Brain Tumor Detection Techniques: A Review

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Abstract

According to the International Agency for Research on Cancer (IARC), brain tumors have a high mortality rate of 76%. Early detection is critical to providing timely treatment and preventing fatal outcomes. With advancements in technology, it has become possible to automatically identify tumors from images, such as Magnetic Resonance Imaging (MRI) and computed tomography (CT) scans, using computer-aided design. Machine learning and deep learning techniques, particularly Convolutional Neural Networks (CNNs), have become increasingly important in the medical field due to their ability to process and classify large, complex image datasets. This review article aims to provide a comprehensive overview of the techniques, including preprocessing, machine learning, and deep learning, that have been used over the past 15 years for brain tumor detection. Additionally, it offers a detailed comparative analysis of these approaches.

Keywords

Brain Tumor, Machine Learning, Deep Learning, MRI

1. Introduction

The brain, housing over 100 billion nerve cells, is a colossal and intricate regulator of whole neurological system within the human body, stemming from the core of the nervous system. Consequently, any deviation in brain function can pose significant health risks [1]. Among the most severe are brain tumors, which come in primary and secondary forms, marked by the uncontrolled and abnormal multiplication of brain cells. While initial tumors develop within the brain tissue itself, secondary tumors are transported via circulation from other body regions to the brain tissue. Gliomas and meningiomas are among the primary tumors that pose significant mortality risks if not detected early. Gliomas, in particular, is a common tumor in humans. The WHO classifies them into four categories. Meningiomas and other less aggressive tumors fall under grade 1 and grade 2 [2], while more malignant tumors like gliomas are classified as grade 3 and grade 4. In clinical practice, the incidence rates of meningiomas, pituitary tumors, and gliomas are approximately 15%, 15%, and 45%, respectively. Treatment strategies for brain tumors vary depending on factors such as tumor location, size, and type.

Currently, surgery stands as the primary treatment for BTs, as it poses no negative effects on the brain. Various medical imaging techniques such as CT, PET, and MRI are employed to observe conditions within the body. Among these, MRI is considered the most advantageous owing to its non-invasive nature and ability to provide detailed information about the type, size, shape, and location of brain tumors in both 2D and 3D formats. However, manually examining MRI images can be labor-intensive, chaotic, and prone to errors, especially with the influx of patients. To address this challenge, the development of an automatic computer-aided diagnosis (CAD) system is essential [3]. Such a system would alleviate the burden associated with classifying and diagnosing brain MRIs, offering a valuable tool for physicians and radiologists. Numerous efforts have been made to establish a dependable and highly accurate method for automatically classifying brain tumors.

1.1. Brain Tumour Detection Pipeline

In recent times, there has been a growing interest in automating the identification of brain tumors, with several methods being published. This trend has been facilitated by advancements in image processing and ML techniques. MRI is particularly valuable in this regard, as it can provide detailed information about the location, size, and composition of human tissues and organs without significant exposure to ionizing radiation. The resulting MRI images are exceptionally clear and precise, aiding in the accurate diagnosis of lesions and the planning of surgical procedures. Various methods, including chest X-ray scanning and three-dimensional multi-band imaging technologies, are employed for brain tumor MRI [4]. Unlike 2D imaging, 3D multiband MRI provides the precise coordinates of the lesion area, aiding clinicians in accurately pinpointing its location. Additionally, MRI imaging can capture multiple tissue architectures by leveraging the growth process, a feature that is often underutilized. As depicted in Figure 1, the conventional workflow for brain tumor classification (BTC) typically involves image capture, preprocessing, region of interest (ROI) segmentation, feature extraction and selection, dimensionality reduction, classification, and performance evaluation.

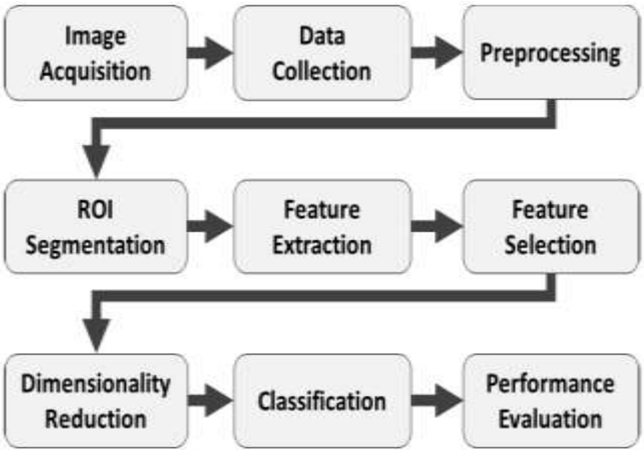

Figure 1: Basic workflow of the traditional BTC and analysis methods.

i. Pre-processing: Image pre-processing plays a crucial role in enhancing the performance of popular image systems, particularly in image segmentation, recognition, or detection tasks [5]. Techniques employed in image pre-processing can notably improve the performance of deep learning (DL) based algorithms. Researchers commonly utilize image enhancement and skull-stripping techniques during pre-processing. Skull stripping, for instance, helps eliminate extraneous information from learning activities by blocking out external signals. Image enhancement techniques are also essential, particularly for addressing issues related to low contrast in source images, which may otherwise negatively impact classifier performance. Moreover, since noise introduced during image acquisition can distort brain images, most systems employ filters prior to enhancement to mitigate these effects. Image enhancing techniques are also employed to recognize important features and for further enhancing the quality of picture [6].

ii. Image segmentation: Accurately segmenting the BTs is vital for improved disease detection, cure, monitoring, and clinical trials, as it enables to discover the tumor's location and size accurately. However, the characteristics of BTs pose significant challenges to accurate segmentation. Tumors can vary in size, shape, and location, making them difficult to distinguish from healthy brain tissue. Additionally, the intensity values of healthy tissue and tumors often overlap, lacking clear contrast, further complicating segmentation efforts. An extensive method to segment image in automated applications is region-based segmentation.

Region-based segmentation takes into account both the spatial proximity of pixels [7], such as Euclidean distance and region compactness, and their pixel values, including grey level variance and difference, to group them together. The effective area-based segmentation techniques for brain tumors combines region growth and clustering methods. Clustering-based segmentation, a successful region-based technique, divides an image into several disjointed groups, where pixels with high similarity are grouped into one region and those with low similarity are grouped into another during the segmentation process based on clustering.

iii. Feature Extraction: The feature extraction stage of this project is crucial for identifying features that effectively convey the characteristics of an image. Various intensity-based features are extracted at this stage, including LOG features, GLCM, PHOG, local intensity features, global intensity features, and modified CLBP descriptors [8]. GLCM texture, a common texture characteristic, is a primary method for determining the frequency of occurrence of pixels with intensity I and pixels with intensity j in a specific spatial connection pattern. This method takes into account the spatial arrangement of pixels in images. Intensity-based features, or statistics on the grey levels of the input images, can be derived from histograms.

In general, intensity characteristics can be categorized into local and global features. Global intensity-based features are derived from [9] the entire image, while local intensity-based features are obtained from specific local areas within the image. Although global intensity-based features characterize brain images on a global scale, they may overlook local image properties, potentially resulting in similar features for different images. To address this limitation, one approach involves dividing input images into distinct segments and extracting intensity information from each section [4]. Additionally, to overcome these challenges, local characteristics are also incorporated into the feature extraction process.

iv. Feature selection and dimensionality reduction: Current approaches to depicting tumor pathophysiology utilize only a few aspects, and no existing work incorporates all available features comprehensively. However, incorporating all heterogeneous data results in high-dimensional feature vectors, which can significantly reduce system accuracy [10]. To mitigate this, a reliable feature selection technique is necessary to reduce irrelevant information and create robust brain tumor descriptors of appropriate size. Dimensionality reduction techniques are commonly employed to achieve this, allowing more efficient algorithms to operate with fewer features. However, reducing features often results in a trade-off with accuracy.

PCA, Kernel Principal Component Analysis, and ICA are techniques which assists in dimensionality reduction, aiming to mitigate the curse of dimensionality, accelerate the learning process, enhance generalization capacity, and improve model interpretability. Common techniques to select features include GA, SBS, SFS, and PSO. By selecting relevant features, feature selection enhances efficacy of learning models. Skipping this step can lead to overly dimensional feature spaces and poor classifier performance [11]. While kernel-based techniques are less affected by high-dimensional input spaces, additional dimensionality reduction typically improves classification accuracy.

v. Classification: Indeed, classification techniques form the backbone of many segmentation algorithms proposed to date. This is largely due to their versatility in handling any selected feature vector, making them well-suited for multi-modal datasets. These algorithms typically operate on voxel-wise intensities and frequently incorporate local textures as input features. The fundamental concept involves using the feature vector of each voxel to classify it into its appropriate class individually. To train a classification model, which enables the labeling of new instances, classification requires access to training data [12].

1.2 Classification Algorithms for Brain Tumor Detection

Artificial intelligence (AI) plays a significant role in the diagnosis and detection of brain tumors, offering valuable support in the inherently challenging field of brain tumor surgery. Subsets of AI, such as machine learning (ML) and deep learning (DL), have revolutionized neuropathological techniques. Examples of popular machine learning techniques for finding brain tumours include SVMs, NNs, RF, and others. An explanation of these methods is given below:

i. Support Vector Machine (SVM): SVM which has great generalization capabilities, is used for categorization. The fundamental goal of an SVM is to locate the hyperplane with the greatest margin to the training samples. SVM is a common type of machine learning method based on statistical learning theory [13]. The goal of SVM is to linearly divide the data by mapping it onto a higher-dimensional feature space. The SVM method's benefit is the effective generalization of a categorization issue.

ii. Neural networks (NNs): Artificial neural networks (ANNs), sometimes known as neural networks (NNs), are statistical learning techniques that were influenced by the functioning of the human brain. NN is made up of a network of basic artificial neurons connected to one another. Adaptive weights that are fine-tuned throughout the learning process identify these linkages. Although NNs were frequently utilized for classification tasks, their use was gradually phased out in favour of more straightforward approaches like SVM because of their computational requirements. After the Deep Learning approach was introduced and was successful in a number of different worldwide picture and speech recognition challenges, their popularity began to rise once more [14].

iii. Random Forest (RF): A collection of decision trees called Random Forest (RF) is used to solve classification and regression issues. Overfitting is a common problem for decision trees. By combining various decision trees and their contributions to the final conclusion, RF is able to solve this problem more effectively. A decision tree (also known as a classification tree) is a straightforward method that can be visualized as a tree-like graph, with each node performing the classification task into a specified number of groups according to a predetermined criterion. The data is divided into more manageable portions via a hierarchical method. These criteria are estimated during learning based on the knowledge gained following the split. For a specific sample, the tree leaves indicate a probability distribution over the classes [15]. Combining the distribution of each tree in the forest yields the final class. A random selection of training samples or features may be used to train all trees.

iv. k-nearest neighbor (k-NN): The non-parametric k-nearest neighbour algorithm (k-NN) is a straightforward classifier. This algorithm is an example of a method for lazy learning. Regarding the structure of the statistical data, no assumptions are made. The training set's k nearest neighbours in the feature space are used to create the test sample label. Depending on the implementation, the Euclidean, Mahalanobis, or Minkowski distance is executed to compute distance, for example. When dealing with noisy or underrepresented data, the algorithm has issues. Another drawback is that since all training samples must be accessible during classification, there is a significant storage need for them [16].

2. Literature Review

J. Wang, et.al (2024) presented a new computer aided detection (CAD) technique known as RanMerFormer for classifying brain tumor [10]. A pre-trained vision transformer was deployed as the backbone model to classify tumor. A merging mechanism was deployed for eliminating the redundant tokens in vision transformer (ViT) to make the technique computational efficient. At last, a randomized vector functional-link (RVFL) was employed as the head for training swiftly. Two datasets were executed for computing the presented technique. The experimental results demonstrated that the presented technique was performed well in contrast to traditional methods and yielded 99% accuracy. Moreover, this technique was applicable in real-time scenarios.

S. Kalaiselvi, et.al (2024) presented a new machine learning (ML)-based technique for detecting brain tumor [16]. First of all, MRI database was employed for extracting Magnetic Resonance Imaging scans. The images were pre-processed using anisotropic filtering and AHE for eliminating noise and improving image contrast. After that, the EFO-OTSU was employed to segment images. PCA and DWT methods were utilized to extract features. The Boosted Multi-Gradient Support Vector Machine (BMG-SVM) was presented for extracting features which split images into the tumor and non-tumor sections. The Black Monkey Optimization (BMO) algorithm was applied for classifying tumors. The simulations exhibited the superiority of presented technique over baselines.

A. M. D. Simo, et.al (2023) suggested a sequential model on the basis of deep learning (DL) in which fully convolutional neural network (CNN) algorithm was utilized [7]. This model was executed in 2 phases such as to differentiate non-neoplastic brain from neoplastic one and classify the kind of tumor. The Brain Tumor MRI Dataset was utilized for training two algorithms. An analysis was conducted on 4 optimizers, namely Adam, Nesterov momentum (NM), root-mean-square (RMS) propagation, and adaptive gradient to classify brain tumor. The initial method was performed well to distinguish tumor from non-tumorous brain at an accuracy of 100% to train the model and 98% to validate model. NM was proved effective to classify 3 tumor types at an accuracy of 100% and 92 % to train and validate the model respectively.

Z. Atha, et.al (2023) introduced a new semi-supervised Deep Learning (SSDL)-based method called Semi-Supervised Brain Tumor Classification Network (SSBTCNet) to classify 3 kinds of brain tumors and non-tumor brain [8]. This method deployed the potential of unsupervised AutoEncoder (AE) with supervised algorithm to train an AE which learned the hidden descriptors and a multi-layer perceptron (MLP)-based method concurrently. The introduced method was employed to tune the way to learn the concealed descriptors when the brain tumor was categorized from Magnetic Resonance Imaging scans. The fuzzy logic (FL)-based method had created the improved instances for training and testing this method. The simulation results depicted that the introduced method was performed well as compared to traditional methods.

C. Tang, et.al (2023) developed Spinal Convolution Attention Network (SpCaNet) which diagnosed and classified brain tumor relied on pathological features [22]. This model was planned on the basis of a Positional Attention (PA) convolution block, Relative self-attention transformer block, and Intermittent fully connected (IFC) layer. This lightweight method was worked efficiently to recognize brain tumors and mitigate the amount of metrics by more than 3 times. Furthermore, the gradient awareness minimization (GAM) algorithm was deployed for tackling the issue related to inadequate generalized potential of existing technique and training the developed model. The developed model outperformed the traditional methods. The simulations indicated that the developed model offered an accuracy of 99.28% in categorizing brain tumors.

R. Vankdothu, et.al (2022) projected a new automated method which diagnosed and classified brain tumor [9]. The adaptive filter was utilized to pre-process images which eliminated the noise available in MRI image. The IKMC model was helped in segmenting images and GLCM was employed for extracting features. Additionally, deep learning (DL) algorithm was exploited for classifying kinds of images into gliomas, meningiomas, non-tumors, and pituitary tumors and RCNN was used to classify images. The Kaggle data set was generated using 394 testing and 2870 training Magnetic Resonance Imaging pictures. The results exhibited that the projected method had offered an accuracy of 95.17% while categorizing BTs.

S. Montaha, et.al (2022) established a hybrid algorithm known as TimeDistributed-CNN-LSTM (TD- CNN-LSTM) in which 3D Convolutional Neural Network (CNN) was integrated with Long Short-Term Memory (LSTM) and wrapping of every layer was done with a TimeDistributed function [15]. The optimal configuration analysis was conducted for layer design and hyper-parameters. Afterward, MRI sequences were considered to train 3D-CNN for comparing efficiency. The next focus was on pre-processing datasets which ensured superior performance. The experimental results revealed that the established algorithm was performed more effectively in contrast to other approaches and yielded 98.90% accuracy. Furthermore, the generalized ability of this algorithm was found higher.

M. Assam, et.al (2021) formulated an innovative technique for differentiating Magnetic Resonance Imaging brain pictures into cancerous and non-cancerous based on individual and hybrid classifiers [23]. The MF was deployed to pre-process images. DWT algorithm was helped in extracting the features, and Color Moments were employed for diminishing the features to an optimal set of 9 features so as the complexity and memory usage was lessened. The supervised methods: Feed Forward-ANN (FFANN), Random Subspace with Random Forest (RSRF) and Random Subspace with Bayesian Network (RSBN) were fed with these features and higher accuracy was attained to classify images into infected and healthy. The accuracy of initial method was 95.83%, subsequent was 97.14% and last one was 95.71%.

A. S. M. Shafi, et.al (2021) intended an ensemble learning (EL) technique for classifying BTs into glioma, meningioma, pituitary adenoma multiple sclerosis from MRI of patients [25]. This technique aimed to pre-process pictures to extract ROI of both tumor and lesion, and Collewet normalization (CN), and Lloyd-max quantization (LMQ) were employed. The support vector machine (SVM) algorithm and prediction model with majority voting were employed for classifying brain tumor. The intended technique provided the weighted sensitivity of 97.5%, specificity of 98.838%, precision of 98.011%, and accuracy of 98.719%. The experiments demonstrated that the intended technique attained an accuracy up to 97.957% while training the data and 97.744% testing it.

2.1 Comparison of existing approaches

Author/ Year	Technique Used	Dataset	Parameters	Results	Limitations
J. Wang, et.al (2024)	RanMerFormer	Kaggle	Accuracy	The experimental results demonstrated that the presented technique was performed well in contrast to traditional methods and yielded 99% accuracy.	The meningioma tumor was not classified accurately using this technique.
S. Kalaiselvi, et.al (2024)	A new machine learning (ML)-based technique	BraTS2018 dataset	Accuracy	The simulations exhibited the superiority of presented technique over baselines.	This model was not localized the tumorous area precisely.
A. M. D. Simo, et.al (2023)	A sequential model on the basis of deep learning (DL)	Brain Tumor MRI Dataset	Accuracy	The initial method was performed well to distinguish tumor from non-tumorous brain at an accuracy around 100% while training and 98% to validate model.	This model was unsuitable on time series data,
Z. Atha, et.al (2023)	SSBTCNet	BRATS dataset	Accuracy	The simulation results depicted that the introduced method was performed well as compared to traditional methods.	The labelled data was not available in this work.
C. Tang, et.al (2023)	SpCaNet	Figshare dataset	Accuracy	The developed model outperformed the traditional methods. The simulations indicated that the developed model offered an accuracy up to 99.28% to	This model was not apposite to greater and varied datasets.

				classify brain tumors.	
R. Vankdothu, et.al (2022)	A new automated method	Kaggle dataset	Accuracy	The results exhibited that the projected method had offered an accuracy of 95.17% to classify brain tumor from MRI images.	The issue of data imbalance was occurred.
S. Montaha, et.al (2022)	TD-CNN-LSTM	Figshare dataset	Accuracy	The experimental results revealed that the established algorithm was performed more effectively in contrast to other approaches and yielded 98.90% accuracy.	It was not possible to reutilize this method for detect the modest number of images.
M. Assam, et.al (2021)	A novel method	Kaggle	Accuracy, complexity and memory usage	The accuracy of initial method was 95.83%, subsequent was 97.14% and last one was 95.71%	The images contained in this dataset were covered only some subjects.
A. S. M. Shafi, et.al (2021)	An ensemble learning (EL) technique	BRATS dataset	Sensitivity, specificity, precision and accuracy	The intended technique provided the weighted sensitivity of 97.5%, specificity of 98.838%, precision of 98.011%, and accuracy of 98.719%.	The restricted size dataset was utilized.

Conclusion

Identifying, extracting, segmenting, and classifying tumors pose significant challenges for physicians and radiologists. Consequently, automating these processes has become a major focus of research in medical imaging. While several detection techniques have demonstrated strong performance across various tumor datasets, a second opinion remains essential for accurate diagnosis, regardless of the reported accuracy of automated tumor detection systems. The contrast in MRI images plays a crucial role, as it greatly impacts the detection of brain tumors. This manuscript discusses freely available data sources for experimentation and offers guidance on their optimal use with various techniques, including traditional methods, hybrid approaches, deep learning, and autoencoders. The goal of tumor research in medical image processing is to accurately locate and highlight the tumor region to facilitate medical procedures. Despite significant advancements in imaging modalities and techniques, numerous challenges persist in detection methods. One major challenge is the computational complexity involved in managing multiple MR image modalities simultaneously. Future research could explore improving parameter tuning and addressing motion artifacts during MR image scans. Additionally, specific difficulties arise with each imaging modality, data source, and pathological setting. Future efforts should focus on overcoming these challenges and making the processes more cost-effective, including seeking expert opinions for more accurate diagnoses.

References

[1] Md K. Islam, Md S. Ali, Md A. Hossain, "Brain tumor detection in MR image using superpixels, principal component analysis and template-based K-means clustering algorithm", 2021, Machine Learning with Applications

[2] G. Manogaran, P. Md Shakeel, A. S. Hassanein, P. M. Kumar, G. C. Babu, "Machine Learning Approach-Based Gamma Distribution for Brain Tumor Detection and Data Sample Imbalance Analysis", 2019, IEEE Access

[3] Md Sharif, J. Amin, S. C. Satapathy, "An integrated design of particle swarm optimization (PSO) with fusion of features for detection of brain tumor", 2019, Pattern Recognition Letters

[4] D. Rammurthy, P. K. Mahesh, "Whale Harris hawks optimization based deep learning classifier for brain tumor detection using MRI images", 2020, Journal of King Saud University - Computer and Information Sciences Available online

[5] Md. Ahasan Kabir, "Early-Stage Brain Tumor Detection on MRI Image Using a Hybrid Technique", 2020, IEEE Region 10 Symposium (TENSYMP)

[6] Ming Li, LishanKuang, Shuhua Xu, Zhanguo Sha, "Brain Tumor Detection Based on Multimodal Information Fusion and Convolutional Neural Network", 2019, IEEE Access

[7] A. Hossain et al., "A YOLOv3 Deep Neural Network Model to Detect Brain Tumor in Portable Electromagnetic Imaging System," in IEEE Access, vol. 9, pp. 82647-82660, 2021

[8] D. Rammurthy and P. K. Mahesh, "Whale Harris Hawks optimization based deep learning classifier for brain tumor detection using MRI images", Journal of King Saud University - Computer and Information Sciences, vol. 51, no. 12, pp. 5859-5870, 15 August 2020

[9] N. Kesav and M. G. Jibukumar, "Efficient and low complex architecture for detection and classification of Brain Tumor using RCNN with Two Channel CNN", Journal of King Saud University - Computer and Information Sciences, vol. 31, no. 5, pp. 1747-1756, 21 May 2021

[10] Md. S. I. Khan, A. Rahman and I. Dehzangi, "Accurate brain tumor detection using deep convolutional neural network", Computational and Structural Biotechnology Journal, vol. 20, no. 1, pp. 4733-4745, 27 August, 2022

[11] C. Han et al., "Combining Noise-to-Image and Image-to-Image GANs: Brain MR Image Augmentation for Tumor Detection," in IEEE Access, vol. 7, pp. 156966-156977, 2019

[12] E. Dandıl and S. Karaca, "Detection of pseudo brain tumors via stacked LSTM neural networks using MR spectroscopy signals", Biocybernetics and Biomedical Engineering, vol. 41, no. 5, pp. 173-195, 30 December 2020

[13] F. Özyurt, E. Sert and D. Avcı, "An expert system for brain tumor detection: Fuzzy C-means with super resolution and convolutional neural network with extreme learning machine", Medical Hypotheses, vol. 22, no. 6, pp. 1754-1764, 15 October 2019

[14] G. Raut, A. Raut, J. Bhagade, J. Bhagade and S. Gavhane, "Deep Learning Approach for Brain Tumor Detection and Segmentation," 2020 International Conference on Convergence to Digital World - Quo Vadis (ICCDW), Mumbai, India, 2020, pp. 1-5

[15] D. O. Patil and S. T. Hamde, "Monogenic Wavelet Phase Encoded Descriptors for Brain Tumor Image Detection," 2020 Third International Conference on Multimedia Processing, Communication & Information Technology (MPCIT), Shivamogga, India, 2020, pp. 40-44

[16] O. Turk, D. Ozhan and M. Yilmaz, "Automatic detection of brain tumors with the aid of ensemble deep learning architectures and class activation map indicators by employing magnetic resonance images", Zeitschrift für Medizinische Physik, vol. 15, no. 2, pp. 716-728, 31 December 2022

[17] J. Wang, S.-Y. Lu and Y.-D. Zhang, “RanMerFormer: Randomized vision transformer with token merging for brain tumor classification”, Neurocomputing, vol. 573, pp. 21-29, 5 January 2024

[18] S. Kalaiselvi and G. Thailambal, “Brain tumor diagnosis from MR images using boosted multi-gradient support vector machine classifier”, Measurement: Sensors, vol. 13, pp. 52-60, 28 February 2024

[19] A. M. D. Simo, A. T. Kouanou and B. M. Lonla, “Introducing a deep learning method for brain tumor classification using MRI data towards better performance”, Informatics in Medicine Unlocked, vol. 44, pp. 657-663, 9 December 2023

[20] Z. Atha and J. Chaki, “SSBTCNet: Semi-Supervised Brain Tumor Classification Network”, in IEEE Access, vol. 11, pp. 141485-141499, 2023

[21] C. Tang, B. Li and Y.-D. Zhang, “GAM-SpCaNet: Gradient awareness minimization-based spinal convolution attention network for brain tumor classification”, Journal of King Saud University - Computer and Information Sciences, vol. 32, no. 2, pp. 560-575, 10 January 2023

[22] R. Vankdothu and M. A. Hameed, “Brain tumor MRI images identification and classification based on the recurrent convolutional neural network”, Measurement: Sensors, vol. 24, pp. 963-971, 23 August 2022

[23] S. Montaha, S. Azam, A. K. M. R. H. Rafid, M. Z. Hasan, A. Karim and A. Islam, “TimeDistributed-CNN-LSTM: A Hybrid Approach Combining CNN and LSTM to Classify Brain Tumor on 3D MRI Scans Performing Ablation Study”, in IEEE Access, vol. 10, pp. 60039-60059, 2022

[24] M. Assam, H. Kanwal, U. Farooq, S. K. Shah, A. Mehmood and G. S. Choi, “An Efficient Classification of MRI Brain Images”, in IEEE Access, vol. 9, pp. 33313-33322, 2021

[25] A. S. M. Shafi, M. B. Rahman and H. M. E. Kays, “Classification of brain tumors and auto-immune disease using ensemble learning”, Informatics in Medicine Unlocked, vol. 24, pp. 129-137, 26 May 2021