential criterion for the diagnosis, follow-up, and prognosis of the disease [2, 3]. Given that different diseases cause lesions in the brain, an accurate diagnosis of MS-related lesions requires great skill and high precision[4].

Currently, MRI images of MS are manually classified. Due to the small size and distribution of lesions in different parts of the central nervous system, their diagnosis is time consuming, less accurate and different diagnoses can be made by different specialists [5].

Another problem with lesion counting is the precise location of the Confluent lesions due to their overlap [6]. Automatic image recognition and classification can be used as a tool for relevant professionals.

Deep learning and traditional image processing methods are used to automatically detect lesions in MRI images. In deep learning, feature extraction is done and it could yield better results than traditional methods [7].

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A conventional method for classifying images is to use multi-layer convolutional networks to extract features with high accuracy, which requires more learning time. Another method is to use transfer learning, which has two different types of feature extraction and fine-tuning.

The first type works based on a pre-trained network. It has a high learning speed but is less accurate in extracting features, whereas in the second type, part of the pre-trained network is trained with new data. This type has a good learning speed and feature extraction is done with high accuracy.

In the present study, our proposed method uses fine-tuned transfer learning to extract features. In this method, we applied the basic EfficientNet architecture, which has a smaller size and higher accuracy than conventional architectures. The top three layers of the network are unfrozen and the network is trained with MS MRI images to be customized for this issue. Also, to increase the accuracy of feature extraction, we employed the Haar Wavelet Transform (HWT) on the input images of the transfer learning network to highlight local features and lesions. Finally, using a fully connected two-layer neural network as a classifier, images are classified into two groups (with and without lesions). The results showed that the proposed method performed satisfactorily.

The rest of this paper is organized as follows: Section 2 surveys the previous related works. Section 3 and 4 provide an overview on the background concepts, including transfer learning, and wavelet transform, respectively. Section 5 describes a detailed description of the proposed method. Section 6 demonstrates the experiments and their results. Finally, section 7 covers the conclusion and the suggested future works.

2. Related Works

This section provides an overview of traditional and deep-learning approaches aimed to diagnose MS from MRI images.

Zhang and his colleagues [8] used the edge detection (EDM) method to extract the features of MS lesions and applied a single layer neural network for classification. They have used the Minkowski-Bouligand Dimension for dimension reduction and have achieved an accuracy of 97.80%.

Ghribi et al. [9] have proposed a segmentation method based on volumetric feature extraction from the gray-level co-occurrence matrix (GLCM), in which spatial and shape information has been used for the detection of lesions. Also, support vector machine (SVM) technique has been applied for classification. The accuracy of the proposed method is reported to be 95.14%. Lopez et al. proposed [10] an MS detection system based on the Haar Wavelet Transform, principal component analysis, and logistic regression (LR) that tested up to four-level decomposition. Experimental results show that three-level decomposition performs best and has an accuracy of 89.64% (HWT-LR).

Zhang et al. developed [11] a 10-layer deep convolutional neural network with seven layers of convolution and three fully connected layers using the combination of a modified Parametric Rectified Linear Unit (PReLU) and a random dropout method. Using the trained network on the University of Cyprus Laboratory Health Data, values of sensitivity, specificity, and accuracy were obtained as 98.22%, 98.24%, and 98.23%, respectively (CNN-PReLU). Shui-Hua et al. presented [12] a combination of a 14-layer convolutional network with three techniques, including batch normalization, random dropout, and random polling. The proposed method has better results than the average and maximum polling. This method has been tested on the University of Cyprus Health Lab data and has achieved 98.77% accuracy (CNN-DO-BN-SP).

To classify MRI images, Ullah et al. [13] used the 2-dimensional Haar wavelet transform to extract features and neural networks for classification and achieved 95.8% accuracy. Rezaee et al. [14] used the conditional spatial fuzzy C-means (csFCM) to classify MRI images and achieved an accuracy score of 97.56%.

The conventional method for classifying images is to use multi-layer convolutional networks. Feature extraction is performed with high accuracy using this method. However, it requires more learning time. Our proposed method uses wavelet transform and fine-tuned transfer learning to extract features. This method has a good learning speed and features extraction is done with high accuracy.

3.Transfer Learning

A very effective approach in applying deep learning to small datasets is the use of a pre-trained network[15]. The purpose of transfer learning is to use the knowledge gained from one problem to improve generalizability to another [16].

The weights of a network for a pre-trained problem with a large amount of training data are transferred to a new problem, usually with less training data, which is less time-consuming and offers better performance[17]. Transfer learning is a suitable approach to deal with issues such as medical images where data is difficult to label and requires time and money.

Transfer learning is used in two ways: feature extraction and fine-tuning. In feature extraction method, representations learned by the main network are used to extract the desirable features from new samples. These features are then run through a new classifier, which is trained from scratch. In other words, a classifier layer is added to the pre-trained network and the classification of new samples is performed using it. Fine-tuning consists of unfreezing a few top layers of a frozen base model used for features extraction, and jointly training both the newly added part of the model and these top layers.

In transfer learning, different types of base models are used depending on the type of problem and the degree of required accuracy, which is explained below. Different CNN-based transfer learning architectures such as VGG16, ResNet-152 [18], and Inception-v3 [19] have been proposed in computer vision. The main problem with previous models is that by increasing the depth or width of the network, the input image size is reduced to balance the operation volume. However, decreasing the image size in MRI images of MS patients may decrease the accuracy of detection.

Le and Tan [20] introduced a new architecture called EfficientNet and compared it with the previous architectures. In this architecture, due to the proper balance between all three factors of the depth, width, and size of the input image, it is possible to use images with appropriate dimensions. Also, its small size compared to other architectures increases learning speed. This model is based on the scaling method and has two main features:

- Accuracy increases with increasing scale of each dimension of the network, such as width, depth, or resolution. However, this increase in accuracy is slower in larger architectures.
- To achieve higher accuracy and efficiency, a balance between network dimensions is essential. It is important to obtain optimal values for these dimensions. In EfficientNet architecture, this is done in a way that achieves higher accuracy.

4.Wavelet transform

The purpose of applying the mathematical transform to a signal is to obtain additional information that is not available in the original signal. Fourier transform is commonly used for image processing. The disadvantage of the Fourier series is that it loses time information in the frequency domain conversion. Therefore, the possibility of specifying the time of occurrence of different frequency components is eliminated. Hence, other transforms like wavelets are used.

Wavelet transform is a time-scale transform with information of both the spatial and frequency domains. It describes the local features and provides a signal analysis at different scales and levels [21, 22], which analyzes sharp changes in the signal. Due to the small size of lesions and their distribution in different parts of the brain in MS, the ability to highlight local and edge features and the use of scale adjustment in this transform can improve the diagnosis of lesions.

The main idea of the discrete wavelet transform is based on high-pass and low-pass filters. The input signal is decomposed into two parts: high frequency (details) and low frequency (approximation). The decomposition steps are repeated to reach the required level.

A two-dimensional signal, called an image, is a matrix of elements arranged in rows and columns. Each column or row of an image can be considered as a one-dimensional signal whose amplitude values indicate the brightness of the dots (pixels) in that particular column or row. The wavelet transform can be applied to each row or column of the image separately. After applying the transform, four different sub-bands are obtained as the wavelet transform coefficients of the image, which are shown in Figure1.

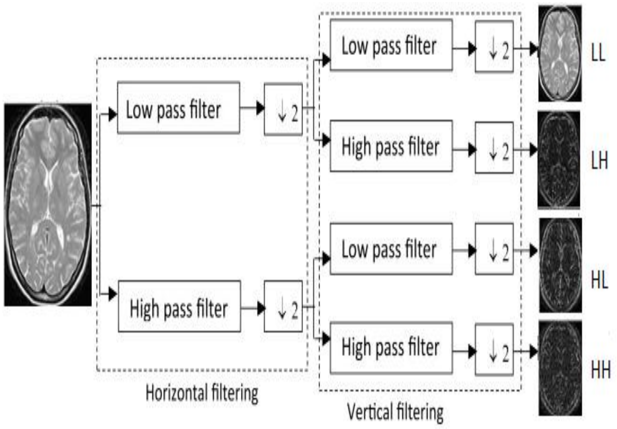

Fig. 1. Decomposition of MRI image with two-dimensional discrete wavelet transform.

As shown in Figure 1, as a result of applying the wavelet transform to the input image, four sub-bands are obtained which are:

- LL sub-band contains general information of the image and is known as the matrix of wavelet approximation coefficients. This sub-band corresponds to the low-frequency component of the image.
- LH sub-band contains horizontal details of the image.
- HL sub-band contains vertical details of the image.
- HH sub-band contains diagonal details of the image.

The transformation may be defined according to the expressions [23]:

$$F_{LL}(x,y) = \sum_{k_1} \sum_{k_2} h(k_1)h(k_2)f(2x-k_1,2y-k_2) \quad (1)$$

$$F_{LH}(x,y) = \sum_{k_1} \sum_{k_2} h(k_1)g(k_2)f(2x-k_1,2y-k_2) \quad (2)$$

$$F_{HL}(x,y) = \sum_{k_1} \sum_{k_2} g(k_1)h(k_2)f(2x-k_1,2y-k_2) \quad (3)$$

$$F_{HH}(x,y) = \sum_{k_1} \sum_{k_2} g(k_1)g(k_2)f(2x-k_1,2y-k_2) \quad (4)$$

Where (x, y) represents coordinates of the images, h and g are the high and low pass filters, respectively, f is the input image, F is the output image, and k represents the size of the filters. The process can be iterated to higher levels, assuming the average image FLL as input for the next level [24]. Figure 2 shows the transformation for two levels.

There are several families of wavelet transforms, such as the Haar, Daubechies, and Morlet wavelets, each with different characteristics. The Haar wavelet is used in this paper, which has a lower computational cost than other wavelets due to its simplicity. Also, by testing four common wavelets, this wavelet was more accurate. The experiment results are given in Table 4.

5.Proposed Method

The general architecture of the proposed method is shown in Figure 2. The method consists of three parts.

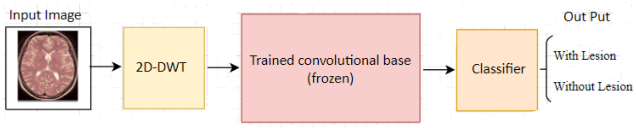

Fig. 2. The general architecture of the proposed method.

In the first part, the input image is decomposed into four images by the Haar wavelet transform to highlight the image features. The second part consists of four fine-tuned transfer learning networks with a base EfficientNet-B3 that extract features. In the third part, there is a fully connected two-layer neural network that classifies images into two groups with and without lesions. The details of the architecture are described below.

The architecture of the proposed method is shown in Figure 3. The input image is firstly decomposed using a two-dimensional Haar wavelet transform into four sub-bands, including the approximate sub-band (LL, LH, HL, HH). Each sub-band is used as the input to a fine-tuned transfer learning network. The outputs of the transfer learning networks are combined, and the combined output is classified to images with and without lesions by a fully connected classifier. Because each sub-band of the WT highlights and maintains specific features of the image, we have used all the sub-bands to extract the features so that all the image information is used for the classification and performs better.

In this research, the proposed method architecture will be achieved in two main stages. In the first part, feature extraction is done by deep learning method based on fine- tuning. Different base networks were tested and finally, the EfficientNet network that had better results was selected. In the second part, where the classification is done with a fully connected network, different activation functions were examined. The SeLU function was selected, which had a better result.

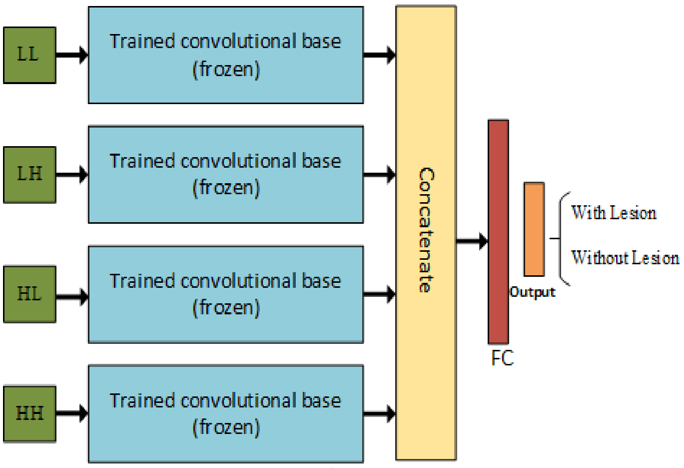

Fig. 3. The Architecture of the proposed method.

The purpose of the first stage is to select the base network of transfer learning. To achieve this purpose, six conventional architectures used in similar work and four different EfficientNet (B0-B3) models are tested and compared on MS disease data. The results of the experiments are presented in Table 2. Since the EfficientNet-B3 network has the highest accuracy among the tested networks, it is selected as the base network in the proposed method. The second stage is based on fine-tuning. Firstly, a new classifier which is a fully connected neural network is added to the already-trained EfficientNet3 base network. Then, the top few layers of the base network will be unfrozen. Finally, the base network and the classifier are trained jointly(Figure 4).

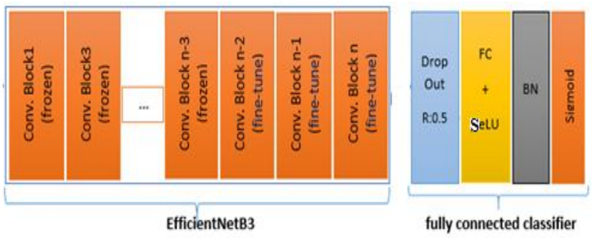

Fig. 4. The Architecture of transfer learning network (EffecientNetB3) and fully connected classifier.

6. Experimental Evaluation

In this section, the experiment results of the proposed method and the implementation process are presented. Firstly, the initial configuration of the test, including the required hardware and software, the hyperparameters, and the network parameters, is presented. Then, the dataset and the evaluation criteria are introduced. Finally, the results of the experiments are presented and compared with the methods studied in Section results.

6.1. Experimental Setup

All experiments are performed on a machine with a Core i7- 2.60 GHz processor, 16G RAM, GeForce GTX 1070 graphics card with 8G RAM. A Python-based TensorFlow [25] And Keras package has been used for implementation. For the training of the proposed network, 80% of the images are used for training and 20% for testing.

The classifier is a fully connected network that has two layers. In the first layer, 512 nodes and the SeLU activation function are used. The second layer has 1 node and the Sigmoid activation function for two-state output. To avoid over-fitting, a Dropout method with a rate of 0.5 is used. The number of epochs and batch sizes are 30 and 32, respectively. The Adam optimization algorithm with a learning rate of 0.0008 is used.

6.2. *Dataset and Pre-processing*

Two datasets have been used in this research. The first set includes 38 MRIs of MS patients owned by the University of Cyprus Health Laboratory. This set contains 676 lesion slices. Since this dataset was only for MS patients, a dataset was prepared by the authors for healthy people. For this purpose, MRI images of twenty healthy individuals in the age and gender range of the first dataset (including 11 men and 9 women with a mean age of 35) were selected. Images of these patients include 645 slices. The information of the two datasets is given in Table 1.

Table 1
Dataset Information

Dataset	Source	Number of Subject	Age	Gender (f/m)	Number of Slice
MS	eHealth	38	34	17/21	676
Healthy	private	20	35	9/11	645

Some histogram images were not uniform or had right/left skew. To increase the contrast of the images, we used the histogram stretching method and made them uniform.

6.3. Evaluation Criteria

The most important evaluation criterion used in classification applications is accuracy. This criterion shows the percentage of correctly classified images compared to all existing images. In medical diagnoses, misdiagnosis of a healthy person with a sick person and vice versa has irreparable consequences. Therefore, in evaluating the results, just using the accuracy criterion is not enough, and the criteria of precision, sensitivity, and specificity are also used. The sensitivity criterion is the ability of the classifier to correctly diagnose the disease and the specificity criterion indicates the ability to correctly diagnose the suspect person. These criteria are obtained as follows:

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \qquad (3)$$

$$\text{Sensitivity}=\frac{TP}{TP+TN} \qquad (4)$$

$$\text{Precision}=\frac{TP}{TP+FP} \qquad (5)$$

$$\text{Specificity}=\frac{TN}{TN+FP} \qquad (6)$$

Where, TP indicates the number of images with lesions that are correctly classified by the proposed method. TN is the number of images without lesions and they are correctly diagnosed without lesions. FP is the number of images without lesions which the classifier is diagnosed with lesions by mistake, and FN is the number of images with lesions that are diagnosed without lesions by mistake.

6.4. Experimental Results and Discussion

In the first step, to select the base network, six common base models including VGG16, VGG19, ResNet50, InceptionResNetV3, Xception, DenseNet169, MobileNet, and four different EfficientNet (B0-B3) models have been tested using feature extraction method. The accuracy values of each network are presented in Table 2.

Table 2
Feature extraction results with different back bond

Base	Parameters (Millions)	Accuracy (%)
VGG16	138	92.72
VGG19	144	96.36
ResNet50	26	74.55
InceptionResNetV3	43	56.36
Xception	23	69.09
DenseNet169	14	76.36
EfficientNet-B0	5.3	81.82
EfficientNet-B1	7.8	83.64
EfficientNet-B2	9.2	86.36
EfficientNet-B3	12	**87.82**

As shown in Table 2, the accuracy of the model increased with increasing number of parameters and model size in conventional base models. The EfficientNet-B3 base network has higher accuracy than the other base models despite its smaller volume. Therefore, this network is selected as the base model of the proposed method.

To select the appropriate activation function in the proposed method classification, we tested various activation functions, including ReLU PReLU, LeakyReLU, and SeLU (Table 3). Based on the results of the evaluation, the SeLU function is selected as the activation function.

Table 3
Comparisons of different activation functions

Activation Functions	Accuracy (%)	Precision (%)
ReLU	93.82	98.54
PReLU	95.28	98.04
LeakyReLU(alpha=0.1)	95.89	98.34
SeLU	**98.54**	**98.75**

After selecting the proposed network components including, the base network and classifier, the fine-tuning method is performed on the network and then the created network is trained with the MRI images dataset. Four types of wavelets have been tested and Table 4 shows that the Haar wavelet had a higher accuracy for classification and was therefore used in the proposed method.

The proposed network of this study, called TL-FT-WA, is compared with five previous methods that have used traditional methods and machine learning. The comparison results are presented in Table 5. The obtained values are the mean values for the criteria after 10 runes network training.

Table 4
Classification accuracy with different wavelets

Wavelet Family	Accuracy(%)
Coiflets 1	96.50
Daubechies 2	97.15
Symlets 1	97.01
Haar	**98.05**

As seen in Table 5, the proposed method has proper values in the considered criteria. Also, compared to other methods, it has higher values of accuracy and specificity. For better analysis, the results of Table 5 are shown for traditional methods in Figure 5 and for deep learning-based methods in Figure 6. In the following, we will discuss and review them.

In the following, a review and comparison of the proposed method with traditional image processing methods are given. In EDM, GLCM, and HWT-LR methods, edge detection, shape information, and multi-level analysis of wavelet transform were used to extract the features, respectively. In the proposed method, the lesions are highlighted by applying a Haar wavelet transform. Then, feature extraction is performed using fine-tuned transfer learning. For this reason, feature extraction has been done with greater accuracy than traditional methods. Image classification in the proposed method is done with a customized, fully connected two-layer network, which is an appropriate method for classification.

Table 5
Comparison of different methods (in %)

Method	Accuracy	Precision	Sensitivity	Specificity
HWT-LR[10]	89.64	N/A	N/A	N/A
GLCM[8]	95.14	N/A	95.27	95.01
EDM[9]	87.8	N/A	97.78	97.82
CNN-PReLU-Dropout[11]	98.23	N/A	98.22	98.24
CNN-DO-BN-SP[12]	98.77	98.75	98.77	**98.76**
TL-FT-WA(proposed)	**98.91**	**99.2**	**99.2**	98.33

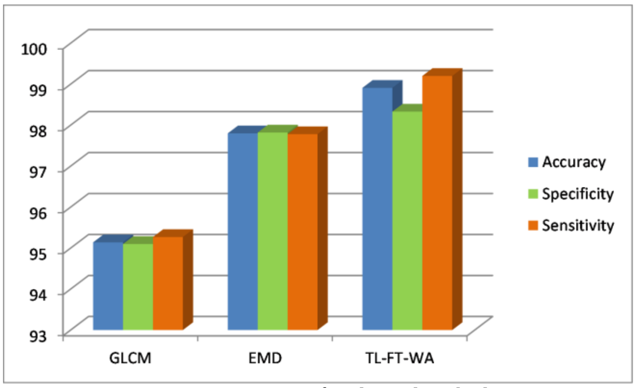

Fig. 5. Comparison of traditional methods.

In compared deep learning methods (Figure 6), the CNN network is used to extract the features. In the proposed method, the wavelet transform is first applied to the input images, which due to the ability to better describe local features and multi-resolution, highlights the lesions, and allows the extraction of lesions in different parts of the brain with different sizes. Then, feature extraction is done by transfer learning based on fine-tuning. For this reason, feature extraction in the proposed method has better results and the evaluated parameter in Figure 5 also shows it.

In the compared and proposed methods for classification, a fully connected network has been used. The proposed method uses the SeLU activation function. As shown in Table 3, this function has better results than the functions used in other methods. Also, it should be noted that the fine-tuned transfer network has less learning time than conventional CNN networks with many layers.

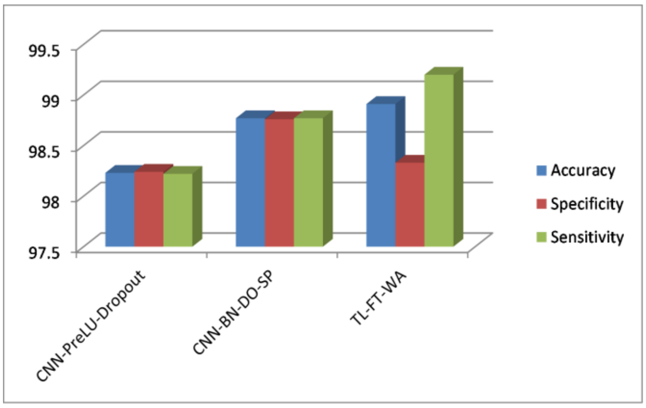

Fig. 6. Comparison of deep learning-based methods.

7. Conclusion and Future Work

Diagnosis of MS lesions on MRI images is one of the important issues in neuro-medicine. Traditional methods of image processing and deep learning have been used to do this. Because of the many difficulties in the preparation and labelling of medical images, transfer learning is a good idea for the classification of images. Transfer learning method is based on pre-trained convolutional networks and can deliver good results with a small number of training samples. The proposed method uses a combination of the wavelet transform and the EfficientNet-B3 architecture. Then, a fully connected neural network is added to the base network as a classifier. This classifier uses the SeLU activation function, dropout method, and weight regularization. The proposed method is tested on a dataset containing images of 38 patients and 20 healthy individuals and compared with six methods. From the experiments, values of the accuracy, precision, specificity and sensitivity are 98.91%, 99.20%, 98.33%, and 99.20%, respectively, which confirms the efficiency of the proposed method in the diagnosis of MS.

For future work, we suggest to use other classifiers in the proposed method instead of the fully connected network and to study their performance.

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