A Computational Segmentation Tool for Processing Patient Brain MRI Image Data to Automatically Extract Gray and White Matter Regions

Ayush Goyal, Sunayana Tirumalasetty, Disha Bathla, Manish K. Arya, Rajeev Agrawal, Priya Ranjan, Gahangir Hossain and Rajab Challoo

Abstract Brain MRI imaging is necessary to screen and detect diseases in the brain, and this requires processing, extracting, and analyzing a patient's MRI medical image data. Neurologists and neurological clinicians, technicians, and researchers would be greatly facilitated and benefited by a graphical user interface-based computational tool that could perform all the required medical MRI image processing functions automatically, thus minimizing the cost, effort, and time required in screening disease from the patient's MRI medical image data. Thus, there is a need for automatic medical image processing software platforms and for developing tools with applications in the medical field to assist neurologists, scientists, doctors, and academicians to analyze medical image data automatically to obtain patient-specific clinical parameters and information. This research develops an automatic brain MRI segmentation computational tool with a wide range of neurological applications to detect brain patients' disease by analyzing the special clinical parameters extracted from the images and to provide patient-specific medical care, which can be especially helpful at early stages of the disease. The automatic brain MRI segmentation is performed based on modified pixel classification technique called fuzzy c-means followed by connected component labeling.

Keywords Segmentation · Medical imaging · Fuzzy c-means · Neurological application

A. Goyal (✉) · S. Tirumalasetty · G. Hossain · R. Challoo
Texas A&M University, Kingsville, TX, USA
e-mail: ayush.goyal@tamuk.edu

D. Bathla · P. Ranjan
Amity University Uttar Pradesh, Noida, UP, India

M. K. Arya · R. Agrawal
G.L. Bajaj Institute of Management and Research, Greater Noida, UP, India

N. R. Shetty et al. (eds.), *Emerging Research in Computing, Information, Communication and Applications*, Advances in Intelligent Systems and Computing 882,
https://doi.org/10.1007/978-981-13-5953-8_1

1 Introduction

In the field of medical image processing, the most challenging task to any neurologist or a doctor or a scientist is to detect the patient's disease by analyzing the patient's clinical information. Patient's data is extracted and analyzed to detect the abnormalities and to measure the illness of the disease which helps a medical practitioner to cure the disease at its early stages. Extraction of brain abnormalities in brain MRI images is performed by segmentation of gray and white matter regions in patient's brain MRI images. After segmentation is performed, patient's clinical data such as the area of the cortex, size of tumor, type of tumor (malignant or benign), and position of tumor are determined which help a [1] doctor to take early decisions for surgery or treatment to cure any brain disease.

During initial days, these segmentation techniques were performed manually by subject matter experts or neurological experts, which consumes time and effort of neurological specialists in the field. The segmentation results obtained [2, 3] from the manual segmentation techniques may not be accurate due to vulnerable and unsatisfactory human errors which may lead to inappropriate surgical planning. Therefore, it has become very much necessary for a neurologist or an academician or a researcher to introduce automatic segmentation techniques which give accurate segmentation results. These segmentation techniques that are performed automatically are of two types typically known as semiautomatic and fully automatic segmentation techniques. In a semiautomatic segmentation process, partial segmentation is performed automatically, and then, the results thus obtained are checked by neurological experts to modify for obtaining final segmentation results. In a fully automatic segmentation technique, there is no need for manual checking by neurological experts which minimizes his time and effort. These fully automatic segmentation techniques are classified as threshold-based, region-based, pixel classification based, and model-based techniques which are determined by the computer without any human participation.

In this paper, regions in the brain are segmented automatically using a technique called Fuzzy C-Means (FCM) algorithm, which is a pixel classification technique followed by component labeling technique which is used widely in biomedical image processing to perform fully automatic segmentation in brain MRI images. This clustering mechanism is the most widely used technique for segmentation and detection of tumor, lesions, and other abnormalities in brain MRI scans. The above pixel classification technique gives accurate results especially while analyzing non-homogenous and dissimilar patterns of [4–7] brain MRI images. FCM is a unique method that can be implemented in most of the MRI images to perform segmentation and obtain efficient results even for the noisy MRI images. The main concept of clustering algorithm is grouping of similar components (in this research, it is pixels of an image) within the same cluster. This simple idea is implemented in this work to develop a disease prediction framework that can automatically segment various regions of multidimensional brain MRI scans.

2 Automatic Segmentation

Recent studies have shown that the atrophy rate in the brain is the valid parameter to measure the severity of diseases such as dementia, Alzheimer's and other brain disorders from brain MRI images. Therefore, the necessity to calculate the atrophy rate has been increased which is the measurement of abnormalities in gray and white matter regions in brain MRI images of the patient [8]. The method herein presents a disease prediction framework that can automatically segment gray and white matter regions of patient's brain using modified adapted pixel clustering method. In the proposed method, the gray and white matter regions of cerebral structures are automatically segmented using a form of adaptive modified pixel clustering technique called Fuzzy C-Means (FCM) in which the pixels having similar intensity values are grouped [9] into similar clusters and followed by connected component labeling in which each pixel of gray and white matter regions are labeled.

A. **Image Acquisition**
The patient's brain MRI image and neurological data used in this research work was obtained from the Image and Data Archive (IDA) powered by Laboratory of Neuro Imaging (LONI) provided by the University of Southern California (USC) and from the Department of Neurosurgery at the All India Institute of Medical Sciences (AIIMS), New Delhi, India. The data was anonymized as well as followed all the ethical guidelines of the participating research institutions.

B. **Segmentation Methodology**
The segmentation methodology used in this research for automatically performing segmentation of gray and white matter regions in brain MRI images using fuzzy c-means clustering algorithm is shown as a block diagram in Fig. 1. The preliminary step in the process of segmentation is to remove the external sections of the image which is not required for brain MRI image analysis. Therefore, it is necessary to detect and remove the skull outline from the patient's brain MRI image. This mechanism is performed using elliptical Hough transform which is used in digital image processing applications that identify the arbitrary shapes such as circles, ellipses, and lines in an image data. After the skull outline removal, the inner brain slice is subjected to adapted fuzzy c-means clustering algorithm which is one of the pixel classification techniques mentioned above. In this process, the brain internal slice is separated into different regions using clustering mechanism which is based on the intensity values of the pixels in this research.
Among the above-described pixel classification segmentation techniques, clustering-based fuzzy c-means algorithm is used for segmentation of gray and white matter regions in this research. Also, this technique generated accurate, reliable, and robust results even with the noisy MR images of patients' brain. After clustering, the next step in the segmentation process is to perform connected component labeling based on the connectivity of the neighboring pixels. Even after performing clustering, some of the pixels positioning adjacent to each other different similar intensity values of pixels may be in the same clus-

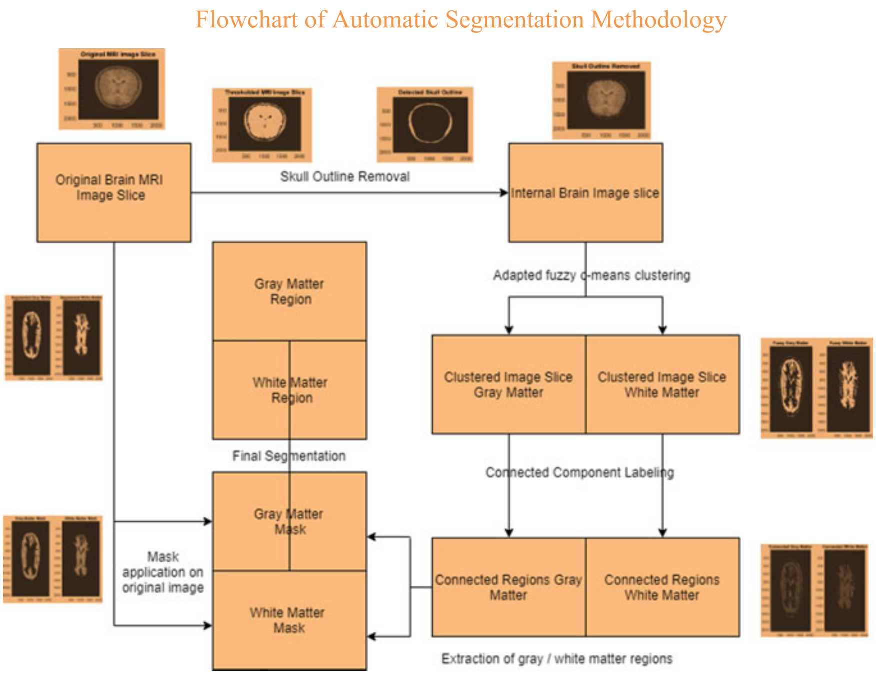

Fig. 1 Block diagram of automatic gray and white matter segmentation

ter. Therefore, it is necessary to perform connected component labeling in which each component of the image is labeled and given a membership to each of the pixels in the clusters to determine and differentiate the pixels accurately. Also, among many other techniques, this modified adaptive pixel classification technique called fuzzy c-means is used for both multi-featured and single featured extraction and analysis using spatial data. The segmentation technique [8, 9] used in this research is fully automatized unsupervised segmentation that can perform feature analysis, clustering in many medical imaging applications. A medical image data is formed with the combination of set of components or data points that have similar or dissimilar parametric values. These similar and dissimilar data points of the image are classified into various similar clusters which can be performed based on similarity criteria. Image pixels of medical image data can be correlated to each other which have similar characteristics or feature information to the data points that are sitting next to the data point in an image. In this segmentation mechanism, spatial data of the adjacent pixels is taken to perform clustering. This research work presents an algorithm for clustering of various regions of brain MRI images into various classes followed by connected component labeling using a knowledge-based algorithm. Below are the steps for fully automatic segmentation algorithm:

(a) **Skull outline detection**:

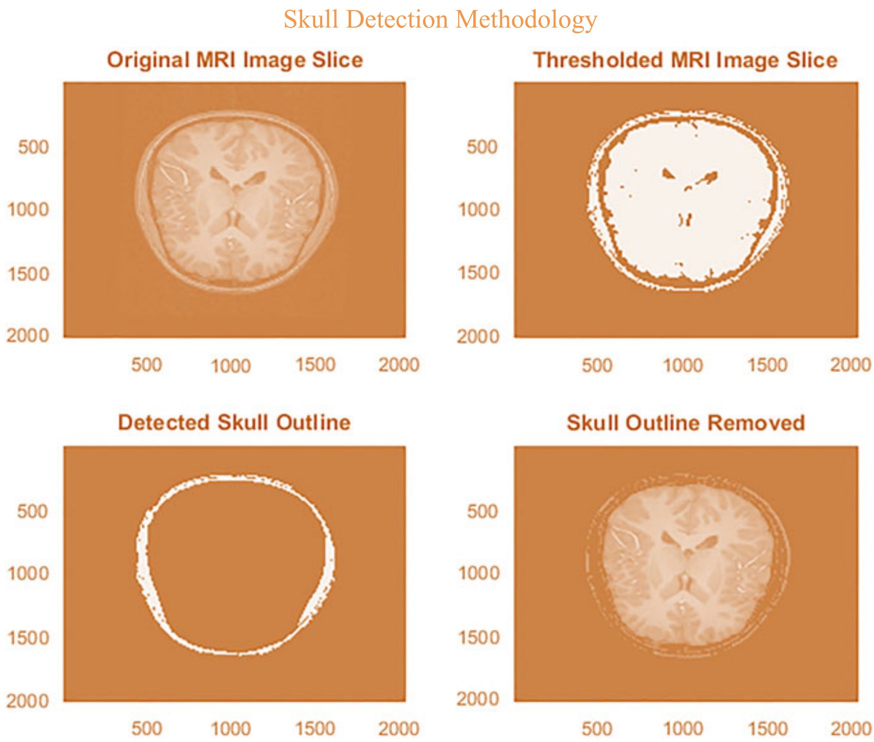

Fig. 2 Skull outline detection in brain MRI images

Skull outline present in the brain MRI scan is not required for analyzing brain abnormalities in this research. Therefore, detection of skull outline and removing it play a vital role during the segmentation process so that feature extraction and analysis becomes easier and results thus obtained without the skull outline part will be accurate. This skull outline sections in brain MRI regions are not our region of interest as this section are filled with fat, skin, and other unwanted materials. This step allows a researcher to focus more on the actual brain sections which are responsible for brain disorders and to obtain reliable outputs [10]. In this skull removal process, a widely used image feature extraction tool in digital image processing is used to detect the superfluous components of the brain MRI image data with in different shapes such as circle, ellipse, and lines. In this research, we have used the elliptical Hough transforms to extract the unwanted material (data objects or pixel components of an MRI image) from the actual brain MRI image data. This elliptical Hough transform is applied to the original brain MRI slice using a voting process in a parametric space [11]. Figure 2 shows the results obtained in the first step of the segmentation process:

(b) **Adaptive fuzzy c-means clustering**:

Once the skull outline sections are detected and removed from the original brain MRI image, the next and very important step in the segmentation process is to perform clustering to the image that is obtained from the first step of the segmentation process. In this clustering, the medical image is classified into various regions of brain such as gray matter, white matter, and cerebrospinal fluid. The concept of clustering helps a researcher especially in digital image processing technique to classify different patterns of the image and for the segmentation of any medical image data. It is a widely used technique for various purposes for medical data analysis in the field of medical sciences. The process of classifying different clusters by grouping the similar components into same cluster based on some criteria is defined as clustering. In this research, clustering of the medical MRI image data having different regions such as gray matter and white matter is performed based on similar intensity values of the pixels. Due to several internal and external parameters, patient's MRI scans in the field of biomedical sciences may have more noise which when analyzed further may produce inappropriate results [12]. This is highly unacceptable as these inappropriate results may lead to improper diagnosis and surgical planning of the patient. And hence, an effective algorithm is required to avoid inaccurate results during the segmentation process. There are several types of clustering techniques available in the field to perform segmentation of brain MRI images in the medical field. In this research, we have used a modified pixel classification technique called fuzzy c-means, which is based on the clustering mechanism. This technique that is used for segmentation generates accurate results equally for noisy MRI patient data [13–18]. Among many other clustering algorithms, fuzzy c-means algorithm is the most popular technique which has a wide number of benefits comparatively as it performs well even with the uncertain medical image data. This technique used in our research enhances the features of fuzzy c-means algorithm minimizing computational errors during the segmentation process and this modified algorithm is called adaptive fuzzy c-means clustering algorithm [19].

(c) **Connected component labeling**:

The next step in the proposed automatic segmentation is to perform connected component labeling to the clustered image based on pixel connectivity mechanism. In this stage, positions of several pixels which are located on the clustered image are extracted and classified. In this process, several disjoint and also connected components are labeled based on the connectivity procedures, which is a very essential step in the segmentation process in order to reduce inaccuracy [20]. Every medical MRI image consists of pixels that are located side by side sitting together forming connected components will have similar intensity values. Therefore, in this method, the image is scanned such that every pixel is detected and examined to extract the connected pixel regions of the MRI image that are positioned adjacent to each other having similar intensity values [21–25]. Each and every pixel component of the image irrespective of which group it belongs to are labeled based on the connectivity of pixels. In this research, connected component labeling is performed using two-dimensional eight-connectivity measures to determine the way in which each pixel is related to its neighboring pixel in the medical MRI image.

(d) **Final segmentation mask after removing noise**:
Last but not the least, the step after skull outline detection, clustering, and connected component labeling is to generate the required segmented gray and white matter regions by superimposing gray and white matter masks on the actual brain MRI image that has to be analyzed. Our major goal in this step is to remove all background pixels and to only keep foreground pixels of region of interest of the original MRI image [25–28]. This process of overlaying masks on original brain MRI image and removing the background pixels from the image improves the segmentation process by further increasing the quality of separability of gray and white matter regions, and thus, accurate segmentation results are obtained. The results obtained by the process of clustering using fuzzy c-means followed by connected component labeling to extract gray and white matter regions as masks and when these masks are further processed for final segmentation of gray and white matter regions are shown in Fig. 3.

3 Graphical Computational Tool

A software tool is developed that can automatically perform the entire process of feature extraction, classification, preprocessing, and segmentation as an effective graphical computational tool with a user interface (GUI). This application is independent and a standalone GUI application that can be installed on the users' machine acting as a desktop application. Neurologists or any user can load the brain MRI image from his local machine and perform automatic segmentation to obtain various results instantaneously. This automated segmentation tool can perform segmentation and display the results as mask, color images, or boundaries of gray and white matter regions of brain MRI image with just clicks of buttons that takes very less amount of time and efforts of neurologists. The developed GUI system assists neurologists or any user making it easy to upload patient's brain image from his local computer, viewing and obtaining the results in very less time reducing efforts due to manual tracings [29–33] by the experts. The GUI has the following features:

(1) Segmentation of brain MRI images is provided as a software.
(2) It is freely accessible to all researchers in the medical field and neurologists, radiologists, and doctors in any part of the world.
(3) It is user-friendly and easy to use.
(4) It automatically segments the brain images and so no manual tracing is required by the user.
(5) It supports all medical image data types (nifty, dicom, png, etc.).
(6) Neurologists disease prediction framework is provided in this software tool.
(7) Automatically calculates the areas of gray and white matter regions or lesions or tumors based on which it predicts disease in brain.

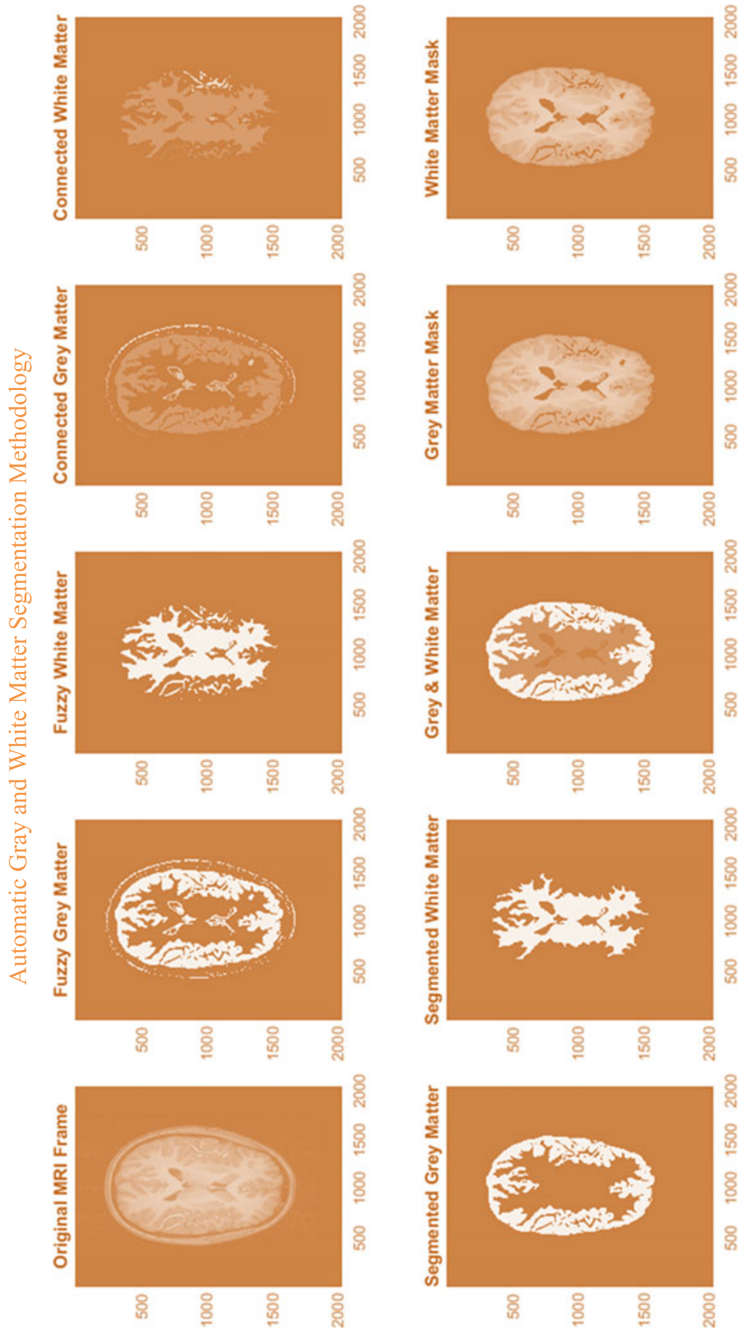

Fig. 3 Gray and white matter segmentation in brain MRI images

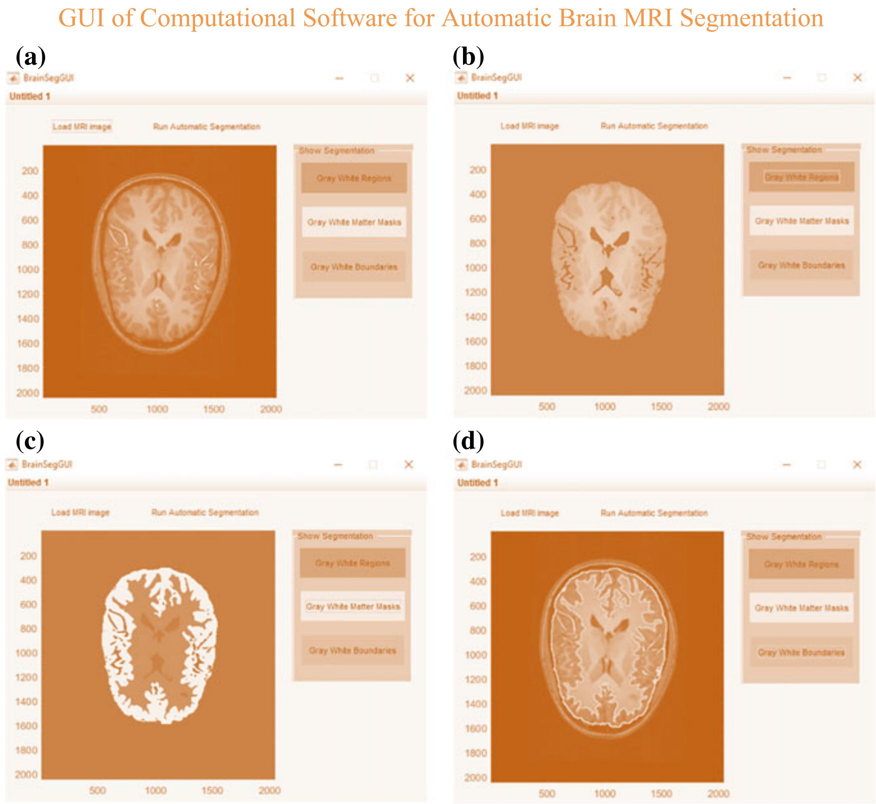

Fig. 4 Graphical User Interface (GUI) of computational brain segmentation software developed to **a** load MRI image, **b** gray and white matter regions, **c** gray and white matter masks, and **d** gray and white matter boundaries

Below are the three screenshots which show running the GUI for loading the brain MRI image (Fig. 4a), viewing the gray and white matter segmented regions (Fig. 4b), viewing the gray and white matter extracted masks (Fig. 4c) and viewing the gray and white matter region boundaries (Fig. 4d).

4 Manual Segmentation

In this research work, the manual segmentation is performed for several patients' MRI image data to validate and verify the automatic segmentation techniques using fuzzy c-means followed by connected component labeling performed in this research with the manual segmentations done by neurological tracings of gray matter and white matter regions by experts [34–38]. Figure 5 presents the manual segmentations

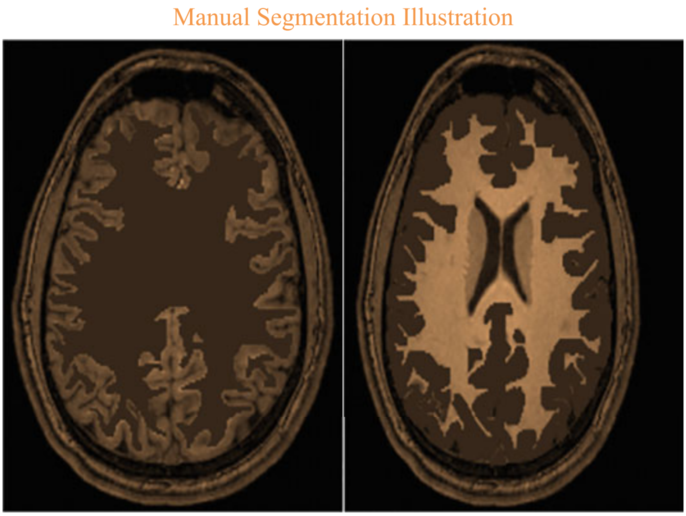

Fig. 5 Manual segmentation (labeling) by neurologist expert of the gray and white matter regions in brain MRI images. Gray matter region (left) and white matter region (right)

performed by neurological experts to segment gray and white matter regions of brain MRI images.

5 Validation

This research work presents the comparison of manual and automatic segmentation results of five different patients' sample MRI images. To compare these results, a statistical measure called Dice coefficients is used to calculate the similarity measures of these two techniques. Figure 6a–c shows the sample manual and automatic segmentation of three of the patients. The automatic segmentations are obtained from the proposed algorithm, and the manual segmentation is obtained here from the neurological tracings by experts in this research. For the validation purpose, five different sample image data are considered, and the manual and automatic segmentations are performed for the [39–42] same to compare both the segmentation results that are obtained. For each of the patient MRI images, a dice coefficient value is calculated between manual and automatic segmentation of patient brain MRI images. Manual segmentation is performed three times by neurological experts for each of the sample patient images among the five different MRI images. Finally, the Dice coefficient values are plotted using box plots for each of the patient brain images that compare manual and automatic segmentations for all sample patient images considered. Figure 7 shows the box plots of the Dice coefficients calculated as the similarity

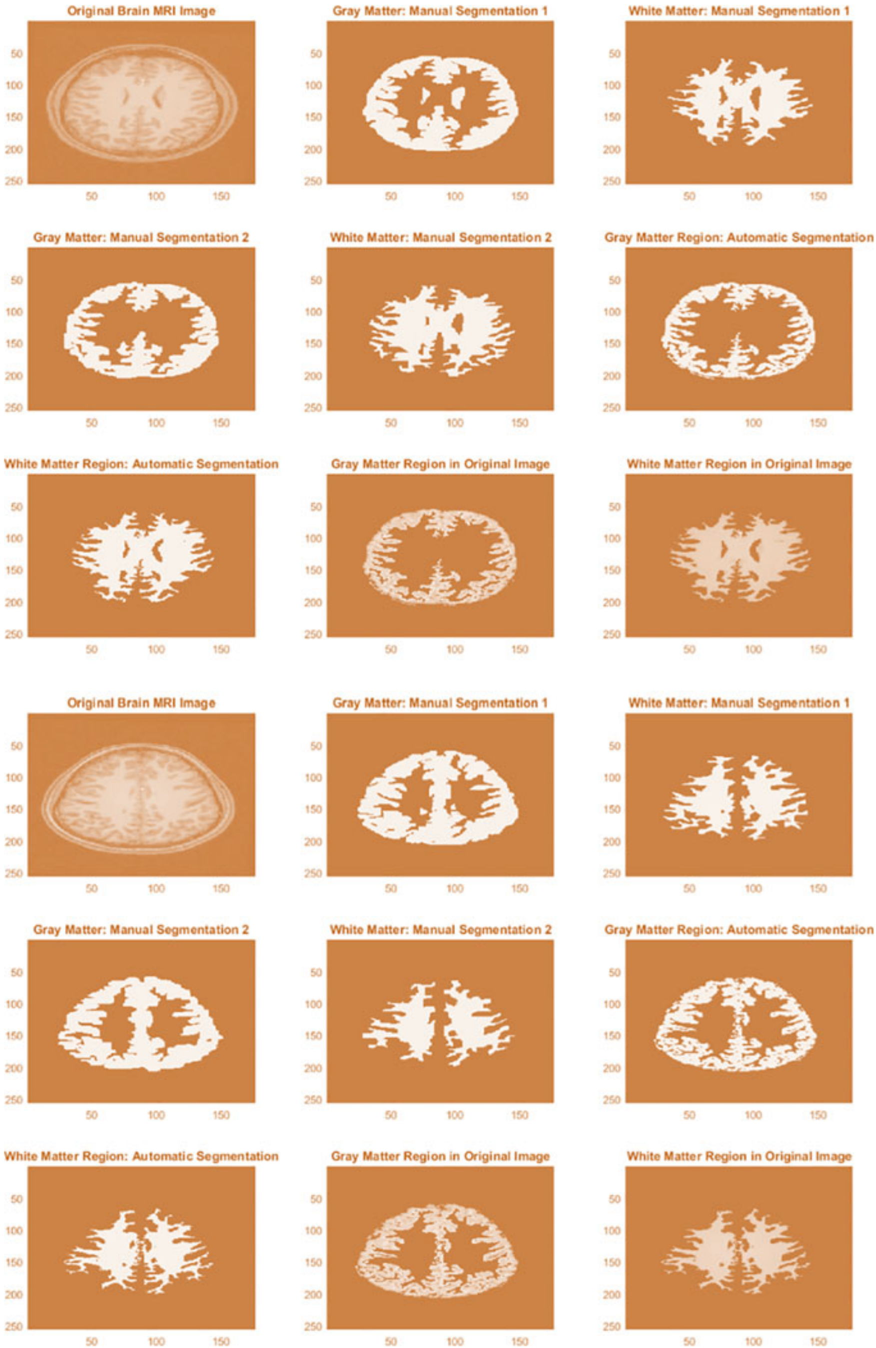

Fig. 6 Sample manual and automatic segmentation of three specimens

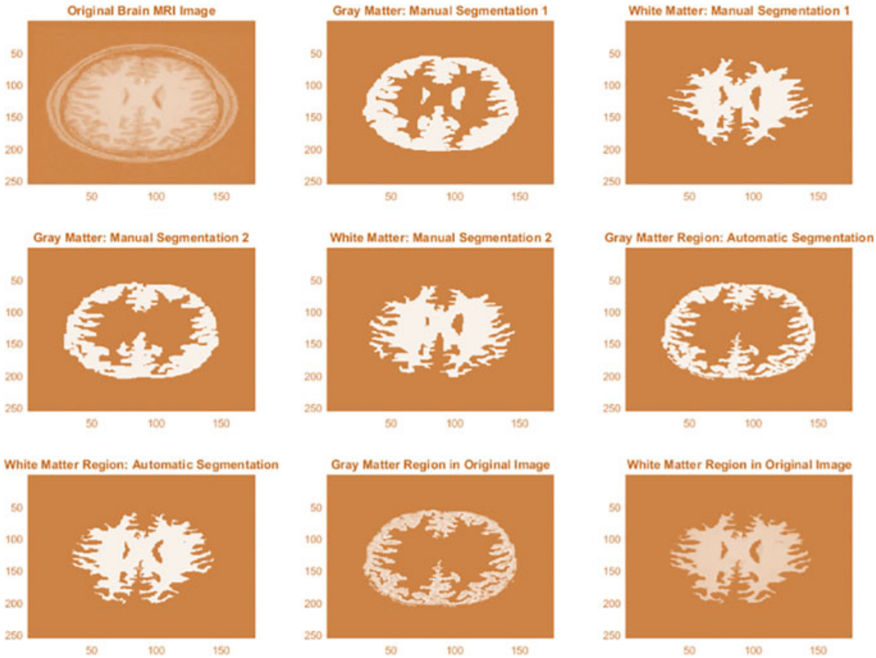

Fig. 6 (continued)

measure to compare manual and automatic segmentation of the brain MRI images for the five sample patients.

6 Discussion and Conclusion

The research presented in this work facilitates efficient and effective automatic segmentation of gray and white matter regions from brain MRI images, which has several clinical neurological applications. A fully automatic segmentation methodology using elliptical Hough transform along with pixel intensity and membership-based adapted fuzzy c-means clustering followed by connected component labeling and region analysis has been implemented in this research to perform segmentation of gray and white matter regions in brain MRI images. The algorithm was tested and verified for several sample brain MRI images. Manual segmentations were performed by neurological experts for several patient brain MRI images. These manual segmentations were used to compare and validate with the results obtained from the automatic segmentations in this research work. Validations were performed by calculating several Dice coefficient values between the automatic segmentation results and the manual segmentation results. The Dice coefficient values are similarity measures

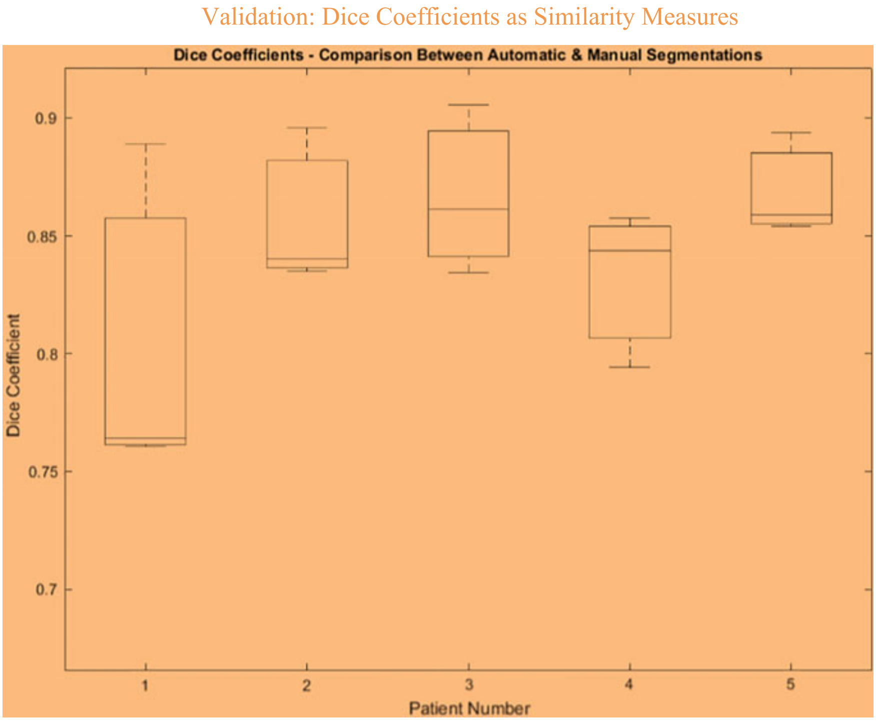

Fig. 7 Box plots for Dice coefficients to compare manual and automatic segmentation of brain MRI images of five patients

that are represented statistically using box plots in this research work. The automatized computational segmentation tool developed in this research can be employed in hospitals and neurology divisions as a computational software platform for assisting neurologist in detection of disease from brain MRI images post MRI segmentation. This tool obviates manual tracing and saves the precious time of neurologists or radiologists. This research presented herein is foundational to a neurological disease prediction and disease detection framework, which in the future, with further research work, can be developed and implemented with a machine learning model-based prediction algorithm to detect and calculate the severity level of the disease, based on the gray and white matter region segmentations and estimated gray and white matter ratios to the total cortical matter, as outlined in this research.

References

1. Shasidhar, M., Raja, V. S. and Kumar, B. V., (June 2011). MRI brain image segmentation using modified fuzzy c-means clustering algorithm. In *2011 International Conference on Communi-*

cation Systems and Network Technologies (CSNT) (pp. 473–478).
2. Despotović, I., Goossens, B., Philips, W. (2015) MRI segmentation of the human brain: challenges, methods, and applications. *Computational and mathematical methods in medicine*, 2015.
3. Gordillo, N., Montseny, E., & Sobrevilla, P. (2013). State of the art survey on MRI brain tumor segmentation. *Magnetic Resonance Imaging, 31*(8), 1426–1438.
4. Suhag, S., & Saini, L. M. (May 2015). Automatic detection of brain tumor by image processing in matlab. In *SARC-IRF International Conference*.
5. Hassan, E., & Aboshgifa, A. (2015). Detecting brain tumour from MRI image using matlab gui programme. *International Journal of Computer Science & Engineering Survey (IJCSES) 6*(6).
6. Sharma, N., & Aggarwal, L. M. (2010). Automated medical image segmentation techniques. *Journal of medical physics/Association of Medical Physicists of India, 35*(1), 3.
7. Tsai, C., Manjunath, B. S., & Jagadeesan, B. (1995). Automated segmentation of brain MR images. *Pattern Recognition, 28*(12), 1825–1837.
8. Despotović, I., Goossens, B., & Philips, W. (2015). MRI segmentation of the human brain: challenges, methods, and applications. *Computational and mathematical methods in medicine*, *2015*.
9. Chuang, K. S., Tzeng, H. L., Chen, S., Wu, J., & Chen, T. J. (2006). Fuzzy c-means clustering with spatial information for image segmentation. *Computerized medical imaging and graphics*, *30*(1), pp. 9–15.
10. Mokbel, H. A., Morsy, M. E. S., & Abou-Chadi, F. E. Z. (2000). Automatic segmentation and labeling of human brain tissue from MR images. In *17th NRSC'2000. Seventeenth National Radio Science Conference, 2000* (pp. K2–1). IEEE.
11. Antolovic, D., (2008). Review of the Hough transform method, with an implementation of the fast Hough variant for line detection. *Department of Computer Science, Indiana University*.
12. Kumar, N., & Nachamai, M. Noise Removal and filtering techniques used in medical images. *Oriental Journal of Computer Science and Tachnology 10*(1).
13. Wang, H. R., Yang, J. L., Sun, H. J., Chen, D., & Liu, X. L. (August 2011). An improved region growing method for medical image selection and evaluation based on Canny edge detection. In *2011 International Conference on Management and Service Science (MASS)* (pp. 1–4). IEEE.
14. Mubarak, D. M. N., Sathik, M. M., Beevi, S. Z., & Revathy, K. (2012). A hybrid region growing algorithm for medical image segmentation. *International Journal of Computer Science & Information Technology, 4*(3), 61.
15. Wong, K. K., Tu, J., Kelso, R. M., Worthley, S. G., Sanders, P., Mazumdar, J., et al. (2010). Cardiac flow component analysis. *Medical Engineering & Physics, 32*(2), 174–188.
16. Zanaty, E. A. (2013). An Approach based on fusion concepts for improving brain magnetic resonance images (MRIs) segmentation. *Journal of Medical Imaging and Health Informatics, 3*(1), 30–37.
17. Zanaty, E. A., & Ghiduk, A. S. (2013). A novel approach for medical image segmentation based on genetic and seed region growing algorithms. *Journal of Computer Science and Information Systems ComSIS, 10*(3), 1319–1342.
18. Zanaty, E. A., & Afifi, A. (2013). A watershed approach for improving medical image segmentation. *Computer methods in biomechanics and biomedical engineering, 16*(12), 1262–1272.
19. Zanaty, E. A. (2013). An adaptive fuzzy C-means algorithm for improving MRI segmentation. *Open Journal of Medical Imaging, 3*(04), 125.
20. [Online] Available: https://en.wikipedia.org/wiki/Connected-component_labeling [Accessed November 9, 2017].
21. Wu, K., Otoo, E., & Shoshani, A. (2005). Optimizing connected component labeling algorithms. *Lawrence Berkeley National Laboratory*.
22. Suzuki, K., Horiba, I., & Sugie, N. (2003). Linear-time connected-component labeling based on sequential local operations. *Computer Vision and Image Understanding, 89*(1), 1–23.
23. Goyal, A., Lee, J., Lamata, P., van den Wijngaard, J., van Horssen, P., Spaan, J., et al. (2013). Model-based vasculature extraction from optical fluorescence cryomicrotome images. *IEEE Transactions on Medical Imaging, 32*(1), 56–72.

24. Sikarwar, B. S., Roy, M. K., Ranjan, P., & Goyal, A. (2016). Automatic Disease Screening Method Using Image Processing for Dried Blood Microfluidic Drop Stain Pattern Recognition. *Journal of Medical Engineering & Technology, 40*(5), 245–254.
25. Sikarwar, B. S., Roy, M. K., Ranjan, P., & Goyal, A. (2016). Imaging-based method for precursors of impending disease from blood traces. In *Advances in Intelligent Systems and Computing* (Vol. 468, pp. 411–424). Springer.
26. Sikarwar, B. S., Roy, M. K., Ranjan, P., & Goyal, A. (2015). Automatic pattern recognition for detection of disease from blood drop stain obtained with microfluidic device. In *Advances in Intelligent Systems and Computing* (Vol. 425, pp. 655–667). Springer.
27. Bhan, A., Bathla, D., & Goyal, A. (2016). Patient-specific cardiac computational modeling based on left ventricle segmentation from magnetic resonance images. *Advances in Intelligent Systems and Computing* (Vol. 469, pp. 179–187). Springer.
28. Ray, V., & Goyal, A. (2015) Automatic left ventricle segmentation in cardiac MRI images using a membership clustering and heuristic region-based pixel classification approach. In *Advances in Intelligent Systems and Computing* (Vol. 425, pp. 615–623). Springer.
29. Chhabra, M., & Goyal, A. (2017) Accurate and robust iris recognition using modified classical hough transform. In *Lecture Notes in Networks and Systems* (Vol. 10, pp. 493–507). Springer.
30. Goyal, A., & Ray, V. (2015). Belongingness clustering and region labeling based pixel classification for automatic left ventricle segmentation in cardiac MRI images. *Translational Biomedicine*, *6*(3).
31. Goyal, A., Roy, M., Gupta, P., Dutta, M. K., Singh, S., & Garg, V. (2015) Automatic detection of mycobacterium tuberculosis in stained sputum and urine smear images. *Archives of Clinical Microbiology*, *6*(3).
32. Bhan, A., Goyal, A., Chauhan, N., & Wang, C.W. (2016) Feature line profile based automatic detection of dental caries in bitewing radiography. In: *International Conference on Micro-Electronics and Telecommunication Engineering (ICMETE)*, pp. 635–640, IEEE.
33. Bhan, A., Goyal, A., Dutta, M. K., Riha, K., Omran, Y. Image-Based Pixel Clustering and Connected Component Labeling in Left Ventricle Segmentation of Cardiac MR Images. In *7th International Congress on Ultra-Modern Telecommunications and Control Systems and Workshops (ICUMT)*, pp. 339–342, IEEE, 2015.
34. Ray, V., & Goyal, A. (2015). Image-Based fuzzy c-means clustering and connected component labeling subsecond fast fully automatic complete cardiac cycle left ventricle segmentation in multi frame cardiac MRI images. In *International Conference on Systems in Medicine and Biology (ICSMB)*, IEEE.
35. Goyal, A., van den Wijngaard, J., van Horssen, P., Grau, V., Spaan, J., & Smith, N. (2009). Intramural spatial variation of optical tissue properties measured with fluorescence microsphere images of porcine cardiac tissue. In *Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 1408–1411.
36. Sharma, P., Sharma, S., Goyal, A. (2016) An MSE (mean square error) based analysis of deconvolution techniques used for deblurring/restoration of MRI and CT Images. In *2nd International Conference on Information and Communication Technology for Competitive Strategies (ICTCS-2016)*, March 04–05, 2016, Udaipur, India, Conference Proceedings by ACM—ICPS Proceedings Vol. ISBN 978-1-4503-3962-9/16/03, http://dx.doi.org/10.1145/2905055.2905257.
37. Goyal, A., Bathla, D., Sharma, P., Sahay, M., & Sood, S. (2016). MRI image based patient specific computational model reconstruction of the left ventricle cavity and myocardium. In *2016 International Conference on Computing, Communication and Automation (ICCCA)*, pp. 1065–1068, IEEE.
38. Duta, M., Thiyagalingam, J., Trefethen, A., Goyal, A., Grau, V., & Smith, N. (2010) Parallel simulation for parameter estimation of optical tissue properties. In *Euro-Par 2010-Parallel Processing* (pp. 51–62).
39. Atkins, M. S., & Mackiewich, B. T. (1998). Fully automatic segmentation of the brain in MRI. *IEEE Transactions on Medical Imaging, 17*(1), 98–107.

40. Wagner, M., Yang, P., Schafer, S., Strother, C., & Mistretta, C. (2015). Noise reduction for curve-linear structures in real time fluoroscopy applications using directional binary masks. *Medical Physics, 42*(8), 4645–4653.
41. Meijs, M., Patel, A., Leemput, S. C., Prokop, M., Dijk, E. J., Leeuw, F. E., et al. (2017). Robust segmentation of the full cerebral vasculature in 4D CT of suspected stroke patients. *Scientific reports, 7*(1), 15622.
42. Bhan, A., Goyal, A., & Ray, V. (2015) Fast fully automatic multiframe segmentation of left ventricle in cardiac mri images using local adaptive k-means clustering and connected component labeling. In *2nd International Conference on Signal Processing and Integrated Networks (SPIN)*, pp. 114–119, IEEE.