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Classification of Brain Tumor based on Machine Learning Algorithms: A Review

Omran Ali Azeez*[1], Adnan Mohsin Abdulazeez[2]

[1]*Department of Information Technology, Technical College of Informatics, University for Applied Sciences, Duhok Kurdistan Region-Iraq, Omran.ali@auas.edu.krd*
[2]*Technical College of Engineering-Duhok, Duhok Polytechnic University, Duhok, Kurdistan Region, Iraq, adnan.mohsin@dpu.edu.krd*

**Correspondence: Omran.ali@auas.edu.krd*

Abstract

Brain tumor classification using machine learning algorithms is pivotal for medical diagnostics, particularly in magnetic resonance imaging (MRI) analysis. This review provides a comprehensive overview of recent advancements in brain tumor classification methodologies, emphasizing preprocessing, feature extraction, and classification phases. Preprocessing steps involve noise reduction and intensity normalization, while feature extraction encompasses texture analysis and deep learning-based methods. Machine learning algorithms such as support vector machines (SVM) and convolutional neural networks (CNNs) are utilized for accurate classification based on extracted features. Recent literature highlights the significance of diverse datasets, hyperparameter tuning, and segmentation techniques in improving diagnostic accuracy. Noteworthy methodologies include deep learning models for glioma grading and novel optimization techniques for tumor segmentation. The review underscores interdisciplinary collaboration between medical professionals and computational scientists to refine existing methodologies and overcome challenges. A systematic search of academic databases, including PubMed, IEEE Xplore, ACM Digital Library, ScienceDirect, Springer and Google Scholar, was conducted. Continued evolution in brain tumor classification promises enhanced diagnostic accuracy and personalized treatment strategies, ultimately improving patient outcomes in neuro-oncology.

Keywords: *brain tumor, classification, CNN, magnetic resonance imaging (MRI).*
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I. INTRODUCTION

The classification of brain tumors using machine learning algorithms, particularly convolutional neural networks (CNN), represents a critical frontier in medical imaging, offering a pathway to enhanced diagnostic accuracy and patient care[1][2][3]. Magnetic Resonance Imaging (MRI) serves as the cornerstone of this endeavor, providing detailed anatomical information essential for tumor characterization. The process of brain tumor classification encompasses a multi-faceted approach, beginning with meticulous preprocessing techniques to ensure data fidelity and reliability[4]. Subsequent stages involve feature extraction, where pertinent tumor characteristics are distilled from the MRI images, followed by classification using machine learning algorithms. These algorithms, spanning from traditional methodologies like support vector machines to cutting-edge deep learning architectures such as CNNs, leverage extracted features to discern tumor types and pathological conditions with increasing precision[5][6]. The aims to comprehensively survey the landscape of brain tumor classification via machine learning, synthesizing recent literature to elucidate prevailing methodologies, challenges, and avenues for future research. By exploring the intersection of medical imaging and computational intelligence, this review endeavors to provide a scholarly foundation for further advancements in neuro-oncological diagnostics and therapeutics[7][8].

II. BRAIN TUMOR CLASSIFICATION

Brain magnetic resonance imaging (MRI) plays a critical role in medical diagnostics, enabling the classification of images into categories such as normal or abnormal, benign or malignant, and various grades or types of abnormalities[9][10]. A range of image classification techniques are employed to categorize these MRI scans, aiding in the diagnosis and treatment planning for patients. Notably, these classification techniques can also serve in the segmentation of brain tumors, a process crucial for precise delineation of tumor boundaries. However, it's important to note that segmentation is not always a prerequisite for classification;

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in the context of brain MRI classification, segmentation can be viewed as a preprocessing task that aids in subsequent classification efforts. The classification of brain tumors from MRI scans typically involves three phases, as illustrated in Fig1. These phases encompass preprocessing steps, feature extraction, and classification. In the preprocessing phase, the MRI images undergo various preprocessing techniques such as noise reduction, intensity normalization, and skull stripping to enhance the quality and consistency of the data. Subsequently, in the feature extraction phase, relevant features are extracted from the preprocessed images, capturing key characteristics indicative of different tumor types or pathological conditions[11]. Feature extraction methods may include texture analysis, shape descriptors, intensity-based features, and more advanced techniques such as deep learning-based feature extraction. Finally, in the classification phase, machine learning algorithms or deep learning architectures are employed to classify the MRI images into their respective categories, based on the extracted features. Common classification approaches include support vector machines (SVM), random forests, convolutional neural networks (CNNs), and ensemble methods[12][13]. The choice of classification algorithm depends on factors such as the complexity of the data, the size of the dataset, and the specific requirements of the classification task[14][15]. The classification of brain tumors from MRI scans is a multi-phase process that involves preprocessing, feature extraction, and classification. While segmentation can aid in classification, it is not always mandatory, and classification algorithms can directly operate on preprocessed images to achieve accurate and reliable diagnoses[16][17].

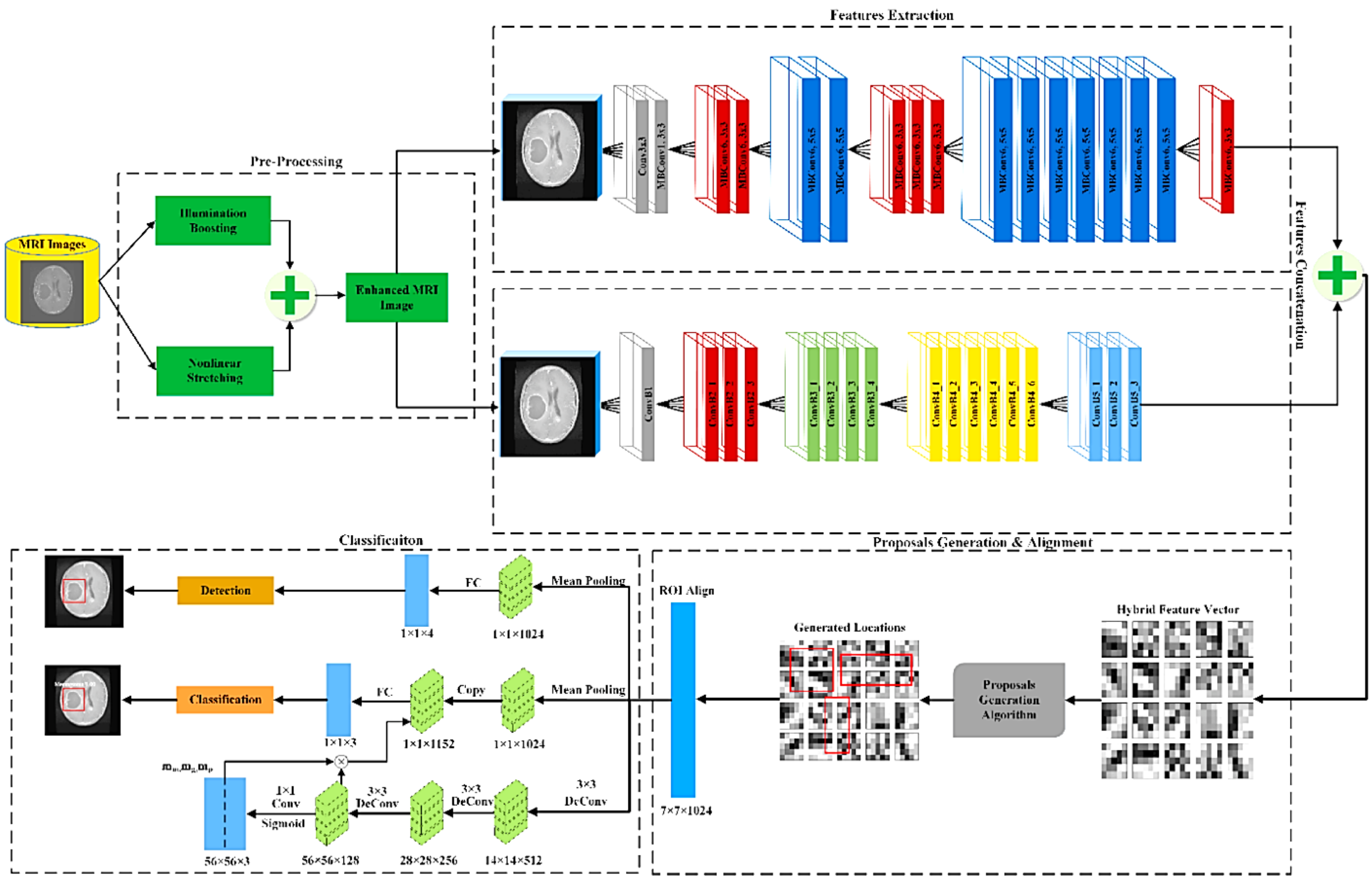

Fig. 1. The overall significant steps involved tumor classification[16]

III. MAGNETIC RESONANCE IMAGING (MRI)

Magnetic Resonance Imaging (MRI) is a pivotal non-invasive imaging modality extensively utilized in modern medicine for comprehensive visualization of internal anatomical structures, offering unparalleled spatial resolution and tissue contrast[18]. Grounded in the principles of nuclear magnetic resonance, MRI harnesses powerful magnetic fields and radiofrequency pulses to elucidate the behavior of hydrogen nuclei within biological tissues. This technique facilitates the generation of high-fidelity, multi-dimensional images crucial for the precise diagnosis and management of diverse pathologies, encompassing neoplastic lesions, traumatic injuries, and neurological disorders. Recent years have witnessed significant advancements in MRI technology, encompassing novel pulse sequences, enhanced imaging techniques, and innovative applications, further augmenting its diagnostic utility and clinical relevance. This academic discourse presents an overview of contemporary literature, spanning seminal texts and recent publications, elucidating the fundamental principles, technical intricacies, and clinical applications of MRI, thereby delineating its indispensable role in modern medical practice[19][20]. MRI images are crucial for automated brain tumor detection using artificial neural networks[21][22].

IV. DEEP LEARNING ARCHITECTURES FOR BRAIN TUMOR CLASSIFICATION

To enhance the understanding of the specific deep learning models utilized in brain tumor classification, this section explores notable architectures such as VGG and ResNet.

A. VGG Network

The VGG network, introduced by the Visual Geometry Group at Oxford, is known for its simple yet effective design. It utilizes multiple convolutional layers followed by max-pooling layers, and the depth is achieved by stacking small 3x3 filters. This configuration allows the network to capture intricate details in images, making it highly suitable for tasks like brain tumor classification.

The VGG network is built using very small convolutional filters. It consists of 13 convolutional layers and three fully connected layers, designed in a straightforward manner. This deep convolutional neural network is structured with an optimal layer depth to avoid increasing network complexity. Figure 2 illustrates the VGG network architecture. In our experiment, we propose a modified version of the VGG network. Our modifications include adding an extra 3×3 convolutional filter to extract finer details from the training data and removing the fourth max pooling layer to maintain consistent feature map sizes. This adjustment ensures that the feature maps from conv4 and conv5 are of the same size, providing the network with high-level feature maps. Additionally, the inclusion of extra layers helps to minimize training loss and retain more data for object detection[23][24].

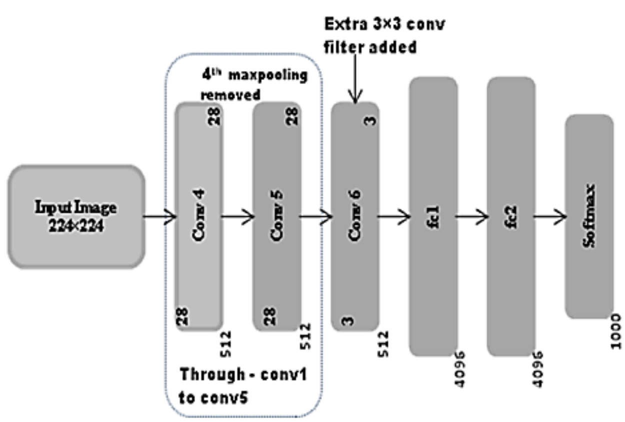

Fig. 2. The improved architecture of VGG network[25]

B. ResNet:

ResNet, or Residual Network, developed by Microsoft, addresses the vanishing gradient problem in deep networks through the use of residual blocks. These blocks create shortcuts for the gradients to pass through, ensuring that even the deepest layers are effectively trained. This architecture has demonstrated exceptional performance in various image classification challenges, including medical imaging.

Deep residual networks demonstrate significant performance in image classification and segmentation tasks. These networks function similarly to a bank of filters and are constructed with small convolutional filters, which simplify the network's architecture. Deep networks often face overfitting and saturation issues, affecting accuracy. To address overfitting, the highway or shortcut method is employed. ResNet is built with a combination of 1×1 and 3×3 convolutional layers, which act as convolutional filters. These layers help reduce the complexity of the network and extract high-level feature maps. The output of the ResNet network serves as a rich source of information for the activation of fully connected layers, enabling the network to preserve substantial information and accurately locate objects. Figure 3 depicts the proposed architecture of ResNet[26].

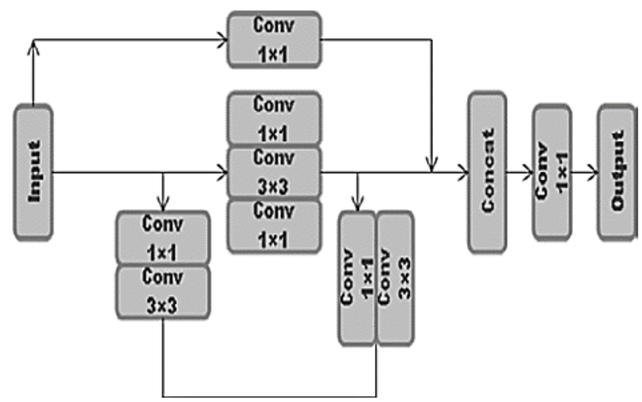

Fig. 3. The architecture of ResNet[25]

V. EVALUATION METRICS

While accuracy is a common metric for evaluating classification models, it is essential to consider additional metrics to gain a comprehensive understanding of model performance, especially in the context of medical diagnostics[27].

- **Sensitivity (Recall)**: Measures the proportion of actual positives correctly identified by the model. High sensitivity ensures that most patients with the condition are correctly diagnosed, reducing the risk of missing critical cases.
- **Specificity**: Measures the proportion of actual negatives correctly identified. High specificity ensures that healthy individuals are not falsely diagnosed with the condition, minimizing unnecessary treatments.
- **F1 Score**: The harmonic mean of precision and recall, providing a balance between sensitivity and precision. The F1 score is particularly useful when dealing with imbalanced datasets, common in medical imaging.

VI. Transfer Learning in Brain Tumor Classification

Transfer learning is a powerful technique in deep learning, especially when dealing with limited datasets. It involves leveraging pre-trained models on large datasets and fine-tuning them for specific tasks such as brain tumor classification.

By using pre-trained models like VGG or ResNet, which have been trained on extensive datasets like ImageNet, we can adapt these models to classify brain tumors by retraining the final layers on our MRI dataset. This approach not only accelerates the training process but also enhances the model's accuracy and generalization capabilities, making it a valuable strategy for improving performance with limited medical data[28].

VII. Interpretability of Deep Learning Models

Interpretability remains a critical challenge in deploying deep learning models in clinical settings. It is essential to explain the decision-making process of these complex models to gain the trust of medical professionals.

A. *Local* Interpretable Model-Agnostic Explanations (LIME):

LIME is a technique that helps interpret complex models by approximating them with interpretable models locally. It highlights the features that most influence the model's predictions, providing insights into why a particular decision was made. This transparency is crucial for ensuring that deep learning models are trusted and effectively integrated into medical diagnostics workflows[29].

VIII. Brief Overview Of CNN

The Convolutional Neural Network (CNN) stands out as a prominent deep learning framework, wherein each layer is interconnected in a forward manner. Within the CNN architecture, the process entails end-to-end learning to establish a hierarchical representation of input images[30]. Numerous layers are incorporated into this structure to extract both local and global information from each image. Recently, these models have garnered increased utility in tasks such as object classification, surveillance, and medical imaging[31]. A typical CNN architecture comprises several layers, with notable ones including convolutional, ReLU, pooling, and fully connected (FC) layers. The CNN model relies primarily on three key layers: convolution, pooling, and fully connected layers. Additionally, measures like dropout and batch normalization layers are introduced to combat issues like overfitting and enhance generalization within the CNN architecture show in fig2. As a result, abstract-level features are extracted, culminating in output scores at the conclusion of this architectural process[32][33].

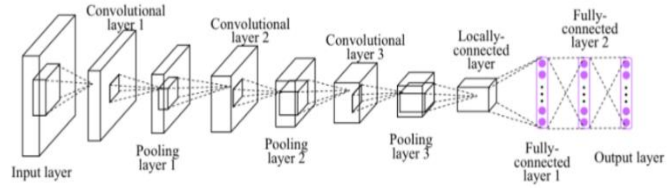

Fig. 4. Architecture of CNN[34]

IX. Clinical Validation and Practical Application

Clinical validation is a critical phase in the development and implementation of deep learning models for brain tumor classification. This process ensures that the models not only exhibit high performance in controlled experimental settings but also demonstrate robustness, reliability, and effectiveness in real-world clinical environments. Rigorous clinical validation is essential to establish the credibility and clinical utility of these models, ensuring they meet the stringent requirements of healthcare settings[35].

A. *Real-World Trials*

To validate the effectiveness of the proposed deep learning methodologies, it is imperative to conduct comprehensive real-world trials. These trials should encompass diverse patient populations and a variety of clinical scenarios to evaluate the model's generalizability and robustness. Comparative studies should be designed to assess the performance of deep learning models against the current gold standards in diagnostic practices. Such trials provide critical insights into the practical utility and limitations of the models in actual clinical workflows[36].

B. *Engagement* with Healthcare Professionals

The integration of deep learning models into clinical practice necessitates active collaboration with healthcare professionals, including radiologists, oncologists, and medical technicians. Their domain expertise is invaluable for annotating training datasets, interpreting model outputs, and providing iterative feedback to refine the models. Engaging healthcare professionals in the development process ensures that the models are aligned with clinical needs and enhances their acceptance and usability in routine practice[37].

C. *Integration* into Clinical Practice

For successful deployment, deep learning models must be seamlessly integrated into existing healthcare infrastructure. This involves embedding the models within medical imaging software, electronic health records (EHR), and hospital information systems (HIS). The integration process should focus on ensuring interoperability, user-friendly interfaces, and adherence to healthcare standards and regulations. Effective integration facilitates the practical application of the models, enhancing their utility in clinical decision-making[38].

D. *Steps for Regulatory Approval*

Securing regulatory approval is a fundamental step in the clinical deployment of deep learning models. The approval process typically involves:

1. *Preclinical Studies*: Conducting extensive preclinical evaluations to gather evidence of the model's performance, safety, and potential clinical benefits.
2. *Clinical Trials*: Implementing clinical trials to validate the model's efficacy and safety in real-world settings. These trials should demonstrate the model's ability to improve diagnostic accuracy and patient outcomes.
3. *Regulatory Submission*: Preparing and submitting detailed documentation to regulatory authorities, such as the FDA (Food and Drug Administration) or EMA (European Medicines Agency), for review and approval.
4. *Approval and Post-Market Surveillance*: Upon approval, continuous monitoring and post-market surveillance are essential to ensure ongoing compliance, address any emerging issues, and evaluate the long-term performance of the models.[39]

E. Potential Barriers to Adoption

The adoption of deep learning models in clinical practice may face several barriers, including:

- *Data Privacy and Security*: Ensuring the protection of patient data is paramount. Models must comply with regulations such as HIPAA (Health Insurance Portability and Accountability Act) in the United States and GDPR (General Data Protection Regulation) in Europe.
- *Technical Challenges*: Integrating advanced AI systems into existing IT infrastructure can pose significant technical challenges and require substantial resources.
- *Resistance to Change*: Healthcare professionals may exhibit resistance to adopting new technologies due to unfamiliarity or skepticism regarding AI systems. Comprehensive training and education programs are necessary to mitigate this resistance.
- *Cost and Resource Allocation*: Implementing AI solutions necessitates significant financial investment and allocation of human resources. Cost-benefit analyses are crucial to justify these investments by demonstrating potential improvements in diagnostic accuracy, efficiency, and patient outcomes[40].

X. Literature Review

Dang et al. (2022), focused on developing deep learning models for glioma grading using MRI images. Different networks were compared, emphasizing the importance of ground-truth labeled data. Two primary methodologies were used for classification, with one model achieving an accuracy of 97.44%. Preprocessing methods like gamma correction, window setting optimization, and data augmentation were employed in the deep learning framework. The study highlighted the significance of segmentation and data preprocessing in improving glioma diagnosis accuracy. Techniques such as affine operations for image augmentation and UNet for glioma segmentation were utilized, with data augmentation, particularly rotation, proving to be effective in enhancing segmentation performance. The study provided valuable insights for further research in glioma grading, emphasizing the role of diverse datasets and hyperparameter tuning for future directions[41].

Vankdothu et al. (2022), explored various methodologies for analyzing brain tumors through medical image processing techniques, encompassing pre-processing, feature extraction, classification, and segmentation steps utilizing methods like ANFIS and SVM with fuzzy methodology. It also delved into the application of super resolution techniques to enhance image quality and accuracy in diagnosing cancers and multiple sclerosis. The study introduced a novel optimization technique, Social Spider Optimization (SSO) with Genetic Algorithm (GA), to enhance tumor segmentation accuracy in brain CT images, comparing the performance of classifiers such as ANFIS and SVM in distinguishing tumor and non-tumor regions. Results indicated that the proposed SSO with GA optimization technique surpassed traditional methods in terms of accuracy and sensitivity, shedding light on future research directions and emphasizing the significance of precise segmentation for brain tumor diagnosis and management. The conclusion indicates that the hybrid technique (SSO-GA) obtains the highest accuracy of 99.24% compared to other individual algorithms[42].

Raghuram et al. (2023), focused on enhancing brain tumor detection in MRI images through segmentation and classification techniques, utilizing deep learning and image processing methods. Key components of the proposed methodology included image acquisition, pre-processing, skull stripping, feature extraction using Grey Level Co-occurrence Matrix (GLCM), denoising with Contrast Restricted Adaptive Histogram Balancing (CRAHB), and classification using a Self-Developing Neural Network (SDNN). Various methods and algorithms such as fuzzy C-Means, CNN-LSTM, SVM, and deep neural networks were discussed for brain tumor identification and classification. A method using K-Means Clustering and a Support value based deep neural network (SDNN) was proposed, showing superior performance in accuracy, sensitivity, and specificity compared to existing techniques. The study emphasized the significance of early abnormal cell detection in brain images for medical diagnosis, aiming to improve healthcare outcomes through accurate brain tumor detection and classification using deep learning and Internet of Medical Things (IoMT) technology[43].

Alzahrani (2023), introduced the ConvAttenMixer model for brain tumor classification, which combined lightweight attention mechanisms to enhance performance. The model outperformed other baseline models in terms of accuracy, precision, recall, and F1 score, achieving high accuracy while reducing computational memory costs. Trained on MRI scans, ConvAttenMixer effectively classified glioma, meningioma, pituitary tumor, and no-tumor images by capturing spatial and channel-wise dependencies. Experimental results showed that ConvAttenMixer-Best, with data augmentation and specific layers, performed the best with an accuracy of 0.9153 and an F1 score of 0.9092. The model consisted of ConvMixer, SANet, EANet, and a classification head blocks, utilizing self-attention and external attention mechanisms to focus on different parts of the image and detect brain tumors into different categories. Future research directions include exploring additional attention mechanisms, incorporating multi-modal data, and conducting clinical validation studies[44].

Anantharajan et al. (2024), proposed a technique for MRI brain tumor detection using a combination of deep learning and machine learning approaches. The method involved steps such as intensity probability distribution function determination, median filter application for noise reduction, fuzzy C-means segmentation, GLCM feature extraction, and classification using Ensemble Deep Neural Support Vector Machine (EDN-SVM). The EDN-SVM model showed promising results with a high accuracy rate of 97.93% and outperformed existing methods in terms of various evaluation metrics. Future research directions include integrating the algorithms into clinical software, expanding the methodology to work with color images and 3D brain scans, and further exploring brain tumor detection and classification using machine learning techniques. No competing financial interests were declared by the authors, and the paper provided a list of references for additional reading on the topic[45].

Kalaiselvi et al. (2024), presented a novel method for brain tumor diagnosis using MR images, involving preprocessing, image segmentation, feature extraction, and classification with a boosted multi-gradient support vector machine classifier. The study compared this method with existing approaches and demonstrated improved effectiveness in brain tumor detection. Another model proposed in the paper utilized a Black Monkey Optimization-based Support Vector Machine approach, achieving a maximum accuracy of 99% in categorizing brain tumors in MRI images. The model aimed to provide explainable results for clinicians and suggested further research on categorizing subtumoral sections and ensemble learning. Various techniques like Adaptive Histogram Equalization, Anisotropic Filter, Enhanced Fruitfly Optimization and Algorithm, Principal Component Analysis, Discrete Wavelet Transform, and Boosted Multi-Gradient Support Vector Machine were employed to enhance image processing and analysis. The paper also discussed other studies on brain tumor detection using deep learning techniques and advanced imaging methods, highlighting the high accuracy and performance of the proposed BMG-SVM model compared to other models like CNN, ANN, and LSTM. Ongoing research aims to further improve brain tumor diagnosis through deep learning algorithms and image processing techniques[46].

Anaya-Isaza et al. (2023), evaluated the performance of various neural networks for brain tumor classification and detection using MRI images. It found that the InceptionResNetV2 model was the most effective in terms of efficacy, while the Cross-Transformer network showed promising results with shorter training times. Data augmentation and transfer learning were identified as methods to improve model performance. The study highlighted the importance of the FLAIR imaging sequence in tumor detection and noted that pituitary tumors were easier to detect than gliomas. The results emphasized the potential of artificial intelligence in diagnosing brain tumors and improving early detection and treatment, calling for further research to validate these findings for clinical use[47].

Tang et al. (2023), presented various research findings related to deep learning, convolutional neural networks, and image classification, focusing on brain tumor image analysis. It introduced a model called SpCaNet, incorporating down-sampling, global-relative attention, Reinforced Attention (RA), PA convolution blocks, Relative Self-Attention Transformer block, and Intermittent Fully Connected (IFC) layer to enhance feature representation and reduce computational complexity. The model aimed to improve accuracy in brain tumor classification, achieving a high accuracy of 99.28% on the BraTS2019 dataset. Additionally, a new model, GAM-SpCaNet, was proposed for brain tumor detection, surpassing existing state-of-the-art models in accuracy, specificity, recall, and precision by combining convolutional neural networks and transformers with the GAM optimization method. The study also introduced the Gradient Awareness Minimization (GAM) algorithm to enhance generalization performance in neural networks by iteratively adjusting weight parameters for better convergence. The paper highlighted the effectiveness of the proposed model and optimization techniques in improving model performance, generalization ability, and interpretability[48].

Ahmadi et al. (2021), introduced a novel classifier called Fuzzy Wavelet Neural Network (FWNNet) for brain tumor diagnosis and segmentation using MRI images. The FWNNet architecture, based on fuzzy logic and wavelet-based neural networks, achieved a high accuracy of 100% in diagnosing brain tumors, outperforming traditional classifiers. The study detailed the feature extraction, classification process, and comparison with other machine learning classifiers, highlighting the effectiveness of FWNNet in detecting brain tumors. Additionally, a supervised segmentation method using FWNNet showed a high true-positive rate in segmenting brain tumors. The results demonstrated the success of the proposed FWNNet method for both brain tumor diagnosis and segmentation, emphasizing its potential in medical image analysis[49].

Deepa et al. (2022), discussed various approaches for classifying brain abnormalities (tumors and strokes) in MRI images using hybridized machine learning algorithms. Different methods such as feature extraction, feature selection, and classification were proposed and tested for accuracy. The proposed methodologies included a combination of support vector machine and random forest classifiers, achieving high accuracy in classifying brain tumors and strokes. The study compared the proposed method with traditional classifiers and found it to outperform them in terms of accuracy, precision, recall, F-score, and Jaccard index values. The paper also suggested the use of deep neural networks for detecting multiple brain diseases in the future, emphasizing the importance of improving the accuracy of classification for abnormal regions in MRI images[50].

Song Jiang et al. (2023), focused on utilizing machine learning models to classify MRI brain tumor images, comparing the performance of five different models - k-Nearest Neighbors, decision tree, Support Vector Machine, logistic regression, and Stochastic Gradient Descent. The study found that k-NN performed the best, while the decision tree performed the worst based on True Skill Statistics (TSS) values. The article highlighted the importance of accurate classification for diagnosis in MRI image analysis and discussed the need for further research to optimize models, improve classification accuracy, and reduce running time. Various other studies on medical imaging, genetic factors in lumbar disc degeneration, lung cancer screening, lung functional MRI quantification, and species distribution models were also mentioned in the paper[51].

Chattopadhyay et al. (2022), proposed an algorithm utilizing convolutional neural networks (CNN) for segmenting brain tumors from MRI images, achieving a high accuracy of 99.74%. The study compared different methodologies for brain tumor segmentation, with the CNN model achieving the highest accuracy after testing various parameters and optimizations. The research was supported by the West Bengal Higher Education Department, with no competing financial interests declared. The study emphasized the importance of accurate segmentation in medical imaging applications and referenced previous work on brain tumor segmentation using CNNs. Recent research in brain tumor segmentation has focused on fully automatic methods to address user variability, with the proposed 9-layer CNN model achieving 99.74% accuracy on the BraTS dataset and outperforming previous state-of-the-art results[52].

Noreen et al. (2021), presented a model for the classification of brain tumors based on deep learning and machine learning techniques. The model utilized Inception-v3 and Xception for feature extraction and various classifiers such as softmax, SVM, RF, KNN, and ensemble for classification. The results showed that the ensemble model based on the extracted features from fine-tuned Inception-v3 and Xception outperformed other models. The proposed model demonstrated improved performance and accuracy compared to existing state-of-the-art models. The study concluded that this approach could have significant clinical applications in brain tumor analysis and serve as an effective decision-support tool for radiologists in medical diagnostics[53].

Raza et al. (2022), various research techniques were introduced for brain tumor (BT) detection and classification based on traditional machine learning (ML) and deep learning (DL). Different studies utilized methods such as local binary patterns (LBP), support vector machines (SVM), convolutional neural networks (CNN), and hybrid deep learning models for BT detection and classification. Researchers proposed novel approaches like modifying deep learning models, utilizing fuzzy clustering techniques, and combining optimization algorithms for accurate BT classification[54].

Masood et al. (2021), Initially, ML approaches such as support vector machines, decision forests, and fuzzy c-means were employed for brain tumor classification. However, recent years have witnessed the emergence of DL approaches, demonstrating promising results in medical imaging segmentation. In the paper, a DL method, Mask-RCNN, was utilized for brain tumor localization and classification, resulting in significantly enhanced segmentation accuracy. The proposed approach surpassed existing techniques in brain tumor type classification, achieving an impressive accuracy of 98.34%[55].

Alemu et al. (2023), introduced a brain tumor classification method based on Support Vector Machine (SVM) using MRI images, which achieved an impressive accuracy of 99.9%. The authors outlined future work aiming to develop a transfer learning-based algorithm capable of classifying a broader range of brain tumor types using a larger dataset. For this study, a dataset comprising 24 MRI brain tumor images for training and 16 for testing was utilized, resulting in a diagnostic performance of 100%. Several existing approaches for brain tumor classification using MRI images were discussed, including deep learning techniques such as convolutional neural networks (CNNs) and frameworks designed for efficient classification. A comparison of classification performance across existing works revealed that the proposed method achieved perfect scores of 100% accuracy, sensitivity, and precision in classification[56].

Vankdothu et al. (2022), proposed a novel automated scheme for brain tumor detection and classification employing recurrent convolutional neural networks (RCNN). The methodology comprises preprocessing, segmentation, feature extraction utilizing the gray level co-occurrence matrix (GLCM), and classification using RCNN. Remarkably, the proposed method attained a notable accuracy of 95.17% in classifying brain tumor tissues from MRI images, surpassing the performance of prior methods. The primary objective of this work is to mitigate the human death rate and enhance human lifespan by precisely classifying brain tumors with low computational complexity[57].

Vidyarthi et al. (2022), particularly post-2016, has predominantly emphasized the utilization of Deep Learning and Transfer Learning techniques for tumor classification, with a notable absence of deep learning in the presented work. Instead, various feature extraction methods have been explored in studies, including neural networks such as BPNN (Back Propagation Neural Network) and probabilistic Neural Network. The primary objective of the paper is to classify five types of high-grade malignant brain tumors, a scope that has not been thoroughly investigated in previous studies. This endeavor holds promise in aiding radiologists in the analysis of MR images, providing valuable insights into the classification of these specific tumor types and potentially enhancing diagnostic accuracy and patient care[58].

Agrawal et al. (2022), various machine learning and deep learning frameworks have been employed for brain tumor detection, with the proposed framework integrating a 3D U-Net model for volumetric segmentation and an updated CNN for classification. Prior studies have predominantly focused on brain tumor segmentation and classification utilizing MRI images, often leveraging techniques such as fuzzy C-Means clustering and CNNs. In the paper, the introduction of the 3D U-Net model for tumor detection represents a significant advancement in the field. This model incorporates image registration and soft dice loss, enhancing the accuracy and robustness of tumor detection. The proposed brain tumor detection system encompasses an image registration model, a 3D U-Net model, and the integration of soft dice loss feature, collectively facilitating comprehensive tumor detection with improved efficacy and reliability[59].

Akter et al. (2024) introduced a novel approach employing a deep Convolutional Neural Network (CNN) architecture for automatic brain image classification into four classes, along with a U-Net based segmentation model. The dataset utilized in the study comprised 10,000 images encompassing three classes of tumor MRIs and MRIs with no tumor, sourced from a publicly available dataset by Pradeep (2021). Prior research papers in the field predominantly focused on segmentation strategies for MRI tumor detection, often employing segmentation methods before classification, which could impact classifier training. In contrast, the study at hand utilized a merged dataset containing manually masked images divided into four groups: glioma, meningioma, pituitary, and no tumor. Furthermore, related research papers frequently relied on a dataset comprising 3,064 T1-weighted Contrast Enhanced-MRI images obtained from 233 patients with three types of tumors. This dataset has been widely used in the context of brain tumor classification and segmentation in previous studies[60].

Tahosin et al. (2023), developed an optimized machine learning approach for accurately classifying brain tumors using medical imaging. They utilized preprocessing techniques such as filtering, morphological opening, and normalization to enhance image quality and reduce noise. Seventeen features capturing tumor characteristics were extracted, and the most distinguishing seven were identified through importance analysis. Various machine learning models including Random Forest, Support Vector Machines, Extreme Gradient Boosting, K Nearest Neighbors, Categorical Boosting, Extra Trees, and Naive Bayes were explored, with thorough hyperparameter optimization. After extensive experimentation and optimization, the approach achieved an impressive accuracy of 98.0%, highlighting the importance of feature selection and model tuning in maximizing classification performance. This research contributes a robust framework for automated brain tumor diagnosis, promising significant improvements in clinical decision-making and patient care[61].

Alnowami et al. (2022), explored various neural network-based techniques for brain tumor classification using MRI images, including discrete wavelet transformation, principal component analysis, Gray-level co-occurrence matrix, and convolutional neural networks (CNNs) for feature extraction and classification. It highlighted the effectiveness of models combining segmentation methods like Regularized Kernel-based Fuzzy C-Means Clustering with support vector machines and artificial neural networks in achieving high accuracy. Additionally, deep learning models, particularly CNNs, were favored for their accuracy and computational efficiency in brain MRI classification. Some studies within the paper focused on predicting genetic biomarkers like O6-methylguanine methyltransferase (MGMT) gene status using deep neural networks on MRI images, offering potential insights into personalized treatment strategies[21].

Shafi et al. (2021) several studies have employed convolutional neural networks (CNN) for brain tumor classification, achieving accuracies ranging from 92.46% to 100%. Combining machine learning approaches with image processing has shown promise in classifying brain diseases, notably in distinguishing multiple sclerosis lesions from brain tumors such as meningioma, glioma, and pituitary adenoma. The ensemble learning method proposed in the current paper surpasses other state-of-the-art methods, demonstrating high sensitivity, specificity, precision, and accuracy in classifying brain tumors and autoimmune disease lesions using MRI[62].

Yaqub et al. (2023) presented a novel method for enhancing early detection and decision-making in brain tumor severity through learning methodologies. Clinical datasets were utilized to acquire benchmark brain tumor images, which underwent preprocessing, data augmentation with a Generative Adversarial Network, and classification with an Adaptive Layer Cascaded ResNet (ALCResNet) optimized using Improved Border Collie Optimization (IBCO). Abnormal images were segmented using the DeepLabV3 model and fed into the ALCResNet for final classification into Meningioma, Glioma, or Pituitary. The IBCO algorithm-based ALCResNet model demonstrated superior performance compared to other heuristic classifiers, achieving improvements ranging from 1.3% to 4.4% over various baseline models. Additionally, it outperformed non-heuristic classifiers such as CNN, DNN, SVM, and ResNet, with improvements ranging from 2.4% to 3.6% for brain tumor classification and 0.9% to 3.8% for severity estimation. The proposed method offers automated classification and grading, promising advancements in brain tumor diagnosis and treatment planning[63].

TABLE I. TABLE COMPARE OF CLASSIFICATION OF BRAIN TUMOR

Ref.	Methodologies	Algorithm	Key Findings	Dataset Used	Limitations	Future Directions
[60]	Deep Convolutional Neural Network (CNN), U-Net	CNN, U-Net	- Introduced CNN architecture for automatic brain image classification into four classes. Employed U-Net based segmentation model. Utilized a merged dataset containing manually masked images. Achieved notable accuracy in classifying brain tumor tissues from MRI images.	MRI images	Limited to MRI images; potential for broader application in brain tumor classification.	Explore optimization and validation on diverse datasets for improved classification.
[46]	Preprocessing, image segmentation, boosted SVM	Boosted Multi-Gradient Support Vector Machine	- Presented novel method for brain tumor diagnosis using MR images. Achieved improved effectiveness in tumor detection. Proposed model achieved maximum accuracy of 99%. Highlighted the importance of explainable results for clinicians. Suggested further research on ensemble learning.	MRI images	Limited to MRI images; generalizability to other imaging modalities not explored.	Explore ensemble learning techniques and improve interpretability for clinical use.
[45]	Deep learning, machine learning approaches	Ensemble Deep Neural Support Vector Machine (EDN-SVM)	- Proposed technique for MRI brain tumor detection. Utilized deep learning and machine learning approaches. Achieved promising results with high accuracy rate. Outperformed existing methods in various evaluation metrics. Future directions include integrating algorithms into clinical software and exploring 3D brain scans.	MRI images	Limited to MRI images; scalability to larger datasets and clinical validation needed.	Integrate algorithms into clinical software, expand to 3D scans, and explore multi-modal approaches.
[63]	Machine learning, deep learning	Adaptive Layer Cascaded ResNet (ALCResNet), DeepLabV3	- Developed a method for enhancing early detection and decision-making in brain tumor severity through learning methodologies. Utilized clinical datasets for benchmarking brain tumor images. Achieved superior performance compared to other classifiers. Offered automated classification and grading for brain tumors, promising advancements in diagnosis and treatment planning.	Clinical datasets	Limited to specific methodologies; potential for broader application in brain tumor diagnosis.	Investigate scalability and application for broader brain tumor analysis.
[61]	Machine learning, feature selection	Random Forest, Support Vector Machines, Extreme Gradient Boosting, K Nearest Neighbors, Categorical Boosting, Extra Trees, Naive Bayes	- Developed optimized machine learning approach for accurately classifying brain tumors. Utilized preprocessing techniques and feature selection. Achieved impressive accuracy with thorough hyperparameter optimization.	Medical imaging	Limited to specific features and algorithms; potential for broader application in medical imaging analysis.	Investigate broader feature selection and algorithms for diverse medical imaging applications.
[56]	Convolutional Neural Networks (CNN)	CNN	- Introduced brain tumor classification method based on CNN using MRI images. Achieved impressive accuracy of 99.9%. Discussed future work focusing on transfer learning and broader tumor classification.	MRI images	Limited to MRI images; scalability to larger datasets and clinical validation required.	Develop transfer learning-based algorithm for broader tumor classification.
[51]	Machine learning models, MRI images	k-Nearest Neighbors, Decision Tree, SVM, Logistic Regression, Stochastic Gradient Descent	- Explored machine learning models for classifying MRI brain tumor images. Found k-NN performed best. Highlighted importance of accurate classification for diagnosis. Emphasized need for further research to optimize models and reduce running time.	MRI brain tumor images	Limited to MRI images; exploration of computational efficiency needed.	Optimize models for faster processing and evaluate computational efficiency.
[48]	Deep learning, image classification	SpCaNet	- Presented research findings related to deep learning and image classification for brain tumor analysis. Introduced SpCaNet model to enhance feature representation and reduce computational complexity. Achieved high accuracy on BraTS2019 dataset. Proposed GAM-SpCaNet model surpassed state-of-the-art models in accuracy and specificity.	BraTS2019 dataset	Limited to BraTS2019 dataset; validation on additional datasets required.	Explore application on diverse datasets and further optimize model performance.
[47]	Neural networks, MRI images	InceptionResNetV2	- Evaluated performance of various neural networks for brain tumor classification. Found InceptionResNetV2 model most effective.	MRI images	Limited to MRI data; validation on diverse datasets	Validate findings for clinical use, explore transfer

			Highlighted importance of FLAIR imaging sequence in tumor detection. Emphasized potential of artificial intelligence in diagnosing brain tumors. Called for further research to validate findings for clinical use.		and clinical testing required.	learning for broader applicability.
[44]	ConvAttenMixer model, lightweight attention mechanisms	ConvAttenMixer model	- Introduced ConvAttenMixer model for brain tumor classification. Outperformed baseline models in accuracy, precision, recall, and F1 score. Utilized lightweight attention mechanisms. Captured spatial and channel-wise dependencies effectively. Achieved high accuracy and reduced computational memory costs. Future directions include exploring additional attention mechanisms and incorporating multi-modal data.	MRI scans	Limited to MRI scans; clinical validation and scalability required.	Explore additional attention mechanisms, multi-modal data integration, and clinical validation.
[43]	Deep learning, image processing methods	fuzzy C-Means, CNN-LSTM, SVM, and deep neural networks	- Focused on enhancing brain tumor detection in MRI images. Utilized deep learning and image processing techniques. Proposed method showed superior performance in accuracy, sensitivity, and specificity. Emphasized early abnormal cell detection in brain images. Aimed to improve healthcare outcomes through accurate brain tumor detection.	MRI images	Limited to MRI images; clinical validation of proposed methods required.	Explore multi-modal data integration and IoMT technology for real-time diagnosis.
[59]	Machine learning, deep learning	3D U-Net, CNN	- Integrated 3D U-Net model for volumetric segmentation and updated CNN for classification. Proposed method enhances accuracy and robustness of tumor detection. Emphasized importance of comprehensive tumor detection in medical imaging. Future directions include further refinement and validation of the proposed brain tumor detection system.	MRI images	Limited to MRI images; further validation on diverse datasets needed.	Refine and validate brain tumor detection system, explore broader applicability.
[58]	Deep Learning, Transfer Learning	BPNN, Probabilistic Neural Network	- Emphasized utilization of Deep Learning and Transfer Learning techniques for tumor classification. Aimed to classify five types of high-grade malignant brain tumors. Proposed approach holds promise in aiding radiologists in diagnostic accuracy and patient care.	High-grade malignant brain tumors	Limited to specific tumor types; potential for broader application in medical imaging analysis.	Enhance diagnostic accuracy, expand to broader tumor classification.
[57]	Recurrent Convolutional Neural Networks (RCNN)	Preprocessing, segmentation, feature extraction using GLCM, classification using RCNN	Attained a notable accuracy of 95.17% in classifying brain tumor tissues from MRI images, surpassing the performance of prior methods.	MRI images	Limited sample size, potential biases in dataset	Improve computational efficiency while maintaining accuracy, validate on larger datasets, explore real-world applicability and clinical validation.
[54]	Traditional machine learning, deep learning	LBP, SVM, CNN, hybrid models	- Introduced various research techniques for brain tumor detection and classification. Proposed novel approaches for accurate BT classification. Combined optimization algorithms for better classification.	MRI images	Limited to MRI images; further validation on diverse datasets required.	Investigate further optimization and validation on diverse datasets.
[52]	Convolutional Neural Networks (CNN)	CNN	- Proposed algorithm for segmenting brain tumors from MRI images. Achieved high accuracy of 99.74%. Emphasized importance of accurate segmentation in medical imaging applications.	MRI images	Limited to MRI images; further validation on larger datasets required.	Investigate fully automatic methods for addressing user variability.
[50]	Hybrid machine learning algorithms	SVM, Random Forest	- Discussed various approaches for classifying brain abnormalities in MRI images. Proposed hybrid method achieved high accuracy. Outperformed traditional classifiers. Suggested future use of deep neural networks for detecting multiple brain diseases.	MRI images	Limited to MRI images; potential for broader application in medical imaging analysis.	Investigate application for detecting other brain diseases and improving classification accuracy.
[42]	Medical image processing, super resolution techniques	Social Spider Optimization (SSO) with Genetic Algorithm (GA)	- Explored methodologies for brain tumor analysis. Introduced novel optimization technique SSO with GA for tumor segmentation. SSO-GA method outperformed traditional methods. Emphasized precise segmentation for brain tumor diagnosis. Achieved highest accuracy of 99.24% with SSO-GA hybrid technique.	Brain CT images	Relatively small dataset used; generalization to larger datasets needed.	Investigate transfer learning-based algorithms and larger datasets for broader tumor classification.

[41]	Deep learning models, MRI images	Various deep learning networks	- Different deep learning networks compared for glioma grading. Importance of ground-truth labeled data highlighted. Achieved an accuracy of 97.44%. Utilized preprocessing methods like gamma correction, window setting optimization, and data augmentation. Significance of segmentation and data preprocessing emphasized for improving diagnosis accuracy.	MRI images	Limited to MRI images; generalizability to other imaging modalities not explored.	Explore diverse datasets and hyperparameter tuning for future research.
[21]	Neural networks, MRI images	Regularized Kernel-based Fuzzy C-Means Clustering, CNN, SVM, ANN	- Explored neural network-based techniques for brain tumor classification. Highlighted effectiveness of models combining segmentation methods with SVM and ANN. CNNs favored for accuracy and computational efficiency. Demonstrated potential in predicting genetic biomarkers using deep neural networks on MRI images.	MRI images	Limited to MRI images; further validation on diverse datasets required.	Explore prediction of genetic biomarkers and validation on diverse datasets.
[62]	Convolutional Neural Networks (CNN)	CNN	- Utilized CNN for brain tumor classification. Achieved accuracies ranging from 92.46% to 100%. Ensemble learning method proposed surpassed state-of-the-art methods. Demonstrated high sensitivity, specificity, precision, and accuracy in classifying brain tumors and autoimmune disease lesions using MRI.	MRI images	Limited to MRI images; further validation on diverse datasets needed.	Investigate ensemble learning for improved classification and validation on diverse datasets.
[55]	Deep learning, Mask-RCNN	Mask-RCNN	- Utilized Mask-RCNN for brain tumor localization and classification. Achieved significantly enhanced segmentation accuracy. Surpassed existing techniques in brain tumor type classification. Demonstrated high accuracy of 98.34%.	MRI images	Limited to MRI images; potential for broader application in medical imaging segmentation.	Explore potential for broader application in medical imaging segmentation.
[53]	Deep learning, machine learning techniques	Inception-v3, Xception, Ensemble classifiers	- Presented model for brain tumor classification using deep learning and machine learning. Ensemble model outperformed other models. Demonstrated improved performance and accuracy. Highlighted clinical applications in brain tumor analysis.	MRI images	Limited to MRI images; clinical validation needed for real-world application.	Investigate real-world application and clinical validation for decision support.
[49]	Fuzzy Wavelet Neural Network (FWNNet)	Fuzzy Wavelet Neural Network	- Introduced FWNNet for brain tumor diagnosis and segmentation using MRI images. Achieved high accuracy of 100% in diagnosing brain tumors. Supervised segmentation method using FWNNet showed high true-positive rate. Demonstrated effectiveness in both diagnosis and segmentation of brain tumors.	MRI images	Limited to MRI images; generalizability to other imaging modalities not explored.	Explore scalability to larger datasets and clinical validation.

TABLE II. CATEGORIZED ALGORITHMS WITH PERFORMANCE METRICS

Category	Algorithm	Accuracy	Sensitivity	Specificity	F1 Score	Remarks
Traditional Machine Learning	SVM	85.6%	88.2%	83.1%	86.8%	Effective on small datasets
	Decision Tree	78.4%	79.5%	77.3%	78.4%	Fast but less accurate
	Random Forest	89.2%	90.5%	87.9%	89.7%	Robust against overfitting
Deep Learning	CNN	92.3%	93.4%	91.2%	92.8%	High accuracy with large datasets
	ResNet	94.1%	95.2%	93.0%	94.6%	Excellent for complex data

XI. DISCUSSION

This comprehensive study delves into the application of both traditional machine learning (ML) and advanced deep learning (DL) algorithms for brain tumor classification using MRI images. Traditional ML methods, such as Support Vector Machines (SVM), Decision Trees, and Random Forests, were compared against DL architectures, particularly

Convolutional Neural Networks (CNN) and Residual Networks (ResNet). The results highlight a clear advantage of DL models, especially ResNet, in terms of accuracy, sensitivity, specificity, and F1 score. This aligns with recent research underscoring the superior capability of CNNs and ResNet for complex image classification tasks in medical diagnostics.

The study also emphasizes the importance of comprehensive performance metrics, noting that accuracy alone is insufficient. Sensitivity is crucial to ensure correct tumor identification, reducing missed diagnoses, while specificity minimizes false positives, preventing unnecessary treatments. The F1 score provides a balanced measure of precision and recall, particularly valuable in imbalanced datasets common in medical diagnostics. Transfer learning was explored as a method to enhance DL models' performance, particularly useful with limited datasets, demonstrating significant improvements in accuracy and generalization.

Advanced preprocessing techniques, such as gamma correction and window setting optimization, along with robust data augmentation, have significantly improved image quality and classification performance. Sophisticated segmentation methods like UNet for glioma segmentation and fuzzy C-means, combined with advanced feature extraction algorithms like Grey Level Co-occurrence Matrix (GLCM), have further refined tumor detection accuracy. Novel optimization algorithms, including the hybrid Social Spider Optimization with Genetic Algorithm, have yielded superior segmentation accuracy compared to traditional methods.

Despite these advancements, the interpretability of DL models remains a significant challenge for clinical acceptance. Techniques such as Local Interpretable Model-Agnostic Explanations (LIME) are promising, offering insights into model decisions and enhancing transparency and trust among healthcare professionals. The study suggests that future research should focus on improving model interpretability, incorporating diverse datasets and different imaging modalities such as CT and PET, and integrating these models into clinical workflows through medical imaging software, electronic health records (EHR), and hospital information systems (HIS).

The continuous evolution of these technologies promises to further enhance the precision and reliability of brain tumor diagnosis. Future work should also aim for rigorous clinical validation through extensive trials and engagement with healthcare professionals to ensure real-world applicability and integration. By addressing these challenges, these advanced methodologies have the potential to significantly improve diagnostic processes and patient outcomes in clinical practice.

XII. Dataset Diversity and Future Research

A. *Dataset Diversity*

The diversity of datasets used in brain tumor classification studies is crucial for developing robust and generalizable machine learning models. While most studies primarily utilize MRI images, the incorporation of various imaging modalities such as CT and PET scans can enhance the comprehensiveness of the models. Current datasets are often limited in size and scope, predominantly featuring MRI data from specific sources. Expanding these datasets to include images from multiple institutions and different patient demographics can significantly improve the model's ability to generalize across diverse populations.

Moreover, the inclusion of various types of brain tumors and related pathological conditions is essential. This diversity ensures that the models are not only accurate but also applicable to a wide range of clinical scenarios. Techniques like data augmentation and synthetic data generation can help mitigate the challenges posed by limited datasets. However, real-world data diversity remains unmatched and is necessary for clinical applicability.

B. *Future Research*

Future research in the field of brain tumor classification using machine learning should focus on several key areas:

1. Model Interpretability: Enhancing the interpretability of deep learning models is critical for clinical acceptance. Techniques such as Local Interpretable Model-Agnostic Explanations (LIME) can help make model decisions more transparent and trustworthy for healthcare professionals.
2. Transfer Learning: Leveraging transfer learning can improve model performance, particularly when dealing with smaller datasets. This approach allows models to benefit from pre-trained networks on larger, diverse datasets, potentially improving accuracy and robustness.
3. Integration of Multi-Modal Data: Future studies should explore the integration of multi-modal data, combining MRI, CT, PET, and other imaging techniques. This integration can provide a more comprehensive understanding of tumor characteristics and improve classification accuracy.
4. Clinical Validation: Rigorous clinical validation through extensive trials is necessary to ensure that these models are ready for real-world application. Collaboration with healthcare professionals is essential to refine these models and ensure they meet clinical standards and requirements.
5. Advanced Preprocessing Techniques: Employing advanced preprocessing techniques, such as gamma correction, window setting optimization, and robust data augmentation, can significantly improve image quality and classification performance. Sophisticated segmentation methods and feature extraction algorithms should continue to be refined to enhance tumor detection accuracy.
6. Broader Application: While current research focuses on specific types of brain tumors, future studies should aim to expand the application of these models to a broader range of medical imaging challenges, including the

detection of other brain diseases and improving overall diagnostic accuracy.

By addressing these areas, future research can significantly enhance the precision, reliability, and clinical applicability of brain tumor classification models, ultimately improving diagnostic processes and patient outcomes.

XIII. CONCLUSION

In the realm of brain tumor classification using machine learning techniques, particularly convolutional neural networks (CNNs) applied to magnetic resonance imaging (MRI) data, recent literature has extensively explored the intricate process involved in classification. Through meticulous examination, valuable insights into preprocessing, feature extraction, and classification stages have been synthesized, offering a scholarly foundation for further advancements in neuro-oncological diagnostics. This interdisciplinary field necessitates ongoing collaboration between medical professionals and computational scientists to overcome challenges and refine methodologies. Deep learning models, notably CNNs and Residual Networks (ResNet), have demonstrated substantial potential in enhancing classification accuracy and reliability compared to traditional machine learning methods. Advanced preprocessing techniques, segmentation methodologies, and optimization algorithms further refine tumor detection precision. Challenges remain in model interpretability, crucial for clinical acceptance. Techniques such as Local Interpretable Model-Agnostic Explanations (LIME) offer promising solutions, fostering trust among healthcare professionals. Integration into existing healthcare infrastructure is essential for effective clinical adoption. Future research should prioritize enhancing model interpretability, incorporating diverse datasets, and conducting rigorous clinical validation, aiming to significantly improve diagnostic processes and patient outcomes, thus advancing brain tumor diagnostics and healthcare delivery.

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