**Matrik: Jurnal Manajemen, Teknik Informatika, dan Rekayasa Komputer**
Vol. 23, No. 3, July 2024, pp. 653∼662
ISSN: 2476-9843, accredited by Kemenristekdikti, Decree No: 200/M/KPT/2020
DOI: 10.30812/matrik.v23i3.3619 

# Improved Image Segmentation using Adaptive Threshold Morphology on Computed Tomography-Scan Images for Brain Tumor Detection

**Syafri Arlis , Muhammad Reza Putra , Musli Yanto**
Universitas Putra Indonesia YPTK, Padang, Indonesia

**Article Info**

***Article history:***

Received December 05, 2023
Revised June 26, 2024
Accepted July 03, 2024

***Keywords:***

*Brain Tumor*
*Computed Tomography-Scan*
*Improved Image*
*Segmentation*
*Threshold*

***ABSTRACT***

Diagnosing disease by playing the role of image processing is one form of current medical technology development. The results of image processing performance have provided accurate diagnoses to be used as material for decision-making. **This research aims** to detect brain tumor objects in Computed Tomography (CT-Scan) images by developing a segmentation technique using the Adaptive Threshold Morphology (ATM) algorithm. the ATM algorithm in the segmentation process involves the Extended Adaptive Global Threshold (eAGT) function to produce an optimal threshold value. **This research method** involves several stages of the process of detecting tumor objects. The preprocessing stage uses the cropping and filtering process optimized using the eAGT function. The next stage is the morphological segmentation process involving erosion and dilation operations. The final stage of the segmentation process using the ATM algorithm is labeling objects that have been detected. The research dataset used 187 Computed Tomography-Scan images from 10 brain tumor patients. **The results** of this study show that the accuracy rate for detecting brain tumor objects in Computed Tomography-Scan images is 93.47%. These results can provide an automatic and effective detection process based on the optimal threshold value that has been generated. Overall, **this research contributes** to developing segmentation algorithms in image processing and can be used as an alternative solution in treating brain tumor patients.



***Corresponding Author:***

Syafri Arlis, +6282174504125,
Department of Information Technology,
Universitas Putra Indonesia YPTK, Padang, Indonesia,
Email: syafri_arlis@upiyptk.ac.id..

How to Cite:
S. Arlis, M. Putra, and M. Yanto, "Improved Image Segmentation using Adaptive Threshold Morphology on Computed Tomography-Scan Images for Brain Tumor Detection", *MATRIK: Jurnal Manajemen, Teknik Informatika, dan Rekayasa Komputer*, Vol. 23, No. 3, pp. 653-662, July, 2024.

## 1. INTRODUCTION

Medical imaging on CT-Scan images is increasingly important for diagnosing brain tumors, but it still has shortcomings, such as noise, which causes detection results not to be optimal. Brain tumors are a disease that is quite dangerous and difficult to detect [1]. This tumor disease can attack and affect parts of the brain, so early detection is very necessary for early prevention [2]. Previous research explains that brain tumors are diseases that have the impact of threatening human life [3]. Tumor attacks on the brain can be the initial cause of psychiatric complications such as depression and other attacks [4]. Furthermore, brain tumors, or what is commonly known as brain cancer, are a form of cells that replicate quickly and have no limits and no control over their growth [5]. Based on this, it is hoped that the CT-Scan image can be optimized using image processing to improve the performance of the diagnosis process.

This improvement can be done using the Digital Image Processing (DIP) concept. The DIP concept can provide image manipulation performance with the practical role of technology [6]. DIP has also been able to assist the performance of medical personnel in diagnosing a disease [7, 8]. Several developments were carried out, which were presented in previous research, which was able to maximize the diagnostic process for brain tumors by carrying out classifications providing an accuracy of 92.44% [9]. The same research also confirmed that DIP, by adopting deep feature classification and extraction in the diagnosis process of brain tumor patients, provides output with an accuracy of 92% [10]. Improving the diagnosis process on CT-Scan images has improved the diagnosis process for brain tumor patients by providing a good accuracy of 93.34% based on Deep Learning (DL) performance with Gaussian and Median filtered images [11]. Furthermore, previous research confirmed that the form of DIP development using the classification method can provide quite an accuracy rate of 89% [12]. Similar research also presents the development of DIP in detecting and classifying brain tumor types, which can provide maximum results based on the classification method CNN, which provides detection results with an accuracy of 91% [13].

Based on previous research, segmentation techniques can still be developed to maximize the detection process [14]. Another form of development also reported that the performance of the Deep Learning (DL) method in the development of the segmentation process with Multiscale context Aggregation and Edge activation U-Net (MAEU-Net) of diagnosing brain tumor patients based on the detection process, providing dice coefficient, sensitivity, and specificity of 0.0590, 0.901, 0.942, and 0.998 [15]. Several developments can also be presented in the performance of medical with the Resnet-50 model in the detection process by producing an accuracy of 95% [16].

**This research aims** to carry out the process of detecting brain tumor objects in Computed Tomography (CT-Scan) images by developing a segmentation technique using the Adaptive Threshold Morphology (ATM) algorithm. The detection process is carried out using the DIP concept by developing segmentation techniques for the performance ATM. **The findings** of this research present the development of segmentation techniques in the ATM algorithm to find optimal threshold values based on the eAGT function in threshold morphological segmentation. The resulting threshold value will become a parameter in the segmentation process of the input image used in detecting tumor objects. This is based on the performance of threshold segmentation in previous research, which has not worked more effectively in the segmentation process [17]. Furthermore, threshold segmentation performance has also been utilized in filtering the detection process [18]. The development of the overall segmentation technique presented in the ATM algorithm is new for research, and the aim of this research is to optimize the process of detecting brain tumor objects in CT-Scan images. Based on this, detecting brain tumor objects in CT-Scan images is expected to provide an effective and efficient algorithm for carrying out an optimal detection process. Overall, this research contributes to helping medical parties diagnose and treat brain tumor patients.

## 2. RESEARCH METHOD

The process of detecting brain tumor objects in this research uses a quantitative approach by playing the role of the eAGT function in developing segmentation techniques. The segmentation technique was developed using the ATM algorithm to generate threshold values for the detection process automatically. The development of this segmentation technique will later be able to provide novelty presented in an ATM algorithm in the process of detecting brain tumor objects. The process of detecting brain tumor objects uses CT-Scan images sourced from the M.Djamil Padang Provincial General Hospital (RSUP). The data consists of 187 images from 10 patients with brain tumors. The stages of the detection process are presented in the research framework, which can be seen in Figure 1.

Figure 1 shows the stages of the ATM algorithm's work process in detecting brain tumor objects in CT-Scan images. The detection process is carried out by developing a segmentation process based on the extended Adaptive Global Threshold (eAGT) function. Extended Adaptive Global Threshold (eAGT) performance will provide updates based on optimal threshold values. The threshold value obtained for each test image varies based on the eAGT performance results. The performance of the segmentation process in the ATM algorithm will later be able to provide precise and accurate object image detection results in diagnosing tumor objects. The segmentation image output with the eAGT function can later be combined with morphological segmentation to display the detected brain tumor object. Overall, the segmentation process can provide optimal brain tumor object detection.

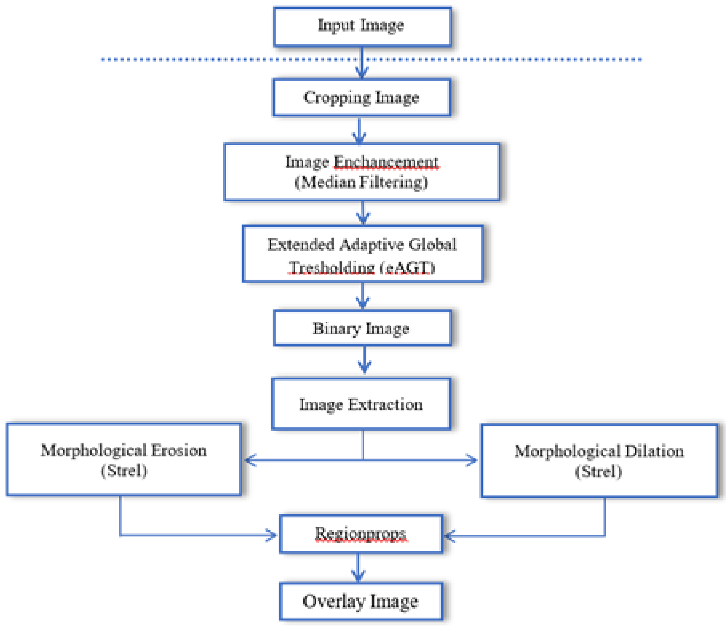



Figure 1. ATM Algorithm in the Brain Tumor Detection Process in CT-Scan Images

### 2.1. Extended Adaptive Global Threshold (eAGT)

The segmentation process obtains the desired object area in an image [19, 20]. The segmentation process separates objects by dividing image objects into several segments from a collection of pixels [21, 22]. eAGT performance is also used to automatically find the optimal threshold value for each image to be tested. eAGT performance can measure and calculate image intensity level values in color dimensions and histogram values. Based on this, the performance of eAGT is presented in Equation (1).

$$eAGT = \frac{\sum_{i:n} k.h_i}{\sum_{i:n} p_i} \tag{1}$$

Formula (1) is the eAGT equation used in the image segmentation process and used to calculate the total number of pixel values with the intensity of pixel values based on the gray color scale from the i histogram normalization process results. The value is the average grayscale color intensity value of the image. The value ranges from 1 to 255. The process of determining the threshold value for eAGT performance is presented in Figure 2. The process of determining the threshold value can be explained using the eAGT function. The eAGT function is adopted to filter image output using median filtering. The threshold value can later be determined so that the threshold value becomes the eAGT performance output.

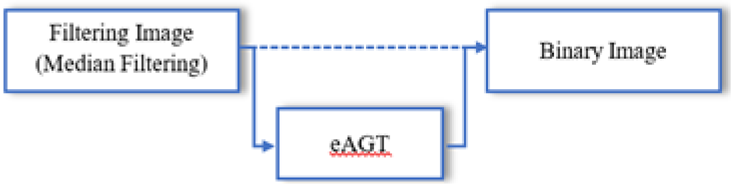



Figure 2. Process of determining binary threshold values with eAGT performance

### 2.2. Morphological Segmentation

Morphological segmentation is one of the methods used in the detection process [23]. Morphological segmentation in the process of detecting tumor objects in the brain involves opening and closing morphological operations. Morphological operations are operations that are commonly used on binary (black-and-white) images to change the shape structure of objects contained in the image [1]. Morphological operations can also carry out the component extraction process in the form of image representation and description [24]. An illustration of strel shape in the segmentation process using morphological operations is presented in Figure 3, which is an illustration of a structure element (strel) in the form of a disk with a size of 2×2. The stretch illustration shows the pivot point with a blue box. Strel has two important components, namely shape and size. This component is very influential on segmentation results using morphological operations.

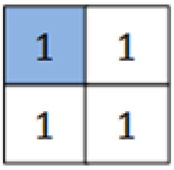



Figure 3. Strel shape illustration

## 3. RESULT AND ANALYSIS

The process of detecting tumor objects in CT-Scan images uses an image dataset of 187 images from 10 patients suffering from brain tumors. The dataset is sourced from the M.Djamil Padang Provincial General Hospital. A sample research dataset on CT-Scan images of brain tumor patients can be presented in Figure 4, which is the result of a CT-Scan image of a patient with a brain tumor. This image will later be used as a research dataset to test the performance of the extended Adaptive Global Threshold (eAGT) function in segmenting brain tumor objects. The performance results of the eAGT function can provide optimal threshold values in the image segmentation process.

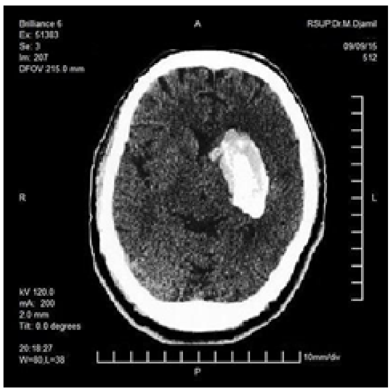
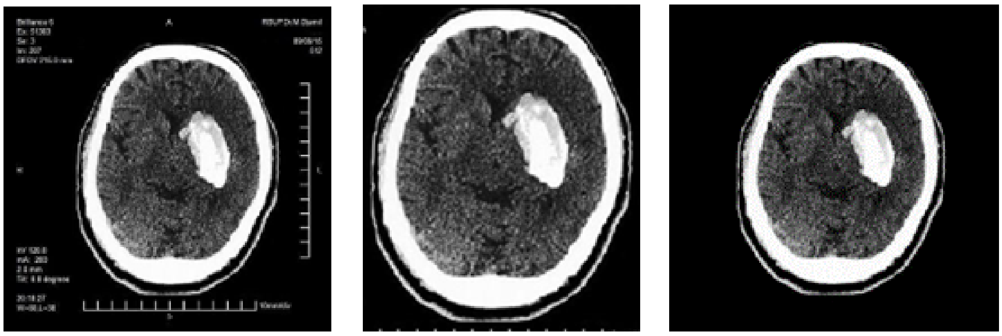


Figure 4. CT-scan image samples of brain tumor patients

### 3.1. Preprocessing

Preprocessing is the initial stage of detecting brain tumors in CT-Scan images. The preprocessing stage involves cropping and enhancement techniques that aim to improve image quality. The preprocessing results can be seen in Figure 5, which is the output of preprocessing results in the process of detecting brain tumor objects. Preprocessing uses cropping techniques intended to cut focused images on brain organ objects. Enhancement techniques are also used to improve image quality, which removes noise in the previous image. The image improvement process with enhancement techniques adopts filtering performance using Median filtering. The performance of the filtering process with median filtering can provide quite good image improvement results. The entire preprocessing image output will be input into the segmentation process to detect brain tumor objects in CT-Scan images.



(a) Input image results (b) Croping image results (c) Image enhancement results

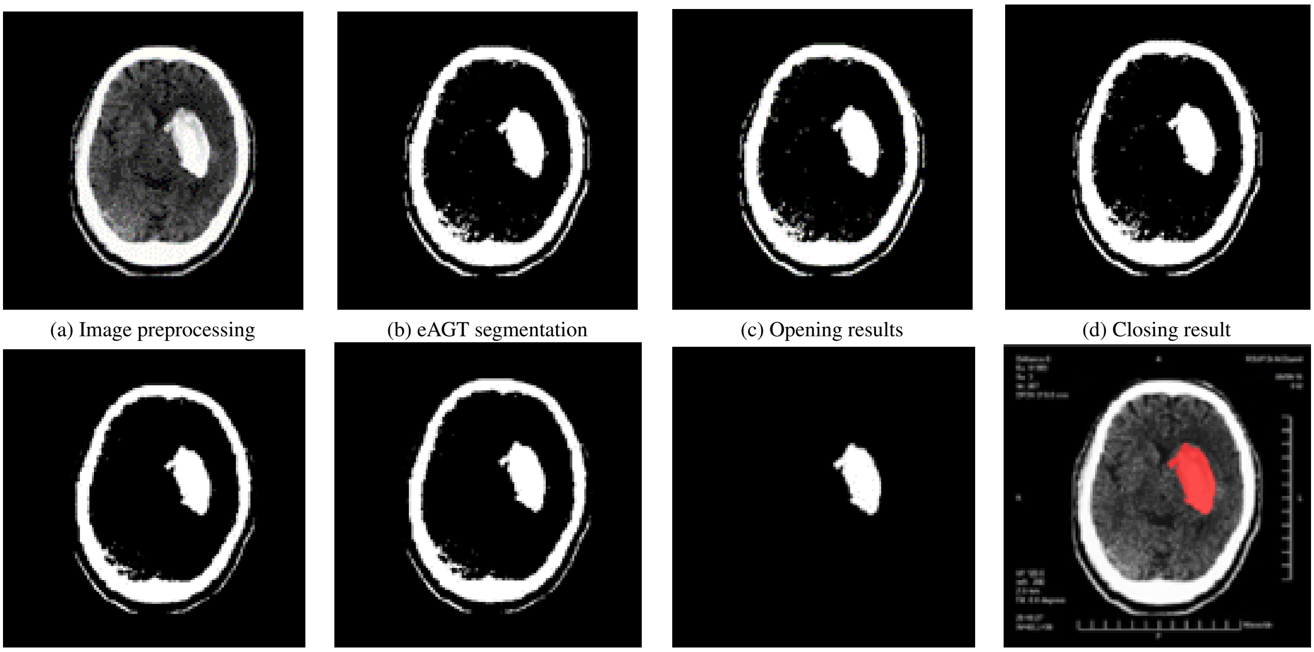
Figure 5. Image preprocessing results in the process of detecting brain tumor objects

### 3.2. Brain Tumor Object Segmentation Process

Brain tumor objects are detected in CT-Scan images by developing a segmentation process using the extended Adaptive Global Threshold function to find the optimal threshold value. This threshold value will later become a parameter for the segmentation process using the Threshold method. The development of the segmentation process is presented in an algorithm, which can be found in Pseudocode 1.

**Pseudocode 1. Extended Adaptive Global Threshold (eAGT) in Morphology Segmentation**
**Function unique, imhist**
**Input:** Im(m,n)
**Initialization**
[m,n,l] = size(Im(m,n))
eAGT, i = 0
IntensitasLevel = unique (Im(m,n))
[px, gL] = imhist(Im(Im ¿= i),i)
eAGT = find (px / IntensitasLevel)
**Output: Object Detection**
**Start**
Read image =Im of size
Calculate image size [m,n,l] = size(Im(m,n))
Calculate the Intensity Level of the image
IntensityLevel = unique (Im(m,n))
Determine the midpoint (y,z), c = fix(size(Im(m,n))/2)
Calculate the number of pixels and normalize the histogram value at each i-th pixel value level
[px, gL] = imhist(Im(Im(m,n) > = i),i)
Calculate Threshold value aAGT = find (px/IntensityLevel)
Show eAT results
Display object detection
alpha_data = values*double(borderbrn);
redOverlay=cat(val,ones(size(borderbrn)),zeros(size(borderbrn)), zeros(size(borderbrn)));
**Finish**

Pseudocode 1 is a development of the image segmentation process using the eAGT function to find the optimal threshold value. The performance of the segmentation process in the algorithm that has been developed can optimize the performance of threshold-based segmentation based on eAGT. The image results obtained from the eAGT segmentation process can be combined using the morphological segmentation process. Morphological operations in the segmentation process involve Opening, Closing, Dilation, and Erosion operations which are based on predetermined stretch values. The results of the segmentation that has been carried out can be presented in Figure 6, is the result of the segmentation process developed with the eAGT function. The performance results of this function present the optimal threshold value. Based on tests that have been carried out, the performance results of the eAGT function present a threshold value of 121. This threshold value can be used as a parameter for carrying out eAGT-based segmentation. The image output resulting from threshold-based segmentation is also combined with morphological segmentation to provide precise and accurate detection images. Based on tests that have been carried out on research datasets, the segmentation process developed provides quite maximum results. These results will later be carried out in an analysis process by measuring the level of accuracy, sensitivity and specificity values. The analysis process is carried out using Equation (2), (3) and (4) [25].



(a) Image preprocessing (b) eAGT segmentation (c) Opening results (d) Closing result

(e) Dilation results (f) Erosion results (g) Tumor object results (h) Detection object

Figure 6. Brain tumor object detection results

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{2}$$

$$Accuracy = \frac{TP}{TP + FN} \tag{3}$$

$$Accuracy = \frac{TN}{TN + FP} \tag{4}$$

Equations (2), (3) and (4) analyze the results of detecting brain tumor objects based on segmentation development with Function and eAGT. The analysis results obtained an accuracy rate of 93.47%, sensitivity of 85%, and specificity of 90%. These results were obtained after testing the performance of the Adaptive Threshold Morphology algorithm using a dataset of 180 images. The ATM algorithm's performance has also improved the detection process based on the threshold value produced by eAGT. The analysis process was also carried out by comparing several previous studies, which can be presented in Table 1. This is a process of comparing the performance results of the ATM algorithm in detecting tumor objects based on previous research. This analysis shows that the ATM algorithm can outperform the methods and algorithms presented in the tumor detection process. Based on the results of this analysis, the development of the segmentation process in detecting brain tumor objects provides maximum results. The development of the segmentation process that has been carried out has been able to provide novelty in the segmentation process to optimize the process of detecting brain tumors in CT-Scan images. The overall results presented are based on developing a segmentation process for detecting brain tumor objects in CT-Scan images and have also provided the development of an effective and efficient image object detection model. This research has also contributed to the medical side in the process of identifying and diagnosing brain tumor patients.

Table 1. Review of Research Results

| No | Previous Research Results | Results of work performed |
|---|---|---|
| 1 | The diagnostic process for brain tumors by carrying out classifications texture-based decision-making criterion to determine whether any of them actually involves a true tumor, providing an accuracy of 92.44% [9] | The ATM Algorithm's performance in the detection process provides an accuracy rate of 93.47%, sensitivity of 85%, and specificity of 90%. |
| 2 | Diagnosis process in brain tumor patients with, providing output with an accuracy of 93% [25] | |
| 3 | DIP development using the classification method can provide quite with results of an accuracy rate of 89% [12] | |
| 4 | Deep Learning (DL) method in the development of the segmentation process with Multiscale context Aggregation and Edge activation U-Net (MAEU-Net) of diagnosing brain tumor patients based on the detection process, providing dice coefficient, sensitivity, and specificity of 0.0590, 0.901, 0.942, and 0.998 [15]. | |

## 4. CONCLUSION

Detecting brain tumor objects by developing a segmentation process has provided optimal image output. The segmentation process was developed based on the eAGT function's performance, which produced threshold values for each image. The resulting threshold value can be a parameter in automatic threshold-based segmentation based on the pixel values presented. Performance testing of the segmentation process that has been developed has provided an accuracy level of 93.47%, a sensitivity of 85%, and specificity of 90%. The development of the segmentation process will later be able to provide novelty presented in an algorithm in the process of detecting brain tumor objects.


## 5. ACKNOWLEDGEMENTS

Thank you to the Chancellor of Universitas Putra Indonesia and the Yayasan Perguruan Tinggi Komputer (YPTK) Padang for supporting this research. We would also like to express our thanks to Rumah Sakit Umum Provinsi (RSUP) M.Djmail Padang, who was involved in providing the research dataset. This article results from research funded by the SIMLITUPI Batch IV 2023 grant program with No. 134/UPI-YPTK/LPPM/P/KP/VII/2023.


## 6. DECLARATIONS

AUTHOR CONTIBUTION

The division of research tasks includes Syafri Arlis, the head researcher responsible for the concept and development of the detection program. Musli Yanto was tasked with interpreting the results and writing down the findings obtained. Muhammad Reza Putra is responsible for validating data for related parties, including the M. Djmail Padang Provincial General Hospital (RSUP).


FUNDING STATEMENT

This research is funded entirely by the Yayasan Perguruan Tinggi Komputer (YPTK) Padang in the SIMLITUPI Batch IV 2023 grant program. This funding program is a form of support from the foundation for lecturers at Universitas Putra Indonesia YPTK Padang in improving the Tridharma of higher education in the field of research.


COMPETING INTEREST

The authors declare there is no competing interest.

## REFERENCES


[1] H. A. Saeed, S. Hamad, and A. T. Hussain, "Analysis the digital images by using morphology operators," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 24, no. 3, pp. 1654–1662, Dec. 2021, https://doi.org/10.11591/ijeecs.v24.i3.pp1654-1662. [Online]. Available: http://ijeecs.iaescore.com/index.php/IJEECS/article/view/25472

[2] A. Soni and A. Rai, "CT Scan Based Brain Tumor Recognition and Extraction using Prewitt and Morphological Dilation," in *2021 International Conference on Computer Communication and Informatics (ICCCI)*, vol. 6, no. 1, 2021, pp. 1–6, https://doi.org/10.1109/ICCCI50826.2021.9402677. [Online]. Available: https://ieeexplore.ieee.org/document/9402677/

[3] R. Ranjbarzadeh, A. Caputo, E. B. Tirkolaee, S. Jafarzadeh Ghoushchi, and M. Bendechache, "Brain tumor segmentation of MRI images: A comprehensive review on the application of artificial intelligence tools," *Computers in Biology and Medicine*, vol. 152, no. 1, pp. 1–13, Jan. 2023, https://doi.org/10.1016/j.compbiomed.2022.106405. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0010482522011131

[4] A. H. Khan, S. Abbas, M. A. Khan, U. Farooq, W. A. Khan, S. Y. Siddiqui, and A. Ahmad, "Intelligent Model for Brain Tumor Identification Using Deep Learning," *Applied Computational Intelligence and Soft Computing*, vol. 2022, pp. 1–10, Jan. 2022, https://doi.org/10.1155/2022/8104054. [Online]. Available: https://www.hindawi.com/journals/acisc/2022/8104054/

[5] A. Younis, L. Qiang, C. O. Nyatega, M. J. Adamu, and H. B. Kawuwa, "Brain Tumor Analysis Using Deep Learning and VGG-16 Ensembling Learning Approaches," *Applied Sciences*, vol. 12, no. 14, pp. 1–20, Jul. 2022, https://doi.org/10.3390/app12147282. [Online]. Available: https://www.mdpi.com/2076-3417/12/14/7282

[6] Y. Cheng and B. Li, "Image Segmentation Technology and Its Application in Digital Image Processing," in *2021 IEEE Asia-Pacific Conference on Image Processing, Electronics and Computers (IPEC)*. Dalian, China: IEEE, Apr. 2021, pp. 1174–1177, https://doi.org/10.1109/IPEC51340.2021.9421206. [Online]. Available: https://ieeexplore.ieee.org/document/9421206/

[7] Dr. U. Palani, D. Vasanthi, and S. Rabiya Begam, "Enhancement of Medical Image Fusion Using Image Processing," *Journal of Innovative Image Processing*, vol. 2, no. 4, pp. 165–174, Oct. 2020, https://doi.org/10.36548/jiip.2020.4.001. [Online]. Available: https://www.irojournals.com/iroiip/V2/I4/01.pdf

[8] S. Ali, A. Tanveer, A. Hussain, and S. Ur Rehman, "Identification of Cancer Disease Using Image Processing Approahes," *International Journal of Intelligent Information Systems*, vol. 9, no. 2, pp. 6–15, 2020, https://doi.org/10.11648/j.ijiis.20200902.11. [Online]. Available: http://www.sciencepublishinggroup.com/journal/paperinfo?journalid=135&doi=10.11648/j.ijiis.20200902.11

[9] M. Xu, L. Guo, and H.-C. Wu, "Novel Robust Automatic Brain-Tumor Detection and Segmentation Using Magnetic Resonance Imaging," *IEEE Sensors Journal*, vol. 24, no. 7, pp. 10 957–10 964, Apr. 2024, https://doi.org/10.1109/JSEN.2024.3367123. [Online]. Available: https://ieeexplore.ieee.org/document/10445286/

[10] A. K. Sharma, A. Nandal, A. Dhaka, D. Koundal, D. C. Bogatinoska, and H. Alyami, "Enhanced Watershed Segmentation Algorithm-Based Modified ResNet50 Model for Brain Tumor Detection," *BioMed Research International*, vol. 2022, no. 1, pp. 1–14, Feb. 2022, https://doi.org/10.1155/2022/7348344. [Online]. Available: https://www.hindawi.com/journals/bmri/2022/7348344/

[11] F. Fakouri, M. Nikpour, and A. Soleymani Amiri, "Automatic Brain Tumor Detection in Brain MRI Images using Deep Learning Methods," *Journal of Artificial Intelligence and Data Mining (JAIDM)*, vol. 12, no. 1, pp. 27–35, Feb. 2024, https://doi.org/10.22044/jadm.2024.13148.2452. [Online]. Available: https://doi.org/10.22044/jadm.2024.13148.2452

[12] S. Gajula and V. Rajesh, "An MRI brain tumour detection using logistic regression-based machine learning model," *International Journal of System Assurance Engineering and Management*, vol. 15, no. 1, pp. 124–134, Jan. 2024, https://doi.org/10.1007/s13198-022-01680-8. [Online]. Available: https://link.springer.com/10.1007/s13198-022-01680-8

[13] P. Upadhyay, S. Saifi, J. Koul, R. Rani, P. Bansal, and A. Sharma, "Classification of Brain Tumors Using Augmented MRI Images and Deep Learning," in *2024 2nd International Conference on Computer, Communication and Control (IC4)*. Indore, India: IEEE, Feb. 2024, pp. 1–7, https://doi.org/10.1109/IC457434.2024.10486455. [Online]. Available: https://ieeexplore.ieee.org/document/10486455/

[14] E. Michael, H. Ma, H. Li, F. Kulwa, and J. Li, "Breast Cancer Segmentation Methods: Current Status and Future Potentials," *BioMed Research International*, vol. 2021, no. 1, pp. 1–29, Jul. 2021, https://doi.org/10.1155/2021/9962109. [Online]. Available: https://www.hindawi.com/journals/bmri/2021/9962109/

[15] A. Kulshreshtha and A. Nagpal, "IFAS: improved fully automatic segmentation convolutional neural network model along with morphological segmentation for brain tumor detection," *International Journal of Information Technology*, vol. 16, no. 3, pp. 1517–1525, Mar. 2024, https://doi.org/10.1007/s41870-023-01572-5. [Online]. Available: https://link.springer.com/10.1007/s41870-023-01572-5

[16] P. Saxena, A. Maheshwari, and S. Maheshwari, “Predictive Modeling of Brain Tumor: A Deep Learning Approach,” in *Innovations in Computational Intelligence and Computer Vision*, M. K. Sharma, V. S. Dhaka, T. Perumal, N. Dey, and J. M. R. S. Tavares, Eds. Singapore: Springer, Conference paper, inproceedings, 2021, pp. 275–285, https://doi.org/10.1007/978-981-15-6067-5_30.

[17] A. Shanthini, G. Manogaran, G. Vadivu, K. Kottilingam, P. Nithyakani, and C. Fancy, “Threshold segmentation based multi-layer analysis for detecting diabetic retinopathy using convolution neural network,” *Journal of Ambient Intelligence and Humanized Computing*, vol. 2021, no. March, pp. 1–15, Mar. 2021, https://doi.org/10.1007/s12652-021-02923-5. [Online]. Available: http://link.springer.com/10.1007/s12652-021-02923-5

[18] S. K. Hatcholli Seere and K. Karibasappa, “Threshold Segmentation and Watershed Segmentation Algorithm for Brain Tumor Detection using Support Vector Machine,” *European Journal of Engineering and Technology Research*, vol. 5, no. 4, pp. 516–519, Apr. 2020, https://doi.org/10.24018/ejeng.2020.5.4.1902. [Online]. Available: https://www.ej-eng.org/index.php/ejeng/article/view/1902

[19] N. R. Shenoy and A. Jatti, “Ultrasound image segmentation through deep learning based improvised U-Net,” *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 21, no. 3, pp. 1424–1434, Mar. 2021, https://doi.org/10.11591/ijeecs.v21.i3.pp1424-1434. [Online]. Available: http://ijeecs.iaescore.com/index.php/IJEECS/article/view/22715

[20] N. Hasanah Ali, A. Rahim Abdullah, N. Mohd Saad, A. Sobri Muda, T. Sutikno, and M. Hatta Jopri, “Brain stroke computed tomography images analysis using image processing: A Review,” *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 10, no. 4, pp. 1048–1059, Dec. 2021, https://doi.org/10.11591/ijai.v10.i4.pp1048-1059. [Online]. Available: http://ijai.iaescore.com/index.php/IJAI/article/view/21009

[21] S. Arlis, S. Defit, and S. Sumijan, “Automated model for identification on mastoid of temporal bone image,” *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 31, no. 1, pp. 570–581, Jul. 2023, https://doi.org/10.11591/ijeecs.v31.i1.pp570-581. [Online]. Available: https://ijeecs.iaescore.com/index.php/IJEECS/article/view/30632

[22] M. Z. Nayef Al-Dabagh, “Automated tumor segmentation in MR brain image using fuzzy c-means clustering and seeded region methodology,” *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 10, no. 2, pp. 284–290, Jun. 2021, https://doi.org/10.11591/ijai.v10.i2.pp284-290. [Online]. Available: http://ijai.iaescore.com/index.php/IJAI/article/view/20819

[23] M. N. R. Devi, A. Kumar, G. Swetha, U. S. Chavan, and V. M. Davasam, “Cancer Detection Using Image Processing and Machine Learning,” in *2022 International Conference on Artificial Intelligence and Data Engineering (AIDE)*. Karkala, India: IEEE, Dec. 2022, pp. 96–100, https://doi.org/10.1109/AIDE57180.2022.10059977. [Online]. Available: https://ieeexplore.ieee.org/document/10059977/

[24] R. Godse and S. Bhat, “Mathematical Morphology-Based Feature-Extraction Technique for Detection and Classification of Faults on Power Transmission Line,” *IEEE Access*, vol. 8, pp. 1–13, 2020, https://doi.org/10.1109/ACCESS.2020.2975431. [Online]. Available: https://ieeexplore.ieee.org/document/9004572/

[25] X. Luo, W. Wang, Y. Xu, Z. Lai, X. Jin, B. Zhang, and D. Zhang, “A deep convolutional neural network for diabetic retinopathy detection via mining local and longrange dependence,” *CAAI Transactions on Intelligence Technology*, vol. 9, no. 1, pp. 153–166, Feb. 2024, https://doi.org/10.1049/cit2.12155. [Online]. Available: https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/cit2.12155

**[This page intentionally left blank.]**