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Research paper

Diagnosis of Multiple Sclerosis Disease in Brain MRI Images using Convolutional Neural Networks based on Wavelet Pooling

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Abstract

Multiple Sclerosis (MS) is a disease that destructs the central nervous system cell protection, destroys the sheaths of immune cells, and causes lesions. Examination and diagnosis of lesions by the specialists is usually done manually on the Magnetic Resonance Imaging (MRI) images of the brain. The factors such as the small sizes of lesions, their dispersion in the brain, similarity of lesions to some other diseases, and their overlap can lead to a misdiagnosis. The automatic image detection methods, as auxiliary tools, can increase the diagnosis accuracy. To this end, the traditional image processing methods and deep learning approaches have been used. The deep convolutional neural network is a common method of deep learning to detect lesions in the images. In this network, the convolution layer extracts the specificities, and the pooling layer decreases the specificity map size. In the present research work, we used the wavelet-transform-based pooling. In addition to decomposing the input image and reducing its size, the wavelet transform highlights the sharp changes in the image and better describes the local specificities. Therefore, using this transform can improve the diagnosis. The proposed method is based on six convolutional layers, two layers of wavelet pooling, and a completely connected layer that has a better amount of accuracy than the studied methods. The accuracy of 98.92%, precision of 99.20%, and specificity of 98.33% are obtained by testing the image data of 38 patients and 20 healthy individuals.

1. Introduction

Multiple Sclerosis (MS) is the most common chronic inflammation disease of the central nervous system (brain and spinal cord), destroying the protective layer (sheath) of the nerve cells and causing destructive lesions, called plaque [1, 2]. The severity of damage, as well as its location in the brain or spinal cord can cause a variety of complications, such as impaired vision, loss of learning, and imbalance. The diagnosis and examination of disease progression are made visually by comparing Magnetic Resonance Imaging (MRI) at different times. Due to the small sizes of lesions, different severities of the lesion progression (white, gray, and black hole), the spatial distribution and number of lesions, and the degree of brain shrinkage, it is a time-consuming and difficult process for the specialists, and has a possibility of error [٣]. MS is a complex disease, and a variety of its symptoms are the most important causes of this complication. This variety makes it possible to confuse it with other diseases of the central nervous system, such as the Alzheimer's disease. The disease is chronic and very debilitating, with economic and social consequences [٤] so that it imposes a heavy economic burden on the patients and their families [٥]. It usually begins at the ages of 20 and 40, and is almost twice in women as much as men. In other words, people are involved with it in the best age and work conditions and it imposes high social costs on the other people and the society. The exact cause of this disease is still unknown, and the existing treatments have focused on reducing and managing its seizures [6, 7].

In order to diagnose MS, MRI images of the brain are used after examining its suspected clinical symptoms. In this method, the location and number of lesions in the white matter of brain are shown and it is an important criterion for diagnosis and follow-up of MS [1, 8]. In Figure 1, MRI images are shown with different protocols and lesion segmentation. These images are used to confirm the diagnosis, location of lesion, its severity, and to evaluate the response to the MS treatment [9, 10]. Due to the fact that various diseases cause lesions in the brain, an accurate diagnosis of the lesions relating to this disease requires a great skill and precision [11].

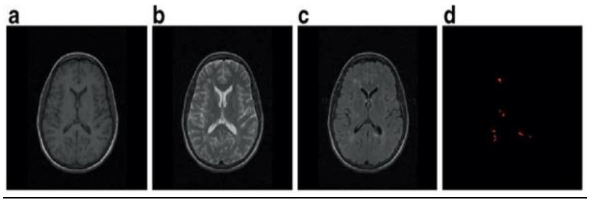

Figure 1. images from the left: T1, T2, FLAIR, and lesion.

The manual segmentation is now performed to diagnose lesions in terms of size and location. However, it is time-consuming, less accurate, and has the problem of different observer variability, especially in inexperienced individuals [12]. Confluent lesions are other problems with the manual system for counting lesions in which several lesions overlap and cannot be easily separated from each other [13]. Also it is difficult to store the results [14].

There are several ways to classify the MRI images of MS, including traditional image processing and deep learning methods. Deep learning has been used in various fields of medical image information analysis such as noise reduction, segmentation, and classification, and has had good results. The proposed method is a model based on a deep convolutional neural network in which the wavelet pooling layer is used. Wavelet transform reduces the size of image, highlights specificity of MS lesions in the MRI images, and classifies images with a higher accuracy.

The rest of this paper is organized what follows. In Section 2, the concepts of convolutional neural network, the function of pooling layer, and the wavelet transform are explained. The proposed method is presented in Section 3. Section 4 demonstrates the experiments and their results. Finally, the research conclusions are provided in Section 5.

2. Basic Concepts

Since the proposed method is based on the changes in the convolutional neural networks, we first examine the structure of these networks, and then described the wavelet transform. Finally, the related works are reviewed.

2.1. Deep Convolutional Neural Network

The convolutional neural networks are types of a deep learning model used in computer vision [١٥]. In such networks, a small kernel of weights is created for each position of image and determines the value of neuron for the next layer (Figure 2). This method copies the convolutional mathematical operators. The extraction of specificity is performed at the convolutional stage, and then it is possible to achieve better results and speed-up training using a non-linear function. At the pooling stage, the extraction map is reduced in order to improve the computational load of the next stages.

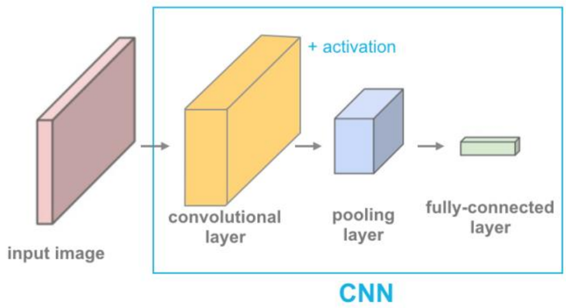

Figure 2. Overall structure of a convolutional network layer.

The pooling layer is used for down-sampling and reducing the input image size in order to reduce the computational load and memory consumption in the network. Decreasing the image size causes the neural network to tolerate small changes in the image. At this layer, the inputs are added using a cumulative function such as maximum or average pooling; and maximum pooling is common.

As shown in Figure 3, the maximum pooling returns the maximum value of a part of image covered by the kernel (motion window), and the average of all values returns from a part of image covered by the kernel in the average pooling.

Maximum pooling is sensitive to over-fitting of the training set, and makes generalization difficult. Zeiler et al.[16] have proposed a method to solve this problem called the stochastic pooling method, in which a random pooling procedure is replaced by a definitive pooling operation.

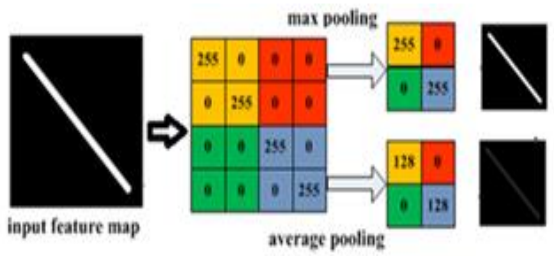

Figure 3. Maximum and Average pooling.

In this procedure, the stochastic selection of values within each pooling zone is based on a multinomial distribution (see Figure 4).

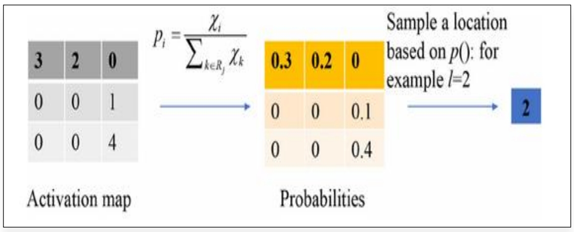

Figure 4. Stochastic pooling.

This operation is similar to standard maximum pooling with a large number of copies of the input image, each with a small local deformation. The stochastic nature prevents over-fitting.

2.2. Wavelet Transform

Wavelet transform is a time-scale conversion that stores the location and frequency information. The use of wavelet transform allows a better analysis of sharp signal changes. In addition, it better describes the local specificity, and provides signal decomposition on different scales at different levels [17,18]. The basis of wavelet transform is that it passes signals through the high-pass and low-pass filters, and performs the decomposition step by step [19]. Each step involves a filter and a downsampler. The outputs of the high-pass and low-pass filters are called the detail and approximation coefficients, respectively. Since the low-frequency content is the most important part in many signals, the decomposition at the next levels of signal continues with the decomposition of approximation coefficients to the required level. The number of decomposition levels depends on the nature of signal and the type of mother wavelet depending on the type of application. The signal wavelet transform x(t) is defined as Equation (1) in which *a* is the scale change parameter, *b* is the amount of shift, and ψ(t) is the mother wavelet.

$$w_a x(b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) \psi^*\left(\frac{t-b}{a}\right) dt \quad a>0 \quad (1)$$

The wavelet transform is divided into two types, continuous and discrete. In the proposed method, a 2Dl discrete transformer is used due to its simplicity and low calculations than the other methods. Lesions of MS are small and vary in size. Since the wavelet transform better shows the failure points and local specificity, it makes possible to highlight the lesions, and because of the multifaceted nature [20] it makes possible to extract lesions in different sizes with a better accuracy. The ability to minimize this transform reduces the image size in the network and reduces the computational load.

The transform of a 2D wavelet is used for a 2D signal. A 2D signal, which is called an image, is a matrix of elements arranged in different rows and columns. Each column or row of image can be considered as a 1D signal, in which the range values indicate the brightness of points (pixels) in that particular column or row. Accordingly, the wavelet transform can be separately applied on each row or column of the image. After applying the transform, four different sub-bands are obtained as the image wavelet transform coefficients, as shown in Figure 5.

Similar to a 1D mode, the first sub-band of the wavelet transform coefficient is related to the approximation coefficients, and it is similar to the original image in terms of value and appearance. The other three sub-bands are related to the detail coefficients including the horizontal, vertical, and diagonal details of the image.

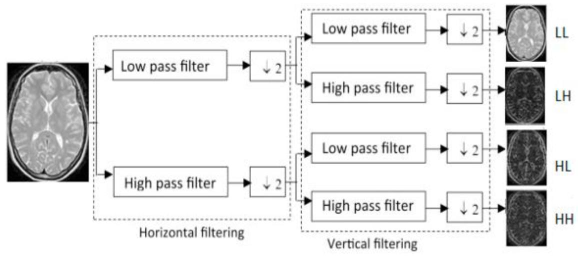

Figure 5. Decomposition of MRI image with 2-D discrete wavelet transform.

As shown in Figure 5, the input of the next step in the network is the sub-band of the approximation coefficients (LL), which is half the size of the original image.

2.3 Related Works

The traditional image processing methods have been used to classify the MRI images of MS. Some examples of them are provided below.

Ghribi et al. [21] have used a partitioning method based on the extraction of volumetric properties from gray-level co-occurrence matrix and have applied a machine vectoring technique for classification (GLCM). Zhang et al. [22] have used the edge-cutting method to extract the specificity of MS lesions, and have used a single-layer neural network for classification (MBD). Xueyan et al. [23] have proposed an MS detection system based on the Haar wavelet transform (HWT), principal component analysis (PCA), and logistic regression (LR) in order to test the four levels of analysis (HWT-LR).

In the recent years, the deep learning techniques have been used to classify images, and have had an acceptable performance. Deep learning can be used in various fields of brain MRI imaging, such as image quality improvement, image type conversion, and lesion diagnosis and isolation [24, 25]. To this end, the relevant images should be first collected and labeled by the relevant specialist, and should then be applied as a deep learning input dataset. The convolutional neural network is a common method for extracting specificity in these techniques and they have a proper performance [26, 27]. Various deep learning methods have been used to classify the images of this disease; for instance, Zhang et al. [28] have used a deep convolutional neural network using a Parametric Rectified Linear Unit (PReLU) and Dropout to classify the MRI images of MS (CNN- PReLU). Shui-Hua et al. [29] have provided a combination of a 14-layer convolutional network with three techniques of batch normalization, dropout, stochastic pooling (CNN-BN-DO-SP).

Williams et al. [30] have examined the wavelet pooling layer on MNIST and CIFAR-10 dataset, and have found a pooling layer with a higher accuracy than the other methods. Allison et al. [31] have used a wavelet pooling layer and Adam's modified optimizer on various datasets such as MNIST and CIFAR-10 and have found a higher accuracy.

The deep learning-based methods have better results than the traditional image processing methods. In the deep learning methods, the average or maximum pooling layer is used to reduce the image size. In our proposed method, the wavelet pooling layer is replaced with the normal pooling layer, leading to the reduction of image size and highlights specificity of lesions. In the next section, we examines the pooling layer and wavelet transform.

3. Proposed Method

The proposed model consists of two parts: first, the extraction of specificity and reduction of dimensions of the image, and secondly the classification, as shown in Figure 6.

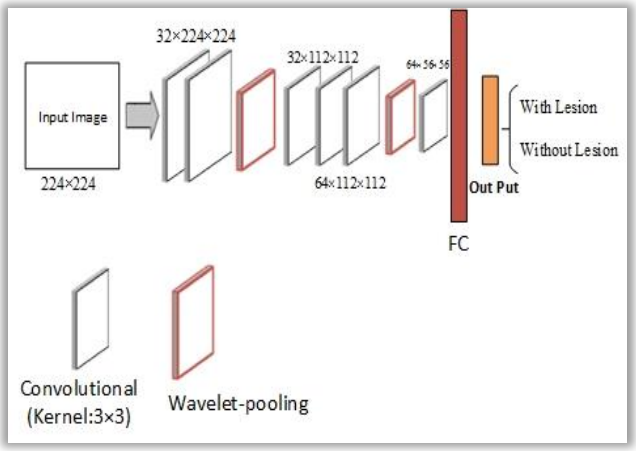

Figure 6. Proposed model.

The first part has 6 convolutional layers and two pooling layers based on the Haar wavelet. The process is as follows, The first the extra-level specificity of the input image is extracted by two convolutional layers with thirty two 3×3 filters, and then a wavelet pooling layer is used to halve the size and highlight some specificity of the lesions. Then, two convolutional layers with 32 filters and a convolutional layer with 64 filters are used to extract specificity of the mid-level image; and at the next layer, dimensions of the image at the stage decreased by a pooling wavelet layer. At the last layer, detailed specificity of the image is extracted by a convolutional layer with 64 filters. In the second part, a classifier, which is a fully connected network, is used in order to classify the image into two types, with and without lesions.

The wavelet pooling uses wavelets to reduce the dimensions of the specificity map. This method works differently from the traditional methods. Traditional methods work on the basis of neighborhood, but the wavelet method act based on the decomposition of the image into sub-bands; and the approximation sub-band is considered as its output. The lesions vary in size, and are scattered throughout the brain. Due to the multi-faceted nature of the wavelet transformer and its better description of local specificity, it is possible to highlight these lesions in the specificity identification section of the proposed method; and the classification can be done more accurately.

The activation function, ReLU, and the weight normalization and dropout techniques at a rate of in the classifier section of the proposed method, a fully connected network with 0.5 is used to prevent over-fitting. The activation function, Sigmoid, is used at the last layer since the problem of the research is a two-state classification (images with and without lesions).

4. Experimental Evaluation

4.1. Dataset and Pre-processing

In this research work, two datasets were used. The first set included 38 MRIs of MS patients belonging to the Health Laboratory of the University of Cyprus. This set included 676 lesions. Since the dataset was for the MS patients only, the authors developed a dataset for healthy individuals. For this purpose, MRI images of 20 healthy individuals in the age and gender range of the first dataset, including 11 men and 9 women with a mean age of 35 years, were selected, which included 615 slices. The information of the two datasets is given in Table 1. In both sets, the null slices were manually checked and removed.

Table 1. Dataset Information.

Dataset	Source	Number of Subjects	Age	Gender (f/m)	Number of Slices
MS	eHealth	38	34	17/21	676
Healthy	private	20	35	9/11	615

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.

4.2. Data Augmentation

Data augmentation is used to increase the size of a small dataset [32]. This refers to common approaches such as scaling, rotation, translation, and flipping. In order to increase the number of samples and improve network learning, the data augmentation method was used with the parameters of 30 ° rotation range, 0.2 shear conversion percentage, and 0.1 zoom range.The learning process for classifying images into lesion and healthy groups is performed on the image collection. Data augmentation is used to increase the number of samples and improve network learning. It has a rotation rate of 30 degrees, shear range of 0.2, and zoom range of 0.1. Image size is changed to 212×212 and dynamic range to 0-1.

4.3. Training Platform and Procedure

The Keras package with TensorFlow [32] backend is used to implement and learn network on a graphics card, GeForce GTX 1070, with an 8 GB RAM. In the proposed method, 80% of images are used for learning and 20% for the test. According to the examination of three different network optimization algorithms, including SGD, RMSDrop, and Adam, the Adam function is used as the *optimization* function with a better learning rate of 0.0008.

4.4. Evaluation Metrics

Various criteria are used to evaluate the research results, the most important of which is accuracy. The accuracy indicates the percentage of images that are correctly categorized compared to the total number of available images. In addition to this criterion, the precision, sensitivity and specificity are usually used in medical diagnoses (Equations 2- 5). The sensitivity criterion is the ability of a classifier to correctly diagnose diseases; and the specificity criterion indicates the ability to correctly diagnose the suspect's health. The way of calculating each criterion is as follows:

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

$$Sensitivity=\frac{TP}{TP+TN} \quad (3)$$

$$Precision=\frac{TP}{TP+FP} \quad (4)$$

$$Specificity=\frac{TN}{TN+FP} \quad (5)$$

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 lesion. 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 lesion that are diagnosed without lesions by mistake.

4.5. Experimental Results

The reported evaluation criteria are the mean values of different training times. Figure 7 shows the network accuracy chart.

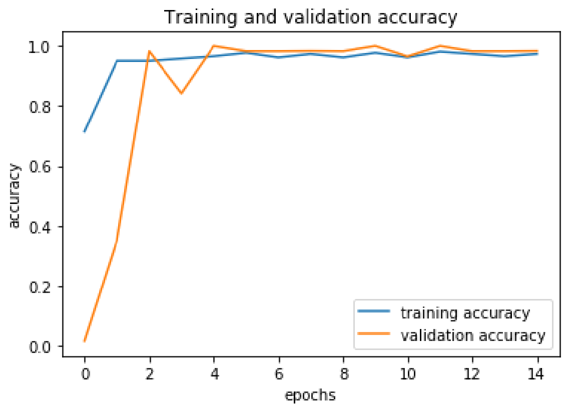

Figure 7. Accuracy chart.

As shown in Figure 7, the network reached the acceptable accuracy value after 14 epochs.

The network was trained by three other pooling methods, including maximum, average, and stochastic. The accuracy and precision values and their results are compared in Table 1.

Table 1. Comparison of different pooling methods.

Method	Precision (%)	Accuracy (%)	Training-time(min)
Average-pooling	98.14	98.60	7.7
Max-pooling	98.43	98.62	7.2
Stochastic-pooling	98.75	98.77	٧
Wavelet-pooling	**99.20**	**98.92**	7.9

In Table 1, the proposed method (wavelet-pooling) is compared with the other three pooling methods in terms of precision, accuracy, and training time. As shown, the proposed method has a higher precision and accuracy. However, it requires more calculations and a little more training time. The accuracy and precision are very important in diagnosing MS lesions. The amount of increase in the training time of the proposed method is acceptable compared to the amount of increase in the accuracy and precision.

Table 2 presents the results of the proposed method and the other methods in the literature for classifying the MRI images of MS.

Table 2. Comparison of different methods (percentage).

Method	Accuracy	Precision	Specificity	Sensitivity
HT-LR	89.72	-	-	-
GLCM	95.14	-	95.01	95.27
MBD	97.80	-	97.82	97.78
CNN-ReLU	98.23	-	98.24	98.22
CNN-BN-DO-SP	98.77	98.75	**98.76**	98.77
Wavelet-pooling	**98.92**	**99.20**	98.33	**99.20**

The methods can be classified into two categories, traditional image processing, and deep learning-based methods. According to the table, the proposed method has a higher value of accuracy and sensitivity than the other methods.

Figures 8 and 9 compare the results of the proposed method separately with the traditional and deep learning-based methods. Given that the value of precision criterion was not reported in all the previous studies, the comparison of methods was performed based on three other criteria in the diagrams.

Figure 8 shows that the deep learning methods yield better results than the traditional image processing methods (MBD and GLCM); hence, the convolutional neural networks, which are the bases for image extraction in deep learning methods, provide a good performance in extracting the specificity of MS lesions in the MRI images.

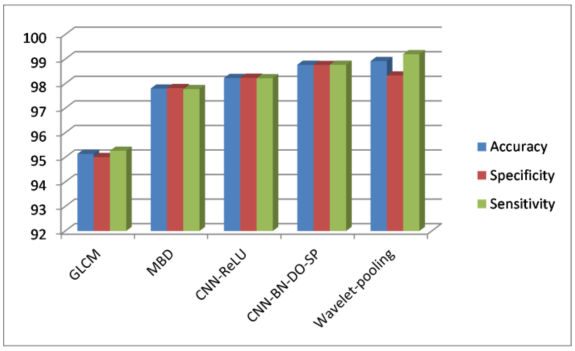

Figure 8. Comparison of accuracy, sensitivity and specificity (percentage).

As shown in Figure 9, the proposed method has a better accuracy and sensitivity than the other two methods based on deep learning, and it can be concluded that the use of wavelet pooling highlights the lesions, and better extracts the specificity of lesions in the images in addition to reducing dimensions of the input image due to the shape, size and texture features of MS lesions in the MRI images.

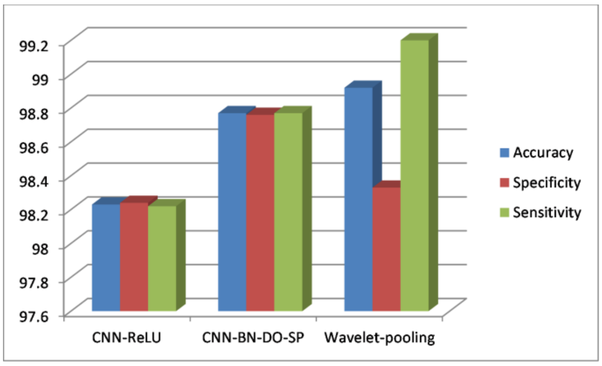

Figure 9. Comparison of deep learning methods (percentage).

5. Conclusions

The classification of medical images by deep learning methods provided the possibility of automatic extraction of specificity from images and yielded better results than the traditional methods of image processing. In deep learning, the convolutional neural networks were used in order to classify images. In the network, a pooling layer was used to reduce the image size and the computational load. In the proposed method, the pooling layer was used based on the Haar wavelet transform, which made it possible to highlight the specificity to extract MS lesions in the MRI images, and also reduced the image size. The proposed method had a higher precision than the traditional and deep learning methods.

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