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BRAIN TUMOR DETECTION FROM MRI IMAGES USING MACHINE AND DEEP LEARNING TECHNIQUES: A REVIEW

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ABSTRACT

Detection of brain tumor is a difficult task that entails identifying malignant tissues from different and diffuse brain medical imaging. This is a crucial stage in computer-aided diagnostic (CAD) systems, as cancerous areas must be identified for viewing and analysis. Image segmentation and classification of brain tumors have to be automated. The principle of this work is to provide an overview of the Magnetic Resonance Imaging (MRI)-based approach for brain tumors detection. Deep learning-based techniques, which automatically create multilevel and separated from unprocessed data, have made significant progress in brain tumor detection recently. These techniques outperformed traditional machine learning techniques that employed handmade characteristics to explain the distinctions between sick and healthy tissues. We provide a complete summary of modern advances in deep learning-based approaches for brain tumor detection (BTD) from MRI in this study. Furthermore, we address the most typical issues and provide potential remedies.

KEYWORDS: Brain tumor detection, deep learning, classification segmentation, deep learning.

1. INTRODUCTION

Brain tumor is an uncontrolled proliferation of abnormal cells in the body. A brain tumor is a lump in the brain that is made up of a cluster of these aberrant cells and these tissue has no physiological function inside the brain that characterizes a brain tumor is a major health risk for adults since it can cause severe impairment of organ function and even death. These tumors come in wide variety of sizes, texture, and locations. Tumors not only increase the size of and pressure in the brain but also cause swelling, all of which cause abnormal neurological symptoms. According to the National Brain Tumor Foundation (NBTF), the number of people in develop countries who die as a result of brain tumors has increased by 300%.

About 130 different forms of tumors can develop in the brain and CNS, ranging from benign to malignant and from extremely rare to common occurrences.[1] These malignancies can either form in the brain (primary brain tumor) or spread there from elsewhere in the body (secondary or metastatic brain tumors). Primary brain tumor refers to tumors that originate within the brain itself. These tumors are formed from the brain cells or can be encapsulated within the nerve cells surrounding the brain. Primary brain tumors can exhibit a range of characteristics, including both bening and malignant forms.[2] Secondary brain tumors, also known as metastatic brain tumors, are the most common type of malignant brain tumor. It is important to note that tumors do not typically spread from one area of the body to another, secondary brain tumors are invariably cancerous and pose a serious treat to health.[3] Tumors are classified as primary, secondary, or metastatic depending on their origin. The term "type of tumor" refers to cancer that originates in the brain. Brain cells, meninges, nerve cells, and glands can all produce them. The metastatic tumor can spread cancer cells to different parts of the body. Glioma and meningioma are the most prevalent kinds of malignant tumors. Adult gliomas are the most common malignant tumor. It begins in glial cells and spreads throughout the body.[4] Gliomas affect children aged 5 to 10 years, as well as adults aged 40 to 65 years, according to the World Health Organization (WHO).[5] Furthermore, these tumors report for 81% of the total malignant brain tumors and 45% of the total primary brain tumors.[6] WHO has classified and rated over 120 tumor types (World Health Organization). According to the WHO, brain tumors are graded from grade I through grade IV. The tumor's classification and grading system aid in predicting the tumor's nature and stage, which may aid in diagnosis. Complex cell structure, diverse distribution of strength, tumor dynamic position, and tumor artifacts, for example, can all impact diagnosis. Heterogeneity in cancer cell proliferation provides significant hurdles in the development of cost-effective and efficient behavior strategies.

Positron emission tomography (PET), X-ray, and computed tomography (CT) are examples of biomedical

imaging modalities. MRI is a most important technique for brain construction study because it provides high-contrast images of soft muscles as well as great spatial resolution. The MRI image pre-diagnosis method involves frequent image sequences T1, T2, T1ce, and FLAIR. Fig. 1 shows the images of dissimilar sequences.

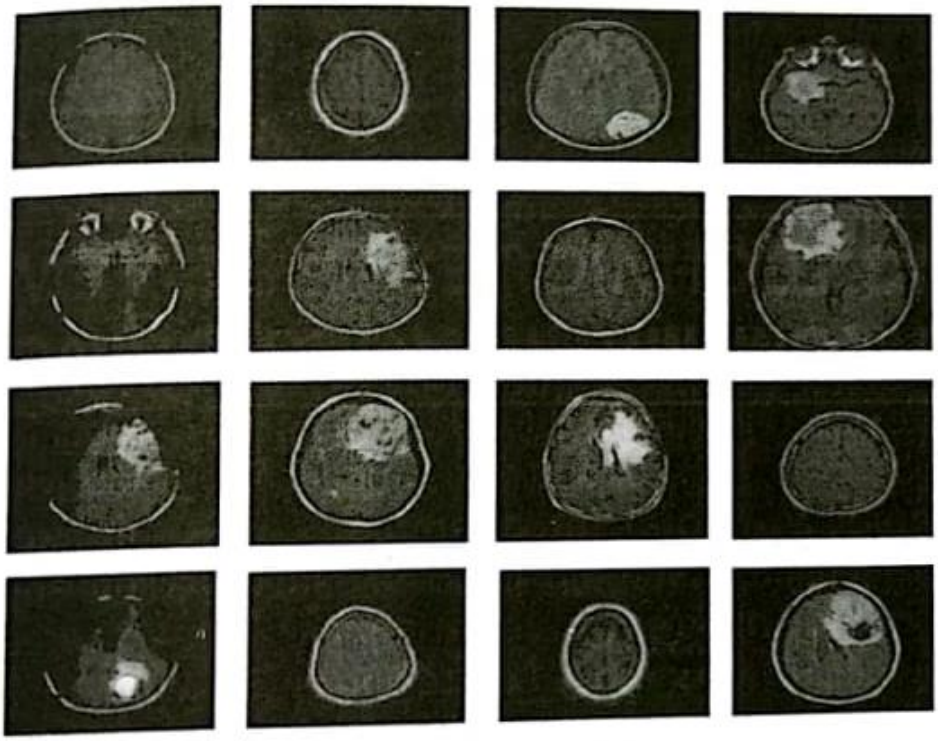

Fig. 1: Sequences of MRI images.

2. LITERATURE SURVEY

In the last two decades, several approaches for brain tumor detection have been planned to identify the position of tumors at a prior stage for a greater survival probability. The most important goal is to distinguish and emphasize the various aberrant brain images using the distinct feature set. Many researchers use a machine and deep learning approaches to detect brain tumors, as follows

When compared to further machine learning techniques, the KNN, or K nearest neighbor method, finds Euclidean distance the label-based, resulting in excellent accuracy. However, it falls short in terms of runtime performance. To accomplish classification, an ANN, or artificial neural network, employs numerous nodes and hidden layers, as well as weights. When comparing the desired output to the weights, the error factor is reduced.[9]

In[10], a novel SVM method was proposed that extracts flexible decision edges based on region processing. This method makes it simple to comprehend nonlinear data. When compared to fuzzy clustering, the final findings reveal a better output. The distinction between different types of cancers was studied using a probabilistic neural networks (PNNs) paired through least-squares features transformation (LSFT) in.[11] The model had achieved a level of accuracy of over 95%. For categorizing normal and Alzheimer's brains, orthogonal DWT paired with intensity histograms[12] achieved a high accuracy of around 100%.[13] proposed an adaptive neuro-fuzzy interface system (ANFIS) for brain tumors recognition using a neural network (NN) and a fuzzy filter. This was tested on 80 normal photos and 40 aberrant images. The auto seed selection technique showed promising accuracy of 81.7% in the experiment.[14] proposed SVM for dimensionality reduction, and this experimental resulted 98% accuracy with extremely selective features. This also emphasizes the significance of selecting the right features. The author of[15] addresses the use of unsupervised machine learning to cluster comparable MRI images. This work was based on detecting important classes by plotting similar pixel vectors. Some of the most widely studied unsupervised algorithms is fuzzy c-means algorithm, k-Means clustering algorithm, SOM (self-organized map), and PCNN algorithm.[16] describes advances in the classification phase of Brian tumors identification. The Feed-Forward neural network (FFNNs) with K-Nearest Neighbors (KNNs) classification methods is discussed by the author.

Concentrating on these categorization algorithms resulted from inaccuracy of 97 and 98%, respectively. It was also suggested that this technology be applied to a variety of MR pictures. In[17] the widespread approval of Deep Learning (DL) in this diligence is discussed. Deep Learning (DL) is used in a variety of fields, including breast cancer, tuberculosis, and brain tumors studies.

CNNs (Convolution Neural Networks) the deep learning techniques that have been developed for recognizing and classify brain tumors. When Deep Learning approach is backed up by additional techniques, their accuracy soars to new heights. In[18] they proposed a Deep Convolution Neural Network (DCNN)-based solution to tackle the problem of over-fitting. The author suggests max- out with drop-out layers and tests the method using the BRATS_2013 dataset. The model was trained with an 80:20 train with test ratio and sensitivity, specificity, and dice similarity coefficients (DSC). In.[19] proposed Fuzzy c-means for segmentations T2-W MRI images were classified using a combination of discrete wavelet transform (DWT) and a DNN (Deep Neural Network). Normal, glioblastoma, sarcoma, with metastatic-bronchogenic-carcinoma tumors, were all included in the classification. The algorithm's performance in a classification rate of 96.97%.

Within a year,[20] [21] discussed an enhanced version of DCNN. Tumor multiplicity adds to the complexity and necessitates greater precision.[22] multimodal-based segmentation with Random forest classification was discussed. Gabor characteristics are taken from each supermodel and used to train Random Forest. Using multimodal images from the BraTS datasets, each supermodel is classified as healthy or tumor. The results are presented in terms of sensitivity and dice score, which are 86% and 0.84%, respectively. Mohsen et al.[23] proposed using a Deep Neural Network to divide brain MRIS into four categories: normal, sarcoma, metastatic bronchogenic carcinoma tumors, and glioblastoma. The discrete wavelet transform (DWT) with principal component analysis (PCA), an effective feature extraction method, were used with the classifier. When the suggested model was compared to other classifiers, such as KNN when k = 1, k = 3, LDA, and SVM, it got the highest AUC score of 98.4% when DWT was employed on CNN. Chang et al.[24] introduced a Fully Convolutional Residual Neural Networks (FCRNNs) based on linear identity mappings, a basic medical picture segmentation approach. The FCR-NN system uses a fully convolutional image segmentation architecture that effectively caters to low-level and high-level picture information. For tumor segmentation, the machine employs two distinct networks: one to segment the entire tumor and the other to segment subregion tissues. The FCR-NN sequencing architecture goes beyond state-of- the-art approaches with validation, and both have been trained for the proposed model. Complete tumor 0.87, core tumors 0.81, and enhanced tumors 0.72 are DSC.

Raja et al.[25] presented a brain tumor classification model hybrid deep autoencoder uses through a Bayesian fuzzy clustering technique for brain tumor segmentation. Initially, during the preprocessing stage, non-local mean filtering is used for denoising purposes. The BFC(block-based fast compression) method is employed in the segmentation brain tumors. They use information-theoretic measurements such as the Wavelet Packet Tsallis Entropy (WPTE) from each brain image with Scattering Transform (ST) approaches after segmentation. The brain tumor classification, a hybrid system comprising the DAE (Deep autoencoder)-based JOA (Jaya optimization algorithm) and softmax regression is applied. According to the results of the BraTS_2015 database, the proposed technique provided high classification accuracy (98.5%).

Kumar et al.[26] proposed employing a Deep Wavelet Autoencoder Neural Networks (DWADNNs) strategy for picture segmentation, which was evaluated and compared to a variety of different classification methods, including the DNN, AEDNN, and others. In broad data distribution, an autoencoder can be thought of as an optimal strategy for extracting and learning principal components. DWA-DNN has been proven to be more accurate than the other exit approaches. It also enables the use of an image classification method for cancer detection that is both reliable and simple. The original encoded image is treated using a Daubechies wavelet of order two via a Discrete Wavelet Transformation (DWT), which bypasses low-pass and high-pass filters to generate estimate and detail coefficients. Sensitivity, specificity, and F1-Score, as well as accuracy results of 93, 94, 92, and 93%, respectively.

3. METHODOLOGY

Computer-aided diagnostic (CAD) for brain tumor detection steps various machine and deep learning techniques uses, the block diagram illustration in shown in fig.2.

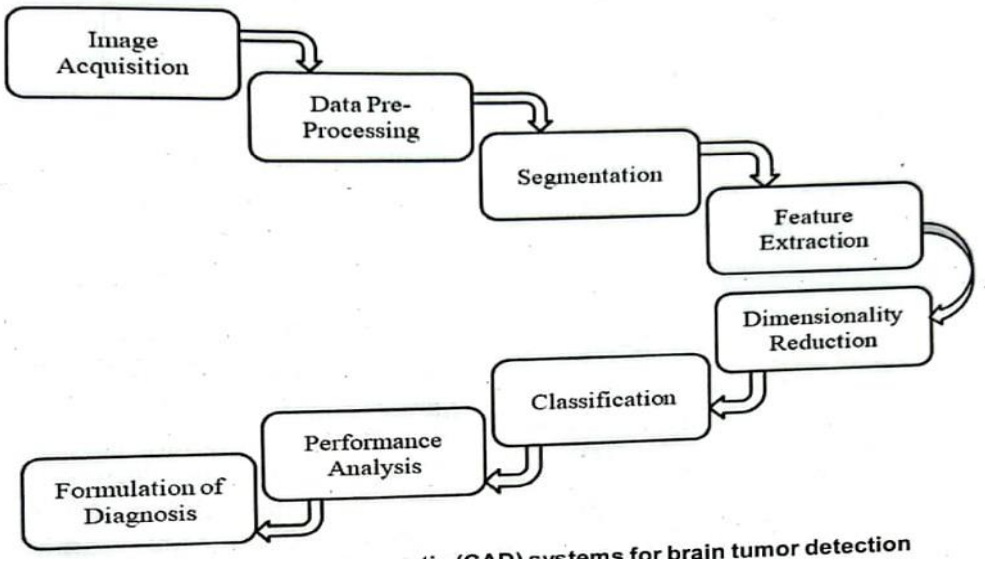

Fig.2: Computer-aided diagnostic (CAD) systems for brain tumor detection.

Collect historical images for training the algorithm. This is the first phase of the Brain Tumor recognition system. The dice coefficient of Internet Brain Segmentation of Repository (IBSR) segmented dataset, and Brain Web with Medical School Harvard Some of the most usually used datasets for brain tumors detection are BraTS.[8] Researchers encountered numerous limitations as a result of a requirement of data for precautions reasons. Data cleaning and data improvisation occur after the data has been collected during the data preprocessing step. The amount of noise in images makes it difficult to distinguish between normal and diseased cells. The segmentation phase is a crucial step in determining the analytical region of interest. Following segmentation, feature extraction extracts features such as texture and intensity with edges. Reduction of dimensionality: PCA (Principal Component Analysis) aids in the reduction or elimination of non-classifiable features. Later, utilizing the collected features, classification models are employed to classify the types of brain tumors.

4. DATASETS

Brain Tumor Detection (BTD) uses Machine and Deep Learning Techniques are brain tumor datasets publically available as shown in Table 1.

Table 1: Publically Brain tumor Datasets.

SI. No.	URL Address	Datasets Name
1	https://www.cancerimagingarchive.net/	TCIA
2	https://www.smir.ch/BRATS/Start2012	BRATS
3	https://brainweb.bic.mni.mcgill.ca/	Brain Web
4	http://www.oasis-brains.org	OASIS
5	http://www.med.harvard.edu/AANLIB/	Harvard Medical School
6	https://imaging.nci.nih.gov/ncia/	NBIA
7	https://www.cancerimagingarchive.net/	TCIA
8	https://www.smir.ch/	ISLES

To ensure the validity of our findings, we used an openly available MRI dataset obtained from kaggle.com.[27,28] MRI scan images are included in this collection, since they are the gold standard for diagnosing brain tumors. Glioma (2548 images), pituitary (2658 images), meningioma (2582 images), and no tumor (2500 images) were the four subsets that made up our dataset of brain tumors. Images were all scaled to 512 pixels on the horizontal and vertical dimensions. We used 8232 MRI images (or 80% of the dataset) for training in our analysis, whereas 2056 MRI images (or 20% of the dataset) were set aside for testing. Brain tumor photos from various categories are shown as examples. For each type of brain cancer (glioma, pituitary, and meningioma), Table 2 provides the number of pictures in various views such as axial, coronal and sagittal. It is important to keep in mind that medical photos, in contrast to natural images, are more complicated and necessitate a greater level of skill to ensure appropriate analysis and interpretation. The brain tumor dataset was labeled with oversight from a medical specialist to ensure precision and consistency. This physician's expertise was crucial, as it established criteria for how the dataset should be labeled. However, not all brain cancers have characteristic imaging findings; therefore, depending entirely on image analysis can be risky. As a result, pathology analysis is essential for diagnosing brain cancers. Our dataset featured abnormal language

descriptions annotated by a medical expert to give rich context for model training. A larger amount of training data aids in the creation of more reliable models. Data augmentation strategies can be used to increase the diversity of the training samples when the volume of available data is low. To improve a model's generalizability, data augmentation can be used to generate new variants of the existing data. In conclusion, our model's predictive power was enhanced by the incorporation of extensive labeled data, curated by medical experts. To further improve the prediction models' accuracy and reliability, data augmentation techniques can be used to increase the diversity of the training samples.

Table 2: Brain tumor dataset and its specification.

Brain Tumor Dataset	Axial	Coronal	Saggital	Total
Glioma	864	857	827	2548
Pituitary	883	885	890	2658
Meningioma	863	859	860	2582
No tumor	837	832	831	2500
Total	3447	3433	3408	10,288

The dataset was split into a training set and a testing set according to MRI view and class to ensure objective model evaluation. The efficacy of the models can then be tested on data they have never seen before, thanks to this separation into training and testing sets. This method is used to evaluate the models' generalizability and performance in detecting brain tumor by testing them on data that has not been used in training. Testing set samples are selected blindly using stochastic collection to eliminate the possibility of bias or selection bias. This eliminates the possibility of introducing biases that might slant the evaluation results in favor of a particular model or set of assumptions.

5. EVALUATION PERFORMANCE

The evaluation performance is precision, recall, accuracy, and F1-score are used to measure the real and expected classes that have previously been expressed in equations 1, 2, 3, and 4, individually, to validate the proposed model. Different metrics may be constructed from a confusion matrix to reflect the performance of classifiers, unique to each tumor type, using each performance metric's mathematical notation. The important measures of accuracy, precision, recall, and F1-score are computed using the following equations.

$$AUC = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$PRE = \frac{TP}{TP + FP} \quad (2)$$

$$REC = \frac{TP}{TP + FN} \quad (3)$$

$$F1\,SCORE = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

Where,
TP used for True Positives, TN used for True Negatives, FP used for False Positives, and FN used for False Negatives.

6. DISCUSSION AND FUTURE DIRECTION

Deep Learning algorithms are gaining traction as the demand for Al and automation grows. Automatic systems are currently a prominent focus of research. This review focuses on the various deep learning algorithms that are currently in use, as well as a discussion of the approaches for segmentation of brain tumor utilized. Deep learning.

based segmentation of brain tumors are detection in this paper. We examine it from two perspective.

The deep learning is a first of the perspective technology and the second is from the perception of tumor types. From a technical aspect, we seem at network building, post-processing, pre-processing, loss function, multimodality, and post-processing. The tumor segmentation approach deep learning-based is concise from two perspective: types of the tumor and procedural architecture. The modern methods are mostly utilized to correctly segment tumors and compensate for the lack of training data. When given adequate training data, deep learning can efficiently segment tumors, and all three approaches are based on the following three perspectives: Remove infrared portions from the image and segment with set limits to provide additional data for pixel categorization. As a result, a large number of networks have been proposed, and the article includes detailed comparison introductions. However, because neural networks require large amounts of data by their very nature, the current methods for compensating for a lack of data are partial, and the most popular ones rely on modify the training technique. Based on the aforesaid situation, we have identified four potential research areas for future: Some of the techniques used include 3D image compression model, segmentation, classification, and transfer learning an overfitting solution.

Future studies can investigate if and how zero-shot learning, few-shot learning, and deep reinforcement learning (DRL) methods can be used to tackle the aforementioned issues. The problem of a lack of training data for tumor classes can be alleviated by employing zero-shot learning to construct recognition models for

unseen test samples. In situations where annotated data are limited, few-shot learning approaches allow deep learning models to learn from a small number of labeled cases per class. In addition, deep reinforcement learning (DRL) may be used to lessen the need for high-quality photos and exact annotations. The absence of validation on actual clinical data should be considered a drawback of this study. While the suggested approach showed promising results on publicly accessible datasets, it still needs to be validated using data from clinical research. This shortcoming is shared by many of the other assessed models, as well as the current analysis. It would be helpful to evaluate the practical use of the suggested strategy by addressing this issue and verifying it on actual clinical data.

Although the deep learning-based tumor segmentation method has yielded promising results so far, there are few relevant research approaches and development points. Based on the method's reasoning, this study evaluates the methodology from the perspective of tumors kind and network architecture. This review contains some important information for researchers and others interested in learning more about this topic quickly.

7. CONCLUSION

To raduce the global death rates, diagnosis of brain cancers is essential. Brain tumors can be difficult to identify because of their complex architecture, size variability, and unusal forms. This research looks at a variety of methodologies and tools for developing automatic brain tumor detection algorithms.

We acknowledge that additional investigation and testing are essential to validate the efficacy of our suggested method thoroughly. The domain of brain tumor identification in medical imaging remains an area of focus in research, to which end our work leverages five distinct convolutional models and transfer learning architectures. However, there is still room for further exploration and improvement in this field. The continuous advancement of brain tumor detection systems through ongoing research holds the potential to enhance diagnostic precision for patients and medical practitioners in the challenging fight against brain cancers. By refining detection systems and pushing the boundaries of knowledge in this domain, we can foster better diagnostic skills and improve patient outcomes.

Despite major advancements in the discipline, deep learning methodologies are still in their infancy. Tumor segmentation techniques based on deep learning are gaining popularity. This article looks at the state-of-the-art technique from two perspectives: tumors type and network building, and technical considerations. The majority of the strategies are based on supervised learning, which necessitates manual ground truth labeling. Because there aren't enough datasets, different strategies for dealing with data or class imbalance issues should be investigated. 3D image transfer learning, model compression, segmentation, classification and an overfitting solution are all areas that will be investigated in the future.

REFERENCES

1. Gore D.V., Deshpande V. Comparative study of various techniques using deep Learning for brain tumor detection; Proceeding of the 2020 IEEE International Conference for Emerging Technology (INCET); Belgaum, India. 5-7 June 2020; 1-4. [Google Scholar]
2. Sapra P., Singh R., Khurana S. Brain tumor detection using network. Int. J. Sci. Mod. Eng, 2013; 1: 2319-6386. [Google Scholar]
3. Soomro T.A., Zheng L., Afifi A.J., Ali A., Soomro S., Yin M., Gao J. Image Segmentation for MR Brain Tumor Detection Using Machine Learning: A Review. IEEE Rev. Biomed. Eng, 2022; 16: 70-90.
4. Deepthi Murthy, Sadashiv G, An analytical research study of MRI brain tumor modalities and classification techniques, IJET, 2019; 8(3): 357-376.
5. Akil, Akil, Mohamed, RachidaSaouli, and Rostom Kachouri. "Fully automatic brain tumor segmentation with deep learning-based selective attention using overlapping patches and multi-class weighted cross- entropy." Medical image analysis, 2020; 63: 101692.
6. Menze, Bjoern H., et al. "The multimodal brain tumor image segmentation benchmark (BRATS)." IEEE transactions on medical imaging, 2014; 34.10: 1993-2024.
7. Zaouche, R., et al. "Semi-automatic method for low-grade gliomas segmentation in magnetic resonance imaging." IRBM, 2018; 39.2: 116-128.
8. A. R and S. S. R. D, "Development of computer-aided approach for brain tumor detection using random forest classifier," Int J Imaging SystTechnol, 2018; 28(1): 48-53.
9. V. V. Cortes C, "Support-vector networks," Machine Learning, 1995; 20(3): 273-297.
10. Z. J et al., "Extraction of brain tumor from mr images using oneclass support vector machine," IEEE engineering in medicine and biology 27th annual conference, 6411- 6414.
11. G. Pet al., "Improving brain tumor characterization on mri by probabilistic neural networks and non-linear transformation of textural features," Comput Methods Programs Biomed, 2008; 89(1): 24-32.
12. C. A. Maitra M, "Hybrid multiresolutionslantlet transform and fuzzy cmeans clustering approach for normal-pathological brain mr image segregation," Medical Engineering Physics, 2008; 30(5): 615-623.
13. G. P. Shanthakumar P, "Performance analysis of classifier for brain tumor detection and diagnosis," Comput Elect Eng, 2015; 45: 302-311.
14. S. L. Zollner FG, Emblem KE, "Svm-based glioma grading: optimization by feature reduction analysis," Zeitschriftf "urmedizinische Physik, 2012; 22(3): 205-214.

15. C. L. Bezdek JC, Hall L, "Review of mr image segmentation techniques using pattern recognition," Medical Physics, 1993; 20(4): 1033-1048.
16. S. A. El Dahshan ESA, Hosny T, "Hybrid intelligent techniques for mri brain images classification," Digital Signal Processing, 2010; 20(2): 433-441.
17. T. Y. Vasilakos AV, "Neural networks for computer-aided diagnosis in medicine: a review," Neurocomputing, 2016; 216: 700-708.
18. M. M. Hussain S, Anwar SM, "Brain tumor segmentation using cascaded deep convolutional neural network," IEEE 39th annual international conference of the ieee engineering in medicine and biology society (EMBC), 2017; 1998-2001.
19. E. H. E.-S. A.-B. Mohsen H, El Dahshan ESA, "Classification using deep learning neural networks for brain tumors," Future Computing and Informatics Journal, 2018; 3: 68-71.
20. H. W. Pan Y et al., "Brain tumor grading based on neural networks and convolutional neural networks," IEEE 37th annual international conference of the ieee engineering in medicine and biology society (EMBC), 699-702.
21. S. D. Singh L, Chetty G, "A novel machine learning approach for detecting the brain abnormalities from mri structural images," IAPR international conference on pattern recognition in bioinformatics, Springer, Berlin, 2012; 94-105.
22. S. M et al., "Supervised learning based multimodal mri brain tumour segmentation using texture features from supervoxels," Computer Methods and Programs in Biomedicine, 2018; 69-84.
23. Mohsen, Heba, et al. "Classification using deep learning neural networks for brain tumors." Future Computing and Informatics Journal, 2018; 3.1: 68-71.
24. Chang, Peter D. "Fully convolutional deep residual neural networks for brain tumor segmentation." International workshop on Brainlesion: Glioma, multiple sclerosis, stroke and traumatic brain injuries. Springer, Cham, 2016.
25. Raja, PM Siva. "Brain tumor classification using a hybrid deep autoencoder with Bayesian fuzzy clustering-based segmentation approach." Biocybernetics and Biomedical Engineering, 2020; 40.1: 440- 453.
26. Mallick, Pradeep Kumar, et al. "Brain MRI image classification for cancer detection using deep wavelet autoencoder-based deep neural network." IEEE Access, 2019; 7: 46278-46287.
27. Sartaj Brain Tumor Classification Dataset. [(accessed on 2 May 2023)]. Available online: https;//www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri
28. Nickparvar M. Brain Tumor Classification Dataset. [(accessed on 2 May 2023)]. Available online: https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset