

# Automatic brain tumor detection using adaptive region growing with thresholding methods

Kadry Ali Ezzat<sup>1</sup>, Lamia Nabil Omran<sup>1</sup>, Ahmed Adel Ismail<sup>2</sup>, Ahmed Ibrahim Bahgat El Seddawy<sup>3</sup>

<sup>1</sup>Biomedical Engineering Department, Higher Technological Institute, 10th of Ramadan City, Egypt

<sup>2</sup>The Higher Institute of Computer and Information Systems, Abo Qir, Egypt

<sup>3</sup>Computer Science and Information System, Arab Academy for Science and Technology and Maritime Transport, Giza, Egypt

## Article Info

### Article history:

Received Sep 13, 2022

Revised Jan 5, 2023

Accepted Mar 10, 2023

### Keywords:

Brain  
Segmentation  
Thresholding  
Tumor  
Visualization

## ABSTRACT

Brain cancer affects many people around the world. It's not just limited to the elderly; it is also recognized in children. With the development of image processing, early detection of mental development is possible. Some designers suggest deformable models, histogram averaging, or manual division. Due to constant manual intervention, these cycles can be uncomfortable and tiring. This research introduces a high-level system for the removal of malignant tumors from attractive reverberation images, based on a programmed and rapid distribution strategy for surface extraction and recreation for clinicians. To test the proposed system, acquired tomography images from the Cancer Imaging Archive were used. The results of the study strongly demonstrate that the intended structure is viable in brain tumor detection.

*This is an open access article under the [CC BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) license.*



## Corresponding Author:

Kadry Ali Ezzat

Department of Biomedical Engineering, Higher Technological Institute

Next to Small Industries Complex, Industrial Area, 10th of Ramadan City, Ash Sharqia Governorate

Email: kadry\_ezat@hotmail.com

## 1. INTRODUCTION

The human intellect is an amazingly complicated organ with an especially tall dealing with constrain unrivaled by any PC system: it can get and prepare at the same time extraordinary numerous unmistakable and mental commitments through locate, scent, contact, taste, and hearing on the millisecond scale, store information within the cerebrum and control our consideration, advancements, exercises, and talk. The cerebrum gets information through our five recognizes: locate, scent, contact, taste, and hearing [1]. Cerebrum cancer is a sickness of the cells, which are the body's basic structure squares. The body persistently makes modern cells to help us with creating, supplant broken down tissue and repair wounds. Regularly, cells copy and pass on in an exact way [2]. In a few cases cells do not create, partition and kick the bucket within the standard manner. This might make blood or lymph fluid within the body gotten to be abnormal, or structure a bulge called a development. A development can be safe or unsafe. The review portrays the rate at which cancers create and the likeliness or capacity to spread into adjoining tissue [3]. Most central tactile system growths do not spread within the body. In any case, your clinical bunch might got to do distinctive tests to check expecting the infection has spread (for case computerized tomography (CT) or magnetic resonance imaging (MRI) channels, or truly taking a see at the cerebrospinal fluid) [4].

Abdullah and Wagiallah [5], this was a pilot study focusing on brain division in MRI images using edge localization and morphological channels. For brain MRI images, each film was examined with a digitizer and then processed with an image processing program (MATLAB) taking into account the division. Brain tissue is clearly visible on the MRI image provided the object is sufficiently distinct from the background. We

use basic edge detection and morphology tools to detect ghosting. Splitting MRI images using the detection and morphology channels involved looking through the image, locating the whole brain, magnifying the image, filling in the holes in the image, and Eject the associated objects on the edges and smooth the object (brain).

The side effect of this study was that it showed an overriding strategy for visualizing the shared item by overlaying a diagram around the shared brain. These channel approaches can help suppress unwanted background data and increase symptomatic brain MRI data. As a general rule manufacturer cannot present Fourier studies in which their properties and uses are concentrated on a large scale. Sandhya *et al.* [6], An MRI brain image subdivision strategy for multi-target edge detection, district selection and programmed power threshold techniques. Multi-target MRI results of mental imaging and brain tissue distribution are provided. The identification of multi-target edges depends on the multi-scale separation strategy.

The programmed force threshold technique is based on a tailored strategy for defining limits. The method is expected to increase the accuracy of stress and brain tissue measurements. In this article, five strategies were performed to divide images in contrast to part of the growth of the MR image dataset [7]. Factual and visual research shows that the cultivated neighborhood development technique is considered the best of all research strategies. This technique has established itself in the light of the idea of clinical images and a precise distribution of those areas with similar properties. Tumors are removed from images in a semi-natural way in the wake of the performance limit. Kamnitsas *et al.* [8] used the cultivated neighborhood development method to get all the pixels in one place with few locations and the district boundaries found by the area development are very graceful and associated. However, this cycle cancer has been removed in the 2D aspect image, so to speak. Muthukrishnan and Radha [9] brain cancer localization proposal where segmentation isolates an image into its sub-regions or sections. In this system, edge detection was an important technique for cropping images. In this thesis, his work focused on presenting the most elaborate edge detection methods for image splitting and also completed the correlation of these methods with a survey. Saritha *et al.* [10] proposed approach incorporating cobweb plots based on wavelet entropy and probabilistic brain network for brain MRI clustering. The proposed strategy includes two characterization steps, for example, wavelet entropy-based web plot for highlight retraction and probabilistic brain network for control. Ghost MRI was acquired, feature extraction was completed by wavelet change and its entropy value was determined, and web plot area estimation was completed.

Nanthagopal and Sukanesh [11] have introduced in their paper a mix of effective wavelet elements (WST) and co-event wavelet surface components (WCT) obtained from two layers. A specific wavelet change was used for the association of an unusual spirit in harmless and threatening matters. The established framework included four phases: division of the area of interest, dissection of individual waves, deliberation of cornerstones, determination, mapping, and evaluation. The Aid vector machine was used for the distribution of brain tumors. A collection of WST and WCT was used, among other things, for the extraction of the cancerous area eliminated by the modification in discrete wavelets at two levels. The probabilistic brain network was used to classify unusual brain tissue into harmless and threatening, and the presentation assessment was completed by comparing the classification side effect of probabilistic neural network (PNN) and other brain network classifiers. The control accuracy of the offered frame is 97.5%.

Laxmi and Samata [12] proposed to work on the data (areas of interest) in the clinical image and thus have immeasurably refined the speed of calculation of the results of the growth division. A critical elements-based approach has been proposed for the subdivision of essential brain tumors. Critical sections of T1-weighted brain MRI images with enhanced contrast were dissected. To separate the foci of the critical elements in the image, a component point extraction calculation was applied in terms of a combination of edge maps using morphological and wavelet techniques. The evaluation of the foci of the elements obtained subsequently was completed for the mathematical modifications and the resizing of the image. Next, an acreage development calculation was used to separate the growth quarter. The baseline results show that our methodology produced excellent divisional results. This procedure was also highly apprehended. Future work includes studying the strategy used in programmed 3D cancer splicing, region of interest (ROI) splicing in other conditions, and the suitability of the method exploited in disease recovery applications. Writing has been significantly expanded to address intellect growth discovery using MRI control images, increasing the need to examine and summarize the systems used, related data sets, and execution performed. Work in this space uses brain cancer recognition using artificial intellect procedures. Artificial intelligence models require information highlighting to grow familiar with the cancer identification framework. Therefore, the most common procedure in written highlight extraction exams is the dark level co-event network (GLCM) [13], [14]. Artificial intelligence methods based mainly on artificial thinking are mainly applied to extrapolated maxima; Some exist support vector machine (SVM) [15]–[17], AdBoost [18], [19], Neural System [20], k-nearest neighbors (KNN) Classifier [21], Naive Bayes [22], Fuzzy C Means [23], morphological reconstruction of the mathematician [24].

**2. METHODS**

The primary reason in favor of this article is to recognize the growth area and specifically determine which growth will be used inside the treatment of the patient with the disease. The limit is a custom format that contains a predefined format; It is used to isolate the quality or area of interest (ROI) from the representation mean. The proposed framework begins with opening a digital imaging and communications in medicine (DICOM) file, which distinguishes the region of interest (ROI) from the intended part where the altitude cycle was applied (for example, the region should contain the brain and local cancer), and thus a multifaceted boundary strategy and a modified variant of the local development method for distributing growth. Finally, painting recognizes and models cancer of the brain and records its volume. Essentially, the framework consists of three phases, and these phases are detailed in the appropriate segment, along with the resources involved and the characteristics highlighted for each phase. The general technique of the proposed framework is shown in Figure 1.

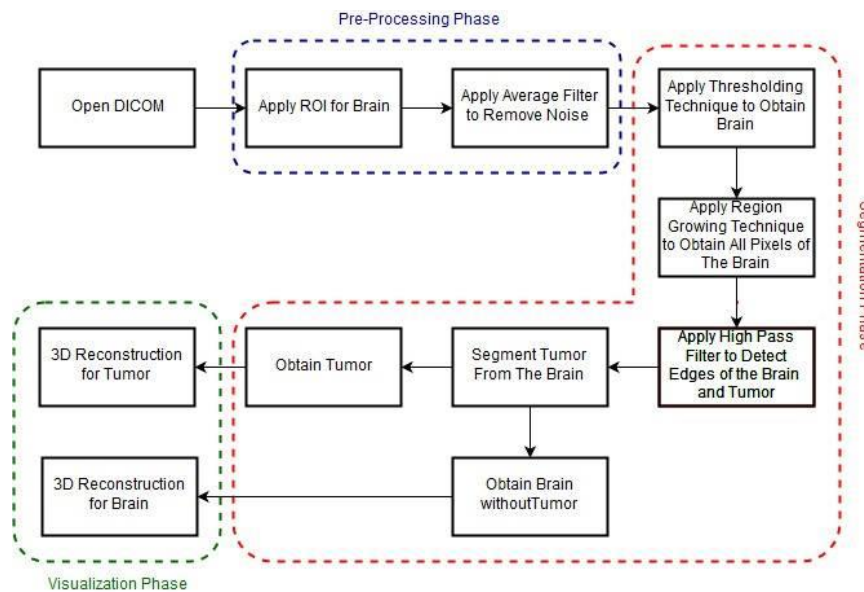


Figure 1. Building block drawing for suggested method

**2.1. Region of interest (ROI) preprocessing**

Before applying the segmentation process [25], [26], it is necessary to define the first image handling step used to detect the region of interest (ROI) of the Figure 2. ROI is used to define the expected range. For example, the brain and skull are cut and grown in a short time and the removal of certain tissues, organs, or bones reduces cutting errors and increases the possibility of recognizing suspicious areas. The best image details are enhanced and image noise is removed. Clinical MRI reduces the resolution of the image when it is contaminated with noise. Several channels are used to eliminate this excitement. A normal conduit was used to eliminate ground movement, and a weighted center conduit was used to eliminate the salt and pepper noise.

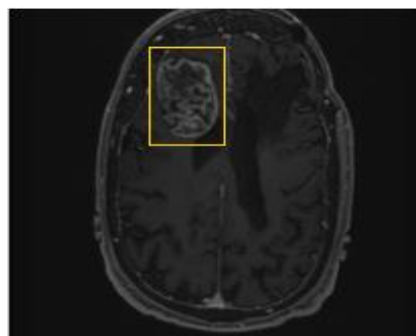


Figure 2. Region of interest in brain tumor

## 2.2. Separation methods

Image segmentation is the method of dividing mental image into little parts. Segmentation is performed to facilitate analysis. There are the following types of image segmentation [14].

### 2.2.1. Thresholding

It is the most commonly used splitting strategy. It's the dark-valve remapping technique, which doesn't see the pixel as activity. With the threshold strategy, the dark image is completely switched to a parallel image. After thresholding, the image has split into two qualities, 0 and 1, as shown in Figure 3.

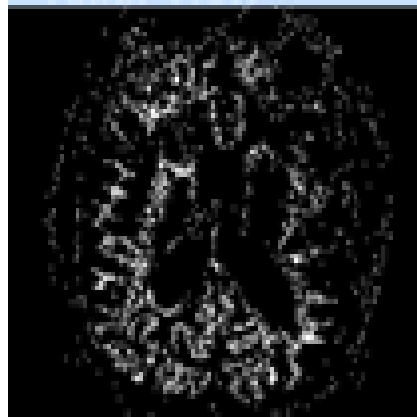


Figure 3. Thresholding of brain pixels

### 2.2.2. Edge approach

In the Figure 4 edge-based splitting strategy, distinct boundaries in an impression are accepted to address the limitations of objects and used to recognize these items. Edge-based splitting seldom provides conclusively the undeniable, closed limits needed for instant splitting. Edge recognition is more likely to be misleading and in a large number of cases edges need to be glued to join incomplete edges into an article boundary.



Figure 4. Edge detection for brain

### 2.2.3. Region growing approach

In Figure 5, the region composition methodology depends on the assumption that adjacent pixels within a locale have comparable qualities. It focuses on detecting the location of the object, not its edges. It matches a pixel and its neighbors, if the coincidence rules are satisfied, the pixel can be defined to have a place in the group as at least one of its neighbors.



Figure 5. Region growing technique for brain

### 3. RESULTS AND DISCUSSION

The findings were concluded on a Core i7 laptop computer with 8GB of RAM and AMD Radeon graphics. I have implemented all graphics and visualization functions using the visualization toolkit (VTK version 8 functions) and C # software. The DICOM tab was unlock with VTK in 3 views (axial view as shown in Figure 6(a), anterior view as shown in Figure 6(b), sagittal view as shown in Figure 6(c)) in 10 cases, as displayed in Figure 6. Brain tumor-specific ROI results were obtained for the cases. This state was the gateway to other phases of the system. The results of the adaptive threshold method were applied with high precision to segment all the pixels of the tumor. True threshold calculations then allow for highly accurate brain segmentation as well as accurate calculations of brain tumors. As shown in Figure 7, the result of applying a brain segmentation threshold.

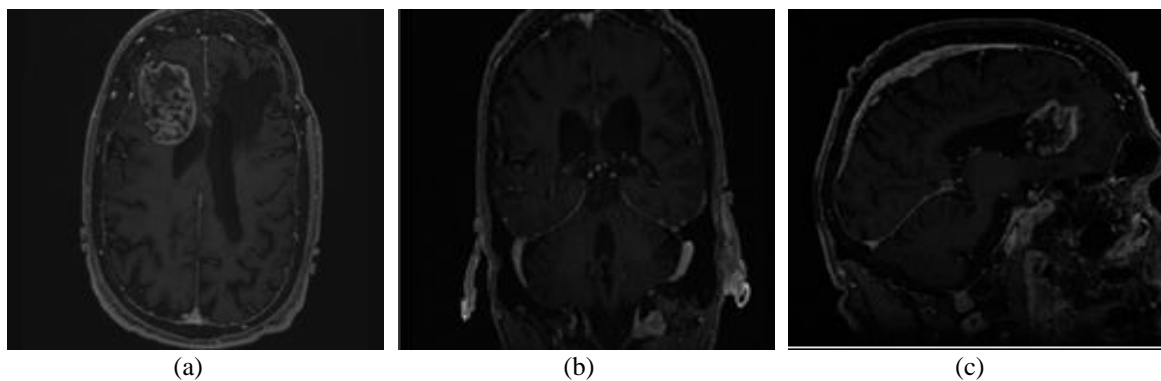


Figure 6. DICOM datasets (a) Axial view (b) Sagittal view (c) Frontal view

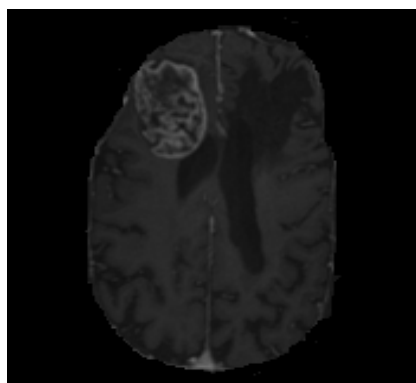


Figure 7. Brain segmented from the skull

In Figure 8, the result showing 3D reconstruction after skull removing. While the tumor was segmented from the brain by applying region of interest and region growing technique displayed in Figure 9. After segmentation tumor from brain the 3D reconstruction of the tumor was applied as indicated in Figure 10.

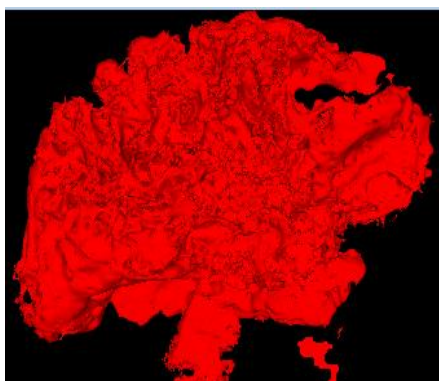


Figure 8. The 3D brain reconstruction



Figure 9. The brain tumor segmentation

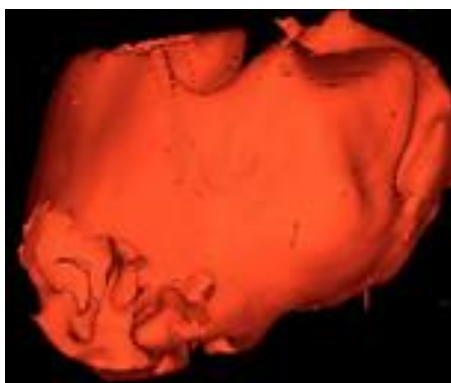


Figure 10. The 3D brain tumor construction

#### 4. CONCLUSION

Recognition of brain development is completed by this initial midline pre-processing stage and, using oblique and anti-angle occlusion, the sliced likeness is rerun and the skull occlusion is finished here. Afterwards covering the skull, fatty flesh and other unwanted details are levelled out. Images preprocess using local developing services are hashed and the hindrances match the extraction of the elements. Image processing is big business these days. Today, image treatment can be used in many fields such as clinical, remote sensing and measurement. Focusing on clinical applications, assume that image segmentation is often used for inference purposes. This paper proposed a framework that can be used to segment MRI images to detect and characterize evidence of brain development. We follow the cancer area and how it grows. Growing up, took a three-layered image of the brain. So, you can also see the size of the growth. For future work, you can assess the type of growth and stage of the cancer.





#### REFERENCES

- [1] S. R. Telrandhe, A. Pimpalkar, and A. Kendhe, "Detection of brain tumor from MRI images by using segmentation and SVM," *IEEE WCTFTR 2016 - Proceedings of 2016 World Conference on Futuristic Trends in Research and Innovation for Social Welfare*, 2016, doi: 10.1109/STARTUP.2016.7583949.
- [2] N. Ibtehaz and M. S. Rahman, "MultiResUNet: Rethinking the U-Net architecture for multimodal biomedical image segmentation," *Neural Networks*, vol. 121, pp. 74–87, 2020, doi: 10.1016/j.neunet.2019.08.025.
- [3] M. Havaei *et al.*, "Brain tumor segmentation with Deep Neural Networks," *Medical Image Analysis*, vol. 35, no. 5, pp. 18–31, Jan. 2017, doi: 10.1016/j.media.2016.05.004.

- [4] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, "Brain tumor segmentation using convolutional neural networks in MRI images," *IEEE Transactions on Medical Imaging*, vol. 35, no. 5, pp. 1240–1251, May 2016, doi: 10.1109/TMI.2016.2538465.
- [5] Y. M. Y. Abdallah and E. Wagiallah, "Enhancement of nuclear medicine images using filtering technique," *International Journal of Science and Research (IJSR) ISSN (Online Impact Factor)*, vol. 3, no. 8, pp. 2319–7064, 2014, [Online]. Available: www.ijsr.net.
- [6] G. Sandhya, G. Babu Kande, and T. S. Savithri, "Multilevel thresholding method based on electromagnetism for accurate brain MRI segmentation to detect white matter, gray matter, and CSF," *BioMed Research International*, vol. 2017, 2017, doi: 10.1155/2017/6783209.
- [7] H. Shen and J. Zhang, "Fully connected CRF with data-driven prior for multi-class brain tumor segmentation," *Proceedings-International Conference on Image Processing, ICIP*, vol. 2017-September, pp. 1727–1731, 2018, doi: 10.1109/ICIP.2017.8296577.
- [8] K. Kamnitsas *et al.*, "Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation," *Medical Image Analysis*, vol. 36, pp. 61–78, Feb. 2017, doi: 10.1016/j.media.2016.10.004.
- [9] R. Muthukrishnan and M. Radha, "Edge detection techniques for image segmentation," *International Journal of Computer Science and Information Technology*, vol. 3, no. 6, pp. 259–267, Dec. 2011, doi: 10.5121/ijcsit.2011.3620.
- [10] M. Saritha, K. P. Joseph, and A. T. T. Mathew, "Classification of MRI brain images using combined wavelet entropy based spider web plots and probabilistic neural network," *Pattern Recognition Letters*, vol. 34, no. 16, pp. 2151–2156, 2013, doi: 10.1016/j.patrec.2013.08.017.
- [11] P. A. Nanthagopal and R. Sukanesh, "Wavelet statistical texture features-based segmentation and classification of brain computed tomography images," *IET Image Processing*, vol. 7, no. 1, pp. 25–32, 2013, doi: 10.1049/iet-ipr.2012.0073.
- [12] A. P. Lakshmi and P. Samata, "Optimization of visual presentation of MRI image for accurate detection of tumor in human brain using virtual instrument," *5th 2012 Biomedical Engineering International Conference, BMEiCON 2012*, 2012, doi: 10.1109/BMEiCon.2012.6465428.
- [13] C. Zhu, K. Huang, and G. Li, "An innovative saliency guided roi selection model for panoramic images compression," *Data Compression Conference Proceedings*, vol. 2018-March, p. 436, 2018, doi: 10.1109/DCC.2018.00089.
- [14] Y. Song and H. Yan, "Image segmentation techniques overview," *AMS 2017 - Asia Modelling Symposium 2017 and 11th International Conference on Mathematical Modelling and Computer Simulation*, pp. 103–107, 2018, doi: 10.1109/AMS.2017.24.
- [15] H. Ravishankar, R. Venkataramani, S. Thiruvankadam, P. Sudhakar, and V. Vaidya, "Learning and incorporating shape models for semantic segmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 10433 LNCS, pp. 203–211, 2017, doi: 10.1007/978-3-319-66182-7\_24.
- [16] O. Oktay *et al.*, "Anatomically constrained neural networks (ACNNs): Application to cardiac image enhancement and segmentation," *IEEE Transactions on Medical Imaging*, vol. 37, no. 2, pp. 384–395, 2018, doi: 10.1109/TMI.2017.2743464.
- [17] R. El Jurdi, C. Petitjean, P. Honeine, and F. Abdallah, "Bb-unet: U-net with bounding box prior," *IEEE Journal on Selected Topics in Signal Processing*, vol. 14, no. 6, pp. 1189–1198, 2020, doi: 10.1109/JSTSP.2020.3001502.
- [18] M. Soltaninejad *et al.*, "Automated brain tumour detection and segmentation using superpixel-based extremely randomized trees in FLAIR MRI," *International Journal of Computer Assisted Radiology and Surgery*, vol. 12, no. 2, pp. 183–203, Feb. 2017, doi: 10.1007/s11548-016-1483-3.
- [19] E. Abdelrahman and A. Hussein *et al.*, "Multiple sclerosis, stroke and traumatic brain injuries," *Int. Work. on Bran*, pp. 129–137, 2020.
- [20] S. Saeed and A. Abdullah, "Recognition of brain cancer and cerebrospinal fluid due to the usage of different MRI image by utilizing support vector machine," *Bulletin of Electrical Engineering and Informatics*, vol. 9, no. 2, pp. 619–625, 2020, doi: 10.11591/eei.v9i2.1869.
- [21] M. Malathi and P. Sinthia, "Brain tumour segmentation using convolutional neural network with tensor flow," *Asian Pacific Journal of Cancer Prevention*, vol. 20, no. 7, pp. 2095–2101, 2019, doi: 10.31557/APJCP.2019.20.7.2095.
- [22] C. G. B. Yogananda *et al.*, "Fully automated brain tumor segmentation and survival prediction of gliomas using deep learning and MRI," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11993 LNCS, pp. 99–112, 2020, doi: 10.1007/978-3-030-46643-5\_10.
- [23] N. Zulpe and V. Pawar, "GLCM textural features for brain tumor classification," *International Journal of Computer Science*, vol. 9, no. 3, pp. 354–359, 2012, [Online]. Available: <http://www.doaj.org/doi/func=abstract&id=1158398>.
- [24] H. T. Zaw, N. Maneerat, and K. Y. Win, "Brain tumor detection based on Naïve Bayes classification," *Proceeding - 5th International Conference on Engineering, Applied Sciences and Technology, ICEAST 2019*, 2019, doi: 10.1109/ICEAST.2019.8802562.
- [25] A. Arora, A. Jayal, M. Gupta, P. Mittal, and S. C. Satapathy, "Brain tumor segmentation of MRI images using processed image driven u-net architecture," *Computers*, vol. 10, no. 11, 2021, doi: 10.3390/computers10110139.
- [26] N. B. Bahadure, A. K. Ray, and H. P. Thethi, "Image analysis for MRI based brain tumor detection and feature extraction using biologically inspired BWT and SVM," *International Journal of Biomedical Imaging*, pp. 1–12, 2017, doi: 10.1155/2017/9749108.

## BIOGRAPHIES OF AUTHORS






**Kadry Ali Ezzat**     He received B.Sc degree in biomedical engineering from the higher technological institute, Cairo, Egypt in 2004 and the M.Sc. and PhD degree in biomedical engineering from Cairo University, Egypt, in 2011 and 2017 respectively. In 2004 he joined the biomedical engineering department in the higher technological institute as researcher assistant then he promoted as assistant Lecturer in 2011 and then he promoted to be Lecturer in 2017. His current research interests are: diagnostic imaging, Robotics, Satellite Communications, Artificial Intelligence, Image processing, Expert Systems, Biomechanics, Data Transmission, Data Structures, Biomedical instrumentation and electronics, Pattern recognition, Microcontrollers, Modeling and simulation. He is now Lecturer in Biomedical Engineering Department at Higher Technological Institute in 10<sup>th</sup> of Ramadan city since 2017, He can be contacted at email: kadry\_ezat@hotmail.com.






**Lamia Nabil Mahdy Omran**    She received B.Sc degree in biomedical engineering from Helwan University, Cairo, Egypt in 2004 and the M.Sc. and PhD degree in biomedical engineering from Cairo University, Egypt, in 2009 and 2016 respectively. In 2004 she joined the biomedical engineering department in the higher technological institute as researcher assistant then she promoted as assistant Lecturer in 2009 and then she promoted to be Lecturer in 2016. Her current research interests are: diagnostic imaging, Robotics, Hospital design, Artificial Intelligence, reproductive surgery, Image processing, Expert Systems, Biomechanics, Computer programming, Data Transmission, Data Structures, Biomedical instrumentation and electronics, Pattern recognition, Microcontrollers, Modeling and simulation, Internet of Things (IoT). She is now Lecturer (PhD) in Biomedical Engineering Department at Higher Technological Institute in 10th of Ramadan city since 2016. She can be contacted at email: englamia\_82@yahoo.com.



**Ahmed Adel Mohammed Ismail**    Lecturer of Information Technology, Higher Institute for Computer & Information Technology, Ministry of Higher Education, Alexandria, Egypt. PhD, Scientific field: Information Technology (IT), Helwan University "Faculty of Computers and Information", Egypt. M.Sc. Scientific field: Information Technology (IT), Alexandria University, "Institute of Graduate Studies and Research", Egypt. Post Graduate Diploma, Information Technology (IT), Alexandria University, "Institute of Graduate Studies and Research", Egypt. B.Sc., Scientific field: Management Information System (MIS), College of Business Administration, Arab Academy for Science & Technology and Maritime Transport, Egypt. He can be contacted at email: gisapp13@gmail.com.



**Ahmed Ibrahim Bahgat El Seddawy**    He is Associated Professor, Vice Dean of Educational Affairs, and Head of Business Information System Department. He received his bachelor from Business Administration, MIS department and M.Sc. degree in college of Computer Science and Information Systems, I.S Department 2008 from, both from AASTMT. Cairo, Egypt. On December 2014, he received his doctoral degree from the Department of Information Systems, College of Computer Science, and Information Systems, I.S department, Helwan University. Working as visitor professor in Ludwigsburg university in Germany and Proto University Italy. He has authored/co-authored several research publications in Selected fields such as, Knowledge Discovery, Data Science, Data Analytics Decision Support Systems, Knowledge Base Systems, Project Management, and Leadership Management using ERP. He can be contacted at email: ahmed.bahgat@aast.edu.