Effective Brain Tumor Classification on MRI Using Deep Belief-convolutional Neural Network with Pixel Change Detection based on Pixel Mapping Technique

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Abstract

Brain tumor is a kind of cancer, in which tissues in the brain grows rapidly and unevenly in the brains and causes huge threats on human life. Brain tumor is recognized as one of the common dreadful cancers among adults and it also affects the children too. This kind of cancer is categorized into two types, such as benign tumor and malignant tumor. However, benign tumor is curable, whereas recovering of patients whoever affected by malignant tumor has less chance to survive. Nowadays, MR images are usually employed to detect the kinds of brain tumor. Early classification and identification of tumor is significant to treat the tumor and saves the human life from early death. However, the classification of brain tumor and percentage in change detection using pre-operative and post-operative MR images is a very challenging task. In order to overcome such issues, this research proposes a new effective technique for brain tumor classification and determination of pixel change detection using proposed Deep Belief Network (DBN) + Deep Convolutional Neural Network (DCNN). The process involves four phases, such as pre-processing, segmentation, feature extraction, and classification. The combination of DBN + CNN is employed for decision making based on error function. The DBN + CNN are trained utilizing the developed BirCat algorithm. Moreover, the proposed approach achieved a maximum accuracy of 0.957, sensitivity of 0.967, and specificity of 0.918.
Keywords

Brain Tumor, Magnetic Resonance Image (MRI), Deep Belief Network (DBN), Deep Convolutional Neural Network (DCNN), Cat Swarm Algorithm (CSA).

Introduction

Magnetic Resonance Imaging (MRI) is a significant process in the domain of medical imaging analysis for full endorsement of neuro radiology while diagnosing the patients. MRI is utilized widely all over the world as it has a wide variety of physiological contrasts to detect the various growing tissues and the development of different tissue configuration present inside the diffuse gliomas. The MRI plays a significant role in diagnosing because it leads to establish different classification mechanisms for multi-grade brain tumor MRI images results in lesser number of surgeries (Muhammad Sajjad et al., 2019). High resolution MRI is considered as the most eminent imaging techniques used in most of the hospitals (Satyasis Mishra et al., 2019). Brain tumor has been recognized as one of the most deadly disease among all adults and the saddest part it does not leave the children. However, early classification and identification of brain tumor and early analyzing its effects are very essential to treat the tumor patients and it increases the survival rate of the patients. Typically, a brain tumor is a huge tissue that develops irregularly in brain and it causes severe impacts on the lives of human. This mass usually happens impulsively due to the tissues enclosing the brain or the skull. The general therapy of the brain tumor is surgical techniques (Togacar M et al., 2020). This huge tissue is broadly categorized into two types, such as benign and malignant. Generally, such tumors develop abnormally in brain and cause over pressure around the brain (Muhammad Sajjad et al., 2019). Due to increased pressure in the brain, it reflects the different type of disorganizations in the brain that collapses entire mechanisms of the body. However, these disorders reflect various symptoms in human body, like headache, fainting, drowsiness, and paralysis. Benign tumors are not severe and it can be cured immediately once it has been identified earlier. However, malignant tumors grow irregularly inside the brain tissues and damage all the tissues in the brain. Surgical techniques are normally chosen for the therapy of brain tumor (G. Gokulkumari, 2020) (Yi Ding et al., 2016). However, if the surgery is not effective, various techniques, like radiation, medication are considered (Danilo Cesar Pereiraa et al., 2014) (Satyasis Mishra et al., 2019).

Generally, brain tumors are widely categorized as benign and malignant tumors that grow abnormally surrounding the brain tissue. Malignant tumor consists of cancerous cells that grow in all regions of the brain because of the uneven structure. However, benign tumors
are of well even in structure and do not contain cancerous cells (Satyasis Mishra et al., 2019). Moreover, manual intervention for diagnosing the brain tumors by analyzing the MRI images in the laboratories become a very big hurdle and it is a time-consuming process for physicians because of the composite structure of tumor and various noises involved in the data of MRI. It is very difficult to convert this noisy image into an appropriate condition using manual intervention that motivates many researchers to concentrate more on developing an automatic classification and detection of brain tumor using MRI data. Thus, identification the location and the type of brain tumor is very much significant to alleviate the deaths occurred by tumors. Similarly, the brain tumor classification is also important to reveal various kinds of tumor contained in the brain. The doctors utilized the classification and segmentation mechanisms to detect the abnormal growth of cancer affected regions at various stages to offer perfect diagnosis at early stage (Avinash Gopal, 2020) (Satyasis Mishra et al., 2019). Nowadays, different types of deep learning techniques are utilized in the therapy of brain tumor diseases and its diagnosing purposes. Deep learning models are normally applied in the domain of biomedical applications. However, the deep learning network consists of large number of hidden layers. Besides, this technique generates the learning procedures automatically on the dataset (Mesut Togacar et al., 2019) (Umit Budaka et al., 2020) (Togacar M et al., 2020).

The main intention of this research is to establish an effective strategy for brain tumor classification and to determine the pixel change detection using pixel mapping technique and pre-operative and post-operative MRI images based on SURF features. However, the integration of two classifiers, such as DBN and Deep CNN is employed to provide better decisions. Besides, the proposed BirCat algorithm is employed to train the network classifiers in order to obtain the optimal weights.

- **Proposed DBN + CNN:** The primary contribution of this research is to design and establish an effective strategy for brain tumor classification and to determine the pixel change detection using pre-operative and post-operative MRI images based on SURF features. However, the combination of DBN + CNN is employed to make better decisions based on error function.

The remaining section of the research is organized as follows: Section 2 elaborates motivation and literature review of the traditional brain tumor classification techniques. Section 3 and section 4 explains the developed DBN and CNN with pixel change detection mechanism. The results and discussion are made in section 5. Finally, the paper concludes in section 6.
Motivation

This section deliberates literature review of the conventional techniques of brain tumor classification along with their advantages and limitations, which motivates the researchers to design an effective strategy for brain tumor classification and change detection.

A. Literature Survey

(Muhammad Sajjad et al., 2019) modeled convolutional neural network (CNN) based multi-grade brain tumor classification setup for effective brain tumor classification. The system was comprised with three major steps. The first step was segmentation of tumor areas from the dataset by means of a CNN system. The second step was data augmentation using various factors to maximize the quantity of data samples, and the final step was training of CNN model for multi-grade brain tumor classification. The developed strategy was effective in classifying the brain tumors based on their grades. However, the method failed to regulate the accuracy and efficiency of CNN architectures. Kaplan Kaplan et al. (Kaplan Kaplana et al., 2020) introduced a technique to classify three kinds of brain tumors using modified Local Binary Pattern (LBP). Here, nLBP and \( \alpha \) LBP were used as a feature extraction methods and the classification mechanism was carried out using K-Nearest neighbor (K-NN), and Artificial Neural Networks (ANN), Linear Discriminant Analysis (LDA) classifiers, and Random Forest (RF). The developed approach was simple, less expensive and had low computational complexity. Mesut Togacar et al. (Togacar M et al., 2020) devised a Convolutional Neural Network called Brain MRNet. This method effectively discriminated the abnormal images from normal brain MRI images. It mainly concentrated on the most significant area on the MR images by exploiting attention schemes. The residual blocks utilized in this scheme considerably reduced the factor that affects the performance of the model. Satyasis Mishra et al. (Satyasis Mishra et al., 2019) modeled a new approach called MASCA–PSO based LLRBFNN model. In order to evacuate the Rician noise present in image, an improved FCM was utilized. The texture features are excerpted from MRI images with the aid of GLCM feature extraction method. The weights of LLRBFNN model was enhanced using the hybrid MASCA + PSO. The method was effective in categorizing the tumor and non-tumor region but, it was limited to small number of datasets.

B. Major Challenges

Some of the limitations confronted by various conventional brain tumor classification techniques are stated as follows:
The major limitation of an improved thresholding model was over segmentation, which was performed when a tumor emerges on the border of the areas. Moreover, the classification accuracy was also affected by unrelated features (Muhammad Sharif et al., 2018).

In (Sridhar et al., 2013), the developed approach only considered the limited number of brain tumor classes. However, the method achieves high recognition rate, while classifying the brain tumors.

**Proposed DBN + CNN for Brain Tumor Classification**

The primary motive of the research is to provide an effective strategy for brain tumor classification and to perform the pixel change detection based on pixel mapping using post-operative and pre-operative MRI image using the newly designed and developed method called DBN + CNN. MRI is a non-invasive, soft and contrast tissue that provides accurate data about the shape, size and position of brain tumors without exposing the humans to harmful radiation. In this research, the process mainly involves four steps, namely pre-processing, segmentation, feature extraction, and classification. Initially, pre-operative images are acquired from the MRI database. Pre-operative image is nothing but the MRI image of a patient before the surgery. The input image is passed through the pre-processing step, where the unwanted noises and external calamities are eliminated using filtering technique as well as ROI extraction. Once the pre-processing is completed, segmentation is carried out. Here, the desired segments are segmented using the Region growing algorithm and further segmentation process is performed using modified Bhattacharya distance. After that, feature extraction is carried out in order to extract the desired and appropriate features, where the features, such as area, coverage, perimeter, BHOG, and LOOP are extracted. Furthermore, brain tumor classification is performed using the two classifiers, like Deep Belief Network (DBN) (Hinton et al., 2006), and Deep Convolutional Neural Network (DCNN) (Ronaoo et al., 2015), where the network classifier is trained by employing the developed BirCat algorithm. However, the developed BirCat algorithm is derived by the incorporation of Bird Swarm Algorithm (BSA) (Xian-Bing Meng et al., 2016), and Cat Swarm Optimization (CSO) (Shu-Chuan Chu et al., 2006). The proposed algorithm is employed to derive the weights in order to train the DBN and DCNN classifiers. The combination of DBN and DCNN enables to make perfect decisions based on error function. Moreover, the pixel change detection is carried out using pixel imaging of segmented image with post-operative and pre-operative image based on SURF features to detect the percentage of change in tumor pixels.
1 represents the schematic view of proposed BirCat-based DBN-CNN for brain tumor classification and pixel change detection.

**Figure 1** Block diagram of proposed BirCat-based DBN-CNN for brain tumor classification and pixel change detection

### A. Acquisition of Pre-operative MRI Image

Let us assume the database as $D$ with $L$ number of MRI brain images and it is represented as,

$$D = \{G_n; 1 \leq n \leq L\}$$  \hspace{1cm} (1)

where, $G_n$ signifies the $n^{th}$ brain MRI image in the database, and $L$ denotes the total number of brain images. Here, a pre-operative MRI image is considered as an input data. Each image $G_n$ from the database is subjected to pre-processing phase in order to remove the external artifacts present in the input brain MRI image.
B. Pre-processing

The input image $G_n$ is passed through the pre-processing phase, where external artifacts and unwanted noises are eliminated using filtering technique and Region of Interest (ROI) extraction. Pre-processing is the most significant step as it provides smoothening to the input image. In this phase, it moulds the image by processing and makes it feasible for detection process. Besides, the pre-processing step is considered as an image enhancement phase in which the input images are enhanced by means of certain process in order to make it highly desirable for the purpose of effective tumor detection and classification.

a) Noise Elimination Using Filtering Technique

Typically, filtering technique is used to eliminate the unwanted noises present in the MRI images during pre-processing stage. The benefit of filtering is usually related with the complexion of the noise distribution in MRI imagers. The primary effect of noise in MRI images is mainly because of the small changes of densities inside a single tissue and this single tissue has the potential to modify the RF emission of the atomic nuclei in the imaging technique. In filtering technique, the external noises and calamities existed in the medical image is eliminated for achieving smoother results.

b) ROI Extraction

It is significant to recognize the ROI, where ROI signifies tumor area. Hence, skull stripping is a technique, which is utilized to detect the ROI region, which is a brain tumor in MRI images. The regions associated with brain tumor are of high precedence and the region other than brain tumor is given a less priority (Muhammad Sharif et al., 2018). The ROI is evaluated for determining the noise variance. Typically, the MRI images consist of additive noise along with the image. Hence, the ROI extraction is exploited for separating the interesting regions present in the MRI images. The pixels in the ROI region are regularized and set to either one or zero. Thus, the ROI extraction provides a binary image that offers a mask for excerpting invariable ROI. The ROI extraction chooses the interesting region based on the pixel intensity. The ultimate goal of ROI extraction is to offer image regions based on certain discriminative characteristics and also depending on the intensity level of image. Generally, ROI extraction illustrates the image in digital form by categorizing the image as light or dark. In order to address challenges of illumination changes, the ROI extraction is employed to extract the values of each pixel in the image. The ROI extraction usually provides better robustness against various impacts with respect to the illumination changes. The major advantages of the ROI extraction is that the
technique is simple, fast, and accurate and the results obtained are identical for the comparison. Hence, the pre-processing is carried out along with filtering technique and ROI extraction in order to eliminate the unwanted and external calamities present in the MRI image. Thus, the result obtained from the pre-processing phase is denoted as $P_n$.  

C. Segmentation of Pre-processed Image Using Region Growing Algorithm

Once the pre-processing is completed, segmentation process is performed for extracting the segments in the image using the region growing algorithm. In region growing, images are divides by rearranging the closest pixel of similar type. In splitting mechanism, the region is partitioned into sub regions that do not accomplish a homogeneity condition. Splitting and merging are commonly used together and it usually depends on the chosen homogeneity condition (Avinash Gopal, 2020).

a) Segmentation Using Modified Bhattacharya Measure

After completing the region growing process, the segmentation is done utilizing the modified Bhattacharya distance. The initial step is formulation of difference between the pixel values of the first seed point and the neighboring pixels based on the modified Bhattacharya distance, which is expressed as,

$$B = \frac{1}{4} \ln \left( \frac{1}{4} \left( \frac{\eta_u^2 + \eta_v^2}{\eta_u^2} \right) + \frac{1}{4} \left( \frac{(\beta_u - \beta_v)^2}{\eta_u^2 + \eta_v^2} \right) + \frac{1}{4} \left( \frac{\delta_u - \delta_v}{\eta_u^2 + \eta_v^2} \right) \right)$$  

(2)

where, $\delta_u$ signifies the skewness of seed point, $\delta_v$ is the skewness of neighboring pixel, $\eta^2$ denotes the variance and the mean is indicated as $\beta$.

The obtained segment result from the modified Bhattacharya distance is expressed as,

$$S^n = \left\{ S_1^n, S_2^n, \ldots, S_i^n, \ldots, S_w^n \right\}$$  

(3)

where, $S_i^n$ indicates the $i^{th}$ segment of $n^{th}$ image and $w$ denotes the total attained segments.

D. Feature Extraction

The segmented image $S^n$ is subjected to feature extraction process, where the desired and appropriate features are separated. The major contribution of the feature extraction is that the feature ease the effective classification of MRI images presented in database so that the individuals with and without brain tumor are detected. The features employed for the
classification process, such as area, coverage, perimeter, Binary Histogram Oriented Gradients (BHOG), and LOOP features.

a) Area

The area feature is utilized to classify the individual pixels based on the area of image. In order to achieve the area feature, the total quantity of pixels exist in image is determined for each segment. Here, $f_{1}^{i,n}$ is the area feature of the $i^{th}$ segment contained in the $n^{th}$ image.

b) Coverage

The purpose of exploiting the coverage feature is to categorize the patient’s MRI image depending on the coverage area of an image. In order to achieve the coverage feature, the mean is determined for extracted important points. The average value signifies the object location based on the coverage. $f_{2}^{i,n}$ is the coverage feature of $i^{th}$ segment contained in the $n^{th}$ image.

c) Perimeter

Perimeter is the feature, which is termed as the total quantity of boundary pixels presented in the individual segments. The perimeter of the image is calculated using the width and length of the image and it is denoted as $f_{3}^{i,n}$ and the expression is given by,

$$f_{3}^{i,n} = 2 \times (\phi + \rho) \quad \text{(4)}$$

d) BHOG

The BHOG (Bongjin Jun et al., 2012) feature specifies each block with eight bits, which obtains to effective processing time. In BHOG feature, the value of one is allocated is the histogram bin holds the larger value than that of the total histogram bins or else the value is assigned as zero. The process includes determination of square of gradient magnitude, orientation of pixels, and finally computation of orientation histogram. The decimal format of the 8-bit BHOG feature for an individual block is given by,

$$f_{4}^{i,n} = \sum_{m=0}^{7} g \left( HOG(m) - \gamma \right) \quad \text{(5)}$$

where, $g(\cdot)$ signifies the sign function and $\gamma$ indicates the average of HOG and it is expressed as,
The sign function is formulated as,
\[ g(e) = \begin{cases} 1; & \text{if } e > 0 \\ 0; & \text{otherwise} \end{cases} \] (7)

e) LOOP

The LOOP utilizes the rotation changes into the local binary descriptor to overcome the existing challenges in the descriptors. The main purpose of utilizing the descriptors is it reduces the complexity of post processing time and enhances the accuracy level.

Let us consider \( I_c \) be the intensity of an image \( G \) at pixel \( (p_c, q_c) \) and \( I_s \) (\( s = 0, 1, \ldots, 7 \)) be the intensity of pixel in \( 3 \times 3 \) neighbor of \( (p_c, q_c) \) at \( I_c \). Hence, LOOP value of pixel \( (p_c, q_c) \) is given by,
\[ f_{5}^{i,n} = \text{loop}(P_c, q_c) = \sum_{s=0}^{2} R(I_s - I_c)2^s.T'^s \] (8)

Where, \( T'^s \) signifies the exponential weight.

Hence the obtained features from the feature extraction process is expressed by,
\[ F = \{ f_1^{i,n}, f_2^{i,n}, f_3^{i,n}, f_4^{i,n}, f_5^{i,n} \} \] (9)

E. Brain Tumor Classification Using Proposed BirCat-based DB-CNN

The extracted feature \( F \) is subjected to brain tumor classification process to distinguish the brain tumor patients from MRI images utilizing the two classifiers, such as DBN and DCNN. However, the classifier is trained using the developed DBN + CNN. The developed DBN + CNN is derived by integrating the Bird Swarm Algorithm (BSA) (Xian-Bing Meng et al., 2016), and Cat Swarm Optimization (CSO) (Shu-Chuan Chu et al., 2006). The proposed BirCat-based DBN-CNN is mainly utilized to modify the performance of DBN by choosing the optimal weights, whereas the DCNN is used for decision making based on error function. In order to make accurate decisions, the combination of DBN and DCNN is employed based on error function. If the error obtained from DBN classifier, which is trained by employing the developed BirCat is less than that of the error obtained from the DCNN classifier, then the classification result is
the output of the BirCat-DBN or else the classification result is the output of the BirCat-DCNN.

The structure of DBN and DCNN along with the training process is deliberated in the subsections as follows:

a) Structure of DBN

The DBN (Hinton et al., 2006) is a segment of Deep Neural Network (DNN) and is comprised with various layers of Restricted Boltzmann Machines (RBMs) and Multilayer Perceptron’s (MLPs). RBMs consist of visible and hidden units that are connected depending on weighted links. The MLPs is assumed as a feed-forward networks that comprises with input, hidden, and output layers. The network of multiple layers has the potential to overcome the complicated tasks. The architecture of DBN is depicted in figure 2.

The input given to the hidden layer and visible layer of initial RBM is formulated as,

$$F = \{F_1^i, F_2^i, ......, F_l^i, ......, F_5^i\} \quad 1 \leq l \leq 5$$

$$J = \{J_1^i, J_2^i, ......, J_h^i, ......, J_b^i\} \quad 1 \leq h \leq b$$

Consider $U$ and $V$ denotes the biases and these biases for initial RBM layer is calculated as,

$$U = \{U_1^1, U_2^1, ......, U_l^1, ......, U_5^1\}$$

$$V = \{V_1^1, V_2^1, ......, V_h^1, ......, V_b^1\}$$

Where, $U_l^1$ indicates the bias similar to $l^{th}$ visible neuron, and $V_h^1$ denotes the bias similar to $h^{th}$ hidden neuron.

Figure 2 Architecture of DBN
The result of hidden layer from the initial RBM is formulated exploiting the weights and bias connected with individual detectable neuron and it is expressed as,

$$N_h^1 = \delta \left[ V_h^1 + \sum_l (C_l^z) o_l^1 \right]$$  \hspace{1cm} (14)

Where, $\delta$ specifies the activation parameter. Hence, the result produced from initial RBM is given as,

$$N^1 = \{N_h^1\}_{1 \leq h \leq b}$$  \hspace{1cm} (15)

The result obtained from hidden layer of next RBM is passed as an input through MLP. The input layer of MLP is formulated as,

$$A = \{A_1, A_2, ..., A_l, ..., A_o\} = \{N_l^2\}_{1 \leq l \leq b}$$  \hspace{1cm} (16)

Where, $l$ depicts the total neurons, contained in input layer that is obtained by output of hidden layer of second RBM $\{N_l^2\}$. The hidden layer of MLP is expressed as,

$$E = \{E_1, E_2, ..., E_o, ..., E_d\}_{1 \leq o \leq d}$$  \hspace{1cm} (17)

Where, $d$ represents the quantity hidden neurons. The output of MLP is calculated as,

$$M = \{M_1, M_2, ..., M_a, ..., M_j\}_{1 \leq a \leq j}$$  \hspace{1cm} (18)

Where, $j$ denotes the total number present in the output layer.

b) Structure of DCNN

Deep CNN (Ronao et al., 2015) plays a vital part in analysis of the compressed signals for high classification results. In deep CNN, a number of neurons are linked to the neuron contained in the second layer. The structure of DCNN is comprised with three layers, like Convolutional (Conv) layer, Pooling (POOL) layer, and a Fully Connected (FC) layer. The structure of Deep CNN is portrayed in figure 3. The layers in Deep CNN shows some important functions, like establishment of feature maps present in the Conv layers, sub-sampling of feature maps in POOL layers and classification is carried out in FC layer. Here, Deep CNN is mainly utilized for decision making process based on error detection.
Figure 3 Structure of Deep CNN

(i) Convolutional layers: The function of conv layers is to achieve the patterns embedded in compressed signal utilizing the conv filters that offers as interconnection among the neurons of the preceding layer with conv layers with the trainable weights. Let us consider the input to DCNN as \( K \), and thus the result of Conv layer is formulated as,

\[
(K_m^i)_{x,y} = (H_m^i)_{x,y} + \sum_{a=1}^{K_a^i} \sum_{y=K_y^i}^{K_y^i} \sum_{\alpha=K_\alpha^i}^{K_\alpha^i} (\theta_{m,a})_{\alpha,y} \ast (K_m^{i-1})_{x+y,y-y} 
\]

where, * denotes the convolutional operator, \((K_m^i)_{x,y}\) signifies the fixed feature map or the output of the \(i^{th}\) conv layers that is centered as \((x,y)\).

(ii) Pooling layers: The pooling layer is a non-parametric layer without weights and bias so that it effectively performs a fixed mechanism.

(iii) Fully Connected layers: The signal from the pooling layer is fed as an input to Fully connected layer. Finally, the signals are converted into a single signal that represents the classes of the signal. The result of the Fully Connected layer is formulated as,

\[
FC_m^i = \sigma(K_m^i) with K_m^i = \sum_{a=1}^{K_a^i} \sum_{y=K_y^i}^{K_y^i} \sum_{\alpha=K_\alpha^i}^{K_\alpha^i} (\theta_{m,a})_{\alpha,y} (K_m^{i-1})_{x+y,y-y} 
\]
c) Training of DBN and DCNN Using Proposed BirCat Algorithm

This section deliberates the training steps of developed BirCat algorithm-based DBN and DCNN classifier. The proposed BirCat algorithm is derived by integrating the Bird Swarm Algorithm (BSA) (Xian-Bing Meng et al., 2016), and Cat Swarm Optimization (CSO) (Shu-Chuan Chu et al., 2006). Moreover, the proposed BirCat algorithm is utilized to compute the optimal weights based on error function. The algorithmic procedures followed in the BirCat algorithm are as follows:

(i) Initialization: Let us initialize the population as,

\[ W = \{W_1, W_2, \ldots, W_{mn}, \ldots, W_O\} \]  

(21)

where, \( O \) is the total bird population and \( W_{nn} \) signifies the \( nn^\text{th} \) bird.

(ii) Evaluate fitness function: The fitness function is employed to determine the best solution. The error is determined that relies on the difference between the desired result and the obtained result is expressed as,

\[ \text{Fitness} = \frac{1}{O} \sum_{nn=1}^{O} (M_a - M_O)^2 \]  

(22)

where, \( M_O \) is the output from the classifier and \( M_a \) denotes the targeted output. Here, \( M_O \in [FC_m^t, M_j] \).

(iii) Determine the update equation: The BSA algorithm is employed to maximize the convergence speed. The update solution according to the BSA algorithm is expressed as,

\[ X_{\text{z,zi}}^{y+1} = \lambda_{\text{z,zi}} X_{\text{z,zi}}^y + H_j \times \text{Rand}(0,1) + J_u - X_{\text{z,zi}}^y + K_i \times \text{Rand}(0,1) \]  

(23)

where, \( \text{Rand}(0,1) \) signifies the uniformly distributed random number. \( H_j \) and \( K_i \) are the constants that represent two positive numbers. \( Z_{\text{z,zi}} \) indicates the best previous position of \( z^\text{th} \) bird and \( J_u \) denotes the best position of th swarm and \( X_{\text{z,zi}}^y \) represents the current position of \( z^\text{th} \) bird in \( z_i^\text{th} \) swarm.

The update equation based on CSO algorithm is expressed as,

\[ X_{\text{z,zi}}^{y+1} = X_{\text{z,zi}}^{y} + \lambda_{\text{z,zi}} X_{\text{z,zi}}^{y+1} \]  

(24)

\[ X_{\text{z,zi}}^{y+1} = X_{\text{z,zi}}^{y} + \lambda_{\text{z,zi}} X_{\text{z,zi}}^{y} + L_n \times N_n (X_{\text{best,zi}} - X_{\text{z,zi}}^y) \]  

(25)
The final update solution is obtained by merging the update equations of BSA and CSO algorithms.

\[
x_{i, t+1} = \frac{\sum_{k, j, n, N, L} x_{i, t+1} \cdot \text{Rand}(0,1)(x_{i, t} - x_{i, t-1}) \cdot H_t - \sum_{k, j, n, N, L} x_{i, t} \cdot \text{Rand}(0,1)(x_{i, t} - x_{i, t-1}) \cdot H_t}{\text{Rand}(0,1)(x_{i, t} - x_{i, t-1})}
\]

(iv) \textit{Re-computation of weights based on error function:} The error is recalculated based on weights using Eqn. (22). The algorithm generates minimum weight is exploited for training the DBN and DCNN.

(v) \textit{Termination:} The process is continued until it achieves the optimal solution.

Pixel Change Detection Using Pixel Mapping based on SURF Features

The pixel mapping is employed for processing the MRI images in order to detect the change in percentage level in tumor pixels. However, the process of change detection is performed using SURF features. The SURF features are usually exploited for extracting the visual contents of the image effectively. The SURF features are used to predict the interesting key points of an image in a safe manner.

Results and Discussion

This section describes the results of the developed DBN + CNN for brain tumor classification with respect to evaluation metrics, like accuracy, sensitivity, and specificity.

A. Experimental Setup

The implementation of the developed DBN + CNN is carried out on MATLAB tool with 2GB RAM and on Windows 10 OS.

a) Dataset Description

The description of two datasets, such as Harvard Brain Tumor Repository, and Synthetic datasets utilized for brain tumor classification is described as follows:

b) The Harvard Brain Tumor Repository (Dataset-1)

The Harvard Brain Tumor Repository (Harvard Brain Tumor Repository, 2021) includes ten tumors with various manual expert segmentations on 2-D slices and is employed for offering a general framework to evaluate the performance.
c) The Synthetic Datasets (Dataset-2)

The Synthetic datasets (M. Prastawa et al., 2005) of simulated tumors consists of five synthetic brain tumor datasets used for evaluating the tumor data.

B. Experimental Results

Figure 4 represents the experimental results of proposed DBN + CNN. Figure 4a) and figure 4b) depicts the input image-1 and input image-2, respectively. However, the excerpted LOOP features of image-1 and image-2 are represented in figure 4c) and figure 4d). The segmented result of image-1 is portrayed in figure 4e), whereas figure 4f) specifies segmented result of image-2.

C. Comparative Methods

The proposed DBN + CNN is compared with the existing techniques, such as such as CNN (Sergio Pereira et al., 2016), Active Contour + Random forest (Chao Ma et al., 2018), ANFIS (A Selvapandiana et al., 2018), DBN + Birdswarm, and BirCat –DBN in order to reveal the performance level of developed scheme.
D. Evaluation Metrics

The proposed DBN + DCNN is evaluated by considering the metrics, such as accuracy, sensitivity, and specificity.

a) Accuracy: Accuracy is termed as the degree of closest value of measurements of a quantity. In other words, accuracy is also stated as the standard of the correct or precise measurement.

b) Sensitivity: Sensitivity is defined as the true positive value that determines the proportions of positives that are perfectly determined.

\[
Sensitivity = \frac{TP}{TP + TN}
\]  
(27)

Where, \( TP \) denotes the number of True positives and the number of true negatives are represented as \( TN \).

c) Specificity: Specificity is referred as the true negative value that determines ratio of negatives that are perfectly identified.

\[
Specificity = \frac{TN}{TN + TP}
\]  
(28)

E. Comparative Analysis

This section deliberates the comparative analysis of developed DBN + CNN with respect to evaluation metrics, like accuracy, sensitivity, and specificity using the two datasets by varying the training data.

a) Analysis Using Dataset-1

Figure 5 illustrates the comparative analysis of developed DBN + CNN using dataset-1 with respect to the evaluation metrics by changing the training data. Figure 5a) portrays analysis of accuracy. When the training data=90\%, the accuracy achieved by developed DBN + CNN is 0.941, whereas the existing methods, such as CNN, Active contour + random forest, ANFIS, DBN-birdswarm, and BirCat-DBN achieved the accuracy of 0.909, 0.907, 0.864, 0.907, and 0.921, respectively. However, the developed DBN + CNN reveals the performance enhancement of proposed with that of the traditional techniques, such as CNN is 3.348\%, Active contour + random forest is 3.643\%, ANFIS is 8.203\%, DBN-birdswarm is 3.643\%, and BirCat-DBN is 2.167\%.
The analysis of proposed DBN + CNN using sensitivity is specified in figure 5b). By varying training data to 90%, the developed DBN + CNN attained the specificity of 0.946 that shows the performance enhancement of developed approach with that of the conventional schemes, like CNN is 3.243%, Active contour + random forest is 3.243%, ANFIS is 7.077%, DBN-birdswarm is 4.036%, and BirCat-DBN is 3.045%.

Figure 5c represents the analysis of developed DBN + CNN using specificity. If the training data=90%, the specificity attained by the conventional methods, like CNN is 0.864, Active contour + random forest is 0.891, ANFIS is 0.629, DBN-birdswarm is 0.850, and BirCat-DBN is 0.920. However, the proposed DBN + CNN outcomes the performance enhancement of proposed with that of the traditional approaches, like CNN, Active contour + random forest, ANFIS, DBN-birdswarm, and BirCat-DBN are 8.715%, 5.924%, 33.523%, 10.265%, and 2.823%, respectively.

![Image](http://www.webology.org)

**Figure 5 Analysis using dataset-1 a) Accuracy b) Sensitivity c) Specificity**

**b) Analysis Using Dataset-2**

Figure 6 portrays the analysis of developed DBN + CNN depending on evaluation metrics using dataset-2 by changing the training data. Figure 6a) illustrates the analysis of
accuracy. When the training data=90%, the accuracy attained by the developed DBN + CNN is 0.957 that shows the performance enhancement of developed approach with that of the existing methods, such as CNN is 9.063%, Active contour + random forest is 14.235%, ANFIS is 17.641%, DBN-birdswarm is 13.983%, and BirCat-DBN is 3.008%.

The analysis using sensitivity is portrayed in figure 6b). If the training data=90%, the sensitivity achieved by the traditional approaches are 0.914 for CNN, 0.933 for Active contour + random forest, 0.898 for ANFIS, 0.919 for +DBN-birdswarm, and 0.939 for BirCat-DBN. However, the performance enhancement while comparing the proposed with that of the conventional techniques, such as CNN is 5.442%, Active contour + random forest is 3.523%, ANFIS is 7.124%, DBN-birdswarm is 4.909%, and BirCat-DBN is 2.883%.

Figure 6c) represents the analysis using specificity. By changing the training data to 90%, the specificity attained by developed DBN + CNN is 0.918 that results the performance improvement of developed with that of the conventional approaches, like CNN is 8.313%, Active contour + random forest is 23.487%, ANFIS is 34.675%, DBN-birdswarm is 22.201%, and BirCat-DBN is 2.012%.

![Figure 6 Analysis using dataset-1 a) Accuracy b) Sensitivity c) Specificity](http://www.webology.org)
F. Comparative Discussion

Table 1 portrays the comparative discussion of developed DBN + CNN. If the training data=90%, the accuracy attained by developed DBN + CNN is 0.957 for dataset-2, and the sensitivity obtained by the existing methods, such as CNN is 0.914, Active contour + random forest is 0.933, and the specificity obtained by the developed approach is 0.918, whereas the traditional methods obtained the specificity of 0.842 for CNN, 0.703 for Active contour + random forest, 0.600 for ANFIS, 0.715 for DBN-birdswarm, and 0.900 for BirCat-DBN, respectively.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Training data</th>
<th>Metrics</th>
<th>CNN</th>
<th>Active contour + random forest</th>
<th>ANFIS</th>
<th>DBN-birdswarm</th>
<th>BirCat-DBN</th>
<th>Proposed DBN + CNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dataset-1</td>
<td>Training data=90%</td>
<td><strong>Accuracy</strong></td>
<td>0.909</td>
<td>0.907</td>
<td>0.864</td>
<td>0.907</td>
<td>0.921</td>
<td><strong>0.941</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Sensitivity</strong></td>
<td>0.915</td>
<td>0.915</td>
<td>0.879</td>
<td>0.908</td>
<td>0.917</td>
<td><strong>0.946</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Specificity</strong></td>
<td>0.864</td>
<td>0.891</td>
<td>0.629</td>
<td>0.850</td>
<td>0.920</td>
<td><strong>0.947</strong></td>
</tr>
<tr>
<td>Dataset-2</td>
<td></td>
<td><strong>Accuracy</strong></td>
<td>0.870</td>
<td>0.821</td>
<td>0.788</td>
<td>0.823</td>
<td>0.928</td>
<td><strong>0.957</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Sensitivity</strong></td>
<td>0.914</td>
<td>0.933</td>
<td>0.898</td>
<td>0.919</td>
<td>0.939</td>
<td><strong>0.967</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Specificity</strong></td>
<td>0.842</td>
<td>0.703</td>
<td>0.600</td>
<td>0.715</td>
<td>0.900</td>
<td><strong>0.918</strong></td>
</tr>
</tbody>
</table>

Conclusion

Brain tumor has been recognized as one of the most dreadful cancer diseases across the globe. It is very commonly found in all age groups including children. Brain tumor is a mass tissue that spreads abnormally and slowly leads to death. However, early identification and classification of brain tumor assists doctors to predict severity level of cancer and increase the survival rate of cancer affected patients. Accurate classification of brain tumor and its pixel change detection using pre-operative and post-operative MR images is a difficult task. To counterpart such limitations, an effective strategy is designed by merging the DBN and DCNN classifiers. Such classifiers are trained using the proposed BirCat algorithm to train the optimal weights. The purpose of the combination of DBN + CNN is to make accurate decisions while classification. The process include in this research are pre-processing, segmentation, feature extraction, and brain tumor classification. The percentage of pixel change detection is performed using pre-operative and post-operative MR images based on SURF features. However, the proposed DBN + CNN achieved maximum accuracy of 0.957, sensitivity of 0.967, and specificity of 0.918.
References


