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Wavelet Transform and WCA Based Deep Convolutional Network for Brain Tumor Detection and Classification from Magnetic Resonance Images

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ABSTRACT

Deep learning is playing vital role in the research of neuroscience for studying brain images. It is the one of the most frequently used diagnosis tool to classify irregularities in the brain. Classifying the type of tumor from Magnetic Resonance (MR) images in the diagnostic system depends on size, shape, and position of tumor which varies from different patient's brain. Many efforts have been made for image detection and classification, but getting accuracy in classification and detection is a challenging task. Motivated by the complexity of classification brain tumors, this paper presents a WCA (Sine Cosine Algorithm) based DCNN (Deep Convolutional Neural Network) model has been developed for classification of brain tumors into malignant (cancerous) and benign (noncancerous) category. The discrete wavelet transform segmentation technique has been utilized to improve the performance of detection process. The Daubechies wavelet is considered for segmentation process and shows its improved capability in performance during detection of brain tumor categories from the magnetic resonance images. Further, the segmented images are given as input to the WCA-DCCN model for classification cancerous and non-cancerous tumors. The WCA clones the sea and rivers in the process of water cycle and through this algorithm the optimization of the weights of the DCCN has been made to improve the performance of the conventional DCCN. Also the different category of hidden neuron functions at the hidden layer has been tested with the new hybrid WCA-DCCN model and comparison results are presented. DCCN+WCA shows an accuracy of 98.93% and 97.23 % during training and testing.

1. Introduction

Brain tumors grown uncontrollable and affects the complete brain nerves where the cells affects the usual functionality of the activity of brain and terminate the healthy brain cells [1]. Benign tumors are non-cancerous and malignant tumors are cancerous and grown in the cell boundaries[2]. MRI is one of the proven technique for acquiring brain tumor images of the affected patients [3]. Salem and Alfonso utilized "Fast Fourier Transform (FFT)" and "Minimal Redundancy-Maximal Relevance (MRMR)" techniques for automatic classification of MRI brain tumor images [4]. Remya et al. utilized "discrete wavelet transform (DWT)" with Fuzzy C-Means method for segmentation [5]. While thresholding and clustering [6-8] utilized for segmentation of brain tumors. Deep learning (DL) is proposed as an extension of neural networks [9]. A convolution neural network (CNN) represents a most eminent DL structure utilized commonly for description and segmentation of brain tumors. In this research paper a WCA based DCNN model for brain tumor classification of benign and malignant tumors is proposed. Further the wavelet transform is considered to decompose the MRI image into different levels of approximate and detailed coefficients.

This paper organizes as follows: Section-2 presents the materials and proposed model, section -3 presents results of segmentation and classification, section -4 presents the discussion of the whole research work and section-5 presents the conclusion and reference.

2. Materials And Methods

A. Wavelet Transform

Fourier transform[10] of a one-dimensional function is defined as:

$$X(f)=\int_{-\infty}^{\infty}x(t)e^{-j2\pi ft}dt \tag{1}$$

In order to resolve this global issue one may use the short-time Fourier transform (STFT). The STFT is given by:

$$X(f)=\int_{-\infty}^{\infty}x(t)e^{-j2\pi ft}w(t-\tau)dt \tag{2}$$

Where, τ is a translation variable that allows the window $\omega(t)$ to translate in time. The wavelet transforms successfully overcome the shortcomings of the STFT [10].

The continuous wavelet transform for a continuous-domain input is given as:

$$W(\tau,s)=\frac{1}{\sqrt{s}}\int_{-\infty}^{\infty}x(t)\varphi\left(\frac{t-\tau}{s}\right)dt \tag{3}$$

Where, τ is a translation variable while s is a scaling parameter.

If an image is decomposed by wavelets, the overlap in the frequency domain becomes non-avoidable. Even though the term "scale" can be approximately interpreted as "frequency" due to its ability in adjusting the size of the basis function.

B. Research flow diagram

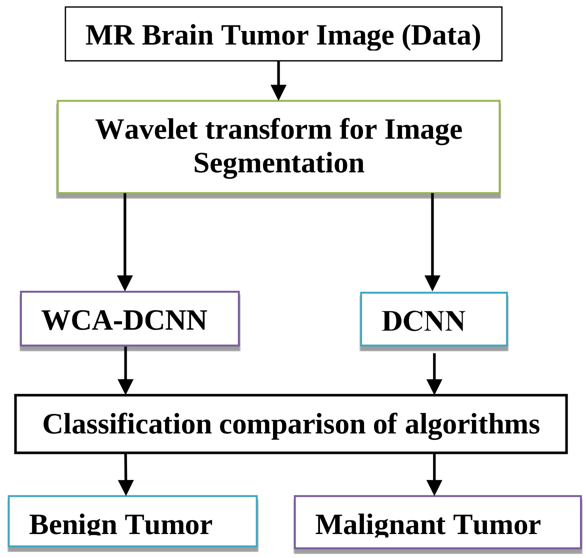

Fig. 1 Research work flow diagram

C. Proposed Deep Convolutional Neural Network

The architecture for deep convolutional networks [11-14] has been presented in Fig.2, and DCNN is considered as more powerful and kinds of CNN containing of several layers of convolutions. Every layer works on simple computational operation as weighted sum. Less number of connections and weights of the CNN make convolutional layers moderately inexpensive in terms computational power and memory. The classification task becomes faster by utilizing the CNN where the output becomes a single class label. The filtering and convolution on images played an important and vital role in classification task. In this research we are considering the weight optimization of fully connected layer by water cycle algorithm to improve the performance of the conventional CNN.

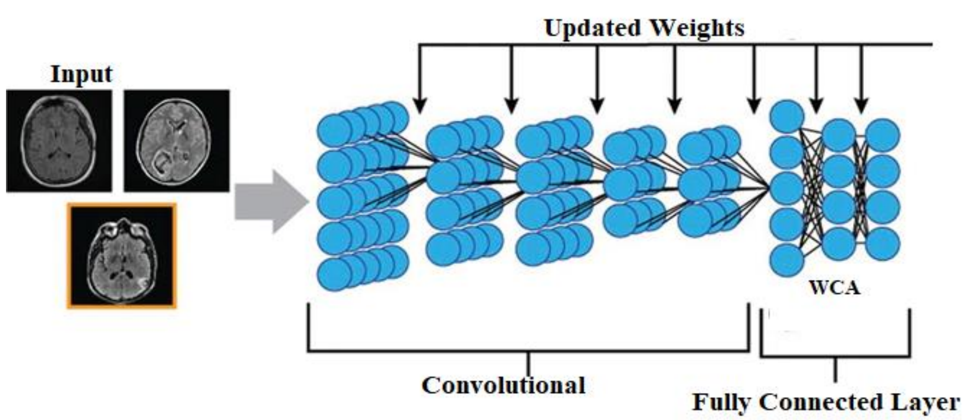

Fig. 2 Architecture of DCNN [17]

D. Water Cycle algorithm

Now considering the WCA [15,16] algorithm which clones the flow of streams and rivers into the sea in the form of a matrix of size $\psi_{Population} \times d$, where "$d$ "represents the dimension and the matrix is given by

$$Total\ population = \begin{bmatrix} Sea \\ River^1 \\ River^2 \\ River^3 \\ \vdots \\ Stream\psi^{sr+1} \\ Stream\psi^{sr+2} \\ Stream\psi^{sr+3} \\ \vdots \\ Stream\psi_{pop} \end{bmatrix} = \begin{bmatrix} x_{11}^1 & x_{12}^1 & \cdots & x_{d(i,j+1)}^1 \\ x_{21}^1 & x_{22}^2 & \cdots & x_{d(i+1,j+1)}^2 \\ \vdots & \vdots & \cdots & \vdots \\ x_{i+1,i}^{\psi_{pop}} & x_{i+1,j+1}^{\psi_{pop}} & \cdots & x_{d(i+n,j+n)}^{\psi_{pop}} \end{bmatrix} \quad (4)$$

Where, $\psi_{Population}$ is population size and ψ_{sr} are selected values as the sea and rivers.

$$\psi_{sr} = No.of\ rivers + 1(sea) \quad (5)$$

$$\psi_{Stream} = \psi_{population} - \psi_{sr} \quad (6)$$

$$\psi s_n = round\left\{\left|\frac{f(River_n)}{\sum_{i=1}^{\psi_{sr}} f(River_i)}\right| \times \psi_{Stream}\right\}, \quad n = 1,2,3 \, ..\psi_{sr} \quad (7)$$

Where, ψs_n represents the "number of streams', and f represents the evaluation function in the algorithm.

Now mapping with the position equation X_{ij}^{n+1} with $\vec{X}_{Stream}, \vec{X}_{Sea}, \vec{X}_{River}$, the best solutions are obtained by updating the WCA parameters.

The updated positions for "streams" and "rivers" have been evaluated as follows.

$$\begin{aligned} X_{Stream}(l+1) &= \lambda X_{Stream}(l) + Rand. \times (\beta.X_{River}(l) - X_{Stream}(l)) \\ X_{Stream}.(l+1) &= \lambda.X_{Stream}(l) + Rand. \times (\beta.X_{Sea}(l) - X_{Stream}(l)) \\ X_{River}(l+1) &= \lambda X_{River}(l) + Rand \times (\beta X_{Sea}(t) - X_{River}(l)) \end{aligned} \quad (8)$$

Where λ is the controlling parameter

And the "velocity equation" is updated by

$$\begin{aligned} V_{Stream(i,j)}.(n+1) &= \zeta.V_{Stream(i,j)}(n) + C_1 \times (V_{Sea(i,j)}(n) - V_{Stream(i,j)}.(n)) \\ V_{Stream(i,j)}.(n+1) &= \zeta V_{Stream(i,j)}(n) + C_1 \times (V_{River(i,j)}(n) - V_{Stream(i,j)}.(n)) \\ V_{River(i,j)}.(n+1) &= \zeta V_{River(i,j)}(n) + C_1 \times (V_{Sea(i,j)}.(n) - V_{River(i,j)}(n)) \end{aligned} \quad (9)$$

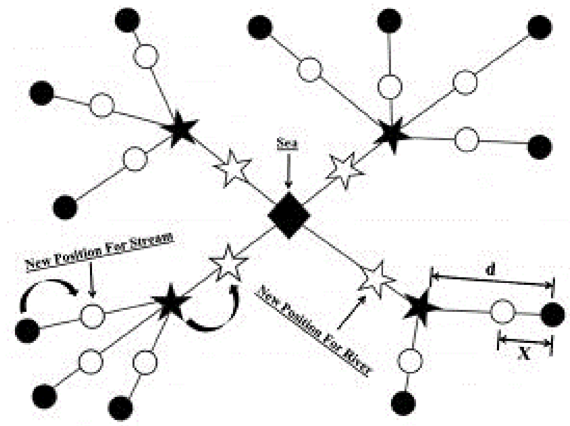

Fig. 3 Representation of streams flowing into a specific river[14]

Pseudo code

1. Initializing particles with random position and velocity vectors and WCA parameters $\lambda, \psi_{sr}, \psi_{pop}$
2. Update particles velocity and position equation (8) and (9)
3. %optimization loop
4.for i=1:k
    for j=1:N
   % update WCA parameter

$$W_{Stream(i,j)}..(n+1) = W_{Stream(i,j)}.(n) + rand \times \left(W_{Sea(i,j)}(n) - W_{Stream(i,j)}(n)\right)$$

$$W_{Stream(i,j)}.(n+1) = W_{Stream(i,j)}.(n) + rand \times \left(W_{River(i,j)}.(n) - W_{Stream(i,j)}(n)\right)$$

$$W_{River(i,j)}.(n+1) = W_{River(i,j)}.(n) + rand \times \left(W_{Sea(i,j)}(n) - W_{River(i,j)}(n)\right)$$

5. end for the loop j and end for the loop j
6. Stop: update the weight till convergence to get fitness optimal solution.

The segmented images are fed as input to the DCCN+WCA model for classification task.

E. Data set

The dataset considered form “Harvard Medical School website (http://med. harvard.edu/AANLIB/)”[17] for training and testing. The proposed methodology was implemented on a python platform with 8Gb RAM,2.34GHz. A total of 500 MRI images are considered for training and testing which contains Benign and Malignant tumor images. Further the images are aligned into groups for refinement. Out of which with 80% were considered for training and 20% for testing.

3. Results

Image Segmentation Result

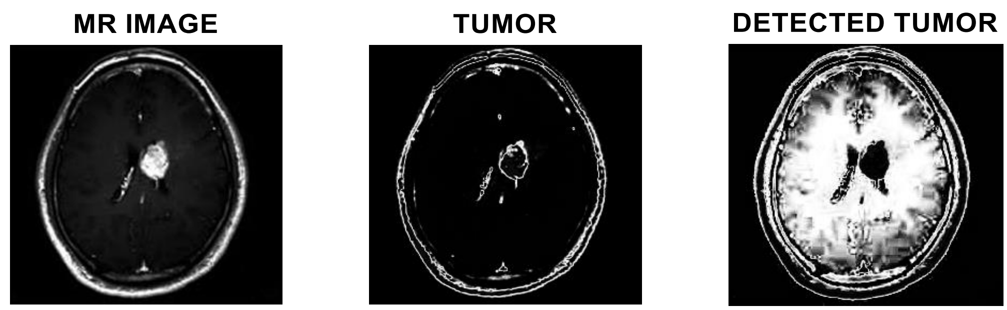

Fig. 4.a Image segmentation using Fuzzy C Means

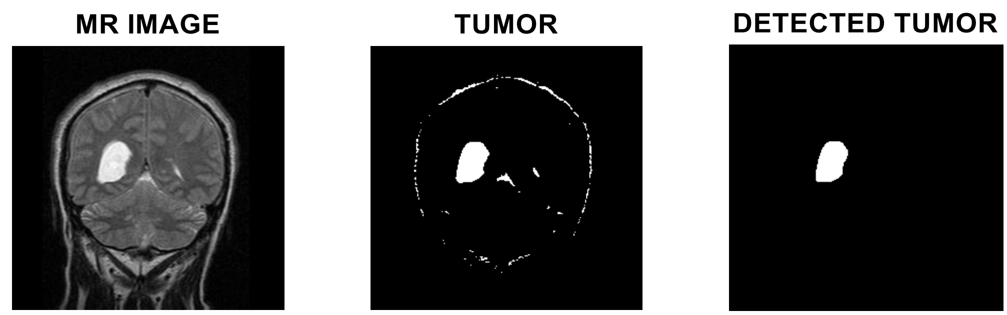

Fig. 4.b Image segmentation using Fast Fuzzy C Means

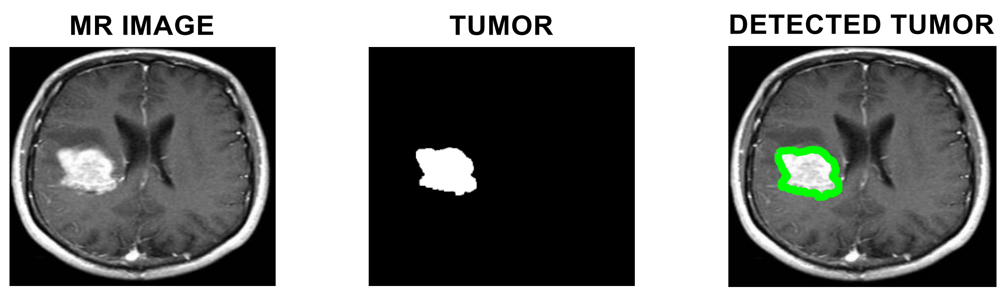

Fig.5 Image segmentation using wavelet transform

Table 1: Segmentation Accuracy and computational time

Model	Computational time	Accuracy
Wavelet Transform	11. 2145	97.93
K-MEANS	29.2144	85.23
Fuzzy C Means	24.2332	93.56
Fast Fuzzy C Means	21.1232	95.82

Classification Results

Classification is performed by using WCA optimization technique for building the DCNN of hidden layers structure. Also for evaluating the performance of the selected classifier, WCA has been employed for optimizing the weights of DCNN [18-19].

Table 2 Performance evaluation

	Elapsed time (seconds)		Accuracy in %	
Models	**Training**	**Test**	**Training**	**Test**
DCNN+WCA	12.7536	13.1611	98.93	97.23
DCNN+ Back propagation	23.2878	26.5673	96.22	95.43

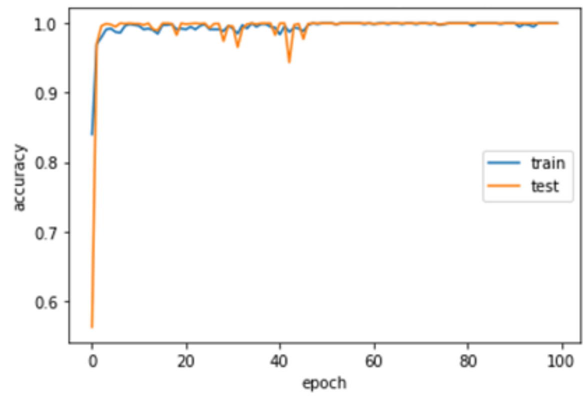

Fig.6 Classification accuracy by using DCCN+WCA

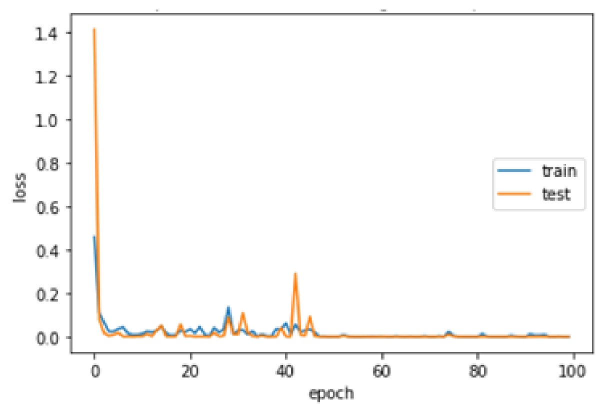

Fig.7 Loss incurred by using DCCN+WCA

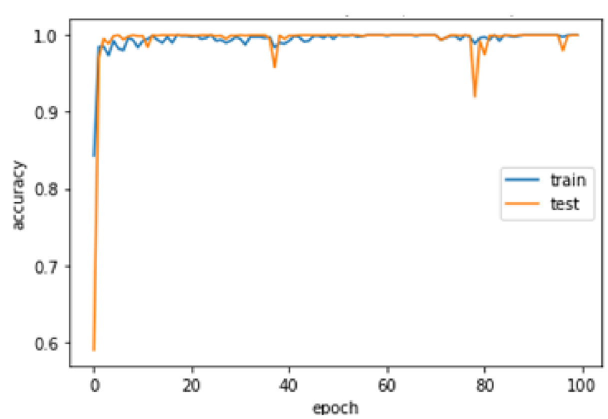

Fig.8 Classification accuracy by using DCCN+Back propagation

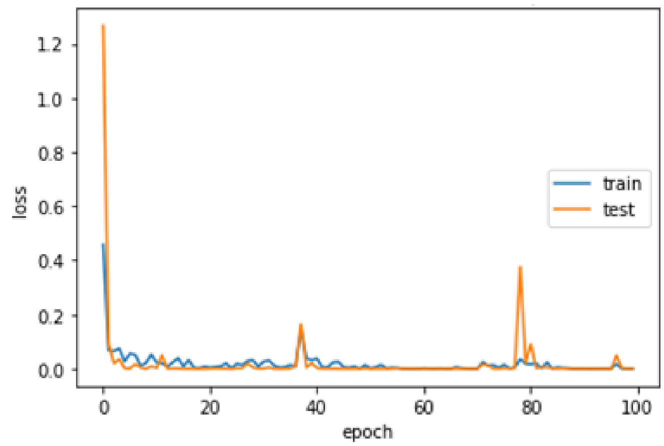

Fig.9 Loss incurred by using DCCN+ Back propagation

4. Discussion

Fig.1 presents the research flow of the proposed work. At the first stage the magnetic resonance images are segmented by wavelet transform. The segmentation accuracy is presented in Table-2. Fig.4a, Fig.4b and Fig.5 show the segmentation results by utilizing Fuzzy c means, Fast fuzzy c means and wavelet transform. It is found that the wavelet transform shows better performance in visual localization of tumor. Further, the segmented images are fed as input to the DCCN+WCA model for classification. The proposed WCA+DCCN has been presented for classification is shown in Fig.2.The fully connected layer weights are updated by WCA algorithm to improve the performance of the DCCN. It is found from the table-2 that the DCCN+WCA achieves 98.93% and 97.23 % of accuracy during training and testing. The computational time also prove better than the DCCN with back propagation algorithm which is presented in Table-3. Fig.6 shows the training and testing accuracy by DCCA+WCA with 100 epochs. It is found that train and test accuracy settles after 55 epochs. Fig.7 shows the loss incurred during training and testing DCCN+WCA. Fig.8 shows the training and testing accuracy by DCCN+ Back propagation with 100 epochs and it is observed that train and test accuracy settles nearly 100 epochs. Fig.9 shows the loss incurred during training and testing DCCN+ Back propagation. It is found that the loss varies in different epochs and becomes more variation around 80epochs. So, it is concluded that the proposed model DCCN+ WCA outperforms in classification.

5. Conclusion

The automatic detection and classification using the proposed DCNN model with WCA training on fully connected layer is proposed in this paper. Images are segmented by utilizing wavelet transform and achieves an accuracy of 97.93% with computational time of 11.2145seconds. Further the statistical features are extracted and fed as input to the WCA+DCCN model. There are seven features are considered for the classification task. The proposed DCNN with WCA model has been assigned for the classification and the results were compared with the conventional DCCN and presented in the results section. Further classification accuracy of 98.93 % is achieved with WCA +DCNN model with soft max function. From the result, it is found that the proposed WCA+DCNN model provides improved classification performance and in terms of computational time. The DCCN model can also be updated with sine cosine algorithm also to show the performance of the classifier.

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