IMAGE & SIGNAL PROCESSING

Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images

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Abstract

In medical image processing, Brain tumor segmentation plays an important role. Early detection of these tumors is highly required to give Treatment of patients. The patient's life chances are improved by the early detection of it. The process of diagnosing the brain tumoursby the physicians is normally carried out using a manual way of segmentation. It is time consuming and a difficult one. To solve these problems, Enhanced Convolutional Neural Networks (ECNN) is proposed with loss function optimization by BAT algorithm for automatic segmentation method. The primary aim is to present optimization based MRIs image segmentation. Small kernels allow the design in a deep architecture. It has a positive consequence with respect to overfitting provided the lesser weights are assigned to the network. Skull stripping and image enhancement algorithms are used for pre-processing. The experimental result shows the better performance while comparing with the existing methods. The compared parameters are precision, recall and accuracy. In future, different selecting schemes can be adopted to improve the accuracy.

Keywords Brain tumor · Segmentation · Hybrid CNN · BAT algorithm · Early detection · Pre-processing · Standardizing intensity scales

Introduction

Uncontrolled growth of cancer cells causes the cancer in any part of the body. There are different types of tumors and their characteristics as well as the treatments differ in different ways [1]. Brain tumors are classified as primary and metastatic brain tumors. They started to grow in brain and will stay in the brain. Latter begin as a cancer in any part of the body and will spread to brain.

Diagnosing the tumor in the primary stage can save the lives significantly. Planning of treatment and intervention by the medical personnel is depends on the Accurate segmentation of brain tumors. Qualified specialist requires longer period of time to segment the

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tumors manually. So it requires automatic segmentation and quantitative analysis of tumors [2].

High variation of Shape, structure, and location makes this process as a challenging task. The layout of the nearby normal tissues is changed by the tumor mass effect [3]. Intensity in homogeneity [4] and varied intensity ranges among the same sequences and acquisition scanners are produced in MRI images.

Diagnosing the tumors in the brain is done usually in a manual way of segmentation by the experts. It is time consuming and a difficult one. The major aim of this work is to introduce a new enhanced classification model to improve the tumor segmentation results. Enhanced Convolutional Neural Networks (ECNN) is introduced to resolve brain tumor segmentation. BAT algorithm is used for automatic segmentation which utilizes the loss function. Skull stripping and image enhancement [5] techniques are used to pre-process the MRI images. By using small kernels deeper architectures are designed. Inspite of having a positive impact with respect to overfitting provided the number of weights are less in a network [6].

Literature review

Shen et al. [7] extended the traditional fuzzy C-means (FCM) [21] clustering algorithm to form a robust segmentation technique. Relative location and characteristics of neighboring pixels defines the neighborhood attraction that influences the segmentation performance. This attraction is optimized by a soft computing approach namely neural network technique. But, still, accuracy of the classifier is not enhanced. The evaluation of the approach is validated with FCM based approaches with varied noise levels. This is the currently deployed segmentation method for MRI images.

Kazerooni et al. [8] modified the traditional GVF algorithm by applying multi scale idea to segment the brain tumors in MRI images. Scaled edge maps are used to evolve the active contour. Edge detection based on thresholding approach is used improve the significance of this method. Active contour is represented by selecting Bspline snake. Bspline snake is selected because of its ability to capture corners and its local control. 30% of accuracy improvement is achieved by using this method when compared to traditional GVF. Currently focusing on the improving the efficiency, security and robustness of the approach in varied levels of noise, but still the detection rate is not improved.

Kalavathiand Ilakkiyamuthu [9] implemented wavelet based FCM Clustering algorithm for segmentation. They have used Grey Level Co-occurrence Matrix (GLCM) feature extraction methods. Jaccard similarity and Dice coefficient values were made used of in evaluating the performances of the method that is currently proposed. Improved segmentation and also classification of the tumors in brain are attained using thid method.

Par meet Knur and HarishKundra [10] improved the intelligent water drops algorithm in order to detect the brain tumors. IWD algorithm is used to detect the brain tumors from the input MRI images. The improvement in the intelligent water drops algorithm is based on the SVM classifier. Cancer and non-cancer cells from the MRI images are classified by the SVM classifier. The output from IWD is fed to the SVM classifier. The performance of this system is detected in MATLAB. It provides a 20% increase in the detection accuracy. The execution time is also reduced to 1.5 s.

Josephine [11] used symmetry character of brain image for segmentation of Brain image. Automatic detection of tumor position and edge is the major goal of this work. Real images are used for experimentation. The experimental results shows the flexibility and convenient of the proposed algorithm. It identifies the tumor region from T1, T2-weighted MRI brain images efficiently. The current classification methods are not applied for tumor types such as benign and malignant.

Yasmeen Khan and AnshulBhatia [12] segmented the MRI image into tumor region and non tumor region image. Segmentation of tumor area is done by utilizing Active Contour calculation. Early preparation is not required in this method. Median filters are used to remove the noise from the image. Different parameters are used for assessment and comparison with existing methods. The results have proven the efficiency of it.

Chen et al. [13] combined the fuzzy clustering and MRF to segment MRI image. Fuzzy clustering exploited the gray level information and to eliminate the disturbances. It also based done on the coarse scale image of multi-scale decomposition. MRF is used to improve the integrity of segmented image and to reduce the noise effect. Maximum a Posteriori Markov Random Field (MAP-MRF) is used to integrate the spatial constraints and the gray level information.

Proposed methodology

Proposed architecture of the brain tumor segmentation is discussed in this section. There are two phases of operation i. pre-processing ii. Segmentation. Skull stripping and image enhancement methods are used in pre-processing. Hybrid Convolutional Neural Network (HCNN) is sued for segmentation. Loss function is optimized using the BAT algorithm. Figure 1 shows the proposed architecture.

Various techniques for Pre-processing are available for dealing the MRI images of the brain. Here, the MRI images gets converted into a grey type of image which are again smoothened by adjusting the contrast.
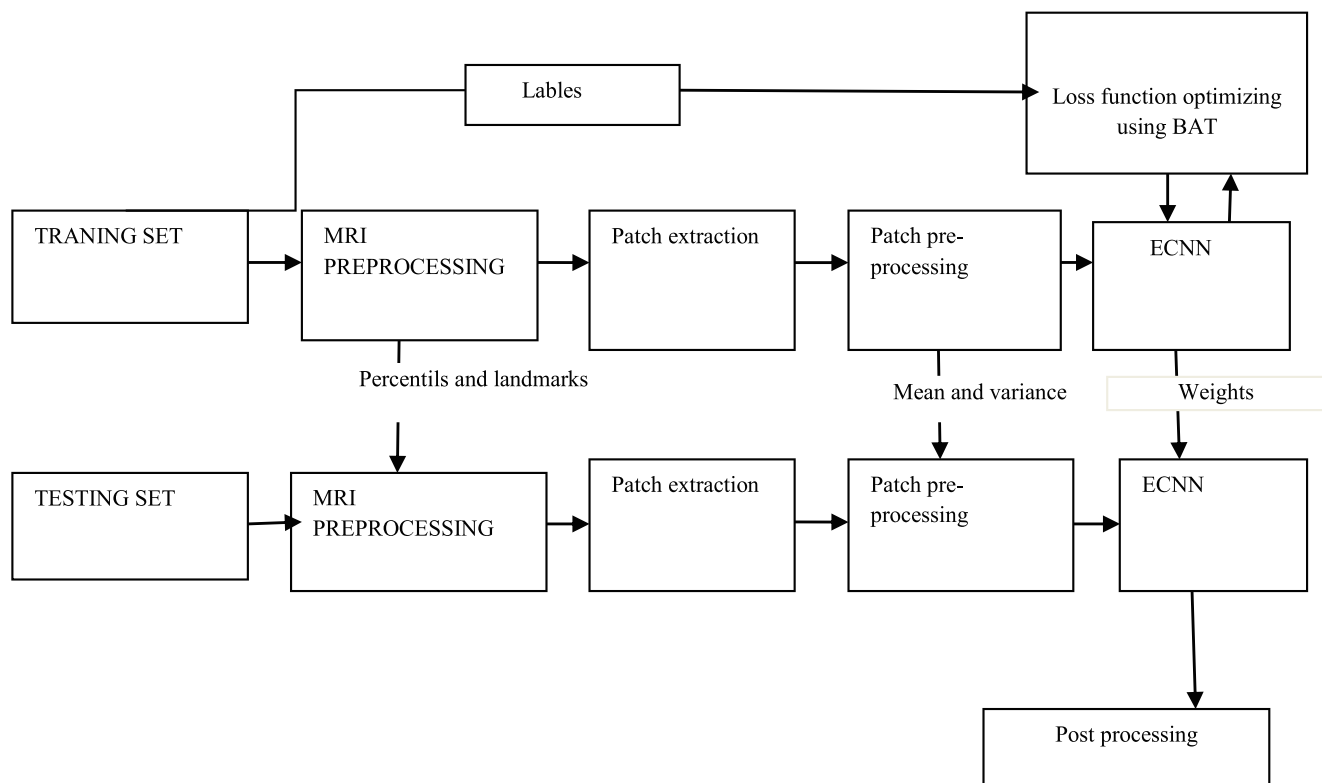
Fig. 1 Overall Architecture of the Proposed Model

Skull stripping

This is one of the popular pre-processing technique that produces improved results. The surroundings of a brain is termed as a skull. The Skull stripping is the process of eradicating the tissues that are not cerebral. It is difficult to distinguish noncerebral and the intracranial tissues because of their homogeneity in intensities. This is the major problem of skull stripping. Seed point selection is affected by this. In-order to identify the range in which the grey value lies in a particular portion in the skull, observations are mandate. Binary images are constructed using contrast adjustment. Crop locations are finding in the binary images. The images with their contrasts adjusted are then cropped for finding the part where the tumor is located in the brain. Cropped contrast adjusted image is converted into binary using a low threshold value and also converted into binary image. Morphological operation 'thicken' is applied to this binary image. Region based binary mask extraction is used to extract the brain region [14].

Region-based binary mask extraction

This process is carried out by exploiting the properties of each block which satisfies the criteria such as Max-min difference and mean values of the blocks. Brain mask is applied on the original MRIdata. This produces the brain image with cortex stripped.

Image enhancement

The resultant images [22] are made suitable for further examination by using Image enhancement techniques. It is termed as the process in which adjustments are made for a digital image. After the process of skull stripping, the cortex of the brain can now be viewed as a unique dark ring which surrounds the brain in a MRI image. Image enhanced methods are used to remove those distinct dark ring surrounding the brain tissues. For example, key features are identified by using the noise removal process. Morphological operation 'thicken' is applied to the binary image. Mean intensity value and standard deviation of all training patches extracted for each sequence after normalization. Patches on each sequence are normalized to have zero mean and unit variance. Enhanced Convolutional Neural Network (ECNN) is used to segment the brain image after pre-processing.

Construction of the central-point-enhanced layer

Feather maps are classified by using the dominant point due to the CNN's characteristics that are invariant. The results from the segmentation process of CNN might not match the brain tumor category if the feather map contains the pixels that belong to other brain parts which are non-brain categories [15].
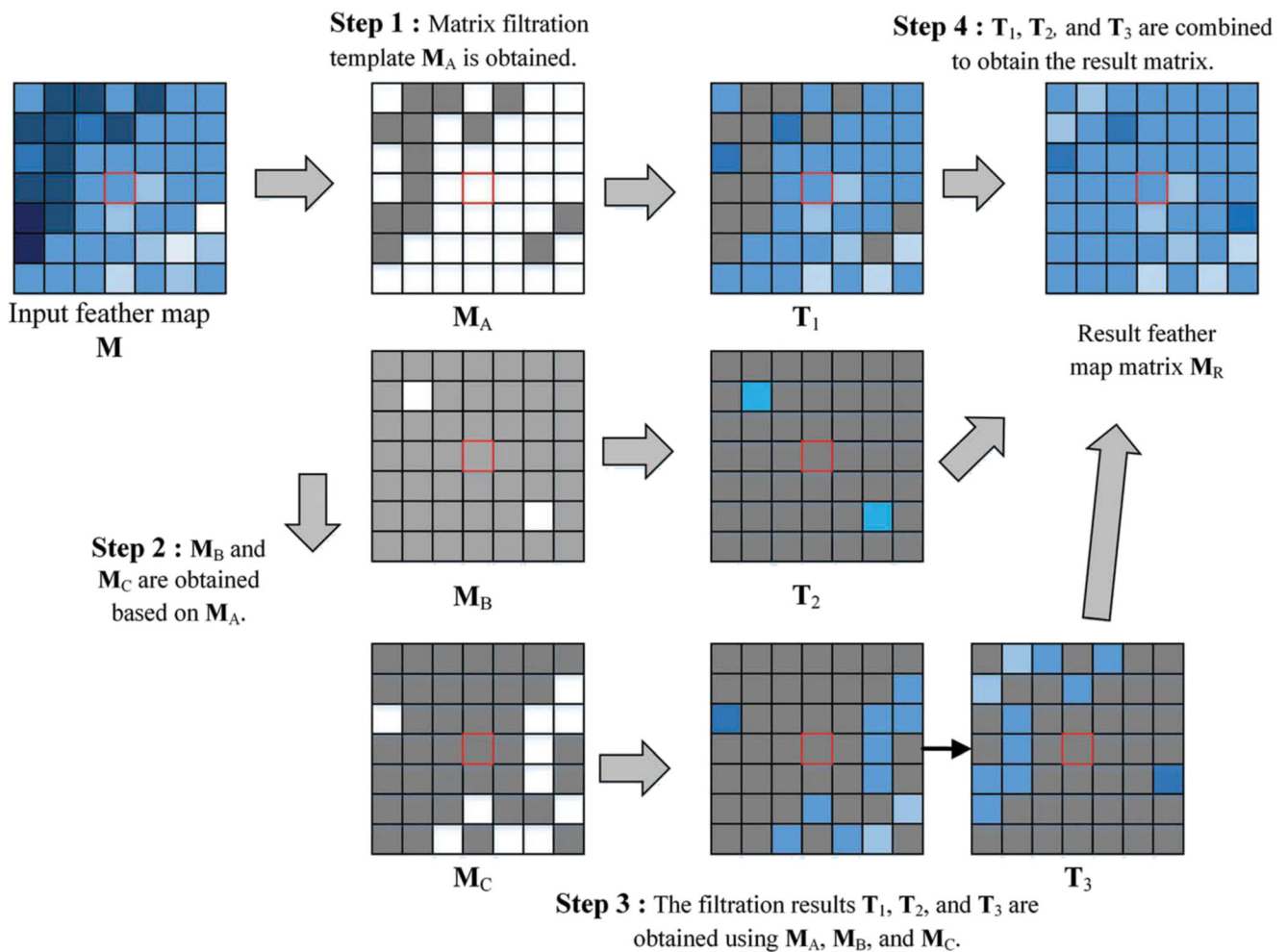
Step 1 : Matrix filtration
template M_A is obtained.

Step 4 : T_1, T_2, and T_3 are combined
to obtain the result matrix.

Input feather map
M

M_A

T_1

Result feather
map matrix **M_R**

Step 2 : M_B and
M_C are obtained
based on M_A.

M_B

T_2

M_C

T_3

Step 3 : The filtration results T_1, T_2, and T_3 are
obtained using M_A, M_B, and M_C.

Fig. 2 Central-Point-Enhanced Algorithm

A new layer is constructed for the CNN to solve this problem. Consider the following aspects:

(1) The layer that are designed freshly have to filter out the pixels which are different as that of the tumor to where the dominant point exists for the prevention of decision being affected. This layer must be with the capacity to preserve the exact texture or the characters in the feather map.

(2) The calculation on the matrix is used for the integration of the new design layer along the structure of the CNN. It is basically because of the fact that the GPU's acceleration which is involved in the process of calculation in a CNN which works the Matrix calculation instead of using the process of conditional branching. Figure 2 depicts the algorithm that is central point enhanced.

In Fig. 2, the layer with an enhanced central point isgenerating for each input feather map. The (CE-Alg) is defined as.

Input: The feather map matrix denoted by M and the difference threshold represented by α.

Output: The MR which is the result from the feather map matrix

Step 1:   Get the template of the matrix filtration represented as MA.

Difference from an element and to the central pointis computed using (1)

$$diff(x) = \left(1 - e^{-5(x - x_{centre})^2}\right) \qquad (1)$$

where x defines an element in matrix M, central point of matrix M is given by x centre. The value of diff approaches 0 as the value of x is approaches the central point's value. The value gets increased with the increase in difference inbetween x to the central point. The Matrix of MA is gained using (2)

$$m_A = diff(m) < a \qquad (2)$$

After the calculation of diff of all the elements in M, they are compared with the logical '<' expression. In the resultant matrix, 0 denote the 'false' and 1 denotes 'true'. MA matrix is constructed using this way. The value '0' corresponds to the high difference from central point and the value '1' denotes the small difference between the central point and in Fig. 2 m_a, '0' and '1' represents the grey and white colour respectively.

Step 2:   Based on m_a, MB and MC are computed. Diagonal matrix J is constructed with width and height equals the width and height M:

$$J = \begin{bmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ \cdot & \cdot & \cdot & \cdot \\ 1 & 0 & 0 & 0 \end{bmatrix} \quad (3)$$

m_b is obtained as follows,

$$m_b = ((m_a - 1`) + (j.m_a.j) - 1 + 2) == \mathbf{0}) \quad (4)$$

Logical equals comparison is denoted by ' = = ' and the dot product of matrix is denoted by '·'. In m_b, logical 'true' corresponds to '1' and logical 'false' corresponds to '0'. Once the rotation of the elements in m_a is done surrounding the central point in MB, the positions remains '0's are marked with '1' and rest of the elements are marked as '0'. The matrix m_c is constructed based on m_a and m_b as,

$$m_c = -((j.m_a.j) - 1) - m_B \quad (5)$$

After rotating, m_a around the central point in MC, the positions with the value equals '1' corresponds to positions '0' in m_b and marked with '1' all the other elements are marked '0'.

Step 3: m_a, m_b, and m_c are filtered to obtain results t1, t2, and t3.m is filtered through the m_a. The values that are retained corresponds to the elements that are similar to the central point in a feather map.

$$t_1 = m \times m_a \quad (6)$$

Elements in the matrix are then multiplied separately by the position with the use of '×'. Matrix t_2 is obtained by assigning the value of the central point value to obtain the '1' in m_b as follows:

$$t_2 = m_b \times x_{centre} \quad (7)$$

The Filtration process of m is executed through m_c. Filtered results then are rotated surrounding the central point. The t_3 type of Matrix is attained using (8).

$$t_3 = j.(m \times m_c).j \quad (8)$$

Step 4:   Result matrix is obtained by combing t1, t2, and t3. The resulting feather map matrix MR is calculated as follows:

$$m_r = t_1 + t_2 + t_3 \quad (9)$$

Elements having huge differences as that of central point in a feather map are filtered using this preceding algorithm. Corresponding position are filled by pixels which are in the positions of symmetry with that of the central point. If happen o filter the elements which are present in the symmetric positions, then the CPV "Central Point Value" is made used of for filling the element. Algorithm for CE-L is shown as follows:

```
Input: Feather map Set S = {M₁, ...., Mₙ}, distance threshold α
Output: Feather map Set R = {R₁, ...., Rₙ}
Begin
Step 1: R = φ
Step 2: for i in 1: N
Rᵢ = CE − alg(Mᵢ, a)
Rᵢ = R ∪ Rⁱ
        End for
Step 3: return R
End
```

CE-Alg processes the every input feather map in I. All feather map sets are formed by input and output CEL's. CE-Alg involves the matrix calculations. This layer can be integrated effectively with CNN structure by using this characteristic.

Structure of the CE-CNN

Figure 3 depicts the primary blocks, The input, process and the output in a CEL. The brain tumor image includes the set of image n whose width is w and height is h. These set of brain images are normalized onto the interval [0 1]. Consider the pixel p with location (x,y). Central point of a square neighbourhood region is denoted as p. It is constructed with one pixel. Square region's width and height is $L = 2l + 1$. The image patch is cut from the image based on neighbourhood square region and it is used to construct the feather map set $S = \{M1, M2, ..., Mn\}$. Each set of similar image corresponds to one feather map Mi. The input of the CE-CNN is given by S and it is processed as,

(1)   Central-point-enhanced layer: for all the feather map inside S, improved feather map set $R = \{R_1, R_2, ..., R_n\}$ is constructed using CE-Alg

(2)   Convolutional layer: W no of feather maps are gained through W kernels with sizes of K × K by convolution calculation.

(3)   Max-pooling layer: a maximum W input feather maps with each of n × n block is conducted. Critical characteristics are obtained by reducing the size of the feather map.
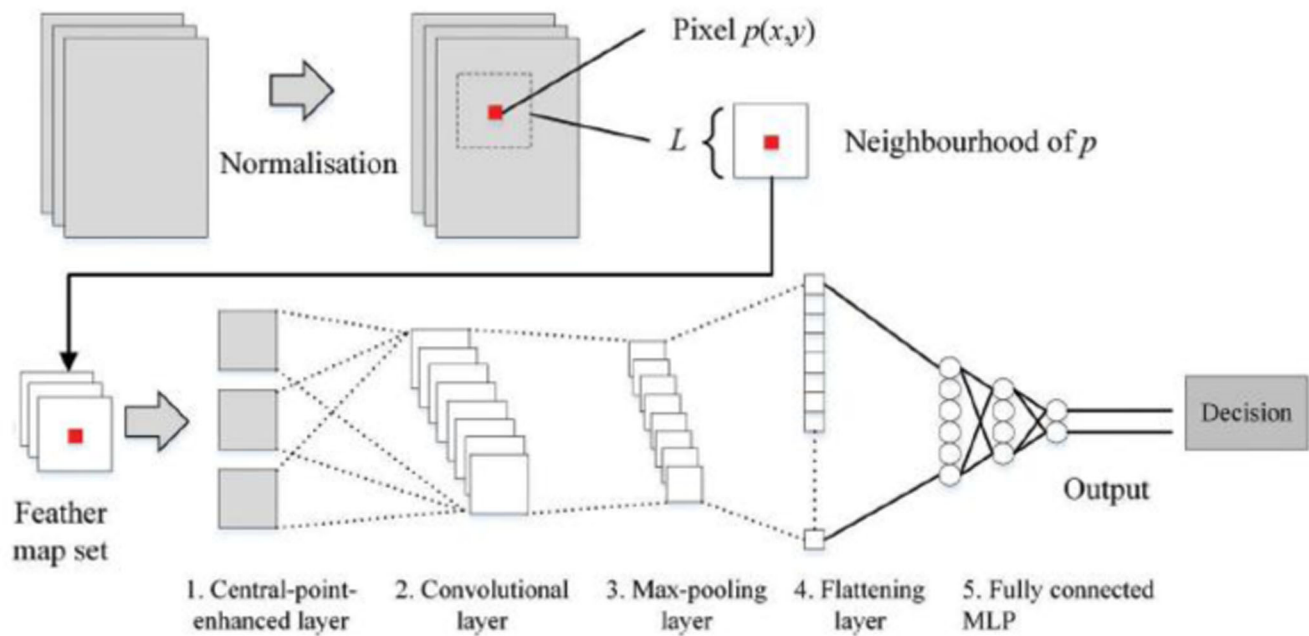
Fig. 3 CE-CNN Architecture

(4) Flatten layer: previous layer output father maps are reshaped. The neurons obtained as output are then changed for gaining the one-dimensional vector.

(5) Fully connected three-layer MLP: This is a multi-layered network which is neural and which has all the input, hidden and the output layers. The first layer is connected directly to the layer that is flat. The count of the neurons present in the hidden layer is double that of the one which is in the output layer.

Transmission function used here is ReLU. More complicated and no-linear pattern in samplesis expressed by hidden layer. The MLP's ability to segment input samples are highly influenced by the number of neurons in the hidden layer.

A minimum number of nodes present in the hidden layer will lead to the non-adequate expression of the neural network which affects the accuracy of the segmentation.

Large numbers of nodes will lead to over-fit to training data. That reduces the network's generalization ability. So twice the number of neurons in the output layer is set as a default number of nodes at hidden layer. MLP was capable of expressing the pattern inside the brain tumour test samples and refrains from overfitting. The count of the criteria will equal to the count of the output layers. The transmission function used here is the Softmax. The ability in terms of the pixel in a CNN is improved by CE-CNN [16]. . In the second section of the CE-CNN, the tiniest kernels (3×3 *in size*) are chosen in the convolution layer. Third section of the CE-CNN deals with the

Maxpooling by the selection of smallest kernel. These two layers are then used for obtaining the spatial data. Reducing the dimensions of the feather map that are taken as inprut will help the consequent CE-CNN for predicting the sample in a more easier manner. This could be possible only with Single group convolutional/max-pooling layers, if the input feather map was small.

Input feather map set $S = \{M_1, M_2, \ldots, M_n\}$ works through these five parts to attain the equivalent brain tumour categories for the pixel p. During the training stage for the CE-CNN, each training sample pixel is transformed into a training feather map set. Each pixel of the image is transformed into the feather map set at the image segmentation stage. The category is obtained by the learned segmentation model. The pixel's category is written into the corresponding pixel's position in the resulting image. The error in prediction is computed using loss function like categorical cross-entropy. After the forward pass, back propagation begins. This is used to update the weight and biases for error and loss reduction. BAT optimization algorithm is used to optimize the loss function.

Novel BAT optimization algorithm (NBOA) for loss function

The ECNN output represents the estimated probability of a pixel belonging to skin tumor. ECNN performs a pixel-wise segmentation. Loss function used here is cross entropy.

A new Novel Bat Optimization Algorithm (NBOA) is proposed to reduce the errors in the brain tumor segmentation. Difference between a non optimal (obstacle) and an optimal

error (prey) is decided based on the Echolocation mechanism. It allows them to hunt even in whole darkness [17, 18]. Ability of echolocation of bats in NBOA methods are used to reduce the error $SU = \{f_1, f_2, \ldots, f_m\}$ from brain tumor image dataset. In NBOA, the echolocation distinctiveness is idealized by the following rules. These rules are formed by the reduction of errors by bats [19]:

Segmentation accuracy is sensed by echolocation by bats. Bats also know the difference between higher brain tumor segmentation accuracy (prey/food) and surroundings barriers.

The velocity, feature position, frequency, loudness and wavelength of bats are given by vel_i, fp_i, $freq_{min}$, A_0 and γ. Bats fly randomly to search for improved tumor segmentation accuracy. Depending on the closeness of their Segmentation accuracy, wavelength and emitted pulses are fine tuned.

Loudness can fluctuate in many ways. It ranges from a large value A_0 to the least value A_{min}.

For every bat b_i, starting feature position fp_i, velocity vel_i, and frequency $freq_i$ are initialized. For each iteration t, the movement of the virtual bats is specified. This is done by updating their velocity and position. They are given by eqs. (10), (11), and (12) as follows: T defines the maximum number of iterations.

$$freq_i = freq_{min} + (freq_{max} - freq_{min})\beta \tag{10}$$

$$vel_i^t = vel_i^{t-1} + (fp_i^t - fp_*)freq_i \tag{11}$$

$$fp_i^t = fp_i^{t-1} + v_i^t \tag{12}$$

Random vector $\beta \in [0, 1]$ is drawn from a uniform distribution. Frequency of each bat is defined by $freq_i$. Current global optimal error is given by fp. It is located after comparing all the solutions among all n number of errors at each iteration 't'. A random number is created, after the error position updating of bats. Fuzzy membership function is used for the same. A new error position will be created around the current best selected error if the random number is larger than the pulse emission rate r_i. It is given by (13).

$$fp_{new} = fp_{old} + \in A^t \tag{13}$$

Where $\in [-1, 1]$, is a random number. Average loudness of all the bats at current iteration is given by A^t. The loudness A_i and $f(fp_i) < f(fp)$. A_i is the pulse emission rate r_i will be updated and a solution will be accepted if a random number is less than loudness A_i and $f(fp_i) < f(fp)$. A_i and r_i are updated by (14–15)

$$A_i^{t+1} = \alpha A_i^t \tag{14}$$

$$r_i^{t+1} = r_i^o[1 - exp(-\gamma t)] \tag{15}$$

where, α, γ are constants. The algorithm iterates until the termination criteria is met. In the proposed NBOA algorithm, the parameters of the bats such as β, $\in$, A^i, γ and r_i are tuned via the use of Gaussian fuzzy membership function (GFMF). The Gaussian membership function is usually represented as Gaussian(x:μ,σ) where μ, σ represents the mean and standard deviation

$$F_A(x, \mu, \sigma, m) = \exp\left[-\frac{1}{2}\left|\frac{x - \mu}{\sigma}\right|^m\right] \tag{16}$$

Where 'm' belongs to Fuzzification parameter (m = 2).

Algorithm 1. Novel BAT optimization algorithm (NBOA).

1. *Bat population is initialized $fp_i(i = 1, 2, \ldots. n)$ and vel_i*
2. *The pulse frequency $freq_i$ at fp is defined.*
3. *The pulse rates ri along with the the loudness A_i are defined*
4. *While ($t <$ Max number of iterations)*
   4.1.   *Generation of fresh solutions by frequency adjustments and update velocities / locations and solutions [equations (10) to (12)]*
   4.2.   *if (rand $> r_i$)*
      4.2.1. *Optimal error column is selected*
      4.2.2. *localerror is generated surrounding the best errors that are selected.*
   4.3.   *end if*
   4.4.   *Generate a new solution by flying randomly*
      4.4.1. *if (rand $< A_i$ & $f(fp_i) < f(fp*))$ //compute A_i via fuzzy membership function*
         i)   *Accept the new solutions*
         ii) *Increaseri and reduce A_i*
      4.4.2. *end if*
   4.5.   *Rank the bats and find the current best $x*$*
5. *end while*
6. *Postprocess results and visualization*
   Can be efficiently integrated into the backpropagation during network training
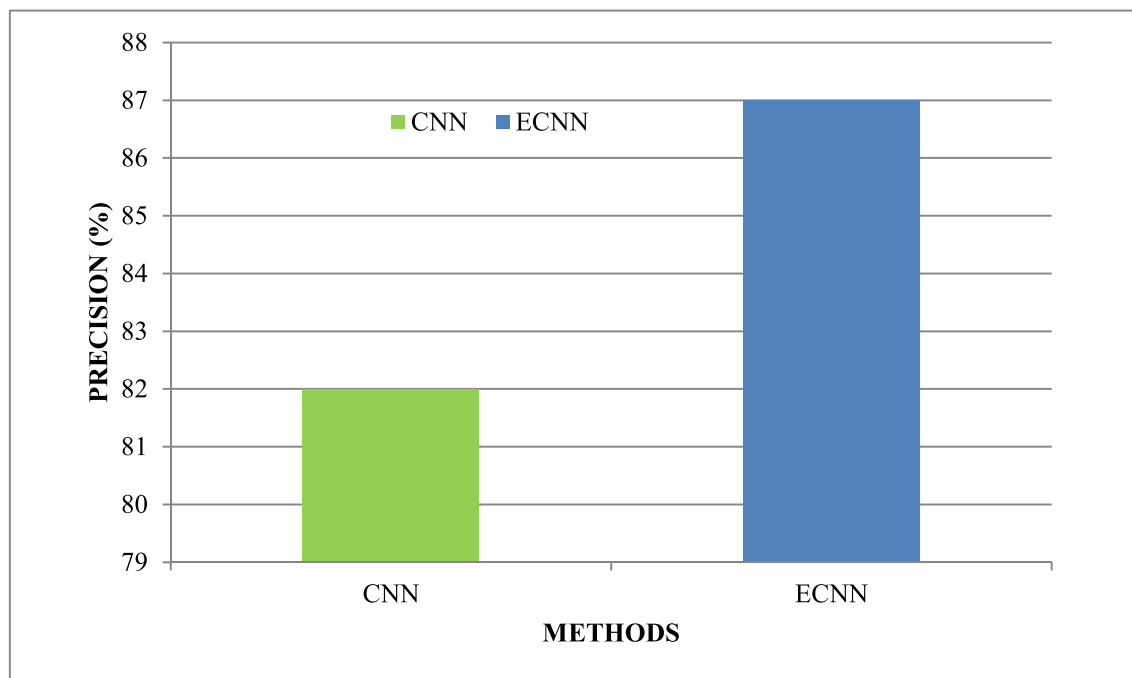
Fig. 4 Precision Results Evaluation of ECNN against CNN

Results and discussion

This section discusses the experimental results of proposed model. The model is implemented using MATLAB. The existing Convolutional Neural Network (CNN) algorithm [20] and proposed Enhanced Convolutional NeuralNetwork (ECNN) are compared in terms of precision, recall and accuracy for the dataset of the Brain Tumor Segmentation Challenge 2015 database (BRATS 2015), obtaining simultaneously the first position for the complete, core, and enhancing regions in Dice Similarity Coefficient metric for the Challenge data set.
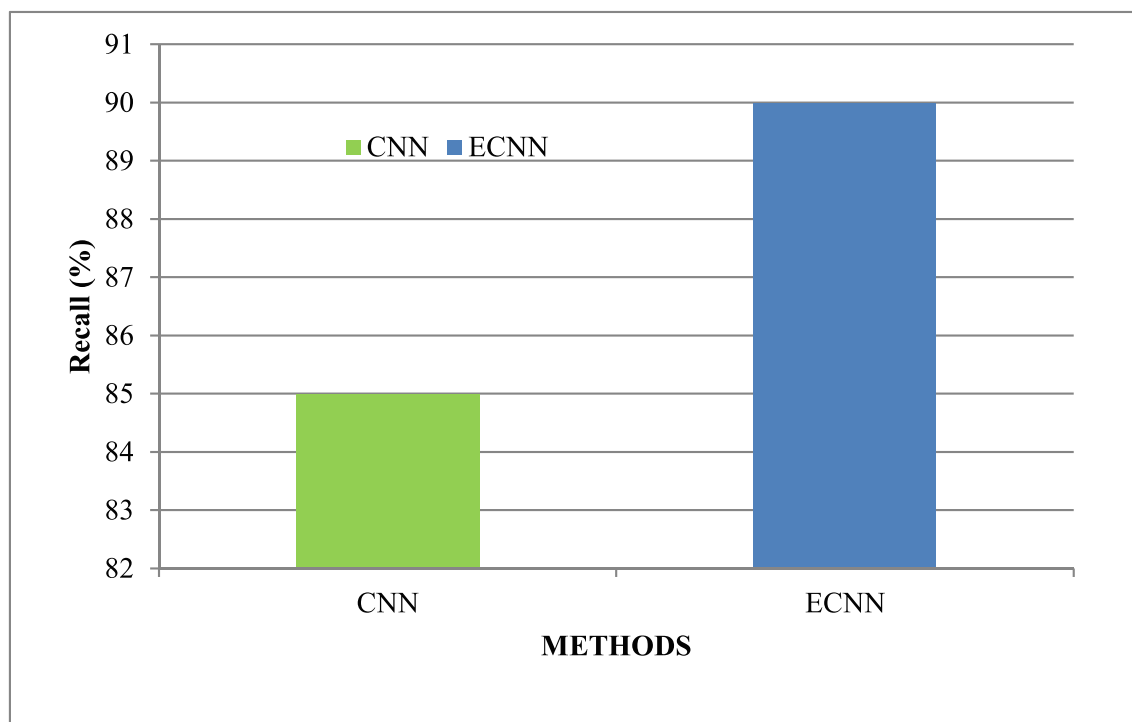

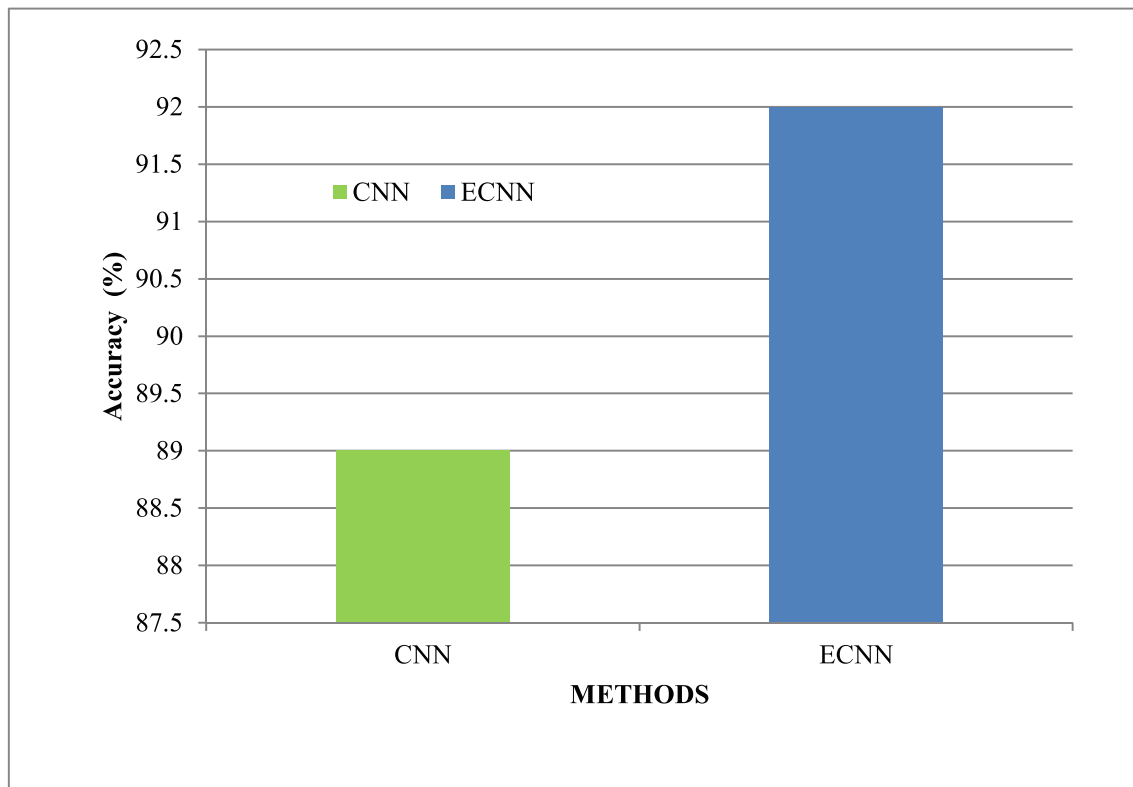**Fig. 5** Recall Results Evaluation of ECNN against CNN

Fig. 6 Accuracy Evaluation of ECNN against CNN

Performance metrics

• Precision

It is the percentage of the results that are relevant and is defined as

$$Precision = \frac{Truepositive}{truepositive + falsepositive} \quad (17)$$

• Recall

The percentage of total relevant results correctly classified by the proposed algorithm which are defined as

$$Recall = \frac{True\ positive}{true\ positive + False\ Negative} \quad (18)$$

• Accuracy

Formally, accuracy has the following definition:

$$Accuracy = \frac{Truepositive + TrueNegative}{Total} \quad (19)$$

Figure 4 shows the performance comparison results of the proposed ECNN method and the existing CNN methods in terms of Precision. From the results it concludes that the proposed ECNN model produces higher precision results of 87% whereas existing CNN method produces only 82% respectively.

Figure 5 shows the performance comparison results of the proposed ECNN method and the existing CNN methods in terms of Recall. From the results it concludes that the proposed ECNN model produces higher recall results of 90% whereas existing CNN method produces only 85% respectively.

Figure 6 shows the performance comparison results of the proposed ECNN method and the existing CNN methods in terms of accuracy. From the results it concludes that the proposed ECNN model. From the results it concludes that the proposed ECNN model produces higher accuracy results of 92% whereas existing CNN method produces only 89% respectively.

Conclusion and future work

Enhanced Convolutional Neural Networks (ECNN) with loss function optimization by BAT algorithm is made used in-order to perform segmentation of a MRI image in an automated

manner. Tiny kernels are used to achieve a deep architecture. It is having a positive effect against overfitting, given the fewer number of weights in the network. Skull stripping and image enhancement algorithms are used for pre-processing. The experimental results show the better performance while comparing with the existing methods. The compared parameters are precision, recall and accuracy. In future, different selecting schemes can be adopted to improve the accuracy.

Compliance with ethical standards

Disclosure of potential conflicts of interest   The authors have no conflict of interests and the paper has not been submitted to any other Journals.

Research involving human participants and/or animals   This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent   It is not required as the dataset is taken online databases.

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