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Encephalon Disease Detection and Classification Using Discrete Orthonormal S-Transform and Sine Cosine Algorithm Based Deep Convolutional Network

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ABSTRACT

Magnetic Resonance Imaging (MRI) is the one of the most frequently used diagnosis tool to detect and classify abnormalities in the brain. Automatic classification and detection is a difficult and complex task for a radiologist or clinical practitioner for identification and extraction of infected tumor areas from the MRI (Magnetic Resonance Imaging).Further, classifying the type of tumor from Magnetic Resonance (MR) images also a vital part of the diagnostic system. Factors like size, shape, and position of tumor vary from different patient's brain. Many efforts have been made for image detection and classification, but getting accurate automated techniques taken higher computational time. Motivated by the above difficulties, this paper proposes S- Transform based Discrete Orthonormal S-Transform (DOST) segmentation technique to improve the performance of detection process. The DOST also utilized for feature extraction of the image. Further, a SCA (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 SCA has been utilized for weight optimization in the fully connected layer of the DCNN model. Also the different category of hidden neuron functions at the hidden layer has been tested with the new hybrid SCA-DCCN

model and comparison results are presented. In this research work an effort has been made improve the accuracy of diagnosis process.

1. Introduction

Brain Cancer deaths are estimated around 9.6 million as per World Health Organization (WHO) reports in 2019 [1]. Brain is one of the most complex organs in the human body and uncontrolled division of cells causes brain tumor which destroys the healthy cells [2, 3]. Brain tumors are mainly divided into two categories such as benign and malignant tumors [4-6]. Imaging techniques related to MRI have a large influence in the automatic detection [7-9]. A person's likelihood of developing primary brain tumor in their lifetime is less than 1%.. and death rate is 60% due to primary cancerous brain tumors. According to the last report from National Vital Statistics Systems (NVSS), the mortality from 1975 to 2016 was higher among men and higher in older individuals. People with age 65+ years had a significant increase in mortality for all tumors, while people aged <20 years had no significant changes in mortality[10,11].

Detection of solid tumors, whether it is benign or malignant, is often difficult in brain MR images. Identifying the exact size and coverage of tumors is also challenging in brain MRI because the original medical image has the problem like noise, low contrast, and bad resolution and so on. So, it takes minutes to get MR images of a subject and more time to view the images generated on a screen and carry out visual assessment. Visual assessment of the MR images is subjective, often time consuming and hardly repetitive which might give rise to inaccurate diagnosis. There is no mechanism that detects tumors and classifies the tumors as malignant or benign in MR. This could be avoided if there exist a tool that could be used for accurate detection of abnormalities in the brain automatically by clever analysis of the MR images non-invasively. This calls for the development of methodology which could be used for effective analysis of the MR images that could robustly detect and classify brain tumors. multimodal brain tumor segmentation[12], Margo Random Field (MRF) [13], decision Tree, Bagging C based wrapper approach[14], the fuzzy based control theory[15] has been presented for segmentation by researchers. Shree and Kumar applied "Berkeley Wavelet Transformation (BWT)" and "Support Vector Machine (SVM)" to detect the tumor [16]. Kumar and Vijaya kumar proposed the "principle component analysis (PCA)" and "Radial Basis Function (RBF)" [17], Ullah et al. [18] used ANN and Haar wavelet for segmentation and classification. To reduce the dimensionality Muneer andJoseph used ANN with (PCA)[19]. Vidyarthi, A., & Mittal [20] proposed threshold segmentation and morphological operations to preserve the background and correct identification of the tumor region. Amasyali and Ersoy [24] proposed ensemble classifier in order to improve the accuracy and execution time.The detection and classification of the brain tumors have been presented by the researchers through different classifiers such as SVM, PNN, RBFNN etc. and found classification results in terms of accuracy and computational time for the cancerous and noncancerous brain tumors.

Deep learning has been applied in lung cancer diagnosis [24], tibial cartilage segmentation [25] and brain tumor detection [26-29]. Among more recent solutions to this problem, Sajid et al. [30] proposed a CNN architecture obtained sensitivity and specificity values for glioma detection are 0.86 and 0.91, with an accuracy of 95.62%[31]. Zikic et al.[32] used a shallow CNN with one fully-connected (FC) layer,Urban et al. [33] proposed 3D filters to receive context view of image [34]. Havaei et al. [35] built a cascade networks, Lyksborg et al. [36] use a binary CNN to identify the complete tumor. Simonyan and Zisserman [37] investigated potentiality of deep architectures for segmentation of gliomas. This proposed research work introduces an efficient model for classification, of benign and cancerous (malignant) brain tumor. In this research work we propose a SCA based DCNN model for brain tumor classification of benign and malignant tumors and also we have proposed Discrete orthonormal S Transform to decompose the MRI image into different levels of approximate and detailed coefficients.

The rest of the paper has been organized as follows: Section -2 presents materials and methods which includes research flow diagram, Discrete orthonormal transform, Proposed SCA based DCCN model, section-3 presents results of segmentation and classification, section -4presents the detailed discussion of the outcomes of segmentation and classification and section -5 presents the conclusion of the research work followed by references.

2. Materials and Methods

In recent years, major effort has been made to assist radiologists in the detection and description of malignant and benign abnormalities. The study of cancerous tumor has appealed the attention of many researchers around the world. Many of researches are being published earlier that argue issues related to the brain tumor and the different methods for its early detection and classification.

1) Research Flow Diagram

The research work steps as (i) The magnetic resonance images has been first collected and segmented by the DOST[38,39] algorithm and statistical feature extraction technique has been applied for feature extraction. Further (ii) the segmented image has been given as input to the proposed SCA-DCNN for the classification of encephalon tumors. (iii) the weights on fully connected layer are updated utilizing SCA algorithm to update the weights of the extreme learning machine model. In the 4th stage (iv), The classification comparison results from the proposed SCA-DCNN and DCNN is performed and presented. The research flow diagram is presented in Fig.1.

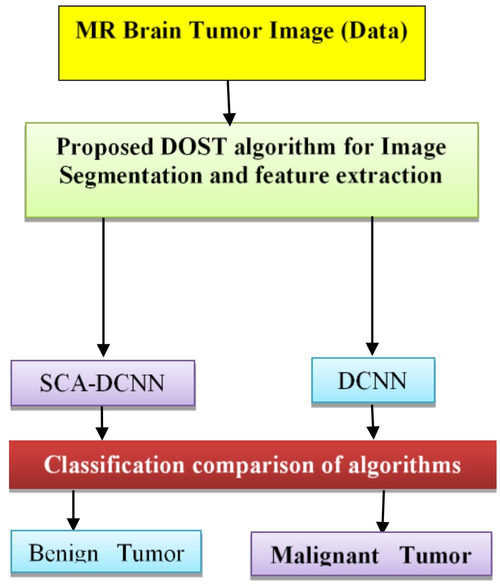

Fig. 1 Research work flow diagram

2) Detailed analysis of Discrete orthonormal S-Transform

The detailed mathematical calculations involved in segmentation based on DOST and SCA-DCNN are presented in this section. The DOST segmentation is proposed because of the energy concentration which provides more information of internal structure of the image than the other conventional wavelet transform segmentation technique.

For a 2-D continuous-domain function $h(x,y)$, the 2-D S transform is defined with a 2-D Gaussian modulate of cosinusoidal functions as:

$$S(X,Y,k_x,k_y) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} h(x,y)\frac{|k_x||k_y|}{2\pi} e^{-\frac{(X-x)^2 {k_x}^2+(Y-y)^2 {k_y}^2}{2}} e^{-j2\pi(k_x x+k_y y)} dxdy \qquad (1)$$

The Gaussian kernel changes shape with respect to spatial frequencies and in the k_x and k_y in the x and y directions, respectively.

Similar to the 2-D Fourier transform, the 2-D S transform is a separable transform over different dimensions [40], Therefore, calculation can be pursued first over one dimension and then over the other dimension. Using the 2D convolution theorem in the Fourier space, the 2-D S transform can be written as:

$$S(X,Y,k_x,k_y) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} F(\alpha+k_x,\beta+k_y) e^{\frac{-2\pi^2\alpha^2}{k_x^2}} e^{\frac{-2\pi^2\beta^2}{k_y^2}} e^{j2\pi(\alpha X+\beta Y)} d\alpha d\beta \qquad (2)$$

Integration of $S(X,Y,k_x,k_y)$ over the variables x and y gives the 2-D Fourier spectrum

$$H(k_x,k_y) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} S(X,Y,k_x,k_y) dXdY \qquad (3)$$

Then the 2-D inverse Fourier transform can be applied to $H(k_x, k_y)$ to recover the original function. For an input 2-D signal (image), the 2-D Stockwell transform is a complex function of *x*, *y*, k_x and k_y which gives convenience and the freedom to manipulate data over spatial and frequency domains. The transformed data has four-dimensional data set which gives a big challenge in possessing, analyzing and visualizing the coefficients. Therefore, we only analyze, process, compute or store relevant components of the (X, Y, k_x, k_y) . We will describe one of the strategies to deal with this challenge later in this section.

The discrete 2-D Stockwell coefficients of an image $h(p,q)$can be expressed explicitly as:

$$S(p,q,n,m) = \sum_{n'=0}^{N-1} \sum_{m'=0}^{M-1} H(n'+n, m'+m) e^{-\frac{-2\pi^2 n'^2}{n^2}} e^{\frac{j2\pi n' p}{N}} e^{-\frac{-2\pi^2 m'^2}{m^2}} e^{\frac{j2\pi m' q}{M}} \quad (4)$$

where $p = 0,1,\ldots,N-1$ and $q = 0,1,\ldots,M-1$.

It is shown in the continuous S transform that integration of $S(X, Y, k_x, k_y)$ over the variables x and y gives the 2-D Fourier spectrum. Similarly summation of $S(p,q,n,m)$ over the variables p and q gives the 2-D discreet Fourier spectrum.

$$\frac{1}{M}\sum_{q=0}^{M-1} \frac{1}{N}\sum_{p=0}^{N-1} S(p,q,n,m) = H(n,m) \quad (5)$$

Where $H(n,m)$ are the discrete 2-D Fourier coefficients.

The original image can be reconstructed using:

$$h(p,q) = \left(\frac{1}{M}\right)^2 \sum_{q'=0}^{M-1} \sum_{m=0}^{M-1} \left(\frac{1}{N}\right)^2 \sum_{p'=0}^{N-1} \sum_{n=0}^{N-1} S(p',q',n,m) e^{\frac{j2\pi np}{N}} e^{\frac{j2\pi mq}{M}} \quad (6)$$

1) Discrete Orthonormal Stockwell Transform

Stockwell transform is an over complete representation. For a signal of length *N*, there are N^2 Stockwell coefficients and therefore the computing of all N^2 coefficients of the Stockwell transform has computational complexity. If the dimension for the input signal is higher, the computational complexity is also higher. The ST gets exponentially more expensive for higher-dimensional signals [39].The Discrete Orthonormal Stockwell Transform (DOST) is the best solution to reduce the computational cost without changing its multi resolution nature and the absolutely-referenced frequency and phase information. The DOST is a pared-down version of the fully redundant Stockwell transform. In the sense of multiresolution, less temporal resolution is required for a lower frequency band based on Nyquist criterion or the sampling theorem [39]. The Nyquist criterion indicates that low frequency band and high frequency band have very different sampling requirements. Lower frequencies have longer periods and high frequencies have smaller periods. So lower frequencies have lower sampling rates and higher frequencies have higher sampling rates. The *kth* basis vector is defined as.

$$D[k][v,\beta,\tau]= \frac{1}{\sqrt{\beta}}\sum_{f=v-\beta/2}^{v+\beta/2-1}\left(e^{-i2\pi\frac{k}{N}f}\right)\left(e^{-i2\pi\frac{\tau}{\beta}f}\right)\left(e^{-i2\pi\tau}\right) \quad (7)$$

for k=0, 1,……., N-1, which can be summed analytically to:

$$D[k][v,\beta,\tau]= i\pi\tau\frac{e^{-i2\alpha\left(v-\beta/2-1/2\right)}-e^{-i2\alpha\left(v+\beta/2-1/2\right)}}{2\sqrt{\beta}sin\alpha} \quad (8)$$

Where $\alpha=\pi\left(\frac{\boldsymbol{k}}{\boldsymbol{N}}-\frac{\boldsymbol{\tau}}{\boldsymbol{\beta}}\right)$ can be regarded the center of the temporal window.

The parameter "ν is center of each frequency band (voice), β is the width of band, and τ specifies the location" in time.

2) Deep Convolutional Neural Network

"Convolutional neural network" is similar to artificial neural network, as both of them are made up of self-optimized neurons, which are imported by inputs and perform a nonlinear transformation [40]. Compared with the artificial neural network, convolution neural network is widely used in pattern recognition on images,[41-43].There are five basic elements within the convolution neural network: input layer, "convolutional layer, non-linear layer, pooling layer and fully connected layer". The architecture of DCCN has been presented in **Fig.2.** A number of fully connected (FC) layers plays vital role in optimization. Finally, CNN comprises a Softmax layer which generates the desired outputs. The SCA[44] algorithm is utilized for the weight optimization of DCNN at the fully connected layer. The detailed mathematical calculation of SCA and DCNN is also presented.

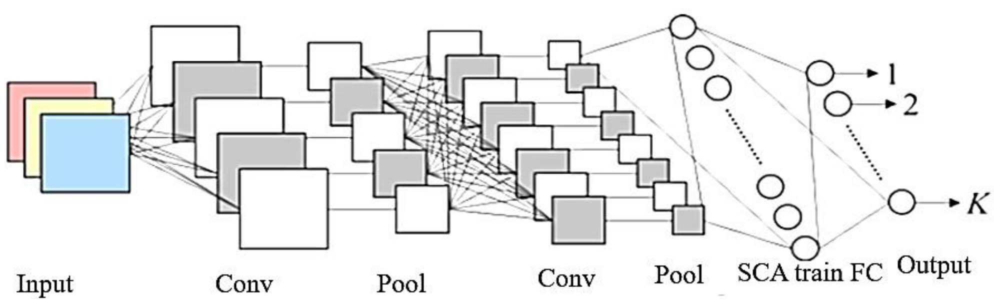

Fig. 2 Architecture of DCNN [42]

3. Proposed SCA-DCCN model

SCA algorithm is a population-based optimization algorithm in solving real problems inunknown search spaces[44]. This research work proposes a novel population-based optimization algorithm based on mathematical analysis of sine and cosine functions for solving the weight optimization of Deep CNN.

According to SCA the position equation is updated as,

$$X_i^{n+1}=\begin{cases} X_i^n+\alpha_1\times\sin(\alpha_2)\times\left|\alpha_3 p^{gbest}-X_i^n\right|, & \alpha_4<0.5 \\ X_i^n+\alpha_1\times\cos(\alpha_2)\times\left|\alpha_3 p^{gbest}-X_i^n\right|, & \alpha_4\geq 0.5 \end{cases} \quad (9)$$

Where α_1, α_2, α_3, α_4 are the random variables and α_1 is given by

$$\alpha_1 = a\left(1 - \frac{n}{K}\right) \quad (10)$$

Where " n is the current iteration", K is the maximum number of iterations. The current position X_i^n and X_i^{n+1} updated position has been mentioned in eqn(9). The parameter α_1 regulates the next position regions, α_2 evaluates the direction of movement from $x_i(n)$ .The parameter α_3 controls the current movement, and the parameter α_4 equally changes between the "sine and cosine "functions.

To have faster speed of convergence of the parameter α_1 is improved as

$$\alpha_m = \exp\left(\frac{1}{1+(\alpha_1)}\right) \quad (11)$$

And the corresponding updated position equation is given as

$$X_{ij}^{n+1} = \begin{cases} X_{ij}^n + \alpha_m \times \sin(\alpha_2) \times \left|\alpha_3 p^{gbest} - X_i^n\right|, & \alpha_4 < 0.5 \\ X_{ij}^n + \alpha_{m1} \times \cos(\alpha_2) \times \left|\alpha_3 p^{gbest} - X_i^n\right|, & \alpha_4 \geq 0.5 \end{cases} \quad (12)$$

Further the weights are mentioned as $W = [w_{i0} + w_{i1}x_1 + ...w_{iN}x_N]$ and the weigthts are mapped and updated using

$$W_{ij}^{n+1} = \begin{cases} W_{ij}^n + \alpha_m \times \sin(\alpha_2) \times \left|\alpha_3 p^{gbest} - W_i^n\right|, & \alpha_4 < 0.5 \\ W_{ij}^n + \alpha_{m1} \times \cos(\alpha_2) \times \left|\alpha_3 p^{gbest} - W_i^n\right|, & \alpha_4 \geq 0.5 \end{cases} \quad (13)$$

Pseudo code: SCA for weight optimization of DCNN Model.

1. Initialize the parameters of SCA parameters $\alpha_1, \alpha_2, \alpha_3, \alpha_m, K$
2. Initialize the position equation and map with the weights

3.Initialize the weights as W_{ij}^n
4.%starting of loop
for l=1:K

update(W_{ij}^n) as

$$W_{ij}^{n+1} = \begin{cases} W_{ij}^n + \alpha_m \times \sin(\alpha_2) \times \left|\alpha_3 p^{gbest} - W_i^n\right|, & \alpha_4 < 0.5 \\ W_{ij}^n + \alpha_{m1} \times \cos(\alpha_2) \times \left|\alpha_3 p^{gbest} - W_i^n\right|, & \alpha_4 \geq 0.5 \end{cases}$$

End

update W_{ij}^{n+1} to obtain minimum weight values
end of for loop
6.Stopping criteria: Continue till optimization gets minimum error values
7. If not converges, repeat until nearly zero error satisfied.

4. Data Collection

The brain tumor data set was taken from "Harvard Medical School website (http://med. harvard.edu/AANLIB/)"[44]. A total of 255 MRI images containing benign and malignant tumors were used. The image size is taken as 256x256 which are under gone segmentation and feature extraction. The proposed methodology was implemented on a MATLAB R2019a platform.

A. Statistical Feature extraction

After segmenting the statistical features are extracted using DOST and presented in the **Table 1.**The normalized features are considered to ease of classification.

TABLE I. Normalized features

Feature	
Correlation	0.2223
Energy	0.1041
Homogeneity	0.8827
Smoothness	0.3866
Kurtosis	0.9893
Skewness	0.2375
IDM	0.2167

5. Results

A. Image segmentation results

Image segmentation is the non-trivial task of separating the different normal brain in brain MR images [56].

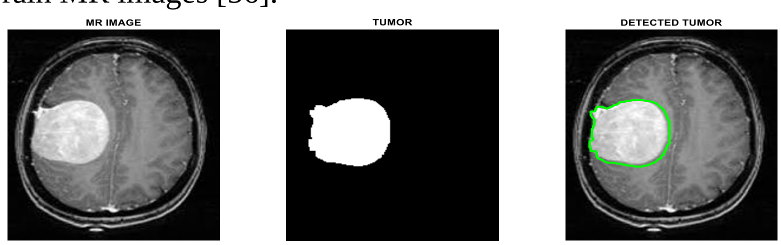

Fig. 3 Image segmentation using wavelet transform

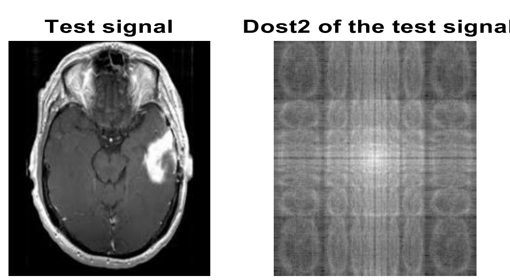

Fig. 4MRI image and Dost of MRI image

TABLE II Segmentation Accuracy and computational time

Model	Computational time	Accuracy
Wavelet Transform	11. 214534	97.93
DOST	12.213146	98.12
S-Transform	34.317874	92.31

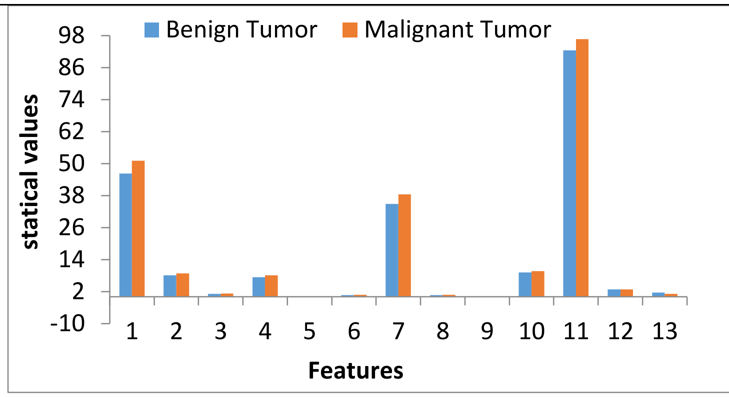

Fig. 5 Feature extraction

B. SCA-DCCN Classification Results

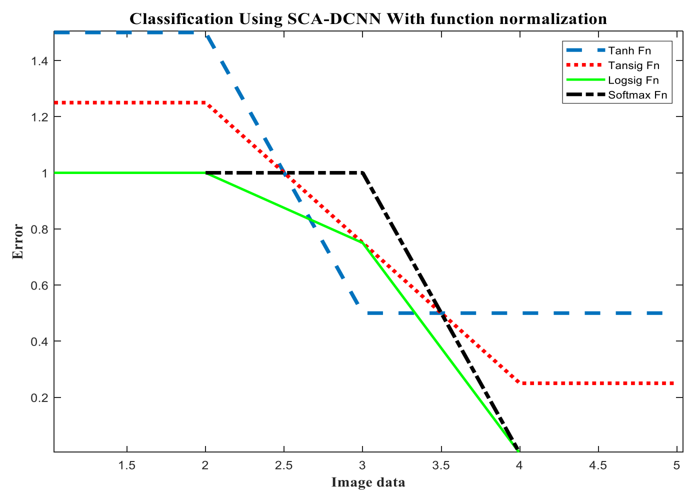

Fig 6 SCA-DCNN with function normalization

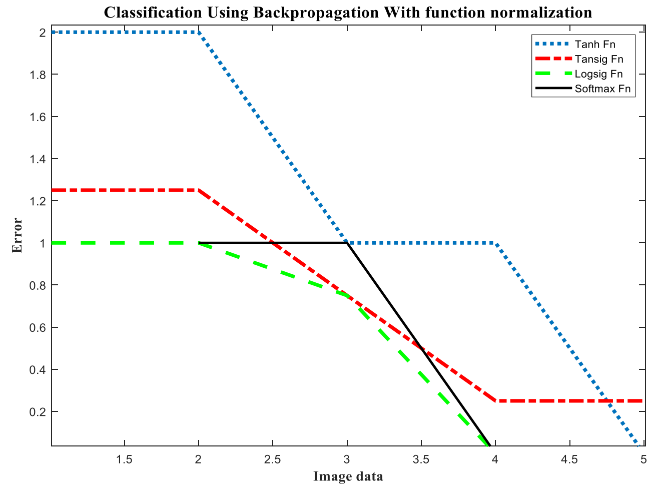

Fig. 7 Back propagation with function normalization.

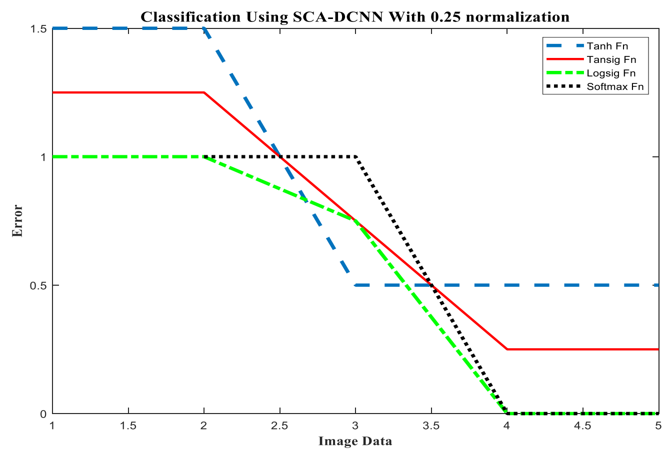

Fig.8 SCA-DCNN with function 0.25 normalization

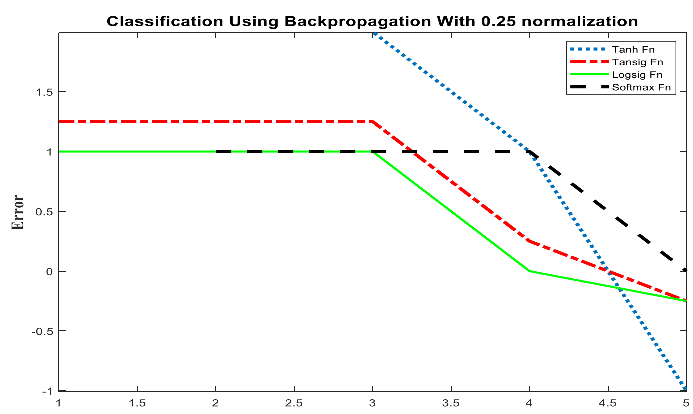

Fig. 9 Back propagation with function 0.25normalization

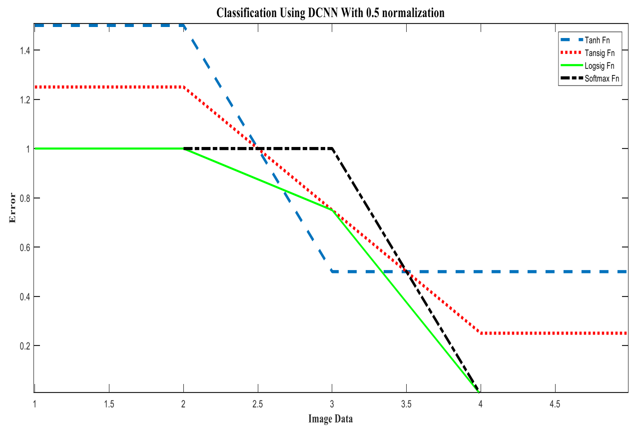

Fig. 10 DCNN with function 0.5 normalization

TABLE III Performance evaluation

	Elapsed time (seconds)		Accuracy in %	
Activation Function	**DCNN+ SCA**	**DCNN+ Back propagation**	**DCNN+SCA**	**DCNN+ Back propagation**
Softmax	2.0224	2.1639	98.28	97.56
tanh	2.2800	2.9633	91.12	90.17
tansig	2.0072	2.1960	95.40	92.16
logsig	2.0677	2.1308	96.37	93.15

6. Discussion

Fig.3 and **Fig. 4** shows the results of segmenting a sample image using Wavelet transform and DOST. It is found form the Fig.3 that the energy concentration is missing in case of the wallet transform. The **Fig.4** shows the density of the tumor in hazed white concentration where the effect of the disease is minute. The wavelet transform is showing the location of the tumor, but could not able to perform the concentration of energy. Even though the computational time is slightly more in DOST, it is preferable for the purpose of application in segmentation process. Table -II presents the segmentation accuracy and computational time for wavelet transform, S-Transform and DOST. It is observed that the DOST takes little more time, but outperforms in terms of accuracy. Classification is performed by using input features to DCNN with SCA optimization of fully connected layers structure. Also for evaluating the performance of the selected classifier, SCA has been employed for optimizing the weights of DCNN. **Fig. 5** shows the comparison of the features and it is found that the homogeneity and kurtosis has great impact on the classification task. While considering Tanh kernel function, in SCA–DCCN, the error settles between 0.4 and 0.6, but the Tansig function settles between 0.2 and 0.4 but takes more time for convergence. The proposed softmax and logsig function converges zero at less time as shown in **Fig.6**. The convergence curve settles after 4 epochs which shows the robustness of the hybrid SCA-DCCN model. While considering Tansig kernel function with back propagation, the error settles between 0.2 and 0.4, but the Tanh function settles at zero but takes more time for convergence. The proposed softmax and logsig function converges at less time as shown in **Fig.7,** but the error amplitude increases**.** While considering tanh kernel function with 0.25 normalization, the error settles at 0.5, But the Logsig function settles at zero but takes more time for convergence. The proposed softmax function takes less time for convergence as shown in **Fig.8**. The softmax function settles at zero but takes more time for convergence. The proposed logsig function takes less time for convergence as shown in **Fig.9**. While considering Tanh kernel function, the error settles between 0.4 and 0.6, But the Logsig function settles at zero but takes more time for convergence. The proposed softmax function takes less time for convergence as shown in **Fig.10**. The proposed DCNN with SCA model has been assigned for the classification and the results were compared with the conventional logsig, tanh, softmax and tansig functions.

From the Table-III we can observe that using logsig, tanh, softmax and tansig functions the computational time achieved as 2.0677, 2.2800, 2.0224 and 2.072 respectively. But the softmax function in SCA-DCCN achieved 2.0224 sec, which shows the robustness of the proposed SCA-DCCN model.

7. Conclusion

In this research work we have proposed S-Transform inspired DOST segmentation algorithm and a novel biologically inspired SCA based DCCN classifiers for automatic detection and classification of brain tumors. Images are segmented and features are extracted using DOST algorithm at the first step. The feature such as correlation, energy, Homogeneity, IDM, DM etc. are considered for the classification task. The proposed DCNN with SCA model has been assigned for the classification and the results are compared with the conventional logsig, tanh, softmax and tansig functions. By using logsig, tanh, softmax and tansig functions the computational time achieved as 2.0677, 2.2800, 2.0224 and 2.072, respectively. But the softmax function in SCA-DCCN achieved 2.0224 sec, which shows the robustness of the proposed SCA-DCCN model. Further classification accuracy of 98.12 % achieved with SCA DCNN with softmax function, approach. From the result, it is found that the proposed SCA-DCNN model provides better classification result and the computations time obtained as less as compared to other conventional methods.

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