The Eurasia Proceedings of Science, Technology, Engineering & Mathematics (EPSTEM)
ISSN: 2602-3199

The Eurasia Proceedings of Science, Technology, Engineering and Mathematics (EPSTEM), 2025

Volume 37, Pages 745-753

ICEAT 2025: International Conference on Engineering and Advanced Technology

Advanced Multiple Sclerosis Data Analysis Using Intensity-Guided Skull Removal and Level Set Method for Enhanced Accuracy

Khawla H. Rasheed
Ibn Sina University of Medical and Pharmaceutical Sciences

Auns Q. H. Al-Neami
Al-Nahrain University

Abstract: Edge detection and segmentation are an important medical image processing task based on many mathematical frameworks like level set method. It provides many advancements over conventional approaches, including the ability to handle complicated topological changes. Efficient differentiation of the lesions associated with multiple sclerosis from medical imaging is vital for the diagnosis and management of many clinical diseases. This study introduces a method to automatically segmenting lesions using an adaptive thresholding followed by a level-set method. The suggested approach tried to help solve the difficulties caused by intensity inhomogeneity, which typically occures in magnetic resonance images of multiple secleroses lesions. The experimental results showed that the proposed method is efficient, which shows good improvements in segmentation accuracy and outlining lesion boundaries. The integration of adaptive thresholding in the pre-processing stage helped in edge enhancement, resulting in more efficient edge detection in the second step. The sensitivity of the suggested method was 0.923. which means that this method is helpful for lesion detection. while, specificity is 0.936, which means this method is accurate in identifying non-lesion areas. The Dice Coefficient, which measures the overlap between the segmented lesions and the ground truth around 0.994, which is quite good. This study tried to enhance the dominion of medical image analysis by introducing a new method for the automatic segmentation of multiple sclerosis lesions from magnetic resonance images. This technique provided valuable support to clinicians in enhancing the precision of disease evaluation and treatment planning.

Keywords: Multiple sclerosis, MRI, Adaptive thresholding, Segmentation, Image processing

Introduction

Magnetic resonance imaging (MRI) was first used in the 1980s, and since then, it has been the main method for detecting multiple sclerosis (MS) lesions, a disease that affects many people. It is a challenging task and may take a significant amount of time. This indicates the need for better and more efficient methods for early and faster detection of this disease (Ahamed et al., 2023). The most important problem with delineating lesions is that they can change in size, shape, brightness, and location.This makes it difficult for many techniques to perform this task correctly on their own (Aggarwal et al., 2023). On the other hand, MRI images sometimes exhibit variations or noise in the brightness of body parts (Spagnolo et al., 2023).MS is a permanent autoimmune condition that affects the central nervous system, particularly the brain and spinal cord. The condition is characterized by the formation of lesions, showing regions of inflammation and damage to the protective layer surrounding nerve fibers. These lesions obstruct the typical functions of the brain, resulting in various symptoms such as fatigue, cognitive decline, and muscle weakness.Early identification and precise delineation of MS lesions play a crucial role in evaluating disease progression and determining treatment effectiveness (Danelakis et al., 2018).

The segmentation of affected areas is very important and makes it feasible to recognize and outline both the location and size of MS lesions (McKinley et al., 2020). Using unique MRI features like voxel intensity, many automated segmentation algorithms and methods have been developed to precisely identify and delineate MS lesions (Ansari et al., 2021).These algorithms employ complex image processing and machine learning techniques, such as convolutional neural networks (CNNs), to accurately detect and separate lesions, as shown in a 2021 study (Hill et al., 2015). outlining MS lesions accuratley helps in achieving a more accurate diagnosis, better treatment planning, and improves monitoring of disease progression. Researchers have proposed various approaches to improve this process, including using multiple types of computational models at same time, enhance edge detection, and optimizing differences in image contrast . They aimed to ensure the process is efficient and accurate every time, as evidenced by findings from recent studies (Hill et al., 2015; Cetin et al., 2020). These methods aimed to address challenges such as noises and variabilities in MRI images and complex shapes and sizes of the lesions (Otsu, 1979). Advancements in intelligent image segmentation methods will enhance our understanding of MS and play a major role in improving diagnosis, treatment, and patient monitoring. Ashtari et al. (2022) have also reported significant developments in this area. Identifying regions associated with MS depends strongly on the process of image segmentation. Many techniques and steps have been developed to accurately delineate these regions in medical images. A common method involves using a boundary between different image regions, depending on thier densities, defining the point at which normal tissue transitions to pathological tissue, which helps in distinguishing healthy pixels from abnormal backgrounds (Otsu, 1979).

This method is pretty simple and efficient, making it suitable for primary segmentation tasks (Hill et al., 2015). Making the detection of issues linked to MS highly depends on image segmentation techniques that have been used. Various computational models have been developed to accurately outline these regions in medical images. one of typical methods involves drawing a boundaries to partition the image, by determining a threshold that distinguishes affected pixels from background pixels (Alshayeji et al., 2018; Kailan et al., 2023). This method is more computationally complex and therefore its more effective for difficult segmentation tasks (Hill et al., 2015).However, its accuracy could be limited in cases where lesion boundaries are poorly defined or when lesions has significant variabile intesity in different regions, as noted by Zhang and Oguz (2021). Earlier studies showed that deep neural networks could be effective for detecting MS lesions. However, still there is a need for more performance improvements.Techniques like artificial learning and level-set methods are studied to build stronger models for outlining MS lesions in MRI brain scans (Ansari et al., 2021).The primary goal was to develop a segmentation method capable of automatically segmenting MS lesions in MRI scans. This method must be able to process large volumes of data quickly and provide results comparable to manual segmentation by expert (De Arruda et al., 2020). Clinicians will depend on these techniques to improve diagnostic accuracy and follow up disease progression in clinical practice, which is very important for advanced patient care (Darwish et al., 2023). Another way to segment MS lesions involves region-based segmentation methods. These techniques identify areas of interest by detecting specific features like intensity, texture, or shape (Mortazavi et al., 2011).

An example is the use of active contour models, which can gradually adjust the contours to match the boundaries of a lesion (Osher & Sethian, 1988). Region-based segmentation methods can achieve greater accuracy than thresholding-based approaches, especially when dealing with lesions that have irregular shapes or variations in intensity.These methods may need high processing power or some adjustment of their parameters, but they can still work very well when used properly (Faraj et al., 2022). The level set method is a strong and flexible tool for dealing with shape- or intensity-related problems in images. It is widely used for image segmentation and analysis. This method works by representing object boundaries with implicit functions that can smoothly change over time, as explained by Li et al. (2011).With this approach, tumour boundaries appear as contours or edges placed in higher-dimensional spaces, which makes it easier to handle changes in shape or structure. The method detect these contours using mathematical equations so that the boundaries become sharper and the objects are separated more accurately. Because of this, the level set method has been used in many fields, like medical image segmentation and computer graphics. It is useful for complex boundaries because it can adapt when shapes split or merge or in the presence of intensity inhomogenouty (Carass et al., 2017; Aghazadeh et al., 2022). The technique has shown excellent performance in tasks like edge detection and boundary tracing in many applications, including medical images. Segmentation of medical images is essential in healthcare, as it helps detect problems and supports computer-assisted diagnosis, as highlighted by Xiang et al.(2020). Edge detection identifies the borders between regions in an image, which is a key step in segmentation across all areas of computational imaging. Identifying parts of an image that reveal detailed anatomical structures and signs of disease is very important.This process, known as image segmentation, which helps to visualize and better understand medical conditions such as MS. One of the major challenges in this field is segmentation accuracy of MS lesions in brain MRI scans. Clearly outlining these lesions is important for diagnosis, tracking how the disease develops, and evaluating how well treatments work. Growing evidence shows that improving the detection and outlining of lesions can lead to better patient outcomes (Valverde et al., 2017). However, variations in image brightness, noise, and uneven textures make it very difficult to separate different tissue regions accurately. For this reason, the aim of this study is to improve MS lesion segmentation by combining several advanced techniques (García-Lorenzo et al., 2013). Many researchers have suggested different tools and methods to enhance segmentation results in MS scans. The main goals here are to show how effective these combined methods can be, compare them with traditional techniques, and highlight their practical value (Sweeney et al., 2013).

This article begins with an overview of recent progress in medical image segmentation, especially the challenges of segmenting MS lesions. This article describes how the proposed method combines level-set techniques with adaptive thresholding. Tests performed on several brain lesion datasets show that this approach works very well for segmenting MS lesions, improving both accuracy and consistency in identifying the affected areas. These outcomes support ongoing progress in medical image analysis and offer valuable benefits for diagnosing complex neurological conditions.

Method

Separating brain parts from MRI data is a key part of studying the brain. This method joins adjustable level-setting with the use of embedded barriers to get exact, good results in splitting brain parts. This method has different steps; each step is made to make the separation process more accurate and keep scientific honesty in place. Figure 1 shows the steps that make up the suggested separation method. In this study, the implementation of the suggested segmentation method was carried out using MATLAB R2023a.

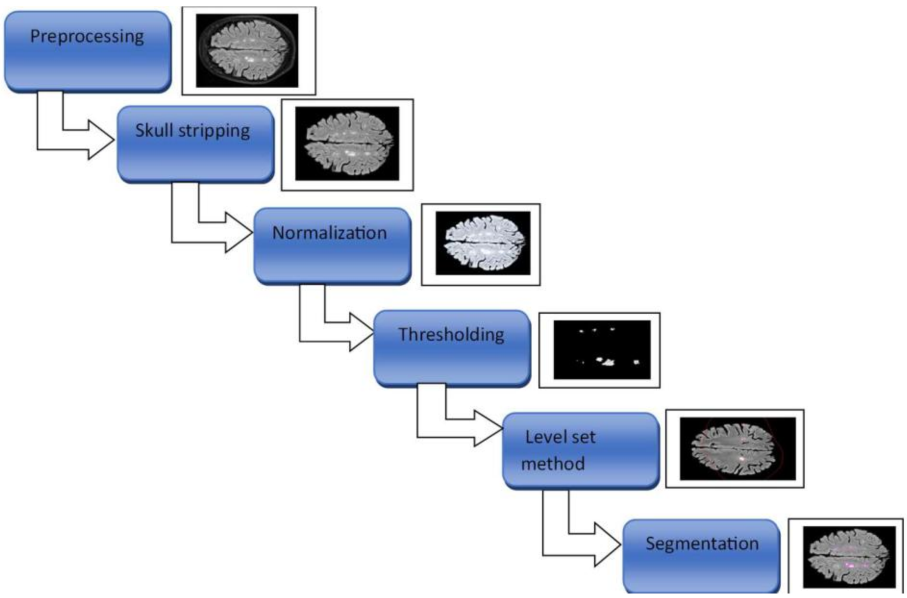

Figure 1. Flow chart for the suggested module.

Data Preparation

The data includes 60 MS patients from Neurosciences Hospital in Baghdad, Iraq; it was acquired using a standardised imaging protocol. Images are pre-processed to ensure uniformity in orientation, scale, and resolution.

Skull Stripping from Brain MRI Images

Separating different brain regions from MRI data is an important step in researches related to multiple sclerosis. The proposed method combines adjustable level-set techniques with intensity inhomogeneity to achieve clear and accurate separation of it from other brain structures. It follows specific stages, each designed to improve precision and maintain scientific way throughout the process. Figure 1 illustrates all the steps involved in the proposed segmentation approach. In this study, the method was implemented using MATLAB R2023a.

This preprocessing step is important because it separates the brain structures from the surrounding tissues to allow accurate analysis. The process involves several main stages. First, the DICOM brain MRI image is converted into a grayscale format to ensure a uniform intensity range. Then, Otsu's method (Otsu, 1979) is used through a binarization function to determine the threshold, creating a binary mask that highlights the brain tissue and removes non-brain regions. This mask is then refined by selecting the largest connected component, which is assumed to be the brain because of its size and continuity. As a result, non-brain regions, including the skull, are effectively removed. Finally, the pixels of these non-brain areas in the original grayscale image are set to zero using the binary brain mask, allowing the final image to clearly display the brain structures (Monteiro et al., 2021).

Contrast Enhancement and Preprocessing

Grayscale conversion of the images is performed. Then histogram equalization is applied to enhance the contrast of the grayscale images, facilitating better differentiation of tissue types.

Adaptive Thresholding

This approach makes dealing with intensity variations easier and improves segmentation results in varying conditions. It includes thresholding based on Gaussian Mixture Model and intensity related operations that can help with noise reduction, smoothing edges, and filling small gaps in brain images.

Two-Phase Level Set Formulation

To enhance the accuracy of brain tissue segmentation, a two-phase level-set method has been used. This method can detect the unique characteristics of each region and facilitates smoother transitions along their boundaries. This approach is consistent with the methodology described by (Li et al. 2011). The two-phase level set method utilizes the segmentation mask derived from adjusting various intensity levels. This includes the following:

Representation of Regions

The primary objective of the proposed two-phase level set method is to partition the image into two seperated regions, denoted as R1 and R2. These regions correspond to different brain tissue types, and their representation has been achieved using a level-set function ϕ. The regions are defined by their membership functions: H1ϕ for region R1 and H2ϕ for region R2, where H1ϕ is the "Heaviside function" that smoothly transitions from 0 to 1 across the contour of ϕ. A Gaussian Mixture Model (GMM) has been fitted fitted to the histogram of pixel intensities in the enhanced image. The GMM check probabilities to each pixel belonging to different tissue types. A threshold is determined based on the probabilities to separate the brain tissues from the background.

Energy Formulation

For the two-phase case, the energy formulation can be adapted to the level set framework as shown in Eq. (1):

$$E_{two\ phase} = \mu \int_{\Omega} H_1(\Phi) \mid \nabla\Phi \mid + \mu \int_{\Omega} H_2(\Phi) \mid \nabla(1-\Phi) \mid + \lambda(\int_{\Omega}(I - C1)2H_1(\phi) + \int \Omega(I - C_2)2H_2(\phi))d\Omega \quad \text{... (1)}$$

Here, μ controls the trade-off between the length of the evolving curve and the area change of the regions, and λ balances the data fidelity term with the regularisation terms. C_1 and C_2 represent the mean intensities of the two regions, and I is the intensity of the image. The level-set function ϕ evolves according to the gradient flow derived from the energy formulation.

Evolution of ϕ

The evolution of the level set function ϕ is governed by the gradient descent equation, as shown in Eq. (2):

$$\frac{\partial\phi}{\partial t} = \delta\epsilon(\phi)(\mu\text{div}(|\nabla\phi|\nabla\phi) - \lambda(F'(\phi)(I - C1)2 - F'(\phi)(I - C2)2)) \quad \text{... (2)}$$

Where $F'(\phi)$ is the derivative of the smoothed Heaviside function and $\delta\epsilon(\phi)$ is a Dirac delta function regularized by a small positive constant ϵ to prevent division by zero.

Three-Phase Level Set Formulation

Extending our methodology to include three distinct brain tissue regions, such as white matter, gray matter, and lesion regions, a three-phase level set formulation has been proposed. This advanced formulation should be able to deal with the variations of the three distinct regions by using three level set functions: $\phi 1$, $\phi 2$, and $\phi 3$. These functions define characteristics for each respective region. This includes the following:

Representation of Three Regions

In the context of the three-phase level set formulation, the objective was to partition the brain MRI image into three non-overlapping regions: R1, R2, and R3. Each region characterized by its corresponding level set function: $\phi 1$ for R1, $\phi 2$ for R2, and $\phi 3$ for R3. These functions employ membership functions H1(ϕ1), H2(ϕ2), and H3(ϕ3) utilising the Heaviside function for smooth transitions.

Energy Formulation for Three-Phase Segmentation

The energy formulation for the three-phase case evolves the previous framework to include three regions as in Eq. (3):

$$E_{three\ phase} = \mu \int_{\Omega} H_1(\Phi_1) \mid \nabla\Phi_1 \mid + \mu \int_{\Omega} H_2(\Phi_2) \mid \nabla\Phi_2 \mid + \mu \int_{\Omega} H_3(\Phi_3) \mid \nabla(1 - \Phi_1 - \Phi_2) \mid + \lambda \sum_{i=1}^{3} \int_{\Omega} (I - C_i)^2 H_i(\Phi_i) d\Omega \qquad \dots (3)$$

In this formulation, the balance between length, area change, data fidelity, and regularisation has been regulated by μ and λ. Where constants C_1, C_2, and C_3 denote the mean intensities of the three regions. The of ϕ_1, ϕ_2 and ϕ_3 aligns with the gradient flow determined by this energy formulation.

Evolution of $\phi 1$, $\phi 2$ and $\phi 3$

The evolution of the level set functions is orchestrated by the following gradient descent formulas (Krüger et al., 2020):

$$\frac{\partial\Phi_1}{\partial t} = \delta\epsilon(\Phi_1)\left(\mu\, \mathrm{div}\left(\frac{|\nabla\Phi_1|}{\nabla\Phi_1}\right) - \lambda F'(\Phi_1)(I - C_1)^2\right) \qquad \dots (4)$$

$$\frac{\partial\Phi_2}{\partial t} = \delta\epsilon(\Phi_2)\left(\mu\, \mathrm{div}\left(\frac{|\nabla\Phi_2|}{\nabla\Phi_2}\right) - \lambda F'(\Phi_2)(I - C_2)^2\right) \qquad \dots (5)$$

$$\frac{\partial\Phi_3}{\partial t} = \delta\epsilon(\Phi_3)\left(\mu\, \mathrm{div}\left(\frac{|\nabla\Phi_3|}{\nabla\Phi_3}\right) - \lambda F'(\Phi_3)(I - C_3)^2\right) \qquad \dots (6)$$

The derivative $F'(\phi_i)$ corresponds to the smoothed Heaviside function. The algorithm operates within an iterative framework, consisting of two loops, an outer and an inner loopes. The outer loop iterates over a predetermined number of iterations, monitoring overall improvement of the segmentation process. On the other hand, the inner loop monitors the iteration count for each phase, ensuring accurate adjustment to bias fields and level set functions.

Results and Discussion

The visual evaluation of the segmentation outcomes and its efficiency to highlight the facilities introduced by the proposed methodology. The used MRI highlights the method's potential clinical value in addition to providing a significant indicator of its efficacy. The utilization of the thresholding method outlined tumor regions effectively based on intensity values facilitating the subsequent steps. Figure 2. shows a sample of the segmented datasets side by side with thier ground truth images.

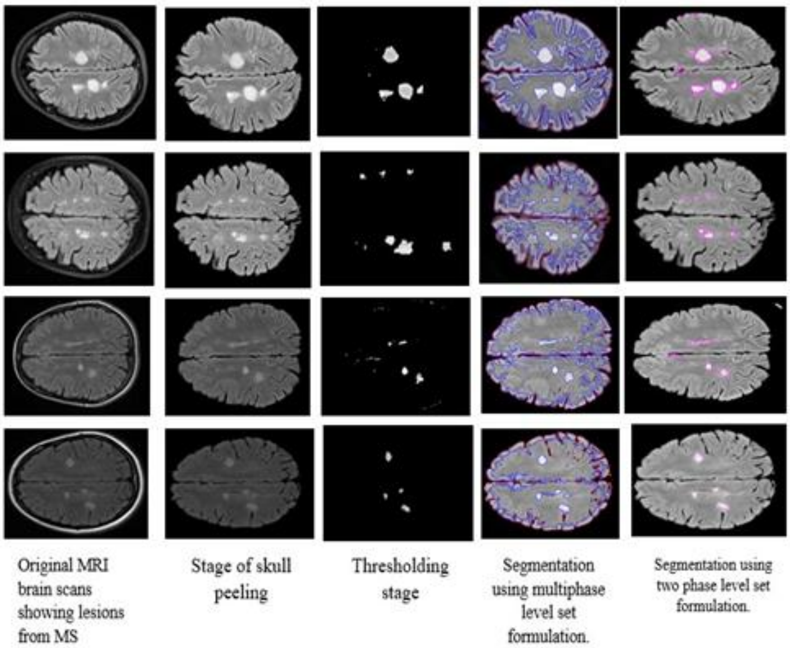

Figure 2. The outcomes of proposed segmentation method

The sequence illustrates, from left to right, the initial column displaying the original brain MRI images featuring multiple sclerosis lesions. The second column depicts skull stripping applied to the original images, the third column represents the thresholding stage, and the fourth column demonstrates segmentation through a multiphase-level set formulation. The final column shows segmentation results of the two-phase level set formulation.

The quantitative results hilight how well the suggested approach segments MS lesions. Table 1 shows the true positives (TP), false negatives (FN), false positives (FP), and true negatives (TN) through comparisons of with the ground truth annotations of brain MRI scans from 60 patients. These counts are used as the starting point for the Dice coefficient, sensitivity, and specificity calculations. The quantitative assessment provides a thorough insight into the method's effectiveness concerning lesion detection and differentiation from the background.

Sensitivity, also referred to as the true positive rate, represents the percentage of original lesion pixels recognized accurately by the segmentation method. The calculated sensitivity is about 0.923. This indicates that the used method is suitable for detecting lesions. The proportion of non-lesion pixels identified correctly by the segmentation method showing the true negative rate, determined by 0.936 Specificity. Dice Coefficient calculates the overlap between the segmented lesions, and the ground truth is about 0.994 showing a good degree of agreement.

Table 1. Quantitative results of MS lesion segmentation.

Metrics	Value
True Positives	673,803 ± 10
False Negatives	4,530± 0.2
False Positives	3,286 ± 0.4
True Negatives	905,981± 7

This qualitative assessment provides good understandings about method performance beyond numerical measurements, showing its ability to accurately detect lesions with various sizes and forms. However, the presence of false negatives and false positives suggests a need for enhancing the segmentation outcomes of the method. Easier methods needed to Find tiny tumors to make wrong guesses go down. At the same time, we can see that this method is good because it cleverly handles problems linked to changes in strength when looking at pictures of brains. With bias field correction added to the level set method, it can draw sketches of defected areas. This is possible even when there is picture deformations and no consistent brightness levels in an image. The method shows its top skills in dealing with complex shapes of lesions, which is very important for correctly separating many kinds and tough spots found in people who have MS. The clinical outcomes of this study are of great importance. Accuracy in classifying MS lesions is an important strategy for disease progression monitoring , evaluating treatment effectiveness, and assessing individual patients The potential of the proposed method for irregularities so accurately in dealing with severe and large complex lesions lays the foundation for more reliable diagnosis and better patient management.

Conclusion

The findings of this study show that the proposed method holds great promise for the accurate classification of MS lesions in MRI scans. While the results can be classified as satisfactory, there is clearly room for refinement to achieve accuracy considered more reliable in clinical practice. In contrast to previous methods of classifying MS lesions, the proposed method shows significant improvement in addressing reflex-specific symptoms and reducing acute variability Our findings are consistent with those of Cost are consistent with the findings of his colleagues (Shanmuganathan et.al., 2020) which highlighted the importance of combining spatial information for accurate lesion that causes increasing in temperature classification in line with the demonstrated increase in sensitivity and specificity in our method (Sweeney et al., 2013)However, additional effort is needed to apply the level of accuracy reported by a lot of traditional research and investigations related to the brain signals science (Valverde et al., 2017).

Recommendations

There is much room for improvement. One approach is to incorporate bias field correction and fine-tuning to efficiently capture different intensity profiles on different scan scanner protocols and, sophisticated feature extraction methods, such as texture analysis and context. Through integration, the reliance of the method on local images can be extended Also, the search for collaboration using deep learning techniques. can increase classification accuracy and will increase both under classification and overclassification If a hybrid approach combines the advantages of traditional methods with the learning power of neural networks together, they can produce more reliable results.

Scientific Ethics Declaration

* The authors declares that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

Conflict of Interest

* The authors declare that they have no conflicts of interest

Funding

* This work has recieve no funding.

Acknowledgements or Notes

* This article was presented as an oral presentation at the International Conference on Engineering and Advanced Technology (ICEAT) held in Selangor, Malaysia on July 23-24, 2025.

* The authors thank the conference committee.

References

Aghazadeh, N., Moradi, P., Castellano, G., & Noras, P. (2022). An automatic MRI brain image segmentation technique using edge–region-based level set. *The Journal of Supercomputing, 79*(7), 7337–7359.

Ahamed, M. F., et al. (2023). A review on brain tumor segmentation based on deep learning methods with federated learning techniques. *Computerized Medical Imaging and Graphics, 110*, Article 102313.

Aggarwal, M., Tiwari, A. K., Sarathi, M. P., & Bijalwan, A. (2023). An early detection and segmentation of brain tumor using deep neural network. *BMC Medical Informatics and Decision Making, 23*(1), 78.

Alshayeji, M. H., Al-Rousan, M. A., Ellethy, H., & Abed, S. (2018). An efficient multiple sclerosis segmentation and detection system using neural networks. *Computers & Electrical Engineering, 71*, 191–205.

Ansari, S. U., Javed, K., Qaisar, S. M., Jillani, R., & Haider, U. (2021). Multiple sclerosis lesion segmentation in brain MRI using inception modules embedded in a convolutional neural network. *Journal of Healthcare Engineering, 2021*, Article 4138137.

Ashtari, P., Barile, B., Van Huffel, S., & Sappey-Marinier, D. (2022). New multiple sclerosis lesion segmentation and detection using pre-activation U-Net. *Frontiers in Neuroscience, 16*, 975862.

Basaran, B. D., Matthews, P. M., & Bai, W. (2022). New lesion segmentation for multiple sclerosis brain images with imaging and lesion-aware augmentation. *Frontiers in Neuroscience, 16*, 1007453.

Carass, A., Roy, S., Jog, A., Cuzzocreo, J. L., Magrath, E., Gherman, A., ... & Pham, D. L. (2017). Longitudinal multiple sclerosis lesion segmentation data resource. *Data in brief*, *12*, 346-350.

Cetın, O., Seymen, V., & Sakoglu, U. (2020). Multiple sclerosis lesion detection in multimodal MRI using simple clustering-based segmentation and classification. *Informatics in Medicine Unlocked, 20*, Article 100409.

Chan, T. F., & Vese, L. A. (2001). Active contours without edges. *IEEE Transactions on Image Processing, 10*(2), 266–277.

Danelakis, D., Theoharis, T., & Verganelakis, D. A. (2018). Survey of automated multiple sclerosis lesion segmentation techniques on magnetic resonance imaging. *Computerized Medical Imaging and Graphics, 70*, 83–100.

Darwish, S. M., Shaheen, L. J. A., & Elzoghabi, A. A. (2023). A new medical analytical framework for automated detection of MRI brain tumor using evolutionary quantum inspired level set technique. *Bioengineering, 10*(7), Article 819.

De Arruda, L. C., Vital, D. A., Kitamura, F. C., Abdala, N., & Moraes, M. C. (2020). Multiple sclerosis segmentation method in magnetic resonance imaging using fuzzy connectedness, binarization, mathematical morphology, and 3D reconstruction. *Research on Biomedical Engineering, 36*(3), 291–301.

Faraj, M. K., Kailan, S. L., & Al-Neami, A. Q. H. (2022). A new simple, cost-effective navigation system (EASY navigator) for neurosurgical interventions. *World Neurosurgery, 164*, 143–147.

García-Lorenzo, D., Francis, S., Narayanan, S., Arnold, D. L., & Collins, D. L. (2013). Review of automatic segmentation methods of multiple sclerosis white matter lesions on conventional magnetic resonance imaging. *Medical Image Analysis, 17*(1), 1–18.

Hill, J., Matlock, K., Nutter, B., & Mitra, S. (2015). Automated segmentation of MS lesions in MR images based on an information theoretic clustering and contrast transformations. *Technologies, 3*(2), 142–161.

Jabbar, Z. S., Al-Neami, A. Q., Khawwam, A. A., & Salih, S. M. (2023). Liver fibrosis processing, multiclassification, and diagnosis based on hybrid machine learning approaches. *Indonesian Journal of Electrical Engineering and Computer Science, 29*(3), 1614–1622.

Krüger, J., et al. (2020). Fully automated longitudinal segmentation of new or enlarged multiple sclerosis lesions using 3D convolutional neural networks. *NeuroImage Clinical, 28*, Article 102445.

Li, C., Huang, R., Ding, Z., Gatenby, J. C., Metaxas, D. N., & Gore, J. C. (2011). A level set method for image segmentation in the presence of intensity inhomogeneities with application to MRI. *IEEE Transactions on Image Processing, 20*(7), 2007–2016.

Monteiro, H. A., De Brito, A. V., & Melcker, E. U. K. (2021). Image normalization in embedded systems. *Journal of Real-Time Image Processing, 18*(6), 2469–2478.

Mortazavi, D., Kouzani, A. Z., & Soltanian-Zadeh, H. (2011). Segmentation of multiple sclerosis lesions in MR images: A review. *Neuroradiology, 54*(4), 299–320.

Osher, S., & Sethian, J. A. (1988). Fronts propagating with curvature-dependent speed: Algorithms based on Hamilton-Jacobi formulations. *Journal of Computational Physics, 79*(1), 12–49.

Otsu, N. (1979). A threshold selection method from gray-level histograms. *IEEE Transactions on Systems, Man, and Cybernetics, 9*(1), 62–66.

Shanmuganathan, M., Almutairi, S., Aborokbah, M. M., Ganesan, S., & Ramachandran, V. (2020). Review of advanced computational approaches on multiple sclerosis segmentation and classification. *IET Signal Processing, 14*(6), 333–341.

Sweeney, E. M., et al. (2013). OASIS is automated statistical inference for segmentation, with applications to multiple sclerosis lesion segmentation in MRI. *NeuroImage Clinical, 2*, 402–413.

Valverde, S., et al. (2017). Improving automated multiple sclerosis lesion segmentation with a cascaded 3D convolutional neural network approach. *NeuroImage, 155*, 159–168.

Xiang, Y., et al. (2020). Segmentation method of multiple sclerosis lesions based on 3D-CNN networks. *IET Image Processing, 14*(9), 1806–1812.

Zhang, H., & Oguz, I. (2021). Multiple sclerosis lesion segmentation: A survey of supervised CNN-based methods. In *Lecture Notes in Computer Science* (pp. 11–29). Springer.

Author(s) Information

Khawla H. Rasheed
Ibn Sina University of Medical and Pharmaceutical Sciences
College of dentistry, Baghdad, Iraq
Contact e-mail: *eng.khawlarasheed@gmail.com*

Auns Qusai Al-Neami
Al-Nahrain University, Biomedical Engineering
Department/College of Engineering, Baghdad, Iraq

To cite this article:

Rasheed, K. H., & Al-Neami, A.Q. (2025). Advanced multiple sclerosis data analysis using intensity-guided skull removal and level set method for enhanced accuracy. *The Eurasia Proceedings of Science, Technology, Engineering and Mathematics (EPSTEM), 37,* 745-753.