Grenze International Journal of Engineering and Technology, January Issue

Innovations in Brain MRI Tumor Segmentation and Classification: Machine Learning and Deep Learning Perspectives

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***Abstract*—The most demanding task in medical imaging is the identification and categorization of tumors in magnetic resonance images (MRI) of brain. This article provides a broad analysis of machine learning (ML) and deep learning (DL) models that are engaged in the identification and categorization of tumors. The study covers the traditional ML methods like support vector machines (SVM) and K-nearest neighbors (KNN), as well as DL models like convolutional neural networks (CNN) and fully convolutional networks. Further hybrid models are also reviewed to show the performance of these combinations. Moreover, challenges like imbalance in datasets, variability in tumors, and noise artifacts are examined with proper performance metrics with bench-mark datasets. Further future directions are explored by synthesizing the present knowledge to overcome the key challenges. It also offers prospective research advancements in the implementation of ML and DL approaches in brain tumor imaging. Last but not least, this article provides scope, is objective, and is clear and concise on medical imaging.**

***Index Terms*— Brain Tumor, Machine Learning, Deep Learning, Tumor Classification, Feature Extraction, Evaluation Metrics.**

I. INTRODUCTION

Brain is one of the most delicate and vital organ in human body it coordinates and controls all the body functions. Because of the shifts in the present day life, pattern, and standard of living, diseases of the brain such as a brain tumour are prevailing among humans. Brain tumors refer to growths that take place in parts of the brain. An abnormal growth of cells within the brain can cause development of tumors [1]. It can affect anyone at any age, and in any areas of the brain. These may vary in size from that of a few individuals to a whole group, which is a feature that will be elaborated in the following section. Magnetic resonance imaging MRI or computed tomography CT are some of the diagnostic tests that can be used to diagnose brain tumors [2]. Identifying brain tumors is one of the most crucial challenges of the current scenario and health concerns due to the existing environment [3]. Thus, if such tumors are diagnosed at an early stage, the patient will have a long time left, prognosis, and quality of life. It requires considerable diagnosis, treatment and appropriate observation for the recognition and categorisation of a tumor.

Grenze ID: 01.GIJET.11.1.810

When it comes to tumor classification and recognition, many methods are available; moreover, they help the radiologist for improved comprehension and further action. To overcoming aspects such as being timely consuming, inconsistent and subjective, ML and DL methods provide early identification of tumors [4][5]. SVM, Random Forest, and KNN based approaches are used to get higher accuracy in tumour detection [6]. For using these methods, it is necessary to obtain specific measures in the domain that open the possibility to obtain better outcomes. But, the range of application of these methods is severely restricted by their sensitivity and image acquiring conditions. Moreover, revolution has been emerging in the tumor detection phase, namely the beginning of the DL methods, including the CNN method that receives hierarchical features that it may then use for thorough analysis[7]. There are several derivatives that are used in DL-based methods that are used when conducting classification tasks. Learning methods are advanced, however, the tutor's noise, irregularity of tumor appearance as well as artifacts pose formidable issues in identification as well as categorisation of tumours. As a matter of fact, while DL based methods require a high density of datasets to apply their methods. In the clinical practice, with these advancements, there arose a practice that requires interpretability and reliability in tumor detection. The primary motive of this article is to present a detailed literature review on the classification and recognition of brain tumor using ML and DL techniques. By using this study, one may comprehend the advantages of advanced learning approaches; also, there is a chance to realize how one can manage the situations regarding these techniques to deal with these challenges and limitations. It is also able to help with synthesing the current study which is supposed to guide the researchers and put in their endeavours and get a model that is better than the current one which is more clinically appropriate.

From the outline of this study, one can obtain considerable information regarding the detection of tumours and the novelties that are brought by the ML as well as the DL techniques that address tumours. However, there are difficulties related to such factors as appearance of the tumor, artifacts, and poor quality which create an important challenge in the proper segmentation of the data. Managing these difficulties may necessitate that the researchers avail holistic approaches that combine the concepts of ML and DL for better efficiency in tumor identification and classification.

A. Objectives of the paper

The objectives of the paper "Innovations in brain MRI tumor segmentation and classification in machine learning and deep learning perspectives" typically focus on providing a broad overview and critical analysis of the present methods and advancements in the field. Here are the key objectives that such a review paper would aim to achieve:

- Conduct a thorough review of obtainable ML and DL procedures for the detection and classification of tumors in MRI images of brain.
- Highlights recent advancements and promising trends in the application of ML and DL.
- Discusses key challenges and limitations of current techniques, including data disparity, noise, and integration into clinical workflows.
- Suggests future research directions and innovative ways for improving model accuracy and competence.
- Provides benchmarking and evaluation of sophisticated methods.
- Discusses the practical consequences of ML and DL techniques for clinical applications.
- Highlights the interdisciplinary nature of the field and the importance of collaboration between clinicians, radiologists, and data scientists.

B. Contributions of the paper

- Acquaintance Synthesis: Synthesizes existing field knowledge for understanding advanced methods.
- Framework for Evaluation: Establishes a framework for objective review and benchmarking.
- Regulation for Research and Development: Identifies challenges and improvement directions.
- Clinical Insights: Provides insights into the clinical significance and impact of ML and DL methods.

Apart from this, rest of the study is planned as follows: Section 2 details the previous work done in the various domains; followed by section 3 details the procedure of brain MRI tumor identification approaches; followed by section 4 provides an account into the theme, research challenges; section 5 provides performance metrics and availability of brain MRI datasets, and lastly section 6 offers the conclusion of the paper.

II. LITERATURE REVIEW

The application of DL techniques to improve the precision of brain tumor diagnosis from MRI scans is done by ZheshuJia and Deyun Chen [8]. The authors erect a solid dataset of MRI images using a range of DL architectures, such as CNNs, residual networks (ResNets), and dense networks (DenseNets). Parameters like accuracy, recall, F1-Score, precision, and the area under the ROC curve are then used to judge the models. The outcomes exhibit the superior performance of the ResNet and DenseNet designs, obtaining fine generalization and high accuracy. The authors propose using these models in clinical procedures to help radiologists make more accurate diagnoses. Potential research possibilities encompass expanding the dataset, combining multi-modal imaging data, and evaluating their pragmatic applicability in the authentic clinical domain.

The exploitation of DL techniques to classify the brain tumours, a study is conducted by Muhammad Aamir and Ziaur Rahman [9], which emphasizes the important precise classification in tumour detection. A wide number of images are utilized to identify hierarchical distinctiveness by using the CNN method. A thorough test has been done before implementing the CNN architecture to fine-tune the hyperparameters further, which avoids dropout and overfitting problems. The given DL-based model proves to be more accurate when compared to the classic approaches of the ML theory, meaning that medical imaging has made considerable progress in this aspect. Furthermore, the outcomes of this study is revealing that DL approaches provide significant benefits in the processing of MRI images.

Momina Masood and Tahira Nazir [10] propose a sophisticated environment to identify the exact location of a tumor based on MRI image data. The model that is set up in this article is trained and verified with a wide range of data. This training enables the model to discriminate between various forms of tumors. The model's performance is obviously better compared to other traditional approaches. Also indicating a potential analytic process for reducing the work pressure of radiologists. It is also proven that the proposed model is flexible and capable of real-world clinical processes. In the future, the current model may be optimized for multimodal imaging with advanced DL architectures.

This article describes, by Soheila Saeedi and Sorayya Rezayi et al. [11], an incorporated methodology for accurately detecting brain tumors in MRI images. The authors pre-process MRI data to increase image quality and normalize input for the study, then utilize a CNN to mine significant characteristics. They also employ ML methods like support vector machines (SVM) and random forests to the classification process. The hybrid model exhibits considerable improvement in accuracy, specificity, sensitivity, and F1-score contrast compared to making use of either approach alone. The study concludes that such combined methods can boost the diagnostic process and decrease medical professionals' workload. In the future, work comprises mounting the dataset, including novel imaging modalities, and refining the hybrid model for early detection of tumours.

Abdul Hannan Khan and Sagheer Abbas et al. [12] suggested a DL model for the diagnosis of tumors in brain MRI scan images. Diagnosing malignant brain tumors is one of the hardest challenges in tumor detection. This task is resolved by initiating a confined CNN structure, which may be able to process complex patterns and also ensure the diagnosis of the type of tumor. This model is pre-trained with a wide range of datasets with suitable measures, which increases the quality of tumor detection. Metrics like precision, recall, and accuracy are measured to identify the significance of the proposed model in diagnosing tumor-affected areas.

Now a days, a cutting edge technology is the implementation of DL-based methods, which were introduced by Muhannad Faleh Alanazi and Muhammad Umair et al. [13] to improve the accuracy of tumor identification. In this method, certain elements are scanned, and a fine-tuned, pre-trained CNN is implemented to capture the independent properties of brain tumors. This model ensures accuracy and reliability in classifying the forms of tumors.

Integrated classical ML and DL approaches are proposed by Jaeyong Kang, Zahid Ullah, et al. [14] for tumor classification. Features are extracted using CNN, and further ML classifiers are implemented for the classification of tumors. This model outperforms when compared with typical DL models and independent ML classifiers. The rapid diagnosis is assured by the authors with this proposed ensemble model.

Ramdas Vankdothu and Mohd Abdul et al. [15]suggests a novel method to segment brain tumours using SVM and fuzzy classifiers. The researchers expect to better the accuracy and robustness of tumor identification, which is crucial for accurate diagnosis and treatment. The fuzzy logic classifier addresses the uncertainty and imprecision in the data, offering a refined classification that accompaniment the SVM's result. This approach achieves enhanced segmentation performance with respect to utilizing SVM or fuzzy classifiers unaccompanied. Future research areas include studying novel ML techniques, escalating the dataset, and validating the model in real-world circumstances.

Javeria Amin, Muhammad Sharif, et al.[16]proposes an integrated approach with cutting-edge algorithms. In this work, numerous feature extraction methods are implemented to attain the required features that are useful for segmentation. SVM, RF, and KNN are used to identify an accurate tumor area by using the feature set. It also enhances the model's accuracy and computational complexity. Further, this kind of work is useful to make more precise and timely decisions.

A complete framework by Sarita Simaiya, Umesh Kumar Lilhore et al. [17] is designed to identify and classify the tumors using a variety of ML methods. The authors highlight the need for accurate and quick tumor detection methods. The procedure begins with pre-processing MRI images and feature mining to recognize tumors. The model's performance is measured with the usual parameters. The study proposes a novel model that can aid radiologists in making accurate diagnoses.

Ehsan Ghafourian, Farshad Samadifam [18] suggested a strong ensemble method used to find out brain tumors, which is presented in this work. ML algorithms like CNNs, SVMs, and Random Forests are implemented. The standard metrics are used to examine the efficiency of the model. The results indicate that the combined approach achieves better performance than other methods.

Dheepak, Anita Christaline J. et al. [19] implemented texture-based feature extraction strategies with local binary patterns (LBP) and gray level co-occurrence matrix (GLCM). This combination improves flexibility in the recognition of tumor locations accurately. It is also able to distinguish between tumors and healthy tissues. The main advancement in this work is the consideration of composite patterns to diagnose the tumors.

Mohamed Wageha, Khaled M. Amina, et al. [20] suggested a method that extracts fine-grained texture features from MRI images using GLCM and LBP. After dimensionality reduction, they rank instructive features using principal component analysis (PCA) and information gain (IG) to convert the features into orthogonal components. To discriminate between healthy and tumor-affected tissues, the integrated feature set is further trained using ML classifiers. The study's realistic implications point out that radiologists can use it to help them diagnose patients more accurately in clinical situations.

In order to separate benign from malignant tumors, the authors G. Ramesh Babu and Bankuru Surya Bharghav Naidu [21] make use of methods such as GLCM and statistical measurements like skewness and kurtosis. These characteristics are then used to train ML models. The work recommends a sizable dataset and proposes an improved ML model that can recognize malignant tumors.

From the above survey the following gaps are noted further they may be considered for future research.

- The dataset considered in the article may not be sufficient for diversity in tumor types and different environmental issues and sensing conditions.
- The researchers need to concentrate on dropouts and overfitting of the data with respect to real time clinical process.
- Consideration of genetic data provide more appropriate information in tumor detection which is a challenging task for the researchers for implementation.
- It is essential to concentrate on multi modal data to attain enhanced accuracy in tumor diagnosis.
- The researchers need to explore integrated mechanisms with advanced learning techniques by considering novel modality image datasets in tumor detection.
- Implementation of the model with practical applicability in various diagnosis scenarios is a massive challenge in tumor identification.

III. Methodology

A. Brain MRI Image Segmentation

The image processing techniques involved in brain MRI image segmentation and tumor detection have been examined. Below are the key steps in the process:

Image Acquisition

Get high resolution MRI brain scans. Whether for T1 weighted, T2 weighted, or FLAIR sequences, this could be selected. Typically, the MRI scan is 3D, so it might be processed slice by slice.

Preprocessing

The goal of preprocessing is to enhance the quality of these MRI images and then allow further analysis. This step typically includes:

- Noise Reduction (Denoising): Noise removal using techniques like a gaussian filters, median filters, or anisotropic diffusion whilst preserving edges is used.
- Image Normalization: Enhance contrast or to standardize variations for images across images by rescaling the intensity values to a common range.
- Skull Stripping (Brain Extraction): Cut the brain free and take out the skull from the MRI images. Thresholding, morphological operations or region growing algorithms are used as methods.
- Bias Field Correction: Compensating for MRI machine or patient movement caused intensity inhomogeneity artifacts. Such algorithms are often used.

Segmentation

After that step of segmentation, we find different regions in the brain such as healthy tissues and abnormal tissues like tumors.

- Thresholding: Simple intensity range selection followed by segmentation. Intensity thresholding can separate from the MRI bright (hyperintense) or dark (hypointense) regions depending upon the value of the ROI.
- Region Growing: An initial seed point is chosen, and neighboring pixels within such a given intensity range are grouped together to form a region.
- Clustering Algorithms (e.g., K-Means, Fuzzy C-Means): Find clusters of group of pixels for which the mean intensity is similar. Despite robustness to noise, Fuzzy C means is frequently chosen over other models because it is more computationally efficient.
- Edge Detection and Contour-Based Methods: Boundary detection on tumors for Sobel or Canny edge detectors. Snakes (active contour models) are also used to evolve curves to the boundaries of tumors.
- Advanced Segmentation (Deep Learning): We use automated and accurate segmentation, using Convolutional Neural Networks (CNNs) or U-Net or Fully Convolutional Networks (FCNs).

Feature Extraction

Then, features within the tumor or lesion are extracted after segmentation to scale the tumor and analyze its properties. Important features include:

- Texture Features: Texture based analysis using Gray-level co-occurrence matrix (GLCM), local binary patterns (LBP).
- Shape Features: Segmented tumor contours, area, perimeter and 3D shape.
- Intensity Features: Intensities within the tumor region - mean intensity, standard deviation, and intensity variance.
- Morphological Features: Elongation, compactness, total, regional and selective volume, irregularity of the tumor.

Tumor Detection and Tumor Classification.

Extracted features can then be used to handle and classify the segmented region as a tumor of its type (benign or malignant).

- Machine Learning: Such classifiers include Support Vector Machines (SVM), Random Forest, Decision Trees and k-Nearest Neighbors (k-NN) to classify tumor from non-tumor.
- Deep Learning: End to end tumor detection and classification can be achieved from CNN based architectures.
- Thresholding for Tumor Detection: However, tumors often show reduced intensity profile compared to the normal tissues. MRI scans can be flagged with abnormal regions by threshold-based detection.

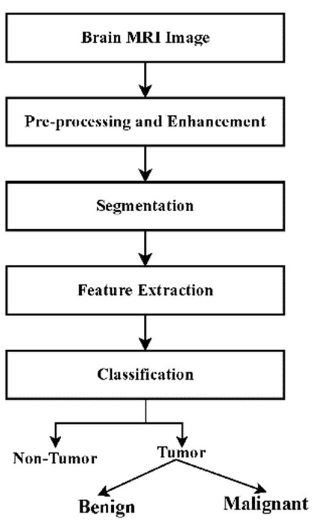

Figure 1. Brain MRI Image Segmentation and Tumour Detection Steps

Figure.1 showing the sequence of steps in brain MRI image segmentation and tumor detection. The identification and categorization of tumors in MRI brain images have been determined and created using some or most of the following techniques from the prior studies: image analysis, neural networks, and most recently, deep neural networks [22] [23] [24]. Below are brief descriptions of some of the existing methods:

B. Traditional Image Processing and ML Methods

- Preprocessing Techniques: Noise and normalization are used to reduce noise and improve the stability of images
- Feature Extraction: Features such as texture, shape, and intensity histograms are extracted by using methods like Gabor filters, wavelets, and Local Binary Patterns (LBP) [21].
- Segmentation: The data has been segmented by using various techniques like thresholding, region growing edge detection and clustering.
- ML Classifiers: The importance of classifier is to build the information into number of groups based on the certain rule. Mostly used classifiers are K-Nearest Neighbors, SVM, and Random Forest (RF) [17].

C. DL Methods

Learning by experience is the base objective of DL models which are used to classify the data. These models basically divided into three layers input, output and hidden layers subsequently. These methods have their pre-trained network to perform the above operation, but also provides a facility to build a own network. The important architectures used for classification is CNN, DCNN, FCN, GAN etc.[8]. Further Combining DL models with traditional ML classifiers like SVMs or Random Forests to influence the strengths of both approaches.

D. Benchmark Datasets and Assessment

Consideration of benchmark datasets which are globally recognized are very crucial in the implementation of proposed work depending on the domain and application Kaggle, UCI, NCBI organizations provide appropriate datasets which are globally recognized by the researchers[25][26][27]. When comes under to the assessment classification, prediction and segmentation had their own assessment metrics to evaluate the performance of the work.

IV. Research Challenges

Identification of brain tumors in MRI images presents versatile challenges. These confrontation with variability in image quality due to factors like movement of patient, magnetic field in homogeneities, and hardware-related problems, which can obscure important information and conciliation tumor delineation[3]. Furthermore, explicate MRI data accurately to recognize brain tumors is complex due to the diverse features of different tumor types (such as gliomas, meningiomas, pituitary tumors) and understanding “no tumor” situation in terms of size, shape, and position[28][29]. Researchers are aggressively addressing these points by implementing sophisticated AI-driven approaches that join accuracy with interpretability.

Identification and classification of tumors in brain MRI images is a decisive task in medical imaging, but it poses several challenges due to the complexity and variability of brain tumors. Here are some of the key research summons in this area:

- Variability in Tumor Appearance: Brain tumors can contrast greatly in size, shape, and facade. Even the same type of tumor can look different in diverse patients or in different regions of the brain. Some tumors have alike intensity patterns to normal brain tissues, making it tricky to discriminate them.
- Imaging Artifacts and Noise: MRI images can undergo from different artifacts such as movement artifacts, incomplete quantity effects, and magnetic field in-homogeneities. The occurrence of noise in MRI images can obscure significant features necessary for accurate recognition and classification.
- Multimodal Imaging Data: Diverse MRI sequences (e.g., T1, T2, FLAIR) offer corresponding information, but integrating these different ways for improved tumor recognition and classification is complex.
- Data Annotation: Annotated medical imaging data is limited because manual labeling is time-consuming and requires skilled radiologists. Even skilled radiologists may have different opinions on the limits and classification of tumors, foremost to inconsistencies in the training data.
- High Dimensionality: Brain MRI images are usually high-dimensional, making processing and analysis computationally rigorous. Identifying and extracting significant features that confine the essential characteristics of tumors exclusive of losing important information is a considerable challenge.

- DL and Model Generalization: DL models, mainly convolutional neural networks (CNNs), can over fit to the training data, sinking their generalization to unseen data. DL models frequently act as black boxes, making it hard to understand their decision-making procedure and gain trust from clinicians.
- Segmentation and Classification: Specific segmentation of tumors is important for accurate classification but is complicated due to the jagged shapes and unclear boundaries of tumors. Differentiating between different kinds of brain tumors (e.g., meningiomas, metastases, and gliomas) adds as additional layer of complexity.
- Clinical Integration: For practical use in clinical settings, algorithms need to process images in real-time or near real-time, which is demanding under computational aspect. Budding interfaces that radiologists and clinicians can simply use and trust is necessary for combining these technologies into routine clinical practice.

A. Research Directions

- Advanced ML Techniques: Exploring more sophisticated ML and DL techniques, including semi-supervised and unsupervised learning, to enhance the variability and complexity of brain tumors.
- Improved Data Annotation Methods: Developing better tools and methods for annotating medical images, probably incorporating active learning where the model queries the most instructive samples for annotation.
- Multimodal Data Integration: Creating methods to integrate and utilize data from several MRI sequences and other imaging types (e.g., PET, CT).
- Robust and Interpretable Models: Concentrating on creating models that not only perform well but are also robust to variations in data and offer interpretable results that can be trusted by clinicians.

These challenges need ongoing research and collaboration between computer scientists, radiologists, and other professionals to employ effective and trustworthy solutions for tumor detection and classification in brain MRI images.

V. Performance Measures and Analysis

A. Performance Measures

While considering the evaluation of the various ML and DL models used in the identification of tumors and, more specifically, in the classification of MRI images, some special indicators are taken into account. These measurements assess various aspects of the model's performance specifications like accuracy measure, measure of precision, measure of recall and so on[30][31]. Here's an overview of the performance evaluation metrics commonly used.

$$Accuracy=\frac{TP+TN}{Total\ Instances} \quad (1)$$

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

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

$$Specificity=\frac{TN}{FP+TN} \quad (4)$$

$$F1\ Score=\frac{2\times Precision\times Sensitiviy}{Precision+Sensitivity} \quad (5)$$

$$MSE=\frac{1}{N}\sum_{i=1}^{N}(Predicted-Actual)^2 \quad (6)$$

$$MAE=\frac{1}{N}\sum_{i=1}^{N}\left|Predicted\text{-}Actual\right| \quad (7)$$

$$Dice\ Coefficient=\frac{2\times\left|A\cap B\right|}{\left|A\right|+\left|B\right|} \quad (8)$$

$$Jaccard\ Index = \frac{|A \cap B|}{|A \cup B|} \quad (9)$$

B. Availability of Datasets

Some of the commonly available large scale image databases are public and may be used for the study of tumor identification, segmentation and classification in MRI images of brain. Among them, the BraTS Challenge datasets [32] from 2012 to 2023 are highlighted since it comes with multi-modal MRI scans and tumor segmentation of the glioma patient. In the same manner, MICCAI Brain Tumor Image Segmentation Benchmark (BRATS) is directly related to these challenges with containing large annotated datasets both for high-grade and low-grade gliomas [33]. Also, the Harvard Whole Brain Atlas [34] contains MRI images of patients diagnosed with different brain diseases such as tumors This is also accompanied by multi-omic and imaging data including glioblastomas contained in the National Cancer Institute's Clinical Proteomic Tumor Analysis Consortium (CPTAC)[35]. Another more extensive collection of brains in MRI is available via the Open Access Series of Imaging Studies (OASIS)[36], although it is not a tumor database per se but can be rather helpful when making comparisons to the presented data. The Cancer Imaging Archive (TCIA)[37]and the REMBRANDT dataset [38]offer large amounts of MRI images associated with rich clinical data concerning a wide variety of brain tumors. Each of these datasets collectively aids in the creation of state-of-the-art references and benchmark for algorithms in brain tumor imaging. The Table.1 shows the performance evaluation of the various models.

TABLE 1. PERFORMANCE ANALYSIS BETWEEN DIFFERENT MODELS

Ref. No.	Approach	Extracted Features	No. of Images used	Overall classification Accuracy	Assessment Method
[8]	FAHS-SVM	Mean, SD, Entropy, Skewness, Kurtosis, Energy, Contrast, Homogeneity, Direction Moment, Correlation, Coarseness, SSIM, MSE,PSNR	500	98.51%	--
[9]	EfficientNet-B0,ResNet50	CNN	3064	98.95%	5-fold cross-validation
[10]	Custom Mask-RCNN	CNN	3064	98.34%	
[11]	2D CNN+ Conv Auto Encoder	CNN	3264	96.47%	5-fold cross-validation
[12]	Hierarchical Deep Learning based CNN	CNN	2870	92.13%	--
[13]	Isolated-CNN Model	CNN	3000	96.89%	--
[14]	Ensemble of Deep leaning + Machine learning classifiers	ResNet, DenseNet, VGG, AlexNet, InceptionV3, ResNeXt, ShuffleNet V2, MobileNet V2, MnasNet	Three Datasets used with different classes 1. 253 (normal/tumor) 2. 3000 (normal/tumor) 3. 3064 (normal, glioma, meningioma, and pituitary tumor)	1. 92.37% 2. 96.13% 3. 84.99%	--
[15]	ANFIS+SVM	GLCM	210	99.24%	--
[16]	Random Forest	GWS, HoG, LBP, SFTA	BRATS 2015	98.9%	5-fold and 0.5 Holdout cross validation
[17]	Hybrid Machine Learning based Approach Fuzzy CMean + Expanded SVM	GLCM	200	97%	--

[18]	NaiveBayes + SVM + KNN	SVD	120 images of BRATS 2014 & 3000 images of BTD 2000	98.61%	10-fold cross validation
[19]	Composite feature extraction method	GLCM, LBP and Composite features	3064	99.84%	--
[20]	Integration of GLCM & LBP features with PCA and IG	GLCM & LBP	253	98%	--

VI. CONCLUSION

In conclusion, the review of sophisticated methodologies for the recognition and categorization of tumors in images of brain MRI using ML and DL culmination advancements and importunate challenges in the field. Novel ML and DL approaches have revealed outstanding potential in betterment the accuracy and efficacy of tumor identification and categorization, leveraging the power of CNN, SVM, and a range of fusion models.
The combination of multimodal imaging data and the use of classy preprocessing methods enhances the performance of these models. Conversely, several key challenges stay behind, due to tumor facade, the occurrence of imaging noise, artifacts, and the scarcity of well-interpret in training data.
Future research directions ought to focus on these problems during the development of more advanced ML techniques, improved data explanation methods, and the helpful combination of multimodal data. Emphasis should also be placed on creating models that are not only accurate but also worthy, interpretable, and clinically practicable. Continued interdisciplinary association and novelty will be decisive in overcoming existing limitations and realizing the full potential of ML and DL techniques.

REFERENCES

[1] J. R. McFaline-Figueroa and E. Q. Lee, “Brain Tumors,” American Journal of Medicine, vol. 131, no. 8. Elsevier Inc., pp. 874–882, Aug. 01, 2018. doi: 10.1016/j.amjmed.2017.12.039.
[2] B. J. M. Goldman Sergeand Pirotte, “Brain Tumors,” in Positron Emission Tomography, O. S. Juweid Malik E.and Hoekstra, Ed. Totowa, NJ: Humana Press, 2011, pp. 291–315. doi: 10.1007/978-1-61779-062-1_16.
[3] I. Despotović, B. Goossens, and W. Philips, “MRI segmentation of the human brain: challenges, methods, and applications,” Comput. Math. Methods Med., vol. 2015, no. 1, p. 450341, 2015.
[4] J. Liu and L. Guo, “A new brain MRI image segmentation strategy based on K-means clustering and SVM,” in Proceedings - 2015 7th International Conference on Intelligent Human-Machine Systems and Cybernetics, IHMSC 2015, Nov. 2015, vol. 2, pp. 270–273. doi: 10.1109/IHMSC.2015.182.
[5] I. Mecheter, M. Abbod, A. Amira, and H. Zaidi, “Deep learning with multiresolution handcrafted features for brain MRI segmentation,” Artif. Intell. Med., vol. 131, Sep. 2022, doi: 10.1016/j.artmed.2022.102365.
[6] T. A. Soomro et al., “Image segmentation for MR brain tumor detection using machine learning: a review,” IEEE Rev. Biomed. Eng., vol. 16, pp. 70–90, 2022.
[7] Z. Akkus, A. Galimzianova, A. Hoogi, D. L. Rubin, and B. J. Erickson, “Deep Learning for Brain MRI Segmentation: State of the Art and Future Directions,” Journal of Digital Imaging, vol. 30, no. 4. Springer New York LLC, pp. 449–459, Aug. 01, 2017. doi: 10.1007/s10278-017-9983-4.
[8] Z. Jia and D. Chen, “Brain Tumor Identification and Classification of MRI images using deep learning techniques,” IEEE Access, 2024, doi: 10.1109/ACCESS.2020.3016319.
[9] M. Aamir et al., “A deep learning approach for brain tumor classification using MRI images,” Comput. Electr. Eng., vol. 101, Jul. 2022, doi: 10.1016/j.compeleceng.2022.108105.
[10] M. Masood et al., “A novel deep learning method for recognition and classification of brain tumors from mri images,” Diagnostics, vol. 11, no. 5, Apr. 2021, doi: 10.3390/diagnostics11050744.
[11] S. Saeedi, S. Rezayi, H. Keshavarz, and S. R. Niakan Kalhori, “MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques,” BMC Med. Inform. Decis. Mak., vol. 23, no. 1, Dec. 2023, doi: 10.1186/s12911-023-02114-6.
[12] A. H. Khan et al., “Intelligent Model for Brain Tumor Identification Using Deep Learning,” Appl. Comput. Intell. Soft Comput., vol. 2022, 2022, doi: 10.1155/2022/8104054.
[13] M. F. Alanazi et al., “Brain Tumor/Mass Classification Framework Using Magnetic-Resonance-Imaging-Based Isolated and Developed Transfer Deep-Learning Model,” Sensors, vol. 22, no. 1, Jan. 2022, doi: 10.3390/s22010372.
[14] J. Kang, Z. Ullah, and J. Gwak, “Mri-based brain tumor classification using ensemble of deep features and machine learning classifiers,” Sensors, vol. 21, no. 6, pp. 1–21, Mar. 2021, doi: 10.3390/s21062222.
[15] R. Vankdothu and M. A. Hameed, “Brain tumor segmentation of MR images using SVM and fuzzy classifier in machine learning,” Meas. Sensors, vol. 24, Dec. 2022, doi: 10.1016/j.measen.2022.100440.

[16] J. Amin, M. Sharif, M. Raza, and M. Yasmin, "Detection of Brain Tumor based on Features Fusion and Machine Learning," J. Ambient Intell. Humaniz. Comput., vol. 15, no. 1, pp. 983–999, Jan. 2024, doi: 10.1007/s12652-018-1092-9.
[17] U. K. Lilhore, S. Simaiya, D. Prasad, and K. Guleria, "A Hybrid Tumour Detection and Classification Based on Machine Learning," J. Comput. Theor. Nanosci., vol. 17, no. 6, pp. 2539–2544, Sep. 2020, doi: 10.1166/jctn.2020.8927.
[18] E. Ghafourian, F. Samadifam, H. Fadavian, P. Jerfi Canatalay, A. R. Tajally, and S. Channumsin, "An Ensemble Model for the Diagnosis of Brain Tumors through MRIs," Diagnostics, vol. 13, no. 3, Feb. 2023, doi: 10.3390/diagnostics13030561.
[19] G. Dheepak, A. C. J, and D. Vaishali, "Brain tumor classification: a novel approach integrating GLCM, LBP and composite features," Front. Oncol., vol. 13, 2023, doi: 10.3389/fonc.2023.1248452.
[20] M. Wageh, K. M. Amin, A. A. Zytoon, and M. Ibrahim, "International Journal of Computers and Information (IJCI) Brain Tumor Detection Based on A Combination of GLCM and LBP Features with PCA and IG." [Online]. Available: https://ijci.journals.ekb.eg/
[21] G. R. Babu, B. Surya Bharghav, N. Student, C. Sruthi Varma, A. V. Praneeth, and B. Pavan, "EFFICIENT FEATURE EXTRACTION AND CLASSIFICATION TECHNIQUE FOR IDENTIFICATION OF BRAIN TUMORS IN MRI," J. Data Acquis. Process., vol. 38, no. 2, p. 4146, doi: 10.5281/zenodo.777407.
[22] M. A. Balafar, A. R. Ramli, M. I. Saripan, and S. Mashohor, "Review of brain MRI image segmentation methods," Artificial Intelligence Review, vol. 33, no. 3. pp. 261–274, Mar. 2010. doi: 10.1007/s10462-010-9155-0.
[23] S. Yazdani, R. Yusof, A. Karimian, M. Pashna, and A. Hematian, "Image Segmentation Methods and Applications in MRI Brain Images," IETE Technical Review (Institution of Electronics and Telecommunication Engineers, India), vol. 32, no. 6. Medknow Publications, pp. 413–427, 2015. doi: 10.1080/02564602.2015.1027307.
[24] H. Peni Agustin Tjahyaningtijas, "Brain Tumor Image Segmentation in MRI Image," in IOP Conference Series: Materials Science and Engineering, Apr. 2018, vol. 336, no. 1. doi: 10.1088/1757-899X/336/1/012012.
[25] T. Ciceri et al., "Fetal brain MRI atlases and datasets: A review," NeuroImage, vol. 292. Academic Press Inc., Apr. 15, 2024. doi: 10.1016/j.neuroimage.2024.120603.
[26] F. Lüsebrink, A. Sciarra, H. Mattern, R. Yakupov, and O. Speck, "T 1 -weighted in vivo human whole brain MRI dataset with an ultrahigh isotropic resolution of 250 μm," Sci. Data, vol. 4, Mar. 2017, doi: 10.1038/sdata.2017.32.
[27] J. Zbontar et al., "fastMRI: An Open Dataset and Benchmarks for Accelerated MRI," Nov. 2018, [Online]. Available: http://arxiv.org/abs/1811.08839
[28] N. Ghorpade and H. R. Bhapkar, "Brain MRI segmentation and tumor detection: Challenges, techniques and applications," in Proceedings - 5th International Conference on Intelligent Computing and Control Systems, ICICCS 2021, May 2021, pp. 1657–1664. doi: 10.1109/ICICCS51141.2021.9432346.
[29] S. Krishnapriya and Y. Karuna, "A survey of deep learning for MRI brain tumor segmentation methods: Trends, challenges, and future directions," Health and Technology, vol. 13, no. 2. Springer Science and Business Media Deutschland GmbH, pp. 181–201, Mar. 01, 2023. doi: 10.1007/s12553-023-00737-3.
[30] A. Kumar, "Study and analysis of different segmentation methods for brain tumor MRI application," Multimed. Tools Appl., vol. 82, no. 5, pp. 7117–7139, Feb. 2023, doi: 10.1007/s11042-022-13636-y.
[31] S. Saladi et al., "Segmentation and Analysis Emphasizing Neonatal MRI Brain Images Using Machine Learning Techniques," Mathematics, vol. 11, no. 2, Jan. 2023, doi: 10.3390/math11020285.
[32] U. Baid et al., "The RSNA-ASNR-MICCAI BraTS 2021 Benchmark on Brain Tumor Segmentation and Radiogenomic Classification," Jul. 2021, [Online]. Available: http://arxiv.org/abs/2107.02314
[33] BraTS Challenge Datasets (2012-2023), "BraTS Challenge Datasets (2012-2023)." https://www.med.upenn.edu/cbica/brats2023/data.html (accessed Aug. 10, 2024).
[34] Harvard Whole Brain Atlas, "Harvard Whole Brain Atlas." https://www.med.harvard.edu/AANLIB/home.html (accessed Aug. 10, 2024).
[35] National Cancer Institute's Clinical Proteomic Tumor Analysis Consortium (CPTAC), "National Cancer Institute's Clinical Proteomic Tumor Analysis Consortium (CPTAC)." https://cptac-data-portal.georgetown.edu/ (accessed Aug. 10, 2024).
[36] Open Access Series of Imaging Studies (OASIS), "Open Access Series of Imaging Studies (OASIS)." National Cancer Institute's Clinical Proteomic Tumor Analysis Consortium (CPTAC) (accessed Aug. 10, 2024).
[37] The Cancer Imaging Archive (TCIA), "The Cancer Imaging Archive (TCIA)." https://www.cancerimagingarchive.net/ (accessed Aug. 10, 2024).
[38] REMBRANDT (REpository for Molecular BRAin Neoplasia DaTa) Dataset, "REMBRANDT (REpository for Molecular BRAin Neoplasia DaTa) Dataset." https://wiki.cancerimagingarchive.net/display/Public/REMBRANDT (accessed Aug. 10, 2024).