Retraction Notice

The Editor-in-Chief and the publisher have retracted this article, which was submitted as part of a guest-edited special section. An investigation uncovered evidence of systematic manipulation of the publication process, including compromised peer review. The Editor and publisher no longer have confidence in the results and conclusions of the article.

RD, KKH, BPD, and AKV either did not respond directly or could not be reached.

Deep belief network-based image processing for local directional segmentation in brain tumor detection

Ruchi Doshi,[a] **Kamal Kant Hiran**,[b] **Bhanu Prakash Doppala**,[c] **and Ajay Kumar Vyas**[d,*]

[a]Universidad Azteca, Department of CSE, Chalco, Mexico
[b]Symbiosis University of Applied Sciences, School of Computer Science and IT, Indore, Madhya Pradesh, India
[c]Academy Xi, Department of Data Analytics, Sydney, Australia
[d]Adani Institute of Infrastructure Engineering, Department of Information Communication Technology, Ahmedabad, Gujarat, India

Abstract. Brain tumor data have recently been analyzed using deep learning techniques. Segmentation and classification of brain tumors and distinguishing tumorous and nontumorous cells are fascinating when it comes to distinguishing brain cell with tumorous and without tumorous and differentiate the tumorous cells to find their class label. For this purpose, segmentation is an appropriate method for classifying the brain image and it is commonly employed by researchers. To achieve accurate classification, it is necessary to begin with the extraction of relevant features. In this work, the probabilistic Fuzzy *C*-means (FCM) algorithm, is utilized to further refine the segmentation process. This analysis makes it possible to distinguish the regions of interest for magnetic resonance imaging (MRI) scan of the brain revealed, which provides a framework for reducing the dimensionality of MRI brain image. Local directional pattern (LDP) is applied to the segments after they have been segmented to extract the significant regions of features that have been identified by the segmentation method. Next to deep belief network, the features are provided, which determines whether the images are normal or abnormal, and whether MRI can be used to detect or rule out the presence of tumors. Experimentation is conducted with the help of the proposed method and brain tumor segmentation database; the accuracy has been assessed in relation to the highest percentage of 95.78% is obtained. © *2023 SPIE and IS&T* [DOI: 10.1117/1.JEI.32.6.062502]

Keywords: imaging processing; computer vision; probabilistic fuzzy *C*-means algorithm; local directional pattern; deep belief network; brain tumor segmentation database.

Paper 220909SS received Sep. 3, 2022; accepted for publication Nov. 11, 2022; published online Jan. 4, 2023; corrected Jan. 6, 2023; retracted Jun. 24, 2023.

1 Introduction

Magnetic resonance imaging (MRI) has a better spatial resolution and a lot of valuable information for diagnosing brain tumours.[1,2] A solid mass of brain tissue has developed in the uncontrolled growth of unwanted cells found in various locations in the brain. Multiple strategies, such as random woodland and support vector machine (SVM) classifiers, are employed in the classifier. The MRI images are intermixed when the wavelet transforms are applied. It is computerized and is highly accurate when determining abnormalities in the brain. Despite the fact that there is no radiation and no harmful side effects, the information provided is very accurate and trustworthy. However, the tumor's shape and size make it difficult to detect. Four slices, such as C1, C2, fluid-attenuated inversion recovery (FLAIR) images, and C1 contrast, are used to identify the tumors in an MRI [(biological tissues (BT)]. This MRI method therefore yields an abundance of information about the brain tissues, which provides a foundation for a BT diagnosis.[3]

*Address all correspondence to Ajay Kumar Vyas, ajay_ap7@yahoo.com

Biological tissues are known as tissues in the body made of living cells. However, segmentation is required to diagnose the disease and thus is employed in the medical field to detect sudden growth. That said, there is also time and error involved with human examination and identifying the brain MRI tumor and classifying them. Different techniques are used to detect the BT, which are categorized as supervised and unsupervised.[4] The classifier algorithms for tumor segmentation, such as SVMs and random forests, each include classifiers to classify the pattern and the data classification algorithms. Deep learning[5–7] is in semantic segmentation, object detection, and image classification. Accuracy is particularly important when classifying BT. The research project aims to apply deep belief network (DBN) to the analysis of brain tumors. Successfully deploying an effective learning method using restricted Boltzmann machines (RBMs).[8] This unsupervised learning is implemented in stages, and a multilevel structure is built by layering new layers on top of existing ones, building increasingly more abstract representations in the process.[9] Deeper neural networks (DNNs) can be trained with a process that follows this, as they are fed into adjacent layers (DBN-DNN).[10,11]

It delves into the classification of brain tumors, the two stages of which are known as progressive multifocal leukoencephalopathy and diffuse astrocytoma. The tumor present in a complete image is passed to the segmentation module for processing, which segments a tumor to reduce processing time and make the process simpler. To reduce the overall dimensionality, the LDP is fed with segment features and then extracts texture features for classification. To diagnose the tumor patients,[12,13] either the input image is normal or abnormal depending on the classifier. The structure followed in the paper: Sec. 1 illustrates the start of the document as an introduction, and in Sec. 2, MRI can assist with various medical imaging techniques due to the ability to obtain superior spatial resolution, while also supplying detailed information on the presence of a brain tumor. Computerized imaging systems participate in the exactly accurate determination of brain abnormalities. With MRI, there is no radiation, and this offers true and accurate information. Due to the tumor's size and shape, tumor detection is not effective. To localize a brain tumor, images, such as C1, C2, and C1 contrast, and FLAIR, show slices, such as C1, C2, C1 contrast, and FLAIR. Because of this, MRI scans provide a wealth of information about the brain tissues that support tumor diagnosis. A brain tumor is made up of different biological tissues and is made up of diverse types of tissue. Detecting the segments is critical for the diagnosis of the disease, so segmentation is important in healthcare.[14,15] The brain tumor segmentation (BraTS) technique is employed to analyze tumor mass and diagnose the sudden growth.[16,17]

However, in contrast, an examination of a human is prone to errors and requires more time and resources to identify and classify the brain MRI tumor. Brain tumor detection can be further divided into supervised and unsupervised approaches.[10] Classification refers to the process of assigning distinct classes to individual observations. Dataset classification uses classifiers, such as random forests and SVMs. Deep learning methods,[18] until recently, has used in BT segmentation studies to identify objects, classify images, and categorize texts. Whereas there are a multitude of classification techniques applied in classifying brain tumors, the effectiveness is crucial. The paper aims to use DBN to perform the brain tumor classification.

The paper focuses on two major steps that are taken when classifying brain tumors: (1) beginning a classification and (2) proceeding to advance the classification. The tumor in the input image can be segmented using a segmentation module, which speeds up processing and simplifies the image. In this process, the texture features extracted by the local directional pattern (LDP) are fed to the classification to further reduce the dimensional complexity. To detect the tumor patients, it classifies the image as input whether as normal or abnormal. The paper's organization is as follows: First, Sec. 1 introduces the topic, and second, Sec. 2 addresses the reasoning behind the study. Section 3 illustrates the brain tumor classification, whereas Sec. 4 explains the results of the study. This paper finishes with Sec. 5 and focuses on the reasoning behind the study.

2 Related Work

Using a three-dimensional super voxel to segment the brain tumor from MRI image was developed by Soltaninejad et al.,[2] tumor segmentation had better robustness thanks to the method.

The major drawback of the method is that it takes an enormous amount of time to complete. Using a method known as pillar K-means, which processes segmentation and classification (SC). While applying k-means clustering, Anitha and Murugavalli[19] employs a decision boundary for hard assignments between classes. Initial conditions and the presence of outliers are required for accurate clustering with k-means clustering. Instead, soft decision boundaries are provided by fuzzy clustering. However, when dealing with noise or outliers in the data, FCM efficacy is only partial.[20] Another crucial factor is that the FCM's results are affected by the starting values of the parameters. In their work on possibilistic CM (PCM) clustering, Ramakrishnan et al. and Zhang et al.[21,22] suggested a new method called PCM. However, PCM almost eliminates the interdependence of the data points, which causes an increase in the parameters' complexity in determining which values to use. The new clustering algorithm proposed by Keller[23] was known as FPCM.[24]

However, the method could not sufficiently describe the pathological conditions. The feature extraction used though a higher classification accuracy; the features produced by Xiong[25] were ineffective as they were no different from the other available features. Ramakrishnan and Sankaragomathi[21] created an SVM classifier that offered deficient performance with sequential minimal optimization. Zhao[18] used convolutional neural networks and CRFs for an optimization on the appearance. When developing their brain SC method, researchers developed a technique that required fewer computational steps, but included multiple features to be effective.[1,26]

Other methods, such as image alignment, intensities, textures, and edges, were traditionally used based on the parameters. Using these features, you can obtain a classification system, but it never reveals the actual anatomical significance of brain tumors. The manual analysis segmentation process is painstaking and time-consuming.[1,27] Additionally, because the classification accuracy is open to question, segmentation may have required an inordinate amount of manual effort.

The analysis of tumor images is critical in assisting people in diagnosing various disorders.[28] The classification of tumors is an important aspect that is dependent on the neurosurgeons experience and knowledge. To assist physicians, it is necessary to have a computerized system that can recognize and classify various types of brain tumours.[27,29]

While modeling multiimages that contain classified information, which has no image representation modalities, and combining this information for identification is a difficult undertaking.[7] To address the problem of multimodeling medical segmentation, strategies have been proposed. The 3D approaches produced more exact results than the two dimensional (2D) methods, due to volumetric information retains 3D data when 2D slices are which is lost used by independently as input.[30]

3 Proposed Method and Procedure

Because SC of brain tumors is critical to early diagnosis and treatment, brain tumor mortality is reduced. Distinct reasons contribute to the tumor being overlooked by the traditional classifications. One of the system's biggest advantages is that it can conduct an accurate classification using features that are utilized for classification. Additionally, the selection of the most effective segmentation methods takes place.

Because of this, it focuses on the approach for increasing the classification accuracy using deep learning in the context of pixels in image of brain tumor. Classification of pixel in different level is a process of grouping image portions together that is related to similar classifier class.[31,32]

This entails processing each image as if it belonged to the same class. Identification relates to the localization and classification of objects. Image segmentation can be thought of classifying each pixel in level wise prediction because it categorizes each pixel.[28,33,34] Feature extraction is done on the image segments that are obtained using the LDP-based feature extraction methodology[35,36] and used in the probabilistic fuzzy clustering algorithm to determine classification accuracy. In Fig. 1, the proposed brain tumor SC methodology is depicted as a block diagram.

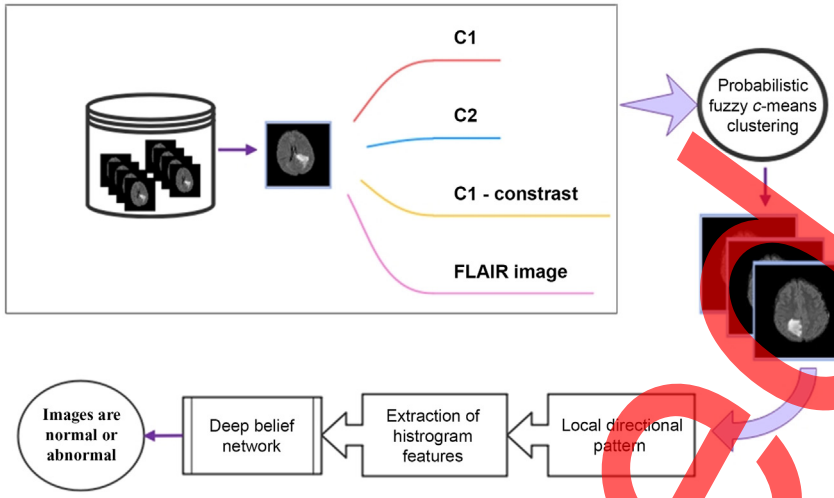

Fig. 1 Proposed brain tumor SC methodology.

MRI brain image I is used to segment and classify the brain tumor $(p \times q)$. In this image, FLAIR is used for the following classification processes. It is made up of thin slices of food, fed one at a time to the segmentation. The probabilistic fuzzy clustering method is used at the beginning to form clusters that contain the tumour region. Once segments have been LDP'ed, features are extracted and those features are used for classification.[14]

3.1 *Using the Probabilistic FCM Clustering for Segmentation*

To form segments from the input image M, perform segmentation on the result probabilistic fuzzy cluster algorithm. FCM clustering, on other hand, uses the membership function to cluster the data points, with the results being better for data points that are overlapped.[15] It produced a more statistically aware algorithm, which is better able to manage random chance and instability. The marriage of probabilistic and fuzzy theory is described as

$$S_h(q, p) = q_h p_{h.} \tag{1}$$

It denotes the function of fuzzy membership as q_h and the membership function of probabilistic membership as p_h. Where, $q = \{q_{k,i} : k = 1, \ldots, x; i = 1, \ldots, n\}$ and $p = \{p_{k,i} : k = 1, \ldots, x; i = 1, \ldots, n\}$.

Probability is represented as

$$P^*_{k,i} = P_{k,i} p_{ki.} \tag{2}$$

That is, the total of the i'th column of the partition matrix J

$$J_1 = \sum_{k=1}^{x} U_{k,i} p_{ki}, \tag{3}$$

where $i = 1,2,3, \ldots, k$ (here k is cluster) and p_{ki} representing the probability that i'th data point is present in the cluster k. To put it another way, the objective function is best defined as

$$H^*_n(J, v) = \sum_{i=0}^{k} \sum_{k=1}^{x} (P^*_{k,i})^n E^2_{k,i}, \tag{4}$$

where $J = \{J_{k,i} : i = 1,2,3,4, \ldots, n; k = 1, \ldots, x\}$; J and V is matrix with i column; and $V = \{v_{k,i} : i = 1,2,3,4, \ldots, n; k = 1, \ldots, x\}$

$$v_k = \frac{\sum_{i=1}^{k} (P_{k,}^{*})^n z_i}{\sum_{i=1}^{k} (P_{k,i}^{*})^n}. \tag{5}$$

The clustering algorithm uses cluster centroids, which is derived from the membership functions, to determine clusters. Membership functions create clusters of data points by grouping similar points together. To arrive at the membership function, it is determined as such as

$$P_{k,i}^{*} = \frac{J_1}{\sum_{i=1}^{x} \left(\frac{E_{ki}}{E_{li}}\right)^{\frac{2}{n-1}}}. \tag{6}$$

Segments are created and with each segment being referred to as a segment

$$M = \{m_1, m_2, m_3, \ldots\ldots\ldots\ldots\ldots m_n.\} \tag{7}$$

M is the segmentation of segments.
It denotes n is the total no. of the segments.

3.1.1 *Directional pattern locally*

Using the probabilistic fuzzy clustering algorithm, we can generate random segment segments, which we then feed to the LDP for feature extraction.[37,38] This approach reduces the classification complexity. To get around the problem of feature dimension, for problem solving, proposed method is extracted from the segmented and applied. The image intensity at (m, n) is defined as J_a, whereas the image intensity at (m, n) ranges from 0 to 7. the intensity of the pixel that is located at (m, n) and which has an LDP value of 8

$$\mathrm{LPD}_i(m, n) = \sum_{b=0}^{7} L(K_b - K_j) 2^b, \tag{8}$$

$$L(z) = \begin{cases} 1; & \text{if } z \geq 0 \\ 0; & \text{otherwise} \end{cases}, \tag{9}$$

where the terms K_b and Krish mask refer to the directional component integrated with the Krish mask that ensures LDP. If the intensity of a pixel is greater than that of a pixel at (m, n), a pixel value of 1 is applied. Otherwise, zero is assigned to the pixel's value. Because of this, the input image has texture features represented in beta sequence, and the picture shows its frequency histogram. For LDP features, we apply a histogram representation that makes use of histogram features and describes their importance. These features are specified by the classes and dimensions of the histogram $[1 \times 96]$ by the presence of histogram features. Features can be set as

$$H = \{h_1, h_2, h_3, \ldots\ldots\ldots\ldots\ldots h_{96}\}, \tag{10}$$

where h includes the features of the histogram.

3.2 *Convolution Models*

Figure 2 demonstrates VGG-16 deep network, which processes input image of dimension $128 \times 128 \times 2$ for classifying the availability of brain stroke. By applying the max pool technique, the input image is resized to $64 \times 64 \times 128$ with stride of 2. This procedure is repeated until the image size reaches to 8×8 with 512 parameters. The outcome is passed to a fully connected layer with 25,088 parameters to identify the tumor.[39]

Fig. 2 VGG-16 architecture.

3.3 *Deep Belief Network*

Training a classification model using the steepest descent algorithm results in classifications that use the DBN.[9,40] To ensure accurate classification, you must employ a DBN. As shown in Fig. 3, the basic architecture of the DBN. In contrast, DBN comprises two models: RBM and multilayer

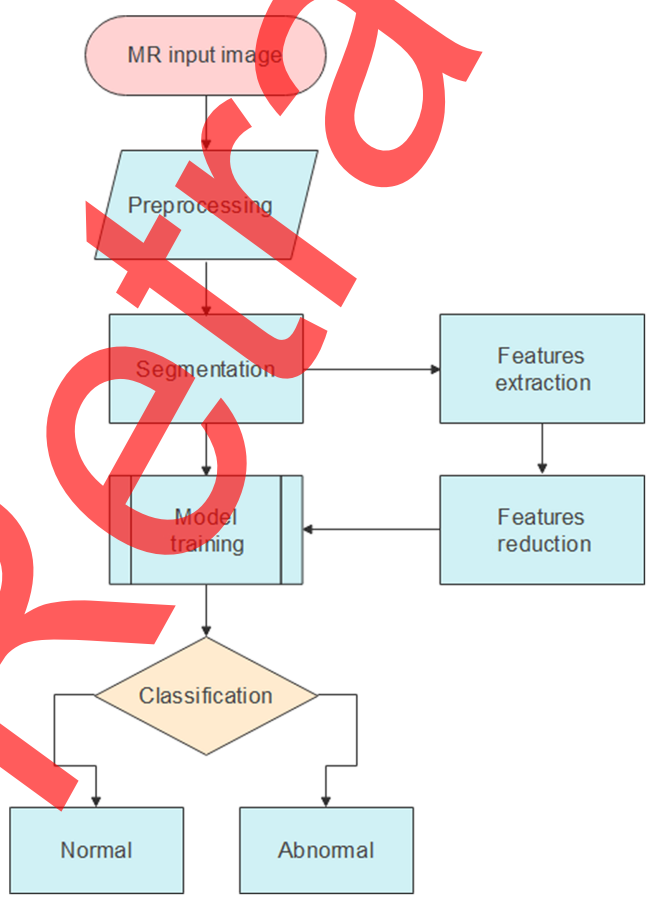

Fig. 3 Flowchart of proposed method.

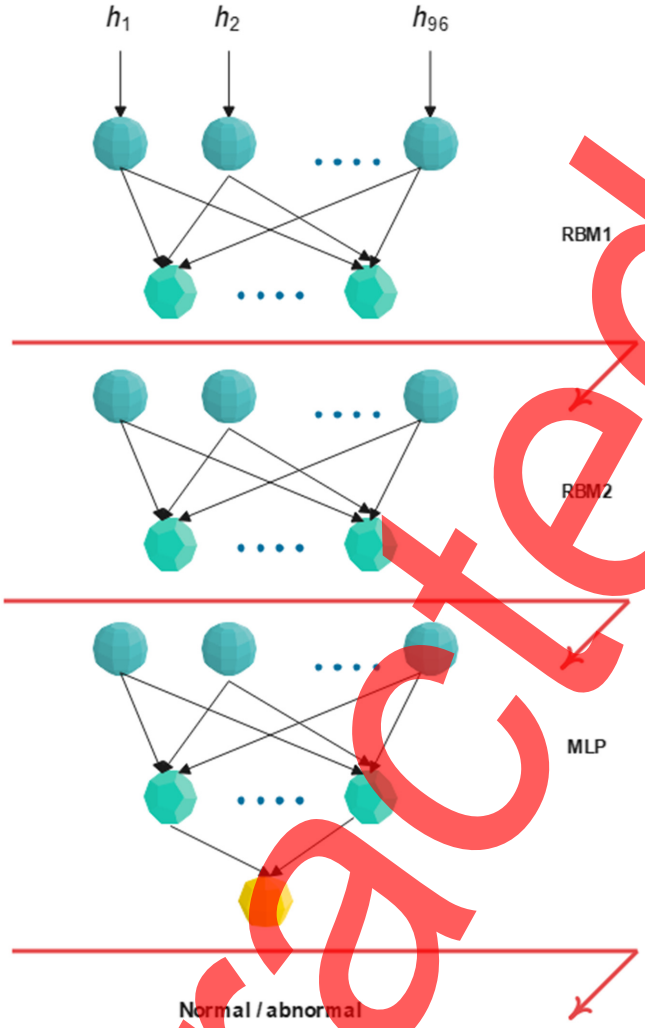

Fig. 4 DNN architecture.

perceptron (MLP). When modelling the connectivity of the neurons, suppose there are two RBM layers and that the neurons within each layer are interconnected.[8]

The data are processed by the neurons, using the various input–output connections available between the DBN layers. The data from the image are stored in the DBN, and the total number of features is: $[1 \times 96]$. A training set of images and attributes are used to construct a DBN classifier. The weights of the successive layers of DBN are then applied to process the classifier (Fig. 4).

The basic concept of DBN is that once the training data for DBN have been generated based on whether tumor is present, DBN classifies the test data upon arrival.[41] The hidden layers of RBM1 contain the input for the hidden layers of RBM2. Also, the RBM2 has its input and hidden layers to the MLP layer the output of the RBM2 is as an input. RBM2's hidden layer is a major component of the MLP.[40,42,43] The output reports the input image that it is normal MRI, whether the person is abnormal even after being found to have a significant tumor. A binary classifier's two class labels are normal and abnormal.

3.4 *Training*

RBM and MLP in training use such an approach to derive the weights based on the minimum error. Because the data's details are important in determining the class label, weights guarantee efficient data processing. Gradient descent is used to find the best weights for the algorithm, and the minimum objective value is used as the parameter for the algorithm. We are given mean square error to serve as our objective function

$$\mathrm{MSE} = \frac{1}{s}\sum_{y=1}^{s}[T - C]. \tag{11}$$

If we had 100 or more training samples and they could be referenced as s and the ground truth is T, and the estimated output is C, then the expression above would be true. The weight values of RBM and MLP layers are adjusted based on the minimum error value. Correcting misclassification ensures an effective diagnosis and benefits the patients.

4 Method Experiments and Results

This section discusses the results of study and conclusion reached regarding the proposed method as well as the analysis of the various methods.

4.1 *Descriptive Dataset Documentation*

BraTS is the database of patient images that was used for this project,[14,44] which has 30 patient images each with different slices (Fig. 5).

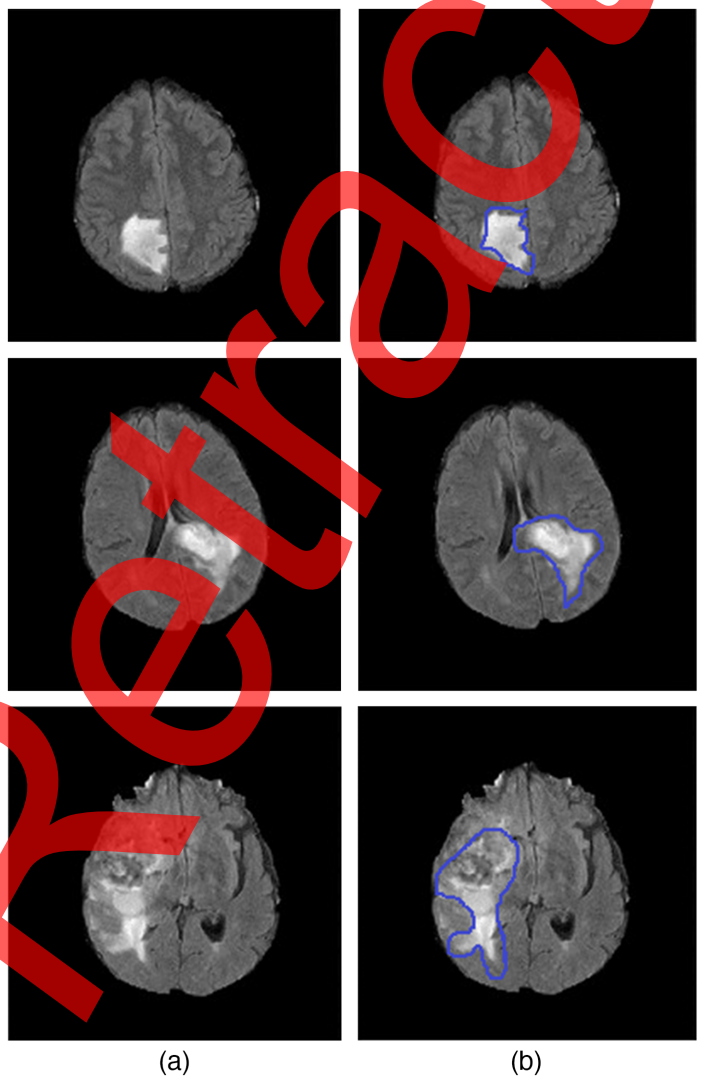

Fig. 5 BraTS training data with tumor regions as inferred results of segmentation: (a) input and (b) segmented image.

Table 1 Comparative analysis of segmentation results by accuracy.

Methods	Training accuracy 40%	Training accuracy 60%	Training accuracy 80%
Active contour	0.7486	0.7935	0.7985
SVM	0.8157	0.8203	0.8465
KNN	0.8597	0.9298	0. 9532
VGG-16	0.8623	0.9356	0.9565
Proposed DBN	0.8736	0.9368	0.9578

4.2 *Comparative Research Using Experimental Methods*

Using the methods proposed, we look at active contour,[45] SVM, k-nearest neighbors (KNN), VGG-16, and proposed DBN for the analysis (see Table 1). Figure 6 shows the methods' accuracy that can be expected to increase with training percentage.

In the analysis, training percentages range from 0.4 to 0.8. Methods such as those listed above, active contour, SVM, and KNN, VGG-16, and proposed DBNs have an accuracy of 0.7486, 0.8157, 0.8597, 0.8623, and 0.8736 for the training percentage of 40%. Percentage values for 60% training accuracies are 0.7935, 0.8203, 0.9298, 0.9356, and 0.9368. At 0.8, the accuracies are 0.7985, 0.8465, 0.9532, 0.9565 and 0.9578. With the above comparisons, it is obvious that the method proposed is more accurate with respect to sensitivity when compared with other observations.

As shown in Fig. 7, the methods that have been proposed, including active contour, SVM, KNN, VGG-16, and proposed DBN have the following sensitivity: training percentage is used in the analysis (Table 2). When evaluating the method's sensitivity, the training percentages are utilized that have values of 0.4, 0.6, and 0.8. Figure 8 shows the increase in methods' specificity with training percentages when compared with existing models. By this observation, it is clearly seen that proposed DBN outperformed well with the training percentages and values obtained for sensitivity 0.9041, 0.9527, and 0.9689. For specificity, the obtained values are 0.9097, 0.9697, and 0.9796 (Table 3).

The receiver operating characteristic (ROC) analysis in Fig. 7 is a visual representation of the methods. The true positive rates (TPRs) (0.7422, 0.7277, 0.7638, and 0.7194) obtained using the proposed, KNN, SVM, and active contour methods are respectively, for 0.1 as false positive rate (FPR), equal to 0.7422, 0.7194, 0.7638, and 0.7277. The method obtained a max accuracy, specificity, and sensitivity from the analysis (Fig. 9).

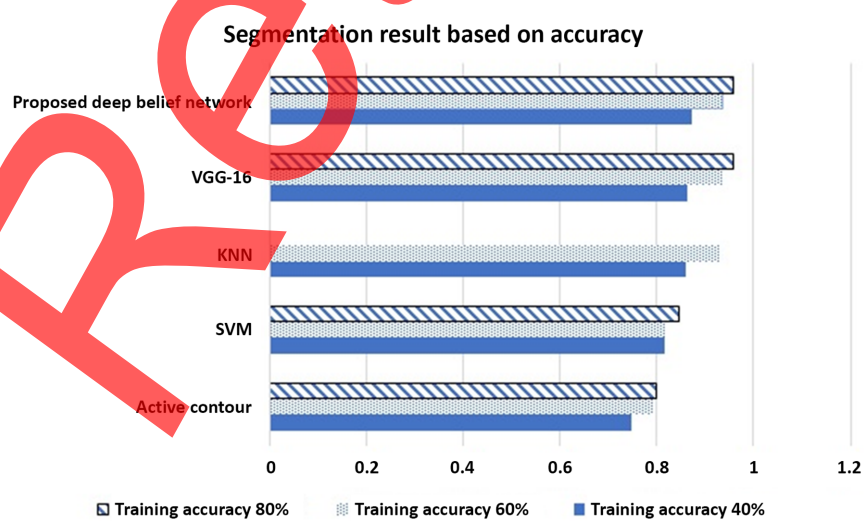

Fig. 6 Comparative analysis on model accuracies.

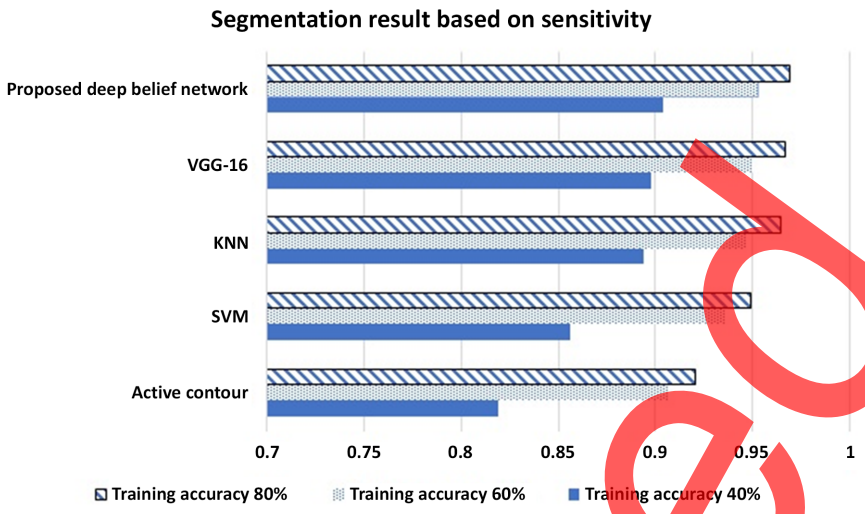

Fig. 7 Using sensitivity in comparative analysis.

Table 2 Comparative analysis of segmentation results by sensitivity.

Methods	Training accuracy 40%	Training accuracy 60%	Training accuracy 80%
Active contour	0.8187	0.9068	0.9203
SVM	0.8562	0.9354	0.9491
KNN	0.8937	0.9468	0.9645
VGG-16	0.8976	0.9501	0.9670
Proposed DBN	0.9041	0.9527	0.9689

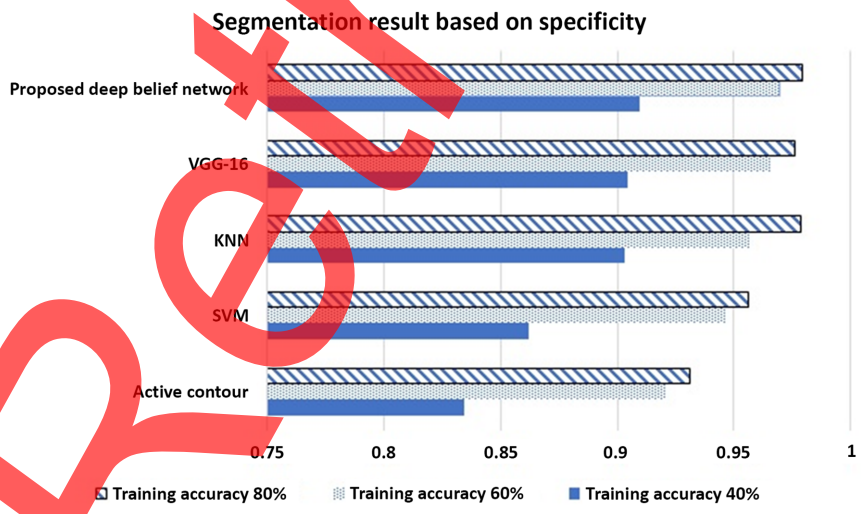

Fig. 8 Using specificity in comparative analysis.

5 Conclusion

This innovative work makes use of probabilistic FCM algorithm and DBN for classification of brain tumors. It is necessary to separate the brain tumor along with MRI brain image to make progress in feature extraction.

Table 3 Comparative analysis of segmentation results by specificity.

Methods	Training accuracy 40%	Training accuracy 60%	Training accuracy 80%
Active contour	0.8347	0.9213	0.9312
SVM	0.8622	0.9463	0.9562
KNN	0.9032	0.9564	0.9786
VGG-16	0.9046	0.9652	0.9764
Proposed DBN	0.9097	0.9697	0.9796

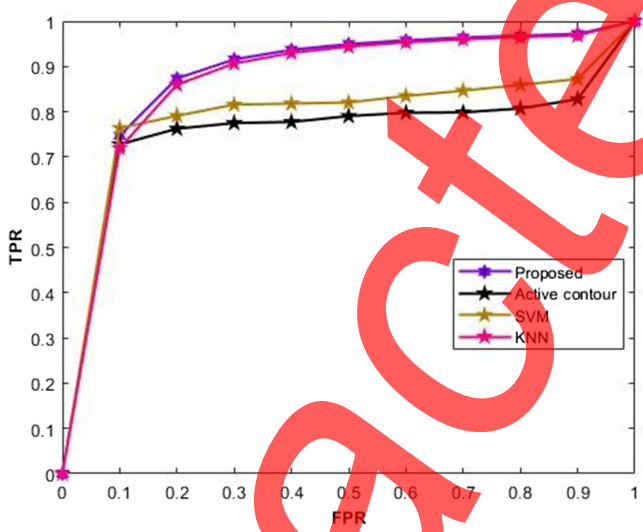

Fig. 9 ROC analysis.

Using neighborhood pixel intensities, the LDP obtains the required pattern. The training and testing steps in the classifier are performed using the steepest descent algorithm. Early and accurate diagnosis of the brain tumor is dependent on accurate classification of the brain MRI image. In experimentation, BraTS is used, and the proposed DBN is evaluated based on positive and negative numbers in outcomes it produces. The greater percentage of the outcomes obtained in the BraTS database was 95.78% on training data of 80%, whereas that in the proposed method was 93.68% on 60% of training data and 87.36% on 40% training data, respectively.

References

1. A. Maruthamuthu and L. P. Gnanapandithan, "Brain tumour segmentation from MRI using superpixels based spectral clustering," *J. King Saud Univ. – Comput. Inf. Sci.* **32**(10), 1182–1193 (2020).
2. M. Soltaninejad et al., "Supervised learning based multimodal MRI brain tumour segmentation using texture features from supervoxels," *Comput. Methods Prog. Biomed.* **157**, 69–84 (2018).
3. K. K. Hiran and R. Doshi, "An artificial neural network approach for brain tumor detection using digital image segmentation," *Int. J. Emerg. Trends Technol. Comput. Sci.* **2**(5), 227–231 (2013).
4. K. K. Hiran et al., *Machine Learning: Master Supervised and Unsupervised Learning Algorithms with Real Examples (English Edition)*, BPB Publications (2021).
5. G. Wang et al., "Interactive medical image segmentation using deep learning with image-specific fine tuning," *IEEE Trans Med Imaging* **37**(7), 1562–1573 (2018).

6. M. M. Mijwil et al., "Deep learning techniques for COVID-19 detection based on chest x-ray and CT-scan images: a short review and future perspective," *Asian J. Appl. Sci.* **10**(3), 224–231 (2022).
7. H. S. Santhosh Kumar and K. Karibasappa, "An effective hybrid deep learning with adaptive search and rescue for brain tumor detection," *Multimedia Tools Appl.* **2022**, 17669–17701 (2022).
8. G. E. Hinton, S. Osindero, and Y. W. Teh, "A fast learning algorithm for deep belief nets," *Neural Comput.* **18**(7), 1527–1554 (2006).
9. W. H. L. Pinaya et al., "Using deep belief network modelling to characterize differences in brain morphometry in schizophrenia," *Sci. Rep.* **6**, 38897 (2016).
10. G. Meena et al., "Performance comparison of network intrusion detection system based on different pre-processing methods and deep neural network," in *DSMLAI "21": Proc. Int. Conf. Data Sci., Mach. Learn. and Artif. Intell.* (2021).
11. K. Lakhwani et al., "An enhanced approach to infer potential host of coronavirus by analyzing its spike genes using multilayer artificial neural network," in *5th IEEE Int. Conf. Recent Adv. and Innov. in Eng., ICRAIE 2020 – Proc.* (2020).
12. K. K. Hiran et al., "Robust & secure digital image watermarking technique using concatenation process cloud computing view project digital image processing view project," *Int. J. ICT Manage.* **1**, 117 (2013).
13. X. Zhang et al., "A robust 3-D medical watermarking based on wavelet transform for data protection," *Comput. Syst. Sci. Eng.* **41**(3), 1043–1056 (2022).
14. T. A. Jemimma and Y. J. V. Raj, "Brain tumor segmentation and classification using deep belief network," in *Proc. 2nd Int. Conf. Intell. Comput. and Control Syst., ICICCS 2018*, pp. 1390–1394 (2019).
15. S. Patel, A. K. Vyas, and K. K. Hiran, "Infrastructure health monitoring using signal processing based on an industry 4.0 System," in *Cyber-Physical Systems and Industry 4.0*, D. Goyal et al., Eds., pp. 249–260, Apple Academic Press (2022).
16. S. Dadhich et al., "Machine learning for weather forecasting," in *Machine Learning for Sustainable Development*, K. K. Hiran et al., Eds., pp. 161–174, De Gruyter, Berlin (2021).
17. S. K. Jha, J. Wang, and R. Shanmugam, "An accurate soft diagnosis method of breast cancer using the operative fusion of derived features and classification approaches," *Expert Syst.* **39**(7), e12976 (2022).
18. X. Zhao et al., "A deep learning model integrating FCNNs and CRFs for brain tumor segmentation," *Med. Image Anal.* **43**, 98–111 (2018).
19. V. Anitha and S. Murugavalli, "Brain tumour classification using two-tier classifier with adaptive segmentation technique," *IET Comput. Vision* **10**(1), 9–17 (2016).
20. T. A. Jemimma and Y. J. Vetharaj, "Fractional probabilistic fuzzy clustering and optimization based brain tumor segmentation and classification," *Multimed Tools Appl.* **81**(13), 17889–17918 (2022).
21. T. Ramakrishnan and B. Sankaragomathi, "A professional estimate on the computed tomography brain tumor images using SVM-SMO for classification and MRG-GWO for segmentation," *Pattern Recognit. Lett.* **94**, 163–171 (2017).
22. Y. Zhang et al., "Deep learning and unsupervised fuzzy c-means based level-set segmentation for liver tumor," in *IEEE 17th Int. Symp. Biomed. Imaging (ISBI)*, pp. 1193–1196 (2020).
23. N. R. Pal et al., "A possibilistic fuzzy c-means clustering algorithm," *IEEE Trans. Fuzzy Syst.* **13**(4), 517–530 (2005).
24. B. K. Chakraborty and M. K. Bhuyan, "Skin segmentation using possibilistic fuzzy C-means clustering in presence of skin-colored background," in *IEEE Recent Adv. Intell. Comput. Syst., RAICS 2015*, pp. 246–250 (2016).
25. S. L. Jui et al., "Brain MRI tumor segmentation with 3D intracranial structure deformation features," *IEEE Intell Syst* **32**(2), 66–76 (2016).
26. K. Lakhwani et al., "Prediction of the onset of diabetes using artificial neural network and Pima Indians diabetes dataset," in *5th IEEE Int. Conf. Recent Adv. and Innov. in Eng., ICRAIE 2020 – Proc.* (2020).
27. K. K. Hiran et al., *Machine Learning for Sustainable Development*, De Gruyter (2021).

28. A. H. Khan et al., "Intelligent model for brain tumor identification using deep learning," *Appl. Comput. Intell. Soft Comput.* **2022**, 8104054 (2022).
29. K. T. Islam, S. Wijewickrema, and S. O'leary, "A deep learning framework for segmenting brain tumors using MRI and synthetically generated CT images," *Sensors* **22**(2), 523 (2022).
30. D. Verma and M. S. Pandey, "Computerized assisted segmentation of brain tumor using deep convolutional network," in *Proc. of Second Doctoral Symp. on Comput. Intell.*, pp. 461–470, Springer, Singapore (2022).
31. S. R. Gunasekara, H. N. T. K. Kaldera, and M. B. Dissanayake, "A systematic approach for MRI brain tumor localization and segmentation using deep learning and active contouring," *J. Healthcare Eng.* **2021**, 6695108 (2021).
32. S. Devunooru et al., "Deep learning neural networks for medical image segmentation of brain tumours for diagnosis: a recent review and taxonomy," *J. Ambient Intell. Hum. Comput.* **12**(1), 455–483 (2021).
33. S. Tripathi, A. Verma, and N. Sharma, "Automatic segmentation of brain tumour in MR images using an enhanced deep learning approach," *Comput. Methods Biomech. Biomed. Eng. Imaging Vis.* **9**(2), 121–130 (2021).
34. B. Easwaran Eds., *Real-Time Applications of Machine Learning in Cyber-Physical Systems*, IGI Global (2022).
35. T. D. Pham, "Image segmentation using probabilistic fuzzy c-means clustering," in *IEEE Int. Conf. Image Process.*, Vol. 1 (2001).
36. J. Ramasamy, R. Doshi, and K. Kant Hiran, "Segmentation of brain tumor using deep learning methods: a review," in *DSMLAI "21": Proc. of the Int. Conf. on Data Sci. Mach. Learn. and Artif. Intell.*, pp. 209–215 (2021).
37. C. L. Chowdhary et al., "An efficient segmentation and classification system in medical images using intuitionist possibilistic fuzzy C-mean clustering and fuzzy SVM algorithm," *Sensors (Switzerland)* **20**(14), 3903 (2020).
38. S. Kollem, K. R. Reddy, and D. S. Rao, "An optimized SVM based possibilistic fuzzy c-means clustering algorithm for tumor segmentation," *Multimedia Tools Appl.* **80**(1), 409–437 (2021).
39. S. K. Jha et al., "A comprehensive search for expert classification methods in disease diagnosis and prediction," *Expert Syst.* **36**(1), e12343 (2019).
40. A. Kharrat and M. Néji, "Classification of brain tumors using personalized deep belief networks on MRImages: PDBN-MRI," in *Eleventh Int. Conf. on Mach. Vision (ICMV 2018)*, p. 38 (2019).
41. A. Sheela, "Segmentation of brain tumor in deep learning," in *ICPECTS 2020 - IEEE 2nd Int. Conf. Power, Energy, Control and Transmission Syst., Proc.* (2020).
42. A. V. N. Reddy et al., "Analyzing MRI scans to detect glioblastoma tumor using hybrid deep belief networks," *J. Big Data* **7**(1), 1–17 (2020).
43. J. Ramasamy and R. Doshi, "Machine learning in cyber physical systems for healthcare: brain tumor classification from MRI using transfer learning framework," in *Real-Time Applications of Machine Learning in Cyber-Physical Systems*, B. Easwaran et al., Eds., pp. 65–76, IGI Global (2022).
44. B. H. Menze et al., "The multimodal brain tumor image segmentation benchmark (BRATS)," *IEEE Trans. Med. Imaging* **34**(10), 1993–2024 (2015).
45. E. Ilunga–Mbuyamba et al., "Automatic selection of localized region-based active contour models using image content analysis applied to brain tumor segmentation," *Comput. Biol. Med.* **91**, 69–79 (2017).

Ruchi Doshi has more than 16 years of academic, research, and software development experience in Asia and Africa. She worked as a founding chair for WIE in the IEEE Liberia Subsection. She worked with the Ministry of Higher Education in Liberia and Ghana for the degree approvals and accreditations processes. She has published numerous research papers in peer-reviewed international journals and conferences. She is a reviewer, advisor, ambassador, and editorial board member of various reputed international journals and conferences.

Kamal Kant Hiran is working as an associate professor in the School of Computer Science and Information Technology, Symbiosis University of Applied Sciences, Indore, Madhya Pradesh,

India. His research interests include cloud computing, machine-deep learning, and intelligent IoT. He has several awards to his credit, such as an International Travel Grant; Best Research Paper Award at the University of Gondar, Ethiopia; IEEE Liberia Subsection Founder Award; and Gold Medal Award in MTech (Hons).

Bhanu Prakash Doppala received his PhD in information technology from Lincoln University College, Malaysia, and his MTech, CSE from Acharya Nagarjuna University, Guntur, Andhra Pradesh, India. He is currently associated with Academy Xi, Australia, as lead course instructor for data analytics. He published several research papers in various reputed Scopus and SCI indexed journals and international conferences. His research interests include machine learning, deep learning, and big data.

Ajay Kumar Vyas received his BE degree in electronics and communication from GEC Ujjain and MTech degree from Shri GSITS, Indore, in field of optical communication with honors. He received his PhD from MPUAT, Udaipur, India. Currently, he is working at the Department of Information and Communication Technology, Adani Institute of Infrastructure Engineering, Ahmedabad, Gujarat, India. He is a fellow member of IETE, a senior member of IEEE, and a life member of ISTE.