**Performing Precise Brain Tumor Classification by Adaptive Deep Super Learner Model together with the aid of Tumor Segmentation based on Trans-Unet with Modified Region Growing Network**

**Introduction**

An intracranial tumor, also referred to as a brain tumor, is an abnormal mass of tissue where cells grow and reproduce out of control, appearing to be unaffected by the systems that regulate normal cells. Although there are more than 150 known types of brain tumors, primary and metastatic are the two basic classifications [9]. A lump or growth of abnormal cells in your brain is known as a brain tumor. There are numerous varieties of brain tumors. Both benign (noncancerous) and malignant (cancerous) brain tumors can occur (malignant) [10]. The main aim of brain tumor segmentation is to locate and map the tumor regions, namely the active tumorous tissue (whether or not it is vascularized), necrotic tissue, and edoema (swelling near the tumor). By comparing aberrant areas to normal tissue, abnormal spots might be found [11]. One of the key steps in the planning of surgery and treatment is brain tumor segmentation. In clinical practice, the majority of brain tumor segmentation on brain tumor pictures is done manually. In addition to taking a lot of time, manual brain tumor delineation is challenging and depends on the operator [12]. Brain tumor segmentation in medical image processing is a difficult issue for medical practitioners to monitor and diagnose the tumor in people. The patient's chance of survival can be increased by early diagnosis [13]. The World Health Organization (WHO) updated its approach for classifying brain tumors in 2016 and made a number of noteworthy improvements. Several formerly accepted diagnoses of brain tumors, including oligoastrocytoma, primitive neuroectodermal tumor, and gliomatosis cerebri, were reclassified or completely disregarded [14].

The MR image segmentation is a crucial task to monitor the variation in volume of tumors. It plays vital role in radiotherapy/ surgical planning where affected/ healthy regions are clearly segregated. Presently, the performance of manual segmentation is more dominative in the clinical routine where more clinical practice and time is required by the radiologists [15]. Moreover, complex glioma features and subtle variations among MRI analysis also generate inescapable challenges for reliable detection through visual examination of MRI even through expert radiologist. Automatic approaches for the detection of brain tumor are more noteworthy and meaningful [16]. Segmentation approaches for brain tumor using 2D slices of MRI are divided into three classes i.e., threshold, region based and pixel based classification. Threshold approaches do not provide <1 threshold to classify the target voxel segmentation through their intensities. Sobel filter is employed to outline the edges of voxels. Then pixel values of each voxel are compared with threshold criteria and every pixel value is assigned to adjacent regions to refine the output. Region based techniques isolate the voxels manually into exclusive districts [17]. It is a classical method in which one seed is at least planted in each district and each voxel similarity with the adjacent seeds is measured. This method might not address the partial volume effect. A modified technique is presented which reduces the partial volume effect and detects more refined edges of voxels through computation of gradient information [18]. The adaptive region growing techniques are used to precise segmentation of tumor region.

The main drawbacks of the conventional models in medical imaging are the limited data availability and high computing expense. Another issue is dimensionality, which makes it difficult to handle and enhance 3D data and necessitates expensive GPUs [19]. The use of 2D Artificial Neural Networks (ANNs) kernels is further constrained because they cannot be applied to 3D volumetric data [20]. Despite their high computational costs, 2D ANNs have a huge potential in a variety of medical applications. The size of these medical picture volumes can be greatly decreased by using interpolation techniques [21]. One of the most important ones is the removal of certain photos from classification and segmentation. As a result, it would be useless to use the non-tumor regions as the input in classification models because the segmented portions of these images are outside the ground facts [22]. Deep learning techniques have recently gained popularity for automatic segmentation because they produce cutting-edge findings and are more effective at solving this issue than previous techniques [23]. The massive volumes of MRI-based image data can also be processed effectively and evaluated objectively using deep learning techniques. To learn intricate patterns, deep learning has been utilized successfully in supervised categorization tasks [24]. Neural networks may learn the shape of a brain and progress towards differentiating between brains with and without tumors by incorporating images of brains without cancer. More generally, this uses deep learning to distinguish between physiological structures [25]. As a consequence, we designed a novel brain tumor segmentation and classification model using the enhanced deep learning approaches.

**Related works**

In 2022, Agrawal *et al.* [1] have aimed to design an efficient framework for brain tumor segmentation and classification using deep learning techniques. The study employed the 3D-UNet model for the volumetric segmentation of the MRI images, followed by the classification of the tumor using CNNs. The loss and precision diagrams were presented to establish the validity of the models. The performance of proposed models was measured, and the results were compared with those of other approaches reported in the literature. It is found that the proposed work was more efficacious than the state-of-the-art techniques.

In 20--22, Tandel *et al.* [2] have proposed a magnetic resonance imaging (MRI) based non-invasive method for low-grade glioma (LGG) versus high-grade glioma (HGG) classification. To maximize the above classification performance, five pre-trained convolutional neural networks (CNNs) such as AlexNet, VGG16, ResNet18, GoogleNet, and ResNet50 were assembled using a majority voting mechanism. Segmentation methods required human intervention and additional computational efforts. It makes computer-aided diagnosis tools semi-automated. To analyze the performance effect of segmentation methods, three segmentation methods such as region of interest MRI segmentation (RSM) and skull-stripped MRI segmentation (SSM), and whole-brain MRI (WBM) (non-segmentation) data were compared using above mentioned algorithm. The highest classification accuracy of 99.06 ± 0.55 % was observed on the RSM data and the lowest accuracy of 98.43 ± 0.89 % was observed on the WSM data. However, only a 0.63 % improvement was found in the accuracy of the RSM data against the WBM data. This showed that deep learning models have an incredible ability to extract appropriate features from images. Furthermore, the proposed algorithm showed 2.85 %, 1.39 %, 1.26 %, 2.66 %, and 2.33 % improvement in the average accuracy of the above three datasets over the AlexNet, VGG16, ResNet18, GoogleNet, and ResNet50 models, respectively.

In 2022, Dang *et al.* [3] have employed a deep learning pipeline with three essential steps: (1) MRI images were segmented using preprocessing approaches and UNet architecture, (2) brain tumor regions were extracted using segmentation, then (3) high-grade gliomas and low-grade gliomas were classified using the VGG and GoogleNet implementations. Among the additional preprocessing techniques used in conjunction with the segmentation task, the combination of data augmentation and Window Setting Optimization was found to be the most effective tool, resulting in the Dice coefficient of 0.82, 0.91, and 0.72 for enhancing tumor, whole tumor, and tumor core, respectively. While most of the proposed models achieved comparable accuracies of about 93 % on the testing dataset, the pipeline of VGG combined with UNet segmentation obtains the highest accuracy of 97.44 %. In conclusion, the presented architecture illustrates a realistic model for detecting gliomas; moreover, it emphasizes the significance of data augmentation and segmentation in improving model performance.

In 2024, Kordnoori *et al.* [4] have developed a unique automatic model included a common encoder for feature representation, one decoder for segmentation and a multi-layer perceptron for classification of three common primary brain tumors (meningiomas, gliomas and pituitary adenomas) in brain MR images. The proposed model was examined on a brain tumor images dataset and the output was evaluated in both multi-task and single-task learning model. The multi-task learning model gains significant improvement in simultaneous classification and segmentation of brain tumors with promising accuracy of 97% for each task. So, this model could serve as a primary screening tool for early diagnosis of common primary brain tumors in general practice with a high success rate.

In 2018, Sharif *et al.* [5] have proposed a new method for the segmentation and classification of brain tumor based on improved saliency segmentation and best features selection approach. The presented method worked in four pipe line procedures such as tumor preprocessing, tumor segmentation, feature extraction and classification. In the first step, preprocessing was performed to extract the region of interest (ROI) using manual skull stripping and noise effects are removed by Gaussian filter. Then tumor is segmented in the second step by improved thresholding method which is implemented by binomial mean, variance and standard deviation. In the third step, geometric and four texture features were extracted. The extracted features were fused by a serial based method and best features were selected using Genetic Algorithm (GA). Finally, support vector machine (SVM) of linear kernel function was utilized for the classification of selected features. The proposed method was tested on two data sets including Harvard and Private. The Private data set was collected from Nishtar Hospital Multan, Pakistan. The proposed method achieved average classification accuracy of above 90% for both data sets which showed its authenticity.

In 2019, Amin *et al.* [6] have presented a new technique for the detection of tumor. The proposed architecture accurately segmented and classified the benign and malignant tumor cases. Different spatial domain methods were applied to enhance and accurately segment the input images. Moreover Alex and Google networks were utilized for classification in which two score vectors are obtained after the softmax layer. Further, both score vectors were fused and supplied to multiple classifiers along with softmax layer. Evaluation of proposed model was done on top medical image computing and computer-assisted intervention (MICCAI) challenge datasets i.e., multimodal brain tumor segmentation (BRATS) 2013, 2014, 2015, 2016 and ischemic stroke lesion segmentation (ISLES) 2018 respectively.

In 2023, Kalam *et al.* [7] have proposed a BT Detection (BTD) in MRI images utilizing Adaptive-Adaptive Neuro-Fuzzy Inference System (Adaptive-ANFIS) classifier with the segmentation of tumor along with edema. Primarily, the input RGB was transmuted into a Grayscale Image (GSI). During pre-processing, the non-brain tissues were eradicated utilizing the Skull Stripping Algorithm (SSA). Next, the resulted image was segmented into ‘2’ parts: (a) tumor and (b) edema utilizing Modified Region Growing (MRG) and Otsu’s thresholding. Then, as of the segmented “tumor part” image, the DWT, WST, Edge, and color histogram features were extracted. Then, the required features were selected as of the extracted features by employing the MGWO algorithm. After that, those features being selected were given to the Adaptive-ANFIS, which categorizes the tumor as (a) Benign and (b) Malignant. The adaptive process was conducted by the K-Means Clustering (KMC) algorithm. Experiential results examined the performances defined by the proposed as well as the prevailing system regarding specificity, accuracy, sensitivity, recall, and precision.

In 2021, Luo *et al.* [8] have designed a hierarchical decoupled convolution network (HDC-Net), which was a light-weight but efficient pseudo-3D model. Specifically, 3D convolutions were replaced with a novel hierarchical decoupled convolution (HDC) module, which could explore multi-scale multi-view spatial contexts with high efficiency. Extensive experiments on the BraTS 2018 and 2017 challenge datasets showed that the method performs favorably against state of the art in accuracy yet with greatly reduced computational complexity.

**Problem Definition**

The effective segmentation and classification of brain tumor can prevent the people from mortality. But the process can be difficult to appropriately separate and classify complicated tumor features. Numerous systems are introduced to alleviate the challenges while processing the performance of brain tumor segmentation and classification. The features and challenges of the existing models are shown in Table 1. 3D-UNet [1] permits early identification of brain tumors and makes accurate and exact diagnoses. But it may give erroneous both favorable or adverse results and it cannot to perform quickly, when it processed using more data. Ensemble model [2] improves patients' knowledge and participation and contributes to the development of personalized medicine techniques. But it could be laborious, thereby postponing choices regarding treatment and has major drawbacks in locality lacks. VGG and GoogleNet [3] generate useful data for medical research and developments and it can effectively tackle the issues during the process of segmentation. However, this model requires skilled personnel to ensure accurate execution and it is not suitable in discriminating the task of segmenting the affected area of brain. UNet-based encoder decoder [4] improves medical expenses by simplifying methods for treatment and it is capable of evaluating all sections of the cerebrum. But it could be restricted by the standard of the imaging methods and technologies used and couldn’t renovate outburst mistakes without interspersed. SVM [5] helps to enhance patients' chances of survival and requires less data amount to complete the entire procedure. But managing different and conflicting tumor data might be challenging and this model is very challenging for learning needs more cost. AlexNet and Google network [6] helps surgeons navigate through brain tumor surgery and it can easily and effectively forecast the targeted data. But there are no established processes or recommendations in some circumstances and it can provide successful presentation through only the usage of more GPU. Adaptive-ANFIS [7] enables tracking of tumor growth and therapy efficacy and it requires less time and less cost and it effectively reduces the processing time and cost. But it creates ethical questions about patients' privacy and consent and the system is comparatively complicated and cannot fully use the tumor characteristics. HDC-Net [8] helps patients with brain tumors organize their treatments and it can accurately segment the low as well as high resolution images. But this model may demand a considerable financial expenditure and in several cases it may lead to the challenge of overfitting. As a consequence, we designed a novel brain tumor segmentation and classification model using the enhanced deep learning approaches.

**Table 1:** Features and challenges of the existing brain tumor segmentation and classification models

|  |  |  |  |
| --- | --- | --- | --- |
| **Author [citation]** | **Methodology** | **Features** | **Challenges** |
| Agrawal *et al.* [1] | 3D-UNet | * It permits early identification of brain tumours. * It makes accurate and exact diagnoses. | * It may give erroneous either favourable or adverse results. * It cannot to perform quickly, when it processed using more data. |
| Tandel *et al.* [2] | Ensemble model | * It improves patients' knowledge and participation. * It contributes to the development of personalised medicine techniques. | * It could be laborious, thereby postponing choices regarding treatment. * It has major drawbacks in locality lacks. |
| Dang *et al.* [3] | VGG and GoogleNet | * It generates useful data for medical research and developments. * It can effectively tackle the issues during the process of segmentation. | * This model requires skilled personnel to ensure accurate execution. * It is not suitable in discriminating the task of segmenting the affected area of brain. |
| Kordnoori *et al.* [4] | UNet-based encoder decoder | * It improves medical expenses by simplifying methods for treatment. * It is capable of evaluating all sections of the cerebrum. | * It could be restricted by the standard of the imaging methods and technologies used. * It couldn’t renovate outburst mistakes without interspersed. |
| Sharif *et al.* [5] | SVM | * It helps to enhance patients' chances of survival. * It requires less data amount to complete the entire procedure. | * Managing different and conflicting tumour data might be challenging. * This model is very challenging for learning needs more cost. |
| Amin *et al.* [6] | AlexNet and Google network | * It helps surgeons navigate through brain tumour surgery. * This model can easily and effectively forecast the targeted data. | * There are no established processes or recommendations in some circumstances. * It can provide successful presentation through only the usage of more GPU. |
| Kalam *et al*. [7] | Adaptive-ANFIS | * It enables tracking of tumour growth and therapy efficacy. * This model requires less time and less cost and it effectively reduces the processing time and cost. | * It creates ethical questions about patients' privacy and consent. * The system is comparatively complicated and cannot fully use the tumour characteristics. |
| Luo *et al.* [8] | HDC-Net | * It helps patients with brain tumours organise their treatments. * It can accurately segment the low as well as high resolution images. | * This model may demand a considerable financial expenditure. * In several cases it may lead to the challenge of overfitting. |

**Research Objectives**

The objectives function of the proposed research methodology is given as follows.

* To design an effective hybrid and ensemble learning model for the early detection of abnormal growth in the brain tissue.
* To develop an accurate segmentation of the exact region of interest using a modified region growing method and a deep learning approach.
* To optimize the number of hidden neurons and feature selection to enhance the classification accuracy.
* To classify the severity level of MRI brain tumour using super learner classifier with enhanced feature extraction method.
* To collect the information from MRI for making the choice of treatment strategy by considering the data with the medical experts of the medical analysis system.

**Future Scopes**

The future scope of the proposed research methodology is given as follows.

* The developed model becomes more complicated in processing with real case data. Therefore, further examinations will be conducted to tackle this issue.
* Investigations will be looking at the enhanced application to produce extremely accurate and precise brain tumour identification technologies to better understanding its mechanism.
* The development will be expanded in the future to reduce overfitting and the disappearing gradient problem by developing efficient optimization approach.
* In future, the developed model will provide superior performance when considering the cost, uniqueness, specialty and the memory usage.
* The designed model is not suitable to provide effective segmentation due to image noise, so we will introduce pre-processing technique in future.

**Research Gaps**

The research gap of the proposed research methodology is given as follows.

* Developing more accurate and efficient automated methods for segmenting brain tumours is a key challenge. This involves finding ways to accurately outline the tumour boundaries in medical images.
* Integrating multiple imaging modalities, such as MRI, CT, and PET scans, is an ongoing complexity. Research is needed to explore how to effectively combine information from different imaging techniques for better tumour segmentation and classification.
* Detecting small tumours or tumour regions within a larger image is a significant issue. Finding ways to identify and accurately segment these smaller tumour areas is crucial for early detection and treatment planning.
* Dealing with uncertainty in brain tumour segmentation and classification is an active area of research. Developing methods to quantify and handle uncertainty can improve the reliability and confidence of the segmentation and classification results.
* Studying the growth and progression of brain tumours over time requires longitudinal analysis. Research is needed to develop algorithms that can track and analyze changes in tumour size, shape, and characteristics over multiple scans.

**Research Methodology**

A brain tumor is a mass of tissue that is structured by a gradual addition of anomalous cells and it is one of the most death defying diseases nowadays. The tumor contains a cluster of abnormal cells grouped around the inner portion of human brain. It affects the brain by squeezing/ damaging healthy tissues. It also amplifies intra cranial pressure and as a result tumor cells growth increases rapidly which may lead to death. Early detection and diagnosis of a brain tumor enhance the medical options and the patient’s chance of recovery. It is important to classify brain tumors from the magnetic resonance imaging (MRI) for treatment and MRI is used to detect and diagnose brain tumors. However, the manual identification of brain tumors from a large number of MRI images in clinical practice solely depends on the time and experience of medical professionals. Presently, computer aided expert systems are booming to facilitate medical diagnosis and treatment recommendations. Numerous machine learning and deep learning based frameworks are employed for brain tumor detection. As a result, we designed a novel brain tumor segmentation and classification model using the enhanced deep learning approaches. Initially the needed images are garnered through the online websites. Then, the collected images will be forwarded to the Trans-Unet with Modified Region Growing (TUNet-MRG)-based hybrid segmentation process. Further, the texture feature, morphological features and optimal features are extracted from the segmented images. The texture features comprises Gray-Level Co-Occurrence Matrix (GLCM) and Local Weighting Pattern (LWP), and the optimal features are selected using the Improvised Energy valley optimizer (IEVO) [26]. Then, the extracted features will be used for brain tumor classification process done by Adaptive Deep Super learner Classification (A-DSL) model, where the parameters will be tuned by the Improvised Energy valley optimizer (IEVO) [26] to enhance the effectiveness of the classification process. The developed A-DSL model provided that the tumor is glioma, maningioma or pituitary tumor. The effectiveness and the performance of the developed model are compared with existing model and Fig. 1 explains the pictorial view of the proposed brain tumor segmentation and classification model.

Final classified outcome (glioma, maningioma or pituitary tumor)

Input images

Segmentation done by TUNet-MRG

Developed IEVO

A-DSL-based classification process

Segmented images

Feature extraction

Texture feature (GLCM, LWP)

Morphological feature

Optimal features

Developed IEVO

**Figure 1:** Diagrammatic representation of proposed brain tumor segmentation and classification model

**Expected Outcome**

The proposed brain tumor segmentation and classification model was evaluated in Python and the performance analysis is carried out. Here, Type I measures are positive measures like Accuracy, Sensitivity, Specificity, Precision, Negative Predictive Value (NPV), F1Score and Mathews correlation coefficient (MCC), and Type II measures are negative measures like False positive rate (FPR), False negative rate (FNR), and False Discovery Rate (FDR).

**References**

1. Pranjal Agrawal, Nitish Katal and Nishtha Hooda, "Segmentation and classification of brain tumor using 3D-UNet deep neural networks," International Journal of Cognitive Computing in Engineering, Vol. 3, Pp. 199-210, June 2022.
2. Gopal S. Tandel, Ashish Tiwari and O.G. Kakde, "Performance enhancement of MRI-based brain tumor classification using suitable segmentation method and deep learning-based ensemble algorithm," Biomedical Signal Processing and Control, Vol. 78, No. 104018, September 2022.
3. Khiet Dang, Toi Vo, Lua Ngo and Huong Ha, "A deep learning framework integrating MRI image preprocessing methods for brain tumor segmentation and classification," IBRO Neuroscience Reports, Vol. 13, Pp. 523-532, December 2022.
4. Shirin Kordnoori, Maliheh Sabeti, Mohammad Hossein Shakoor and Ehsan Moradi, "Deep multi-task learning structure for segmentation and classification of supratentorial brain tumors in MR images," Interdisciplinary Neurosurgery, Vol. 36, No. 101931, June 2024.
5. Muhammad Sharif, Uroosha Tanvir, Ehsan Ullah Munir, Muhammad Attique Khan and Mussarat Yasmin, "Brain tumor segmentation and classification by improved binomial thresholding and multi-features selection," Journal of Ambient Intelligence and Humanized Computing, 2018.
6. Javeria Amin, Muhammad Sharif, Mussarat Yasmin, Tanzila Saba, Muhammad Almas Anjum and Steven Lawrence Fernandes, "A New Approach for Brain Tumor Segmentation and Classification Based on Score Level Fusion Using Transfer Learning," Journal of Medical Systems, Vol. 43, No. 326, 2019.
7. Rehna Kalam, Ciza Thomas and M. Abdul Rahiman, "Brain tumor detection in MRI images using Adaptive-ANFIS classifier with segmentation of tumor and edema," Soft Computing, Vol. 27, pp. 2279–2297, 2023.
8. Z. Luo, Z. Jia, Z. Yuan and J. Peng, "HDC-Net: Hierarchical Decoupled Convolution Network for Brain Tumor Segmentation," IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 3, pp. 737-745, March 2021.
9. P. Mohamed Shakeel, T. E. E. Tobely, H. Al-Feel, G. Manogaran and S. Baskar, "Neural Network Based Brain Tumor Detection Using Wireless Infrared Imaging Sensor", IEEE Access, vol. 7, pp. 5577-5588, 2019.
10. Shan Shen, W. Sandham, M. Granat and A. Sterr, "MRI fuzzy segmentation of brain tissue using neighborhood attraction with neural-network optimization", IEEE Transactions on Information Technology in Biomedicine, vol. 9, pp. 459-467, Sept. 2005.
11. A. Islam, S. M. S. Reza and K. M. Iftekharuddin, "Multifractal Texture Estimation for Detection and Segmentation of Brain Tumors", IEEE Transactions on Biomedical Engineering, vol. 60, pp. 3204-3215, Nov. 2013.
12. C. Ma, G. Luo and K. Wang, "Concatenated and Connected Random Forests With Multiscale Patch Driven Active Contour Model for Automated Brain Tumor Segmentation of MR Images", IEEE Transactions on Medical Imaging, vol. 37, no. 8, pp. 1943-1954, Aug. 2018.
13. J. J. Corso, E. Sharon, S. Dube, S. El-Saden, U. Sinha and A. Yuille, "Efficient Multilevel Brain Tumor Segmentation With Integrated Bayesian Model Classification", IEEE Transactions on Medical Imaging, vol. 27, pp. 629-640, May 2008.
14. Y. Ding et al., "MVFusFra: A Multi-View Dynamic Fusion Framework for Multimodal Brain Tumor Segmentation", IEEE Journal of Biomedical and Health Informatics, vol. 26, pp. 1570-1581, April 2022.
15. T. Zhou, S. Canu, P. Vera and S. Ruan, "Latent Correlation Representation Learning for Brain Tumor Segmentation With Missing MRI Modalities", IEEE Transactions on Image Processing, vol. 30, pp. 4263-4274, 2021.
16. A. Gumaei, M. M. Hassan, M. R. Hassan, A. Alelaiwi and G. Fortino, "A Hybrid Feature Extraction Method With Regularized Extreme Learning Machine for Brain Tumor Classification", IEEE Access, vol. 7, pp. 36266-36273, 2019.
17. M. V. S. Ramprasad, M. Z. U. Rahman and M. D. Bayleyegn, "A Deep Probabilistic Sensing and Learning Model for Brain Tumor Classification With Fusion-Net and HFCMIK Segmentation", IEEE Open Journal of Engineering in Medicine and Biology, vol. 3, pp. 178-188, 2022.
18. Pravin Shivaji Bidkar, Ram Kumar, Abhijyoti Ghosh, "SegNet and Salp Water Optimization-driven Deep Belief Network for Segmentation and Classification of Brain Tumor", Elsevier Gene Expression Patterns, Vol. 45, no.119248, September 2022.
19. Aparajita Nanda, Ram Chandra Barik , Sambit Bakshi ,"SSO-RBNN driven brain tumor classification with Saliency-K-means segmentation technique", Elsevier Biomedical Signal Processing and Control,Vol. 81, no.104356, March 2023.
20. R. Sindhiya Devi, B. Perumal, M. Pallikonda Rajasekaran,"A hybrid deep learning based brain tumor classification and segmentation by stationary wavelet packet transform and adaptive kernel fuzzy c means clustering", Elsevier Advances in Engineering Software, Vol. 170, no.103146, August 2022.
21. Jainy Sachdeva, Vinod Kumar, Indra Gupta, Niranjan Khandelwal and Chirag Kamal Ahuja ,"Segmentation, Feature Extraction, and Multiclass Brain Tumor Classification", Springer Journal of Digital Imaging, vol. 26, pp.1141–1150, 2013.
22. P. Ramya, M. S. Thanabal and C. Dharmaraja ,"Brain tumor segmentation using cluster ensemble and deep super learner for classification of MRI", Springer Journal of Ambient Intelligence and Humanized Computing, vol. 12, pp.9939–9952, 2021.
23. P. G. Rajan and C. Sundar, "Brain Tumor Detection and Segmentation by Intensity Adjustment", Springer Journal of Medical Systems, vol. 43, 2019.
24. R. Thillaikkarasi and S. Saravanan ,"An Enhancement of Deep Learning Algorithm for Brain Tumor Segmentation Using Kernel Based CNN with M-SVM", Springer Journal of Medical Systems, vol. 43, 2019.
25. S. Ramesh, S. Sasikala and Nirmala Paramanandham, "Segmentation and classification of brain tumors using modified median noise filter and deep learning approaches", Springer Multimedia Tools and Applications, vol. 80, pp.11789–11813, 2021.
26. Mahdi Azizi, Uwe Aickelin, Hadi A. Khorshidi and Milad Baghalzadeh Shishehgarkhaneh, "Energy valley optimizer: a novel metaheuristic algorithm for global and engineering optimization," Scientific Reports, Vol. 13, No. 226, 2023.