Deep Learning Algorithm for Brain Tumor Detection and Analysis Using MR Brain Images

Abd El Kader Isselmou
Hebei University of Technology
8 Dingzigu 1st Rd, Hongqiao Qu, China, 300131.
Isselmou_kader@yahoo.com

Guizhi Xu
Hebei University of Technology
8 Dingzigu 1st Rd, Hongqiao Qu, China, 300131.
gz@hebut.edu.cn

Shuai Zhang
Hebei University of Technology
8 Dingzigu 1st Rd, Hongqiao Qu, China, 300131.
zs@hebut.edu.cn

Sani Saminu
Hebei University of Technology
8 Dingzigu 1st Rd, Hongqiao Qu, China, 300131.
20170000008@stu.hebut.edu.cn

Imran Javaid
Hebei University of Technology
8 Dingzigu 1st Rd, Hongqiao Qu, China, 300131.
imranpolitely111@gmail.com

ABSTRACT
Medical image processing paly a good role in helping the radiologists and facility patients diagnosis, the aims of this paper is created deep learning algorithm to detect brain tumor using magnetic resonance brain images and analysis the performance of algorithm based on different values, accuracy, sensitivity, specificity, ndice, nJaccard coeff and recall values. The significance of convolution neural network (CNN) it's the ability to detect brain clearly with high performance. We propose framework is successfully tested on data source on magnetic resonance brain images of the patients suffering from different brain tumor types reaching a Dice similarity 86,785% and high accuracy 98, 33%.

CCS Concepts
Computing methodologies → Computer graphics → Image compression

Keywords
MRI, Deep Learning, Tumor Detection, accuracy, sensitivity, ndice.

1. INTRODUCTION
Brain tumor segmentation is one of the most important difficult assignments in medical imaging. Proper fragmentation Provides quantitative and qualitative cancer information to help doctors find the most effective treatments per patient or in the case of better surgical planning judicial intervention. However, experts leading to a slow, difficult and tedious task usually do this work manually which are subject to errors and differences between standards etc. To solve these problem many methods has been proposed especially when used magnetic resonance brain images.

Brain tumor is a standout amongst the most widely recognized Brain abnormality among youngsters and grown-ups. Cerebrum tumors are the reason for one fourth of all malignant growth passing is on the planet. Mind tumor is a gathering of cells that becomes arbitrarily inside or around the cerebrum. There are two classes of tumors, the first is noncancerous tumor (benign) and the second is a carcinogenic tumor (malignant). Another mind irregularity called Cerebral Edema related with cerebrum tumors is very normal and can happen and encompassing the mind tumors [1].

El-Dahshan, El-Sayed A., et al [2] present a survey of the ongoing segmentation and classification strategies as a computer aided helped analysis of human mind tumor through MRI images.

Nazir, M., Wahid, F., & Ali Khan, S [3] proposed a simple and intelligent approach for brain MRI classification to normal and abnormal regions using Artificial Neural Network. The proposed methodology achieved an accuracy of 91.8% on database of 70 images where 25 normal and 45 abnormal images.

R. Rana et.al. [4] Employed the fast bounding-box algorithm to select the initial contour within the area of tumor and applied the level set method to exactly extract the tumor boundary, but incorrect selection of the initial contour will always lead to an unsatisfactory result.

Havaei et.al. [5] Have successfully integrated the Convolutional Neural Networks (CNN) [6] into the Deep Neural Networks based segmentation framework for segmenting the brain tumor in MR images.

F. Isensee, P. Kickingereder, W. Wick, M. Bendszus, and K. H. MaierHein [7] used the modified version of U-net where they used fragmentation layers in the localization path and merged them to form the network output. However, their work did not explain the performance of the new algorithm for both high-grade and low-grade tumors.

O. Ronneberger, P. Fischer, and T. Brox, The fully connected layer problem was minimized by introducing a pixel-wise best deep convolutional neural network formulation as proposed in [8]
S. Bakas, H. Akbari, A. Sotiras, M. Bilello, M. Rozycki, J. S. Kirby, J. B. Freymann, K. Farahani, and C. Davatzikos, the U-net structure works like an automatic encryption program where the input is identical to the output. Automatic encodings compress

ICIMH 2019, July 1–3, 2019, Ningbo, China

ACM ISBN 978-1-4503-7286-2/19/07…$15.00
DOI: https://doi.org/10.1145/3348416.3348421

inputs in a hidden space and then rebuild the output. Using this U-net structure, authors in [9] first implemented a completely automated automated segmentation method and applied it to the BRATS 2015 dataset, using a small subset of data to overlay their network.

M. Soltaninejad, G. Yang, T. Lambrou, N. Allinson, T. L. Jones, T. R. Barrick, F. A. Howe, and X. Ye, Despite the ongoing research on brain image fragmentation, the large contrast and heterogeneity of MRI data for the brain increases the need for more efficient fractionation techniques. To divide different types of brain tumors, some efforts focused on the use of a supervised algorithm based on a random tree to segment BRATS FLAIR MRI images [10].

In this paper, we proposed supervised method based on CNN algorithm and efficient of brain tumor detection and analysis using fuzzy c–means segmentation and classification of brain tumor using a CNN deep learning neural network.

2. METHODOLOGY

In this proposed methodology, consist six stages, the figure1 explain more the stage as follows:

Stage1: input MR brain image (original image)

Stage2: applied pre-processing consist (remove noise, morphology clean).

Stage3: segmentation using FCM algorithm

Stage4: classification of brain tumor using CNN.

Stage5: detected tumor alone

Stage6: analysis stage (performance of method using values).

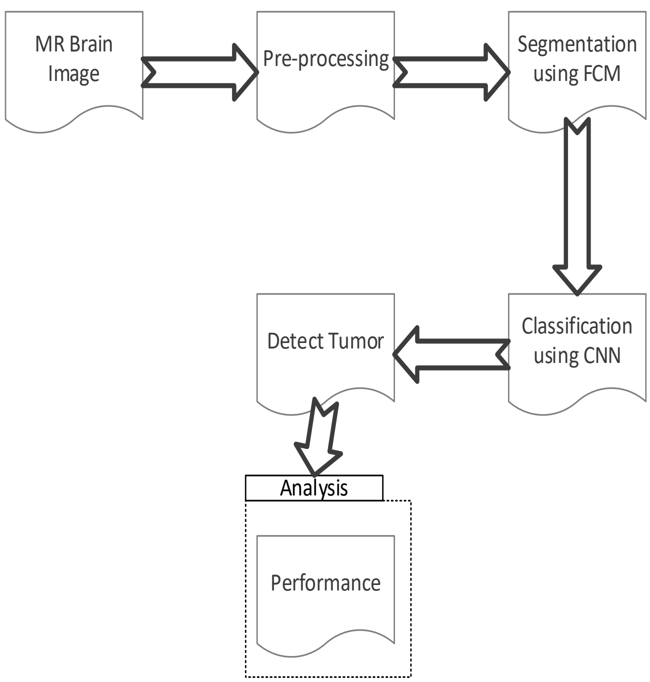


Figure.1 Architecture of proposed based on deep learning

2.1 Pre-processing

Preprocessing process is a significant undertaking in picture handling, This procedure results an improvement of the picture information that stifles commotions or upgrades some significant picture highlights for further precise preparing, numerous calculations and systems are proposed and demonstrate their effectiveness as indicated by the astonishing outcomes acquired [11] [12].

Image denoising using Gaussian filter is widely used method in medical image processing due to the high sensitivity to high frequency; this Gaussian filter is defined as follows:

$$G(x,y) = \frac{1}{2\pi\sigma^2} exp - \frac{x^2 + y^2}{2^{\sigma^2}} \qquad (1)$$

Where σ is the standard deviation of the Gaussian distribution? For Skull stripping in BMRI images many methods are proposed.

2.2 Fuzzy C-Means segmentation

Fuzzy C-means (FCM) algorithm is systematic collection created by Dunn, Bezdek that has been enhanced by additional titivated by Mathieu Patitucci voxels group (data) through the magnetic resonance image (MR) brain images are classified and grouped under n number of clusters specified by PSO algorithm, $\vec{x}\,(t+1)$, the updated position vector of the particle (voxel or pixel) derived with the help of PSO algorithm acts as the centroid value and based upon this value, the number of clusters for FCM algorithm are also assigned using PSO. It is determined membership row centers and cluster repetition to limit the proposed and function of the grouping voxels.

$$J_k = \sum_{i=j}^{N} \sum_{j=1}^{C} \delta_{ij} ||X_i - C_j||^2 \qquad (2)$$

N Describes the number of incoming data points as input to the algorithm (the total number of voxels or voxels in the image). K shows the number of iterations to be performed.

2.3 Classification Using Deep Learning

Image classification is the task of taking an input image and outputting a class (a cat, dog, etc) or a probability of classes that best describes the image. For humans, this recognition task is one of the first skills we learn from the moment we are born and is one that comes naturally and effortlessly as adults. Without even thinking twice, we are able to quickly and seamlessly identify the environment we are in, as well as the objects that surround us. When we see an image or just when we look at the world around us, most of the time we are able to immediately characterize the scene and give each object a label, all without even consciously noticing.

2.4 Accuracy value

Accuracy, reliability also called segmentation accuracy; it is used to determine the effectiveness of the segmentation algorithm evaluation variables. The accuracy is denoted in Equation (3).

$$Accuracy = \left(\frac{k}{m \times n}\right) \times 100 \qquad (3)$$

2.5 Dice Overlap Index (DOI)

It is expressed with the help of the value of the Jaccard index $J(A,B)$. DOI identify the purpose of overlap of the input image (A) , as well the resulting segmented image (B) .DOI mentions calculating in the equation (4).

$$D(A,B) = 2 \times \frac{J(A,B)}{1+J(A,B)} \qquad (4)$$

2.6 Sensitivity

Overlap Fraction (OF) or sensitivity value refers back to the proper segmentation or classification in the input image, Moreover, defines the effectiveness in exact identification of tumor region as well as other tissue regions. It is stated in Equation (5).

$$OF = \frac{TP}{TP+FN} \qquad (5)$$

2.7 Specificity

Specificity defines specific word or algorithms to classify segments of normal tissue that are present in a region in the input image capability, specificity is shown in the Equation (6).

$$Specificity(\sigma) = \frac{TN}{TN+FP} \qquad (6)$$

3. MATERIALS

Approximately 20 FLAIR and T1-T2 weight brain images we obtained from the different patients and different Age groups have been used in this paper, from the **Tianjin Medical University Hospital, China** details are listed below from patients:

1. The clinical image of the patient from the age of thirty-six suffering from used meningioma.

2. The clinical image of the patient age of thirty-one suffering from and using high- quality astrocytes. Figure.2 describe different types of MR brain images with tumor.

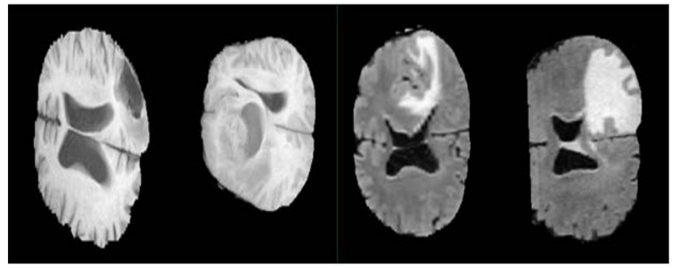


Figure.2 FLAIR, T1-T2weight MRI brain images

4. RESULTS AND DUSCUSSION

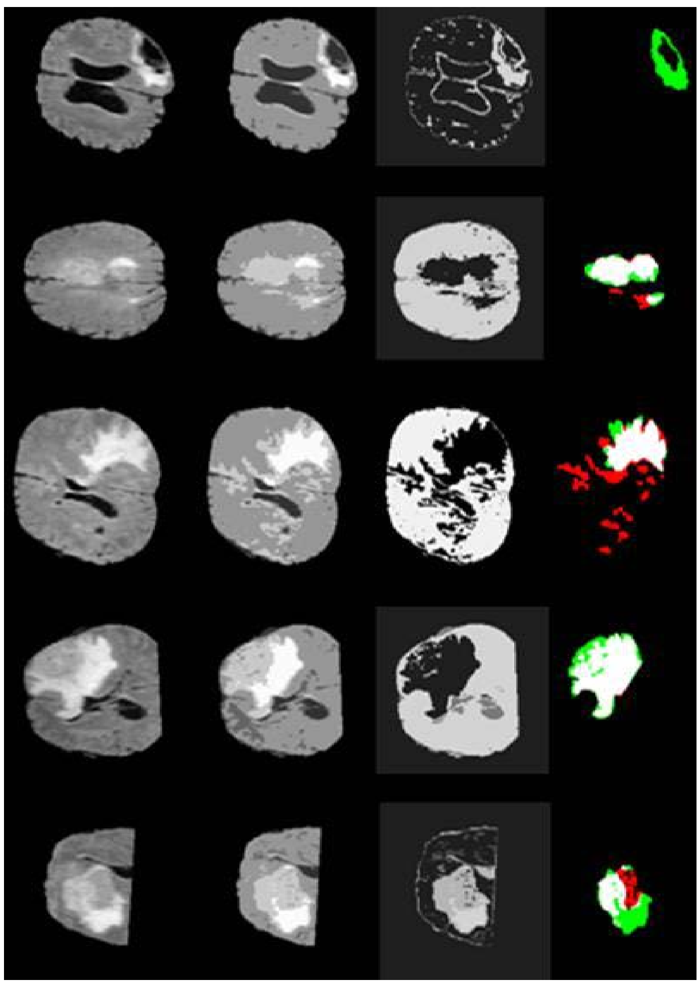
Section a). Deep learning neural network classification can detect tumor area clearly using five MR brain images as shown in figure.3.

Images (a): Original MR Brain images

Images (b): pre-processing (morphological clean, tumor masking)

Images (c): segmented using FCM algorithm

Images (d): detected tumor using deep learning algorithm.



(a) (b) (c) (d)

Figure.3 FLAIR MR Brain images processing using deep learning

The proposed based on deep learning neural network can identify the brain using MR images in the different types of MR brain images FLAIR, T1-T2 weight images.

Section b). Performance of deep learning network algorithm: the accuracy for proposed deep learning network for brain tumor detection and analysis during training network for 24 epochs achieved an accuracy 98, 33% with very good results 50,76% a nJaccard and 86,78% ndice values as shown in the figure.4.

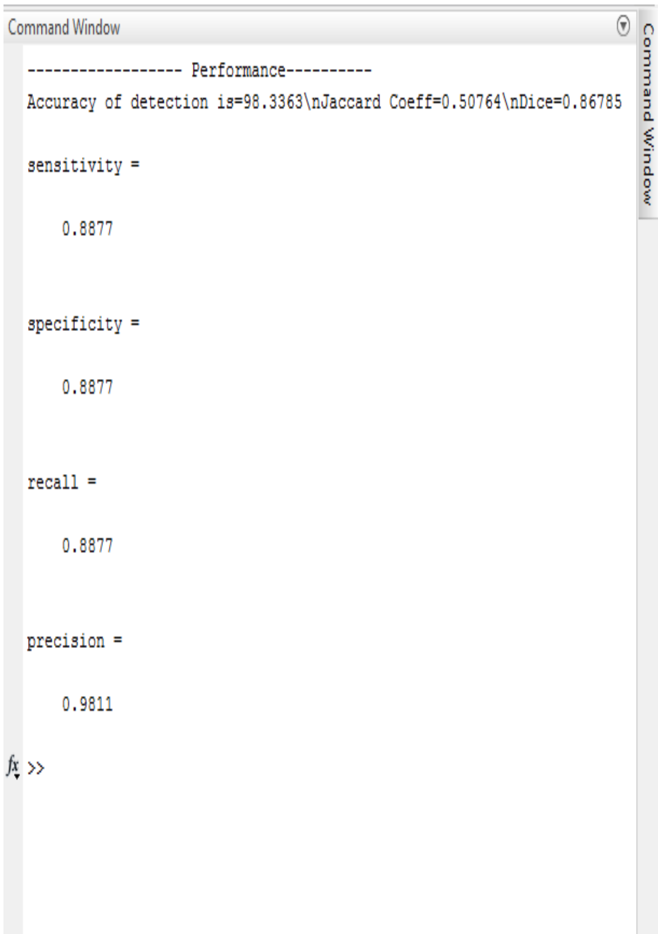


Figure.4 Performance of deep leaning algorithm

Through analysis step, the obtained results in table1 presented the performance of proposed method for brain tumor detection and analysis based deep learning network using sensitivity, specificity, recall and precision values.

Table.1 Performance of Deep learning algorithm using four values.

Algorithm	Sensitivity%	Specificity%	Recall%	Precision%
Deep learning	88,77	88,77	88,77	98,11

Based on the results presented in the figure.5 and Table.1 all the values assessments such as accuracy, nJaccard, ndice, sensitivity, specificity, recall and precision show the robustness and effectiveness of the proposed using deep learning to detect and analysis brain tumor with a high accuracy 98,33% and produce a best value with nJaccard, ndice, sensitivity, specificity, recall and precision values.

5. CONCLUSION

In this paper, we proposed a supervised method for brain tumor detection and analysis in MR brain images using the fuzzy means algorithm for brain tumor segmentation and based on convolution neural network (CNN) to classify and detect brain tumor, according of the results obtained the proposed method, gave a best results and successfully achieve detect brain tumor with high accuracy 98, 78% and best results with other values as show in the figure3.4 and table.1.

6. FUTURE OF WORK

Deep learning technology applied to medical imaging may become the most disruptive technology radiology has seen since the advent of digital imaging. Most researchers believe that within next 15 years, deep learning based applications will take over human and not only most of the diagnosis will be performed by intelligent machines but will also help to predict disease, prescribe medicine and guide in treatment.

7. ACKNOWLEDGMENTS

This work is supported by the National Natural Science Foundation of Hebei province under grant No: E2015202292 and No: E2015202050, high-level talent support project in Hebei province under grant No: C2015005012, Key research and development program under grant No: 15272002 and No: 15275704.

8. REFERENCES

[1] Esquenazi, Yoshua, Victor P. Lo, and Kiwon Lee. ”Critical care management of cerebral edema in brain tumors.” Journal of intensive care medicine 32.1 (2017): 15-24.

[2] El-Dahshan, El-Sayed A., et al. ”Computer-aided diagnosis of human brain tumor through MRI: A survey and a new algorithm.” Expert systems with Applications 41.11 (2014): 5526-5545

[3] Nazir, M., Wahid, F., & Ali Khan, S. (2015). A simple and intelligent approach for brain MRI classification. Journal of Intelligent & Fuzzy Systems, 28(3), 1127-1135.

[4] Rana, R.; Bhdauria, H.; Singh, A. In: Brain tumour extraction from MRI images using bounding-box with level set method, Contemporary Computing (IC3), 2013 Sixth International Conference on, IEEE: 2013; pp 319-324

[5] Havaei, M.; Davy, A; Warde-Farley, D.; Biard, A; Courville, A; Bengio, Y.; Pal, C.; Jodoin, P.-M.; Larochelle, H., Brain Tumor Segmentation with Deep Neural Networks. ArXiv preprint arXiv: 1505.03540 2015.

[6] Krizhevsky, A.; Sutskever, I.; Hinton, G. E. In ImageNet classification with deep convolutional neural networks, Advances in neural information processing systems, 2012; pp 1097-1105.

[7] F. Isensee, P. Kickingereder, W. Wick, M. Bendszus, and K. H. MaierHein, “Brain tumor segmentation and radionics survival prediction: Contribution to the brats 2017 challenge,” in International MICCAI Brain lesion Workshop. Springer, 2017, pp. 287–297.

[8] O. Ronneberger, P. Fischer, and T. Brox, “U-net: Convolutional networks for biomedical image segmentation,” in International Conference on Medical image computing

and computer-assisted intervention. Springer, 2015, pp. 234–241.

[9] S. Bakas, H. Akbari, A. Sotiras, M. Bilello, M. Rozycki, J. S. Kirby, J. B. Freymann, K. Farahani, and C. Davatzikos, “Advancing the cancer genome atlas glioma mri collections with expert segmentation labels and radionics features,” Scientific data, vol. 4, p. 170117, 2017.

[10] M. Soltaninejad, G. Yang, T. Lambrou, N. Allinson, T. L. Jones, T. R. Barrick, F. A. Howe, and X. Ye, “Automated brain tumour detection and segmentation using super pixel-based extremely randomized trees in flair mri,” International journal of computer assisted radiology and surgery, vol. 12, no. 2, pp. 183–203, 2017.

[11] Mohan, J., V. Krishnaveni, and Yanhui Guo. ”A survey on the magnetic resonance image denoising methods.” Biomedical Signal Processing and Control 9 (2014): 56-69.

[12] Manjn, Jos V. ”MRI preprocessing.” Imaging Biomarkers. Springer, Cham, 2017. 53-63.