International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048
Volume 7, Issue 12, pp 77-83, December-2023
https://doi.org/10.47001/IRJIET/2023.712011

Survey of Brain Tumor Image Segmentation Using Artificial Intelligence Techniques

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Abstract **- A brain tumor is an abnormal tissue mass resulting from abnormal cell growth. Brain tumors often reduce the length of a person's life and may cause death in advanced tumor cases. Physician teams rely on early detection and accurate tumor placement by magnetic resonance imaging to assess the tumor's pace and accuracy. Treatment, as well as determining the causes of injury to brain cells, further aids in reducing any potential problems the patient could experience. Segmenting images of brain tumors taken by magnetic resonance imaging is important for neurosurgeons. It is not an easy matter and requires high experience from radiologists. Therefore, there is a need for an expert and intelligent system to segment the abnormal part of the medication that is expert, intelligent and designed to address this task. One of the most promising innovative approaches in the medical industry is artificial intelligence. Automatically identifying the aberrant region of the brain is made possible by the application of artificial intelligence in medical imaging, which is dependent on picture interpretation. The goal of this research is to provide a brief survey on automatic methods for tumor segmentation using artificial intelligence methods, which includes the use of machine learning and deep learning methods, which include several methods, including (CNN, RES NET, MOBILE NET etc) that are applied in medical field, and to identify the most important and most accurate methods to obtain results for the automatic segmentation of brain tumor images.**

Keywords: Brain Tumor, Artificial Intelligence, Magnetic Resonance Imaging MRI, Machine Learning ML, Deep Learning DL.

I. INTRODUCTION

Brain tumors rank as the second leading cause of mortality globally. For the healing process to proceed, brain tumors must be accurately and early identified. [1], Twenty percent or more of cancer patients have brain tumors.[2] The tumor gradually spreads throughout the brain cells after first attacking a portion of them. The brain cell sustains damage following an assault. Brain tumors can either be malignant or non-malignant. Brain tumors can be classified as either benign or malignant, depending on whether they are cancerous or not. Brain cells are the source of a primary brain tumor. Nonetheless, cancer cells from secondary brain tumors have moved from other body parts, including the lung or breast, into the brain. [3], Brain metastasis is the term used to describe the uncontrolled and abnormal development of cells in the brain. Briefs the most prevalent intracranial tumor in adults is brain metastases (BMs), [4] the main symptoms of borderline personality disorder (BTs) are changes in mood and personality, difficulty walking, headaches, difficulty speaking, vomiting, and elevated blood pressure. The World Health Organization classified BTs into four classes (WHO), Lower-level tumors are classified as grade 1 and grade 2, whilst more severe tumors are classified as grade 3 and grade 4. The earlier diagnosis of BT suggests a quicker response to therapy. This helps to improve the patient's chances of survival. To diagnose bone tumors (BTs), radiologists have widely used magnetic resonance imaging (MRI), a non-invasive technique that produces several types of tissue contrast.

[5] MRI sequences are frequently utilized as modalities to enhance sub-region analysis and offer supplementary information. Tumor core is highlighted by T1-weighted (T1), T2-weighted (T2), T1-weighted (T1), contrast enhanced T1-weighted (T1c), and T2 fluid attenuation inversion recovery (FLAIR). Peritumoral edema is highlighted by the final two [6] typically, each MR-imaging modality slice's aberrant areas are manually segmented by the neurologist. Nevertheless, the BTs' laborious and subjective manual MRI image segmentation.[5] Therefore, it is preferable to construct strong and automated BT diagnostic techniques. Several image-processing methods have been used for the treatment and prediction of BTs. The MRI brain image segmentation provided good benefits for more accurate prediction on software-centered medical image evaluation. Systems called Brain Tumor Segmentation (BTS) are used to separate healthy tissues from those containing tumors. In many BTS applications, BT picture segmentation is achieved by categorizing the pixels; hence, the segmentation problem becomes a classification problem.[5]

The achievement of reliable and accurate multimodal segmentation faces three primary obstacles.

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- Segmenting the limits of the subregion (which includes the normal tissue, TC Tumor Core, Enhancing Tumor ET, and Whole Tumor WT) is the most difficult process. Noisy areas such as blood spots, strokes, and other problems make segmentation more challenging. Rather than just layering convolutional layers, we overcome this challenge by developing a deep learning model using dense residual blocks. In order to optimize the characteristic of brain tumors and understand the borders of each lesion tissue, we mix the residual block with U-shaped design in this model.
- A deep neural network's final segmentation performance is directly connected to the optimization strategy used. Inspired by the idea of deep supervision, we move the most complete feature map directly to the output layer and restrict the distribution of its feature map, which in turn keeps the weights constant during the down sampling procedure.
- The network's difficulty in training is the final obstacle. In particular, complex multimodal pictures make network training more challenging while simultaneously offering rich organizational information.[7]

Artificial intelligence (AI) is one of the health innovation strategies that show the most promise. AI's ability to identify pictures greatly broadens study beyond what is possible to see with the human eye. Automatic diagnosis is aided by the use of AI to medical imaging, which depends on image interpretation. AI is contributing to the area of diagnostic radiology being more objective. One essential use of AI in medicine is the automatic segmentation and object detection of medical images. In the fields of computer vision, pattern recognition, and image processing, picture segmentation is an essential and difficult problem. Creating homogenous classes from a picture is the primary objective of segmentation. Every element in every class has the same gray scale, feature, color, texture, intensity, and color properties. [8] Recent developments in the potential for new healthcare paradigms have increased with the advent of machine learning. One use of machine learning in radiography is the classification and identification of organs and diseases. Specifically, a great deal of work has gone into creating deep learning (DL) algorithms that can be used to separate primary brain tumors using the extensive voxel wise labeled MRI data.

II. RELATED WORK

Many academics have put a lot of effort into automating the process of segmenting brain tumors, either completely or partially. Below is a discussion of the various researchers' findings:

The researcher (Wang Liansheng et al. 2019) presents nested dilation networks (NDNs), a sophisticated three-dimensional multimodal segmentation technique, for brain tumor segmentation based on magnetic resonance imaging. The U-Net design served as inspiration for its modification, which improved its performance for brain tumor segmentation. The Dice similarity score, which contains 0.7206 for enhancing tumors and assesses the similarity between the ground truth and projected result, is used to assess the algorithm's success. The study's datasets are available at Medical Segmentation Decathlon, and MICCAI BraTS 2018 offers low-quality data for download. [10]

The researcher (Safia et al. 2020) presented a novel approach to the brain tumor segmentation problem that uses a deep learning based model named U-Net. To adapt the U-Net model for the job of multi-grade tumor segmentation using the Brain Tumor Image Segmentation (BRATS) 2015 dataset, the suggested approach is tested and produces very positive results. 0.8841 T1 It is important to note that we obtained the greatest score for the whole sub-tumor region when we exclusively used the T1 modality. Nonetheless, the T2 modality has produced the best results in the augmenting sub-tumoral region and the superior result in the core sub-tumoral region. [11]

The researcher (Grøvik, Endre, et al et al. 2020) presents using a fully convolutional neural network (CNN)-based deep learning technique for the automatic identification and segmentation of brain metastases on multisequence MRI. The. The work shows that when using multisequence MRI to detect and segment brain metastases, the modified 2.5D GoogLeNet CNN performs very well. Metrics including area under the ROC curve, precision, recall, and Dice score are used to assess the network's performance. Database A total of 138 patients underwent imaging using 3T (SIGNA Architect, GE Healthcare; Skyra, Siemens Healthiness, Erlangen, Germany) and 1.5T (n = 18; SIGNA Explorer and Twin Speed, GE Healthcare, Chicago, IL) clinical scanners. The results for automatic detection and segmentation of brain reach 98% ± 0.04 accuracy [9]

The researcher (Rai et al. 2021) used CNN with the neutrosophic, confident entropy full fuzzy specialist (NS-CNN) to identify brain cancers. The MRI dataset utilized in this study was obtained from TCGA (The Cancer Genome Atlas), a public source of medical imaging data. After adding these photos to CNN, which was used to extract characteristics, the collected features were given into the SVM classifier, which produced an average accuracy of 95.62% when classifying the pictures as benign or malignant. [12]

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The researcher (Iqbal, Muhammad Javaid, et al. 2022) presents model sets the updated parameters and uses the U-Net deep learning segmentation technique with an enhanced layered structure. The BRATS 2018 dataset, which contains multimodal MRI sequences including T1, T2, T1Gd, and FLAIR, is used by the model [3]. In comparison to cutting-edge techniques, the suggested model achieves high Dice Coefficient values for both high-grade and low-grade glioma (HGG) volumes [4]. The segmented tumors' visual findings are presented, and the suggested model's accuracy is estimated to be approximately 97%. [13]

The researcher (Cavieres Eduardo et al. 2022) suggested using a deep neural network built on the U-net architecture to automatically separate brain cancers from magnetic resonance images. The research makes use of the BRATS 2020 database. The investigation's findings indicate a validation DICE value of 91.6%, with 91.6% assigned to necrotic core (NET), 91.7% to peritumoral edema (PE), and 91.4% to enhancing tumor (ET).Following training, NET, PE, and ET had DICE values of 55.5%, 66.5%, and 68.6%, respectively. Additionally, the study assessed the tumor core (TC) segmentation performance, which had a precision of 75.5%, and the total tumor (WT) segmentation performance, which had a precision of 78.8%. [14]

The researcher (Fereshteh et al. 2022) focuses on develop a deep neural network algorithm called Deep-Net utilizing pre-trained Resnet18 weights and the Deeplabv3+ architecture. Datasets from the BraTS 2020 training set were used to train the algorithm. The outcomes demonstrated that Deep-Net could accurately segment glioblastoma tumors, achieving a global accuracy of 97.53% and a loss function of 0.14. The algorithm demonstrated high sensitivity in delineating the enhanced tumor, with a sensitivity of more than 90%. The overall performance of the algorithm was evaluated using different performance metrics, including accuracy, mean IoU, weighted IoU, and mean BF score. [15]

The researcher (Farsi et al. 2023) presents Using Convolutional Neural Networks and Fuzzy K-Means to Segment Brain Tumor Lesion Area The suggested CNN segmentation method has been validated on the BRATS dataset and yields accuracy of 98.64%, sensitivity of 100%, specificity of 99%. It first clusters the important features of the images from the preprocessed images, and then uses the fuzzy K-Means algorithm to extract the tumor area from the primary images. [16]

The researcher (Yanjun Peng et al. 2023) discusses the challenges in extracting multimodal features for deep learning segmentation methods in glioma images. The authors suggest using an automated weighted dilated convolutional network (AD-Net) to extract multimodal features from brain tumors [2]. Using the BRATS 2020 dataset, the suggested segmentation method has been validated. For the entire tumor (WT), tumor core (TC), and enhancing tumor (ET) on the BraTS20 dataset, the AD-Net approach obtained dice scores of 0.90, 0.80, and 0.76. [2] And it compares the results of the AD-Net model with state-of-the-art models, showing its effectiveness in different segmentation tasks. [7]

The researcher (Wang et al. 2023) Using ResNet blocks, a 3D convolutional neural network (CNN) was constructed and examined 737 individuals' MRI records who had gamma knife radio surgery for varicose veins. Therapies scheduling for model creation, T1-weighted isotropic MR and manually contoured gross tumor volumes (GTV) were employed. Each decoder level incorporated modules for spatial attenuation and deep supervision to improve training for the tiny tumor volume on brain MRI. A publicly accessible dataset (n = 242) and 587 and 150 patient records, respectively, from this institution (n = 495) were used to train and test the model. The Dice Similarity Coefficient (DSC), 95% Hausdorff Distance (HD95), Average Symmetric Surface (ASSD), and Relative Absolute Volume Difference (RAVD) of the model segmentation results against the GTVs were used to evaluate the model's performance. Using 50 of the available data and 100 testing patients from this facility, the suggested approach produced a mean DSC of 0.91 ± 0.08. For completely automatic segmentation of VS on T1-Weighted isotropic MRI, a CNN model was created.[17]

The researcher (Faiq et al. 2023) focuses on the automated identification of brain tumors through the application of local binary pattern (LBP) and K-means clustering algorithms. The difficulty in detecting brain tumors using K-means clustering is in determining which cluster portion best represents the tumor. Using 30 MRI scans, the new approach achieves an impressive 87% accuracy. [18]

The researcher (Shah Md et al. 2023) Examine the degree of accuracy with which two CNN models—ResNet-50 and InceptionV3—classify brain MRI images in order to determine whether a tumor is present. Applying the U-Net architecture to the ResNet-50 and InceptionV3 encoders yields encouraging results with accuracy rates of 99.55% and 99.77%, respectively. To categorize the MRI images, two CNN models—ResNet-50 and InceptionV3—are used; the suggested network is selected depending on how well each model performs. When there are no tumorous photos, the suggested model stops the algorithm; otherwise, tumorous images are forwarded to the following stage of the architecture. [3]

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The researcher (Naik Snehalatha et al. 2023) presents a deep learning-based method for classifying brain tumors utilizing linear neighborhood semantic segmentation, GoogleNet, and SLIC segmentation with super pixel fusion. The brain MRI image is segmented using SLIC segmentation with super pixel fusion, and the segments are then fed into a trained GoogleNet model for tumor diagnosis. According to the experimental data, the suggested approach achieves 98% accuracy with linear neighborhood semantic segmentation and 97.3% accuracy with the GoogleNet classification model. The study also shows that the suggested GoogleNet model has a greater accuracy of 98.45% when compared to alternative algorithms.[19]

The researcher (Aleid Adham et al. 2023) presents a harmony search algorithm (HSO)-based multilevel thresholding approach for MRI brain segmentation that is based on a standard automated segmentation method. The outcomes demonstrate that the suggested strategy outperforms CNN and DLA techniques in terms of execution time, computational complexity, and data management while maintaining a competitive accuracy edge. Utilizing MRI brain tumor images from the Brain Tumor Segmentation Challenge BraTS 2017 and 2021 datasets, the paper also compares the proposed method with previous CNN and DLA segmentation algorithms. The Dice result is about 87 percent. [8]

The researcher (Yousef Rammah et al. 2023) proposed examines the highlights continued promise of U-Net for brain tumor segmentation, along with new developments and advances in the architecture and current trends. The BraTS 2020 dataset is used by the authors to compare various U-Net architectures, such as 3D U-Net, Attention U-Net, R2 Attention U-Net, and modified 3D U-Net, quantitatively. This comparison gives a clearer picture of the performance of each architecture in terms of Dice score distance 95%.[20]

The researcher (Emadi M. et al. 2023) suggested a novel approach to increase the accuracy of brain tumor segmentation utilizing rapid primal dual (PD) and super-pixel algorithms. Using Flair-MRI imaging, the suggested approach finds brain tumor tissue in the BRATS2012 dataset. Super-pixel algorithms are used to detect tumors' main borders, and rapid PD is used in Markov random field optimization to enhance the boundaries of brain tumors. White brain regions are removed using post-processing techniques, and the tumor area is shown using an active contour algorithm. Dice similarity measure, accuracy, and F-measure are among the qualitative and quantitative metrics used to assess the suggested approach. The findings obtained demonstrate the effectiveness of the suggested strategy, with an F1-Measure of 86.37 and accuracy and sensitivity of 86.59% and 88.57%, respectively. [21]

Upon studying previous work, it was found that most previous works apply a pre-processing process to MRI images such as resize and normalization, to determine the size of the images according to the used algorithm, and remove noise from the images to improve the process of segmenting the tumor located in the brain. The dataset used in most of the researches by BraTS, summary of previous works will be presented in table 1 as following:

Table 1: Summary of related work

Study	**Techniques**	**Dataset**	**Year**	**Accuracy**
Wang Liansheng et al	Nested Dilation Networks (NDNs)	MICCAI BraTS 2018	2019	72% for ET
Safia et al	U-Net	BraTS 2015	2020	88%
Grøvik, Endre, et al	CNN based on the GoogLeNet architecture	Special clinical scanners	2020	98% ± 0.04
Rai et al	CNN with the full fuzzy specialist (NS-CNN)	TCGA (The Cancer Genome Atlas)	2021	95%
Iqbal, Muhammad Javaid, et al	U-Net with an improved layered structure	BraTS 2018	2022	Around 97%.
Cavieres Eduardo et al	U-net -based deep neural network	BraTS 2020	2022	Around 91%
Fereshteh et al	Deep-Net and pre-trained Resnet18	BraTS 2020	2022	Around 97%.
Farsi et al	CNN Fuzzy K-Means	BraTS 2019	2023	Around 98%
Yanjun Peng et al	AD NET	BraTS 2020	2023	WT= 90%
Wang et al	3D(CNN) built on ResNet		2023	

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	blocks	Special institution		DSC 91% ± 0.08
Faiq et al	K means clustering	30 MRI images	2023	87%
Shah Md et al	U-Net with ResNet-50 and InceptionV3	The cancer imaging archive (TCIA)	2023	Around 99.7%
Naik Snehalatha et al	SLIC segmentation with superpixel fusion, GoogleNet	Special dataset	2023	Around 97%.
Aleid Adham et al	Harmony Search Algorithm (HSO)	BraTS 2017and BraTS 2020	2023	Around 87%.
Yousef Rammah et al	3D U-Net, Attention U-Net, R2 Attention U-Net, and modified 3D U-Net	BraTS 2020	2023	Around 95%.
Emadi M. et al	super-pixel and fast primal dual (PD) algorithms	BraTS 2012	2023	Around 87%.

III. MODELS AND METHODS

The goal of this research is to survey a computerized system that can build an automatic system for segmenting brain tumors using MRI images for training and testing an AI model. This research has been created to help speed up and facilitate the process of automatic segmentation of brain tumor and then detect whether the abnormal tissue is benign or malignant.

Pre-processing with normalization in the following subsections, the most important types of Artificial intelligence explained that are used for the automatic segmentation of brain tumor as follows:

1) Convolutional neural networks (CNN) Researchers are interested in brain tumor segmentation utilizing deep learning approaches based on convolutional neural networks (CNN) to develop precise segmentation methods that improve the process of finding tumor locations. Many convolutional neural network (CNN)-based techniques have recently been put forth for the segmentation of brain tumors.[22]
2) U-Net (CNN algorithm) use its enhanced layer structure and adjusted parameters to the semantic segmentation issue, The tumor segmentation in MRI is improved by the U-Net model's multiple convolution operations on each layer. Convolutional network design, such as that seen in the U-Net model, is utilized for quick and accurate picture segmentation, particularly in medical imaging. It has a multi-channel feature map, with the number of channels often displayed above the architectural design.[23]
3) ResNet (residual neural network): is deep learning approach, which is now the most popular, was first presented by the scientist Kaiming He. What's referred to as the remaining block makes up this portion. With extensive use of "batch normalization," this model—which is based on the idea of "skip connection"—allows for the effective application of hundreds of layers without gradually reducing performance.[22]
4) K-means clustering: is a popular clustering tool and a member of the unsupervised learning technique family. These characteristics help set the things apart from their surroundings. Differentiating a collection of items that belong to one group from objects that belong to other groups based on shared features is the primary goal of the clustering procedure.[24]
5) GoogleNet is a 22-layer deep learning model. Fourteen GoogleNet demonstrates that the convolutional layer and the pooling layer do not have to be stacked consecutively.
6) V-Net is a 3D version of U-Net, It uses fully convolutional neural networks as its foundation (FCN). It is an end-to-end training mode 3D picture segmentation model. In addition, V-Net, an enhanced 3D network architecture of FCN, achieves end-to-end image semantic segmentation of 3D medical pictures by using a convolution layer rather than a complete connection layer.[25]

IV. CONCLUSION

The intricacy of brain tumor anatomy, indistinct boundaries, and extraneous factors make it difficult to infer tumor locations from brain MRI pictures. Thus, the widely used standard BRATS datasets have in recent years given researchers a common way to create their own methodologies and use existing approaches to objectively assess them. Different architectures have been applied in previous works, the U-NET architecture, most used method of deep learning (DL) for brain tumor segmentation. The best results from hybridization Convolutional Neural Networks and Fuzzy K-Means where achieved accuracy around 98% and it used BraTS dataset 2019, and the least accuracy that was achieved in previous works which used nested dilation networks (NDNs) that achieved accuracy rate of up to 72%. Likewise, the method K-mean clustering , by which achieved 87%, is

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also a low accuracy rate compared to the researches that was studied, and therefore we suggest that there be a process of hybridizing U-NET with one of the machine learning methods, for example, Support Vector Machine(SVM) or Swarm algorithm to reach highest accuracy of automatic segmentation.

ACKNOWLEDGEMENT

The research is supported by University of Mosul, Department of Software, College of Computer Science and Mathematics, Mosul, Iraq.

REFERENCES

[1] Kurian, Simy Mary, and Sujitha Juliet. "An automatic and intelligent brain tumor detection using Lee sigma filtered histogram segmentation model." *Soft Computing* 27.18 (2023): 13305-13319.

[2] Anusooya, Govindarajan, et al. "Self-Supervised Wavelet-Based Attention Network for Semantic Segmentation of MRI Brain Tumor." *Sensors* 23.5 (2023): 2719.

[3] Arefin, Abu Shahed Shah Md Nazmul, et al. "Deep learning approach for detecting and localizing brain tumor from magnetic resonance imaging images." *Indonesian Journal of Electrical Engineering and Computer Science* 29.3 (2023): 1729-1737.

[4] Chen, Mingming, et al. "An Effective Approach to Improve the Automatic Segmentation and Classification Accuracy of Brain Metastasis by Combining Multi-phase Delay Enhanced MR Images." *Journal of Digital Imaging* (2023): 1-12.

[5] A.R. Sakthi Prabha, M. Vadivel, "Brain Tumor Stages Prediction using FMS-DLNN Classifier and Automatic RPO-RG Segmentation," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 10, no. 2, pp. 110-121, 2023.

[6] Liu, Hong, et al. "M3AE: Multimodal Representation Learning for Brain Tumor Segmentation with Missing Modalities." *arXiv preprint arXiv*:2303.05302 (2023).

[7] Peng, Yanjun, and Jindong Sun. "The multimodal MRI brain tumor segmentation based on AD-Net." *Biomedical Signal Processing and Control* 80 (2023): 104336.

[8] Aleid, Adham, et al. "Artificial Intelligence Approach for Early Detection of Brain Tumors Using MRI Images." *Applied Sciences* 13.6 (2023): 3808.

[9] Grøvik, Endre, et al. "Deep learning enables automatic detection and segmentation of brain metastases on multisequence MRI." *Journal of Magnetic Resonance Imaging* 51.1 (2020): 175-182.

[10] Wang, Liansheng, et al. "Nested dilation networks for brain tumor segmentation based on magnetic resonance imaging." *Frontiers in Neuroscience* 13 (2019): 285.

[11] Fatima, Safia, et al. "Evaluation of multi-modal mri images for brain tumor segmentation." *2019 15th International Conference on Emerging Technologies (ICET). IEEE*, 2019.

[12] Rai, Hari Mohan, Kalyan Chatterjee, and Sergey Dashkevich. "Automatic and accurate abnormality detection from brain MR images using a novel hybrid UnetResNext-50 deep CNN model." *Biomedical Signal Processing and Control* 66 (2021): 102477.

[13] Iqbal, Muhammad Javaid, et al. "Brain Tumor Segmentation in Multimodal MRI Using U-Net Layered Structure." *CMC-COMPUTERS MATERIALS & CONTINUA* 74.3 (2023): 5267-5281.

[14] Cavieres, Eduardo, et al. "Automatic segmentation of brain tumor in multi-contrast magnetic resonance using deep neural network." *18th International Symposium on Medical Information Processing and Analysis.* Vol. 12567. SPIE, 2023.

[15] Shoushtari, Fereshteh Khodadadi, Sedigheh Sina, and Azimeh NV Dehkordi. "Automatic segmentation of glioblastoma multiform brain tumor in MRI images: Using Deeplabv3+ with pre-trained Resnet18 weights." *Physica Medica* 100 (2022): 51-63.

[16] Fooladi, S., H. Farsi, and Sajad Mohamadzadeh. "Segmenting the Lesion Area of Brain Tumor using Convolutional Neural Networks and Fuzzy K-Means Clustering." *International Journal of Engineering* 36.8 (2023): 1556-1568.

[17] Wang, Hesheng, et al. "Automatic segmentation of vestibular schwannomas from T1-weighted MRI with a deep neural network." *Radiation Oncology* 18.1 (2023): 1-9.

[18] Baji, Faiq Sabbar, Saleema Baji Abdullah, and Fatimah S. Abdulsattar. "K-mean clustering and local binary pattern techniques for automatic brain tumor detection." *Bulletin of Electrical Engineering and Informatics* 12.3 (2023): 1586-1594.

[19] Naik, Snehalatha, and Siddarama Patil. "Brain Tumor Classification using SLIC Segmentation with Superpixel Fusion, GoogleNet, and Linear Neighborhood Semantic Segmentation." *Journal of Scientific & Industrial Research* 82.02 (2023): 255-262.

[20] Yousef, Rammah, et al. "U-Net-Based Models towards Optimal MR Brain Image Segmentation." *Diagnostics* 13.9 (2023): 1624.

[21] Emadi, M., Z. Jafarian Dehkordi, and M. Iranpour Mobarakeh. "Improving the accuracy of brain tumor identification in magnetic resonance aging using super-

ISSN (online): 2581-3048
Volume 7, Issue 12, pp 77-83, December-2023
https://doi.org/10.47001/IRJIET/2023.712011

pixel and fast primal dual algorithm." *International Journal of Engineering* 36.3 (2023): 505-512.

[22] Mohammed, Yahya MA, Said El Garouani, and Ismail Jellouli. "A survey of methods for brain tumor segmentation-based MRI images." *Journal of Computational Design and Engineering* 10.1 (2023): 266-293.

[23] Wang, Guotai, et al. "Automatic brain tumor segmentation using cascaded anisotropic convolutional neural networks." Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries: *Third International Workshop, BrainLes 2017, Held in Conjunction with MICCAI 2017, Quebec City, QC, Canada*, September 14, 2017, Revised Selected Papers 3. Springer International Publishing, 2018.

[24] Neugut, Alfred I., et al. "Magnetic resonance imaging-based screening for asymptomatic brain tumors: a review." *The oncologist* 24.3 (2019): 375-384.

[25] Zhou, Juhua, et al. "scse-nl v-net: A brain tumor automatic segmentation method based on spatial and channel “squeeze-and-excitation” network with non-local block." *Frontiers in Neuroscience* 16 (2022): 916818.

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Citation of this Article:

Mohanad Raied ALkasab, Jamal Salahaldeen Majeed Alneamy, “Survey of Brain Tumor Image Segmentation Using Artificial Intelligence Techniques” Published in *International Research Journal of Innovations in Engineering and Technology - IRJIET*, Volume 7, Issue 12, pp 77-83, December 2023. Article DOI https://doi.org/10.47001/IRJIET/2023.712011

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