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# Deep and Machine Learning Algorithms for Diagnosing Brain Cancer and Tumors

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**Abstract**

In the rapidly evolving field of medical diagnostics, the integration of deep learning (DL) and machine learning (ML) technologies has dramatically advanced the accuracy and efficiency of brain cancer and tumor diagnosis using magnetic resonance imaging (MRI). This review explores the transformative impact of these technologies, highlighting their role in enhancing tumor detection, classification, and early diagnosis interventions. DL and ML algorithms have significantly improved the analysis of complex imaging data, enabling more precise and faster diagnostic decisions, which are crucial for effective patient management and treatment planning. This review encompasses a broad spectrum of studies that illustrate the capabilities of these computational techniques in handling large datasets, learning intricate patterns, and achieving a high diagnostic performance. By delving into various algorithmic approaches and their clinical implications, this study underscores the importance of continued advancements and the integration of AI technologies in the field of oncology, aiming to foster better patient outcomes through innovative diagnostic tools.

 

## A. Introduction

In the current era of rapid technological progress, algorithms and processing stand out as critical fields of study and application. Brain cancer and Tumors diagnoses have seen significant advancements with the integration of deep learning and machine learning algorithms and techniques. These technologies have revolutionized the field of medical imaging, particularly the analysis of MRI scans for brain tumor detection and classification. Researchers have extensively explored the application of deep and machine learning in this domain to improve the accuracy and efficiency of brain tumor diagnosis.

The use of deep learning in brain cancer classification has been a subject of interest, with studies summarizing the pathophysiology of brain cancer, imaging modalities, and computer-assisted methods for brain cancer characterization [1][2]. Additionally, deep and machine learning techniques have been reviewed for brain tumor MRI image segmentation, highlighting their potential in this specific diagnostic area [3][4]. Furthermore, the utilization of deep and machine learning algorithms for brain tumor classification has been emphasized, demonstrating their effectiveness in classifying different types of brain cancer and tumors [5][6][7].

In the context of brain tumor detection, computational intelligence and metaheuristic techniques have been explored for brain tumor detection using MRI devices, shedding light on the gaps in existing algorithms and proposing new methodologies [8][9]. Moreover, the role of deep learning in discovering intricate structures in large datasets has been highlighted, particularly in MRI-based brain tumor classification [10].

Various studies have reported the successful diagnosis of brain cancer and tumors using traditional and deep learning methods, demonstrating the potential of these techniques for accurately classifying brain tumors [11]. Additionally, experiments combining deep learning (DL) and traditional machine learning (ML) techniques have been performed for the early diagnosis of brain tumors, indicating the synergistic potential of these approaches [12][13]. Furthermore, the focus on deep and machine learning techniques for texture, morphological, and statistical feature classification of brain tumors has been emphasized, underscoring their significance in this domain [14][15].

Brain tumor characterization was performed using magnetic resonance imaging (MRI). Notably, the Support Vector Machine (SVM) algorithm demonstrated superior performance in categorizing tumor attributes, potential to enhance diagnostic accuracy, and support early targeted interventions for brain cancer. This reinforces the significance of integrating machine learning techniques in the diagnostic process to improve patient outcomes in oncology [16].

Additionally, a review of commonly used datasets, convolutional neural network architectures, and transfer learning techniques has provided valuable insights into the application of deep learning for brain tumor detection using MRI images [17]. Furthermore, the impact of deep learning-based technologies in medical image analysis, particularly in disease diagnosis, has been emphasized, highlighting the significant advancements facilitated by artificial intelligence and deep learning [18].

Furthermore, Accurate diagnosis of brain tumors is critical for effective treatment and improved patient outcomes. Traditionally, MRI scans analyzed by physicians have been used, but this process can be subjective and time-consuming [19]. Recent advancements in AI, particularly in deep and machine learning algorithms, offer promising solutions. These algorithms analyze medical images with high accuracy and speed, potentially aiding physicians in early detection, classification, and treatment decisions [20][21].

This review aims to critically evaluate recent advancements in deep learning models for brain cancer and tumors, highlighting the iterative improvements and innovative approaches employed to enhance diagnostic accuracy, efficiency, and generalizability. explored multi-modality adaptations and advanced algorithmic strategies to push the boundaries of what is achievable in medical diagnostics.

The remainder of this paper is organized as follows: in presenting a concise overview of deep and machine learning algorithms for diagnosing brain cancer and tumors in Section B. The results of the review analysis, including the most important conclusions, are presented in Section C. A discussion of the review analysis is presented in Section D. Finally, the conclusion and future directions provides a summary of the research findings in Section E.

## B. Background Theoury

### B.1 Deep And Machine Learning Algorithms for Diagnosing Brain Cancer and Tumors

Deep learning (DL) and machine learning (ML) are pivotal for advancing medical imaging, particularly in the diagnosis of brain cancer and tumors. These technologies harness complex algorithms to analyze medical images such as MRI scans for better diagnosis and treatment planning.

### B.2 Advances in Deep and Machine Learning for Medical Imaging

The diagnosis of brain cancer and tumors represents a critical area of medical research, in which precision and accuracy are paramount. Traditional methods, while effective, often have limitations in terms of sensitivity and specificity, necessitating multiple rounds of testing and expert interpretation. With the advent of deep and machine learning, significant efforts have been made to overcome these challenges [22][23].

Machine learning techniques have transformed the landscape of medical diagnostics by enabling more refined analysis of complex datasets. Algorithms such as Support Vector Machines (SVM) and Random Forests (RF) have been pivotal in classifying and predicting pathological features from medical images with high accuracy. These techniques are particularly beneficial for segmenting brain tumors from MRIs, which is critical for effective treatment planning and outcome prediction [24], [25].

In the Figure 1 shows a comparison between classic deep and machine learning approaches applied to a classification task. Both approaches use an artificial neural network organized in different layers (IL, HL, and OL output layers).

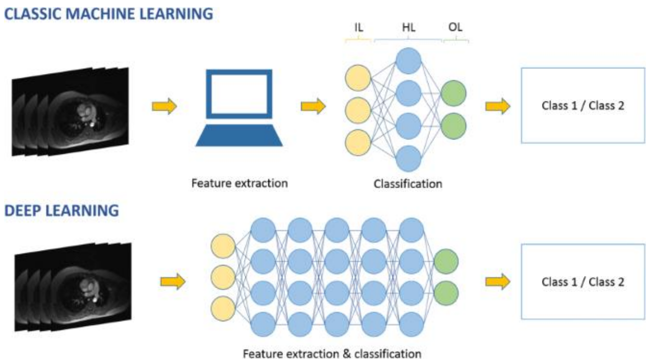


**Figure1.** Artificial Intelligence in Medical

### B.3 Machine Learning in Brain Cancer and Tumor Diagnosis

Machine learning algorithms, including Support Vector Machines (SVM), Decision Trees, and Random Forests, have traditionally been used to classify brain tumors and brain cancer by extracting features from MRI images using techniques like GLCM and Haralick features. Although these models offer moderate accuracy, they require extensive feature engineering to achieve reliable performance and detect brain tumors using machine-learning techniques, as shown in Figure 2 [26].

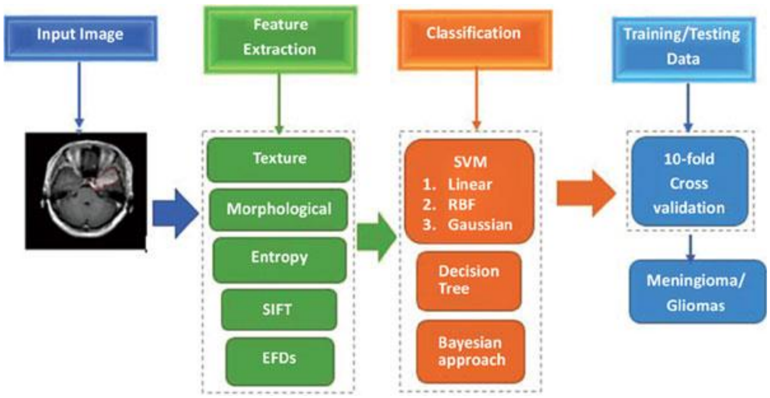


**Figure2.** Detecting Brain Tumor using Machines Learning Techniques

### B.4 Deep Learning Advancements

Deep Deep learning, particularly Convolutional Neural Networks (CNNs), represents a significant advancement over traditional ML techniques. CNNs automate feature extraction and learning directly from MRI images, which simplifies the model architecture and improves diagnostic accuracy. Studies have shown that CNNs achieve higher performance metrics than traditional ML, with accuracy rates often surpassing 90% in identifying and classifying brain tumors, and the deep learning technique CNN and CNN-based hybrid deep learning model CNN-LSTM is applied to detect brain tumors. This technique is illustrated in Figure 3 [27].

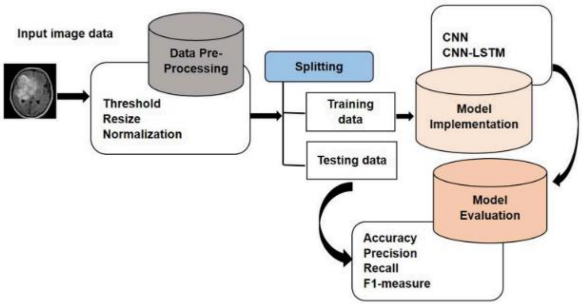


**Figure3.** : CNN and CNN-based hybrid deep learning model

Recent advancements in ML and DL have led to the development of algorithms specifically designed for the segmentation and classification of brain tumors from imaging data. Techniques such as convolutional neural networks (CNNs), support vector machines (SVMs), and other algorithmic approaches have shown promising results for the early detection and classification of these malignancies. These techniques can analyze complex imaging data, identify patterns that are not readily visible to the human eye, and predict disease progression with high accuracy [28].

### B.5 DL and ML Integration into Clinical Workflow

The integration of ML and DL into clinical workflows involves not only the development and training of models but also the validation of these models in clinical settings. This includes assessing the diagnostic accuracy, reliability, and ability of the algorithms to work with real-world data. Furthermore, ethical considerations such as patient privacy and transparency of algorithmic decisions are critical in their adoption. As shown in Figure 4, the framework for building the predictive ML model comprises five steps.

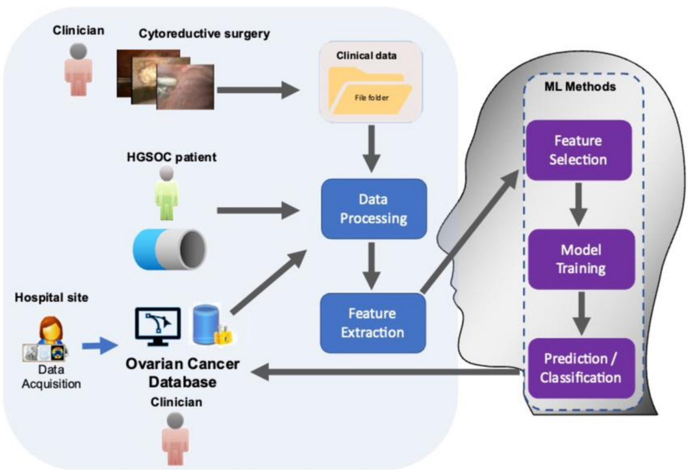


**Figure4.** : Workflow showing integration of ML algorithms to analyse comprehensive resource of clinical, radiological and surgical data for the development of prognostic ovarian cancer models.

## C. Litruture Review

This section provides a concise overview of deep and machine learning algorithms for diagnosing brain cancer and tumors in the context of general investigations:

Kumar et. al. in 2024, explored two deep learning structures to improve brain tumor classification, focusing on a multi-task model that handles classification, segmentation, and localization together. This model uses an enhanced VGG16 architecture with Global Average Pooling to increase efficiency and processing. By combining various diagnostic tasks, it better manages MRI data and significantly outperforms the traditional methods in terms of accuracy and performance. These findings highlight the effectiveness of the model in advancing the precision of brain tumor diagnostics through deep learning. However, its reliance on MRI as the sole imaging modality may restrict its broad application. To overcome this limitation, further adaptation and validation across various imaging modalities, such as CT scans and PET images, may expand its diagnostic utility [29].

Singh, Prasad, and Rastogi in 2022, introduced a convolutional neural network (CNN) model for brain tumor classification using a modified VGG16 architecture with Global Average Pooling (GAP). This model efficiently performs tumor segmentation, classification, and localization from MRI scans, optimizes feature extraction, and reduces complexity. It significantly enhances the accuracy and efficiency, outperforming traditional diagnostic methods for classifying various brain tumor types. However, a limitation is noted in its potential over-reliance on a single architecture, which may not effectively capture all relevant features across different tumor types and stages, thus limiting its generalizability. To address this, the proposed solution involves augmenting the model with additional CNN architectures and training it on a broader dataset that includes a wider variety of tumor types and stages [30].

In 2022 Wu et. al., presented a method for diagnosing brain tumors using MRI scans by integrating the Mobilenetv2 deep learning model with the Contracted Fox Optimization Algorithm (CFOA). This approach utilizes Mobilenetv2 to extract features and the CFOA to optimize the parameters. As shown in the Figshare dataset, the model achieved 97.32% accuracy and 80.12% sensitivity, surpassing the other models. These results validate the effectiveness of merging deep learning with optimization algorithms for medical imaging. However, the applicability of the model is limited by the quality and diversity of the dataset, potentially affecting performance across various clinical contexts. To mitigate this, it is suggested to expand the dataset to cover a broader range of demographics and clinical conditions [31].

Alhassan and Wan Zainon in 2020, explored an advanced method for segmenting and classifying brain cancer from MRI images using the AT Algorithm with Fuzzy C-Ordered Means (BAFCOM) and Enhanced Capsule Networks (ECN). It utilizes fuzzy clustering and deep learning to improve the identification of tumor features such as shape and location. BAFCOM enhances data segmentation, whereas ECN boosts classification accuracy. These results indicate notable advancements in tumor detection, showcasing the benefits of integrating CAD and AI in medical diagnostics. However, this approach faces challenges in terms of computational intensity and scalability, potentially limiting its real-time applications. To address these limitations, one solution is to optimize the algorithms for parallel processing and employ cloud computing to decrease computational demands and facilitate real-time usage [32].

In 2023 Jabbar et., discussed Caps-VGGNet, a hybrid AI model that combines CapsNet and VGGNet to improve brain tumor detection and segmentation. By leveraging VGGNet depth and CapsNet spatial awareness, the model addresses complex imaging challenges. The results showed enhanced accuracy in detecting and segmenting brain tumors and promising better, timely diagnoses. This represents a significant advancement in AI for medical imaging. However, the effectiveness of the model is limited by the need for extensive and varied datasets. To overcome this, it is suggested to form partnerships with multiple healthcare facilities to ensure a diverse data pool for effective training and validation [33].

Deng et. al. in 2020, proposed a brain tumor segmentation model leveraging HCNN and CRF-RRNN, blending Heterogeneous Convolutional Neural Networks with Conditional Random Fields and Recurrent Regression Neural Networks for precise image segmentation. Training involves 2D image patches and fine-tuning with image slices to enhance the accuracy. The model integrates with the Internet of Medical Things (IoMT) platforms, showing robust performance across various MRI scan types through a voting fusion technique for accurate tumor segmentation. However, its dependency on specialized hardware limits accessibility. This limitation could be mitigated by employing model optimization strategies, such as quantization and pruning, to reduce hardware demands and improve accessibility in medical settings [34].

Sakthi et. al. in 2023, introduced a deep convolutional neural network (DCNN) framework for classifying brain tumors using MRI images, employing a detailed architecture with layers including convolutional, pooling, and fully connected sections, optimized with ReLU and global average pooling. This DCNN excels in handling large datasets, significantly reducing computational complexity and execution time. In tests against traditional models, the DCNN showed enhanced classification accuracy, especially in distinguishing cancerous from non-cancerous brain images. These results highlight the capability of the DCNN to use deep learning to improve the diagnostic precision in medical imaging. However, the model faces potential overfitting issues owing to its complexity, which can limit its performance on external datasets or in various clinical settings. To counteract this, regularization strategies such as dropout and data augmentation should be incorporated, and the model should be tested on a broader, external dataset to confirm its generalizability [35].

Jopek et. al. in 2024, presented a deep learning-based multiclass method for classifying cancer types using liquid biopsy data, focusing on improving diagnostic accuracy for various cancers. Advanced machine learning algorithms have been employed to effectively categorize cancers from complex biopsy datasets. Significant results have shown enhanced accuracy and speed in cancer detection, positioning this method as a major progression in non-invasive cancer diagnostics. This approach is a key development in personalized medicine, facilitating quicker and more precise treatment decisions. However, the variability in liquid biopsy sample quality and volume presents a challenge, potentially affecting classification accuracy. Standardizing the sample collection and processing protocols is suggested to improve the consistency and reliability of the data for analysis [36].

Indra, Jusman, and Kurniawan in 2023, proposed innovative advancements in early brain tumor diagnosis using modified CNN architectures, specifically EfficientNetB0, MobileNetV2, and Xception, enhanced with additional layers and transfer learning from ImageNet to improve diagnostic accuracy. These adaptations aim to optimize these models for the complexities of MRI image analysis, targeting more effective early detection capabilities. The results showed significant enhancements in diagnostic accuracy, with all metrics (accuracy, precision, and recall) exceeding 97%. However, a limitation arises from the reliance on pre-trained models and transfer learning, which may not adequately reflect the specific nuances of brain tumor MRI images. Further training or fine-tuning of models with a larger, more varied set of MRI-specific images is necessary to better capture the distinct characteristics of brain tumors, thereby enhancing the models' clinical applicability and diagnostic precision [37].

Vaiyapuri et. al. in 2023, suggested a computer-aided diagnosis model for brain tumor classification using MRI scans, driven by ensemble learning to enhance detection accuracy. It utilizes multiple predictive models within an ensemble framework to refine the diagnostic precision and overcome the limitations of individual models. The integration of diverse algorithms helps to achieve superior accuracy over single-model approaches, marking a significant advancement in MRI-based tumor diagnostics. However, the model faces potential overfitting challenges because of its complexity. To mitigate this, applying regularization techniques and extensive validation across various external datasets is necessary to ensure robustness and generalizability [38].

Lee, Chae, and Cho in 2024, presented a new Patterned-GridMask technique combined with Gaussian filters to improve brain tumor classification in MRI scans. It employs models such as ViT-B/16, MaxViT-B, TResNet-M, and EfficientNetV2-M using strategic data augmentation for optimal deep learning performance. Key findings include a notable increase in F1-scores and accuracy, with ViT-B/16's F1-score rising from 86.63 to 92.08. However, the study was limited by its focus on a specific MRI dataset, impacting its broader applicability. To address this, future research should test the Patterned-GridMask across various medical imaging datasets and clinical conditions, potentially extending to different diseases [39].

In 2022 Asif et. al., explored the use of deep transfer learning models such as Xception, NasNet Large, DenseNet121, and InceptionResNetV2 for detecting brain tumors in MRI scans. By leveraging pretrained models on ImageNet and employing optimizers such as ADAM, SGD, and RMSprop, this study enhances the performance of these models through transfer learning. This approach utilizes pre-trained features, simplifies the training process, and achieves notable results, with the Xception model reaching 99.67% accuracy on a large MRI dataset. However, the study's reliance on established models and datasets could limit its relevance to real-world clinical settings owing to variability. It is recommended to focus on validating these models across various clinical settings and datasets to improve their practical applicability and robustness [40].

Khan et. al. in 2021, presented and evaluated machine and deep learning methods for diagnosing brain diseases like Alzheimer's, tumors, epilepsy, and Parkinson's. It explores ML techniques, such as SVM, RF, DT, and DL techniques, including CNNs and RNNs, using 22 datasets from 147 studies to assess metrics such as accuracy, sensitivity, and AUC. CNNs are particularly important for effectively handling complex brain-imaging data. The study identified a limitation in the narrow dataset and model range, which may not reflect the broader diversity of brain diseases. To address this, including a more diverse array of datasets and advanced models is recommended to enhance diagnostic applicability and accuracy across various populations [41].

In 2023, Atha and Chaki, proposed SSBTCNet, a semi-supervised model for brain tumor classification that leveraged both labeled and unlabeled data. It employs fuzzy contrast enhancement to improve the MRI quality and integrates an autoencoder with a supervised classifier. The dual loss function of the model, focusing on reconstruction error and classification loss, simultaneously enhances feature extraction and classification. Notable results include increased classification accuracy and robust performance across various datasets, outperforming the traditional fully supervised approaches. However, the model relies heavily on high-quality labeled data, which limits its broader application. This limitation can be overcome by using advanced data augmentation and forming partnerships with medical institutions to expand the diversity of labeled data [42].

Saranya et. al. in 2023, explored advanced CNN models like EfficientNet and DenseNet, paired with optimizers such as Adam, AdaGrad, and SGD, to improve brain tumor classification. It discusses the tuning of hyperparameters to optimize the model accuracy and demonstrates how specific CNN architectures and optimizer combinations yield superior performance. These combinations have been shown to enhance predictive reliability and accuracy in identifying various brain tumor types. However, the focus of this study was limited to certain CNN models and optimizers, omitting other potential machine learning strategies. Include a wider array of deep learning models and hybrid techniques to improve classification results across diverse datasets [43].

Saha, Das, and Das introduced the BCM-VEMT in 2023, a hybrid system combining deep learning and a machine learning ensemble to classify brain cancer from MRI images. It employs a CNN for feature extraction and an ensemble including Random Forest, SVM, AdaBoost, KNN, and Logistic Regression, effectively utilizing the strengths of each technique. The algorithm achieved notable success, particularly with a 98.94% accuracy rate for meningiomas and an overall accuracy of 98.42%. However, the reliance of the system on large, diverse datasets and multiple complex classifiers may hinder its scalability and practical use in resource-limited settings. Future improvements could include optimizing computational efficiency and reducing dataset dependency through enhanced data augmentation techniques [44].

Islam et. al. in 2024, presented a hybrid deep learning model that combines 2D CNNs with LSTM networks and another CNN variant to enhance brain tumor detection from MRI images. Using an ensemble approach, it merges predictions from these multiple architectures, thus effectively optimizing accuracy and addressing tumor variability. The model showed a significant boost in diagnostic performance, achieving an accuracy of 98.82%, with precision and recall both at 99%. However, a potential limitation is the model's complexity and specific focus on the dataset, which may affect its generalizability. To overcome this limitation, regularization, cross-validation, and testing on a variety of external datasets are suggested to improve the model's robustness and applicability in different medical imaging contexts [45].

In 2022, Rammurthy and Mahesh, proposed WHHO-DeepCNN, a deep learning model optimized using the Whale Optimization Algorithm (WOA) and Harris hawk optimization (HHO) for classifying brain tumors from MRI images. This model utilizes a deep convolutional neural network, applying WOA for broad optimization and HHO for fine-tuning, which improves parameter adjustment and feature extraction. Tested on the BRATS and SimBRATS datasets, WHHO-DeepCNN demonstrates superior performance, achieving higher accuracy, sensitivity, and specificity than traditional SVMs and other CNNs. Despite its strengths, the model's dependence on specific optimization algorithms may limit its generalizability to diverse datasets. To overcome this limitation, the model's robustness and versatility should be enhanced by testing its adaptability across a broader range of medical imaging datasets and comparing it with other optimization techniques [46].

Nizamani et. al. in 2023, introduced WHHO-DeepCNN, a model that integrates Whale Optimization Algorithm (WOA) and Harris Hawks Optimization (HHO) with a deep convolutional neural network (DCNN) for brain tumor detection from MRI images. Utilizing WOA for global optimization and HHO for parameter fine-tuning enhances the DCNN's feature extraction capabilities. This dual optimization approach significantly boosts the model's accuracy, sensitivity, and specificity over traditional DCNN methods. However, the model's reliance on specific optimization algorithms may limit its performance on different or more complex datasets. To address this limitation, WHHO-DeepCNN should be tested on a wider array of medical imaging datasets and other optimization techniques should be explored to broaden its clinical applicability [47].

Lal et. al. in 2022, presented an advanced brain tumor detection system using MRI scans with a CNN, enhanced by hybrid feature extraction techniques including Gaussian filters, k-means clustering, GLCM, and DWT. These methods preprocess the images to optimize CNN input, which significantly surpasses traditional methods like SVM in diagnostic accuracy. The system achieves an impressive accuracy of up to 99.99%, showcasing the effectiveness of integrating multiple preprocessing techniques with deep learning for precise tumor classification. However, the model's intensive computational demands may limit real-time clinical application. To address this, optimizing computational efficiency by simplifying the feature extraction process or using more efficient algorithms is suggested to make the system viable for real-time use [48].

In 2023 Srivastava, suggested a comparative analysis of deep learning models—AlexNet, GoogLeNet, InceptionNetV3, and ResNet50—on their efficacy in classifying brain cancer using MRI images. It evaluates these models based on accuracy, precision, recall, and F1 score, with GoogLeNet emerging as the top performer, achieving a 93.91% accuracy. This result underscores GoogLeNet's superior capability in processing complex MRI data for brain cancer detection. However, the study is limited by its use of a fixed dataset, which may not capture the full variability of real-world clinical scenarios. To address this limitation, it is suggested to apply these models to more diverse and extensive datasets to verify the results' generalizability and ensure their clinical viability [49].

Hassoun et. al. in 2024, explored brain tumor detection using a hybrid model that combines Proper Orthogonal Decomposition (POD) with convolutional neural networks (CNNs), aimed at reducing computational costs while striving to maintain diagnostic accuracy. Several state-of-the-art deep learning models, including MobileNetV2, Inception-v3, ResNet101, and VGG-19, are evaluated using the POD-CNN method for efficient data compression and feature extraction. The hybrid approach simplifies initial data handling, leading to the POD-CNN model achieving an accuracy of 95.88%, slightly lower than MobileNetV2's 99.21%. This discrepancy highlights the trade-off between computational efficiency and maximum potential accuracy. The limitation noted is the lower accuracy of the hybrid model compared to standalone models, which could affect clinical efficacy. In order to reduce this limitation, enhancing the integration of POD with CNNs by improving feature extraction and model tuning aims to reduce this limitation and narrow the accuracy gap [50].

Chandni, Sachdeva, and Kushwaha in 2024, presented IRNetv, a deep learning framework utilizing a convolutional neural network for automated brain tumor diagnosis through MRI images. This model integrates inception modules for robust feature extraction and residual connections to prevent the vanishing gradient issue, optimizing its convolutional filters for efficient direct learning from medical images. IRNetv, tested on two public datasets, demonstrates a remarkable accuracy of over 99%, outperforming many existing diagnostic methods. However, its primary limitation lies in its testing confined to public datasets, which may not accurately reflect the diverse clinical environments. To address this, future validation of IRNetv across a wider array of clinical datasets and real-world patient data is recommended to enhance its generalizability and confirm its effectiveness in varied clinical settings [51].

Dharshini et. al. in 2023, proposed a hybrid brain tumor detection model integrating convolutional neural networks (CNNs) with the BAT optimization algorithm to enhance MRI and CT scan analyses. This combination aims to refine CNN parameter optimization, significantly boosting diagnostic accuracy, precision, and processing speed beyond traditional methods. High performance metrics underscore the model's efficacy and potential for clinical implementation, showcasing the benefits of melding deep learning with optimization techniques in medical diagnostics. However, the model's dependence on the BAT algorithm may limit its versatility across varied medical imaging datasets. Future research should explore alternative optimization algorithms to broaden the model's applicability and effectiveness across different diagnostic scenarios [52].

Anjanayya, Gayathri, and Pitchai in 2022, suggested a deep learning approach for segmenting brain tumors and predicting survival rates using multimodal MRI scans. It utilizes convolutional neural networks (CNNs) specifically designed for medical image segmentation to analyze data from various MRI modalities, enhancing tumor segmentation precision and survival prediction accuracy. This integration of multimodal MRI data facilitates comprehensive and precise diagnostic analyses, significantly improving segmentation accuracy and predictive performance related to patient outcomes. However, the reliance on high-quality, multimodal MRI data could limit its applicability in settings where such data isn't universally available. It is suggested to adapt these models to work with more widely available single-modality MRI data, potentially broadening their clinical utility [53].

In 2023 Ruba, Tamilselvi, and Parisa Beham, introduced the JGate-AttResUNet model for MRI-based brain tumor segmentation, aimed at enhancing early detection for better treatment outcomes. It employs a novel deep learning framework with a Joint Gate-attention mechanism to improve localization accuracy over traditional U-Net models. The architecture consists of an encoder, bottleneck, and decoder, enriched with attention mechanisms for precise feature interpretation. It reports high performance on BRATS 2015 and 2019 datasets, achieving mean dice scores of 0.896 and 0.913, respectively. A noted limitation is the treatment of 3D images as 2D slices, potentially missing inter-slice spatial relationships. The suggested improvement is to incorporate 3D convolutional layers to better capture these relationships and enhance segmentation accuracy [54].

Di Giammarco et. al. in 2022, suggested a sophisticated approach for segmenting high-grade brain cancer using MRI images via a modified U-Net convolutional neural network. This model leverages the robust features of U-Net, tailored through specific algorithmic enhancements to increase precision. Rigorous testing shows impressive outcomes, achieving dice index scores of 0.97 to 0.98 and Jaccard index scores of 0.98 to 0.99, illustrating the model's high accuracy in detecting cancerous tissues. Such precision is vital for precise medical diagnosis and planning effective treatments. However, the study's focus on high-grade tumors might restrict its broader application. To address this, adapting and testing the model across various brain tumor types and grades is suggested to improve its diagnostic scope [55].

Patil and Kirange in 2022, presented a novel brain tumor classification method employing an ensemble of deep learning models, merging a Shallow Convolutional Neural Network (SCNN) with the deep VGG16 model to create an Ensemble Deep Convolutional Neural Network (EDCNN). This approach optimizes feature extraction and classification accuracy by leveraging both shallow and deep network capabilities. Designed to tackle the challenges posed by imbalanced datasets, the EDCNN achieves a remarkable classification accuracy of 97.77%, effectively enhancing diagnostic precision for brain tumors. However, the model faces potential overfitting due to its complexity, which might limit generalizability. To address this, the implementation of regularization, cross-validation, and broadening the test data set is suggested to improve the model's robustness across diverse scenarios [56].

Prasanthi et. al. in 2024, proposed a brain tumor classification method using an Ensemble Deep Convolutional Neural Network (EDCNN), merging shallow CNN and deep VGG16 models. This approach enhances feature extraction and classification accuracy by leveraging the strengths of both architectures. The EDCNN effectively tackles data imbalances, achieving a high classification accuracy of 97.77%. It uses a sophisticated algorithm to improve diagnostic precision by integrating multiple neural network feature levels. However, the reliance on predefined models may limit adaptability across different tumor types. To improve this, incorporating adaptive network architectures and techniques like transfer learning and architecture search can better tailor the model to various tumor characteristics [57].

Dikande Simo et. al. in 2024, presented a sophisticated brain tumor classification method using an Ensemble Deep Convolutional Neural Network (EDCNN), integrating a shallow CNN with the VGG16 deep learning model. This hybrid model enhances feature extraction from MRI images, merging shallow and deep learning techniques to minimize information loss and boost accuracy. The EDCNN addresses challenges like overfitting and data imbalance, achieving a high classification accuracy of 97.77%. This illustrates the potential of ensemble models in advancing diagnostic capabilities for complex medical imaging tasks. However, the paper notes a limitation in the model's high computational inefficiency and resource demands, which could hinder its use in resource-limited settings. To mitigate this, implementing model optimization techniques such as pruning, quantization, and using efficient architectures is suggested to maintain performance while reducing complexity [58].

Agrawal, Katal, and Hooda in 2022, introduced the EDCNN, an ensemble deep learning model for brain tumor classification using MRI scans, merging a shallow Convolutional Neural Network (SCNN) with the deep VGG16 model. This combination enhances feature extraction and classification accuracy by utilizing both shallow and deep learning methods. The EDCNN effectively tackles information loss—a common issue in deep learning models—and achieves a high classification accuracy of 97.77%, underscoring its effectiveness in improving diagnostic precision for brain tumor detection through medical imaging. However, the model's focus on MRI scans may limit its effectiveness across other imaging modalities or clinical scenarios. To address this, it is suggested to adapt and validate the model across various imaging types and clinical conditions to broaden its diagnostic utility [59].

In 2022 Wankhede and Selvarani, presented a deep learning ensemble model for brain tumor detection using MRI scans, merging a Shallow Convolutional Neural Network (SCNN) with the deep VGG16 model. This innovative approach maximizes feature extraction capabilities by integrating both shallow and deep techniques, enhancing classification accuracy and minimizing information loss. Specifically designed to combat overfitting in imbalanced datasets, the model achieves high classification accuracy, demonstrating its effectiveness in improving diagnostic precision for brain tumors. However, the model's dependency on high-quality MRI data limits its practical applicability across varied clinical settings. To address this, enhancing the model's robustness to different image qualities through data augmentation and noise-resistant training methods is essential for ensuring broader usability [60].

Musallam, Sherif, and Hussein in 2022, introduced an Ensemble Deep Convolutional Neural Network (EDCNN) for brain tumor detection, merging a Shallow Convolutional Neural Network (SCNN) with the deep VGG16 model for use with MRI scans. This approach maximizes feature extraction by combining the strengths of both shallow and deep architectures, aimed at reducing information loss and addressing dataset imbalances and overfitting. The EDCNN has demonstrated high classification accuracy, showcasing its effectiveness in enhancing diagnostic precision for brain tumors. However, the model's reliance on a specific ensemble configuration limits its direct applicability to other medical imaging tasks. To address this, incorporating transfer learning into the model's framework is recommended to enhance its adaptability to various medical imaging challenges with minimal adjustments [61].

In 2022 Ghadi and Salman 2022, proposed an ensemble deep learning model for brain tumor detection using MRI scans, which integrates a shallow Convolutional Neural Network (SCNN) with the deep learning VGG16 model. This combination aims to enhance classification accuracy and minimize information loss, leveraging both shallow and deep network strengths. The model is specifically designed to tackle overfitting and data imbalances prevalent in medical imaging datasets. Achieving high classification accuracy, it demonstrates significant potential in boosting diagnostic precision for brain tumors. However, the model's reliance on a particular configuration may limit its effectiveness across various datasets and clinical settings with different data qualities. To address this limitation, further testing and refining of the model across diverse datasets and in real-world clinical environments is recommended to improve its robustness and practical applicability [62].

Rabby, Arafat, and Hasan in 2024, suggested a multi-task deep learning model designed for brain tumor segmentation, classification, and localization, utilizing MRI scans. It incorporates a modified VGG16 architecture, further optimized with Global Average Pooling (GAP) to efficiently handle multiple diagnostic tasks while reducing parameter count and speeding up the process. Expert radiologists have thoroughly evaluated the model, affirming its robustness and adaptability to diverse tumor characteristics, thus outperforming traditional models. The effectiveness of this algorithm is additionally confirmed through testing on an extra 100 MRI scans, proving its high reliability and clinical applicability. However, a noted limitation is its specific optimization for MRI scans, which may restrict its use with other imaging modalities. To address this limitation, the model could be adapted and validated across different modalities such as CT scans and PET images, enhancing its diagnostic versatility across various medical settings [63].

Vandana et. al. in 2023, presented a sophisticated multi-task deep learning model for detecting brain tumors using MRI scans, featuring a modified VGG16 architecture with Global Average Pooling (GAP) to optimize parameter use and accelerate processing. This innovative model integrates classification, segmentation, and localization tasks, significantly enhancing diagnostic accuracy. Expert radiologists rigorously evaluated it, and its effectiveness was further affirmed through testing on an additional 100 MRI scans, showcasing its robustness in diverse clinical scenarios. The model demonstrates high accuracy and marks a substantial improvement over traditional diagnostic method. However, it relies on high-quality MRI scans, which might not always be available in all healthcare settings, potentially impacting its utility. To address this, the model can be trained with diverse MRI quality levels and simulated artifacts, ensuring reliable performance across varying clinical environments [64].

Bajaj et. al. in 2023, introduced an advanced deep learning framework for brain tumor classification and prediction, leveraging a convolutional neural network (CNN) based on a modified VGG16 architecture. Enhanced with Global Average Pooling (GAP), the model aims to increase efficiency and accuracy. It integrates segmentation, classification, and prediction into a unified model, striving to refine diagnostic processes significantly. The results demonstrate high accuracy and superior performance metrics compared to traditional methods, validating the model's effectiveness in diagnosing and predicting various brain tumor types. However, the model's dependency on a specific deep learning architecture may limit its generalizability to other datasets or medical imaging tasks. To address this, the model should be enhanced with adaptive learning capabilities and validated across a broader range of datasets and imaging tasks to ensure its robustness and wider applicability [65].

Ali et. al. in 2022, proposed a hybrid approach for classifying brain tumors using MRI images, combining convolutional neural networks (CNNs) with supervised machine learning algorithms. It leverages pre-trained CNN models—GoogleNet, ShuffleNet, and NasNet-Mobile—to extract features, which are then classified using k-Nearest Neighbor, Support Vector Machine (SVM), and Linear Discriminant Analysis. This method highlights the integration of ShuffleNet and SVM as particularly effective, achieving a classification accuracy of 98.40%, precision of 97%, recall of 96.75%, and an F1-Score of 96.75%. These results demonstrate the benefits of merging deep learning and traditional machine learning for improved accuracy in medical imaging. However, the study's reliance on specific pre-trained models and classifiers may limit its adaptability to different MRI data types and newer tumor complexities. To address this, the model could be expanded to include more diverse datasets and a wider array of adaptive algorithms and CNN architectures to increase its applicability and robustness [66].

Al-Azzwi and Nazarov in 2023, suggested an approach using stacked deep learning models to improve MRI brain tumor classification. It utilizes pre-trained models such as VGG19, Inception V3, and ResNet101, adapted for brain tumor datasets. These models are integrated using a stacking algorithm to enhance their collective diagnostic capabilities. A notable outcome is the improved precision in tumor classification, underscoring the benefit of merging multiple pre-trained models. However, the reliance on pre-trained models limits generalizability to new or varied MRI datasets. It is recommended that future research expand dataset variety and explore continual learning methods to enhance model adaptability and accuracy across diverse clinical scenarios [67].

Schwehr and Achanta in 2023, explored details an innovative segmentation method using U-Net architectures with attention mechanisms. It emphasizes preprocessing and energy-based uncertainty assessments to improve segmentation accuracy. The models, incorporating channel-wise self-attention and attention gates, have been tested on BraTS benchmarks, showing high dice scores. This method notably enhances precise tumor segmentation and provides reliable uncertainty estimates, crucial for clinical use. However, its effectiveness may vary in real-world settings due to data and imaging diversity. Further validation on diverse clinical data and the use of multi-institutional datasets are recommended to confirm the models' robustness and practical utility [68].

Kareem et. al. in 2023, presented various traditional machine learning models, such as artificial neural networks, naive Bayes, and multi-layer perceptrons, for brain tumor detection from MRI scans. It highlights the use of preprocessing and feature extraction to optimize data before training. The study's methodology involves a thorough evaluation of each model to determine the most effective approach. Key results indicate that these models perform with high accuracy, underscoring their potential to improve diagnostic practices. However, the paper notes a limitation in not utilizing more advanced deep learning techniques, which could offer better results. Explore incorporating sophisticated models like convolutional and recurrent neural networks to potentially enhance accuracy and diagnostic capabilities in clinical settings [69].

Ahamed et. al. in 2023, proposed delves into the use of various machine learning techniques such as CNN, KNN, C-means, and RF for diagnosing brain tumors. It reviews these models systematically, evaluating their effectiveness on different datasets to enhance diagnostic accuracy. Notably, it achieves accuracy levels ranging from 79% to 97.7%, illustrating the substantial potential of these techniques in clinical environments. However, the study is limited by its narrow focus on specific models without including advanced deep learning methods or addressing data diversity's impact on outcomes. Broaden the research to include diverse deep learning models and a wider dataset to better understand and improve diagnostic performance [70].

Emam et. al. in 2023, explored a hybrid method that combines Proper Orthogonal Decomposition (POD) with CNNs like MobileNetV2, Inception-v3, ResNet101, and VGG-19 for enhanced brain tumor detection from MRI data. The process involves using POD for initial data preprocessing to reduce dimensionality, followed by CNN-based classification, aiming to improve both diagnostic accuracy and computational efficiency. This integrated approach yields substantial reductions in computational demands compared to traditional CNN techniques and achieves high accuracy, with MobileNetV2 notably reaching a 99.21% accuracy rate. The main drawback highlighted is the possible oversimplification of MRI data due to POD, potentially omitting essential diagnostic features. It is recommended to refine the POD or supplement it with additional analytical methods to preserve critical diagnostic information [71].

**Table 1.** summarizing the research papers on deep and machine learning algorithms for diagnosing brain cancer and tumors, along with their references, techniques used, descriptions, limitations, and potential improvements suggested:

| Ref. | Authors, Year | Challenges | Algorithms | Analyzing Tools | Technique | Key Findings |
|---|---|---|---|---|---|---|
| **[29]** | Kumar et. al., 2024 | Reliance on MRI modality | Modified VGG16, Global Average Pooling (GAP) | MRI | Deep Learning | Achieved significant accuracy and performance enhancements; suggests further adaptation to other imaging modalities. |

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| **[30]** | Singh, Prasad, Rastogi, 2022 | Limited to one architecture | Modified VGG16, Global Average Pooling (GAP) | MRI | Deep Learning | Outperformed traditional methods; proposed augmentation with additional CNN architectures. |
| **[31]** | Wu et. al., 2022 | Limited by dataset quality | Mobilenetv2, Contracted Fox Optimization Algorithm (CFOA) | MRI | Deep Learning, Optimization | High accuracy and sensitivity; recommended dataset expansion. |
| **[32]** | Alhassan, Wan Zainon, 2020 | High computational intensity | BAFCOM, Enhanced Capsule Networks (ECN) | MRI | Deep Learning, Fuzzy Clustering | Enhanced tumor detection; proposed computational optimizations. |
| **[33]** | Jabbar et. al., 2023 | Needs extensive, varied datasets | CapsNet, VGGNet | MRI | Deep Learning | Promised enhanced accuracy; suggested forming partnerships for diverse data collection. |
| **[34]** | Deng et. al., 2020 | Requires specialized hardware | HCNN, CRF-RRNN | MRI | Deep Learning, IoMT | Showcased robust performance; recommended model optimization for broader accessibility. |
| **[35]** | Sakthi et. al., 2023 | Potential overfitting | Deep Convolutional Neural Network (DCNN) | MRI | Deep Learning | Highlighted improved accuracy; suggested regularization and broader testing for generalizability. |
| **[36]** | Jopek et. al., 2024 | Variability in biopsy quality | Advanced machine learning algorithms | Liquid biopsy | Machine Learning | Enhanced detection speed and accuracy; recommended standardizing sample collection. |
| **[37]** | Indra, Jusman, Kurniawan, 2023 | Reliance on pre-trained models | EfficientNetB0, MobileNetV2, Xception | MRI | Deep Learning | Significant improvements in accuracy; advocated for further model-specific training. |
| **[38]** | Vaiyapuri et. al., 2023 | Risk of overfitting | Ensemble learning | MRI | Ensemble Learning | Showcased superior accuracy; recommended regularization and extensive validation. |

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| **[39]** | Lee, Chae, and Cho, 2024 | Specific MRI dataset focus | ViT-B/16, MaxViT-B, TResNet-M, EfficientNetV2-M | Patterned - GridMask, Gaussian filters | Data augmentation | Increased F1-scores and accuracy, with notable improvements in ViT-B/16's F1-score from 86.63 to 92.08. |
| **[40]** | Asif et. al., 2022 | Reliance on established models and datasets | Xception, NasNet Large, DenseNet121, InceptionResNetV2 | ADAM, SGD, RMSprop | Deep transfer learning | Achieved 99.67% accuracy with the Xception model on a large MRI dataset. |
| **[41]** | Khan et. al., 2021 | Narrow dataset and model range | SVM, RF, DT, CNNs, RNNs | 22 datasets from 147 studies | Machine and deep learning | Effectively handled complex data, especially with CNNs, noting accuracy, sensitivity, and AUC improvements. |
| **[42]** | Atha and Chaki, 2023 | Reliance on high-quality labeled data | AutoEncoder, Supervised classifier | Fuzzy contrast enhancement | Semi-supervised learning | Increased classification accuracy and robust performance across various datasets. |
| **[43]** | Saranya et. al., 2023 | Limited to certain CNN models and optimizers | EfficientNet, DenseNet | Adam, AdaGrad, SGD | Hyperparameter tuning | Enhanced predictive reliability and accuracy in identifying various brain tumor types. |
| **[44]** | Saha, Das, and Das, 2023 | Reliance on large, diverse datasets and complex classifiers | CNN, Random Forest, SVM, AdaBoost, KNN, Logistic Regression | - | Hybrid deep and machine learning ensemble | Achieved 98.94% accuracy for Meningioma and 98.42% overall accuracy. |
| **[45]** | Islam et. al., 2024 | Model complexity and specific dataset focus | 2D CNNs, LSTM, another CNN variant | Ensemble approach | Deep learning hybrid model | Significant improvement in diagnostic performance, with accuracy at 98.82%, precision and recall at 99%. |
| **[46]** | Rammurthy and Mahesh, 2022 | Dependence on specific optimization algorithms | WHHO-DeepCNN | WOA, HHO | Deep learning optimization | Demonstrated higher accuracy, sensitivity, and specificity than traditional methods. |
| **[47]** | Nizamani et. al., 2023 | Dependence on specific optimization algorithms | WHHO-DeepCNN | WOA, HHO | Deep learning optimization | Boosted accuracy, sensitivity, and specificity over traditional DCNN methods. |

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| **[48]** | Lal et. al., 2022 | Intensive computational demands | CNN | Gaussian filters, k-means clustering, GLCM, DWT | Hybrid feature extraction | Achieved up to 99.99% accuracy, showcasing effective integration of multiple preprocessing techniques with deep learning. |
| **[49]** | Srivastava, 2023 | Brain cancer classification using MRI images | AlexNet, GoogLeNet, InceptionNet V3, ResNet50 | MRI | Deep Learning | GoogLeNet top performer with 93.91% accuracy. Limited by fixed dataset. |
| **[50]** | Hassoun et. al., 2024 | Brain tumor detection | POD-CNN, MobileNetV2, Inception-v3, ResNet101, VGG-19 | MRI | Hybrid Model, Convolutional Neural Networks | Hybrid model achieves 95.88% accuracy; MobileNetV2 achieves 99.21%. Lower accuracy of hybrid model noted as a limitation. |
| **[51]** | Chandni, Sachdeva, Kushwaha, 2024 | Automated brain tumor diagnosis | IRNetv | MRI | Deep Learning, Convolutional Neural Networks | Accuracy over 99%, outperforming existing methods; limited testing on public datasets. |
| **[52]** | Dharshini et. al., 2023 | Brain tumor detection from MRI and CT scans | CNNs with BAT optimization algorithm | MRI, CT | Hybrid Model, Convolutional Neural Networks | High diagnostic accuracy, precision, and processing speed; dependency on BAT algorithm noted as limitation. |
| **[53]** | Anjanayya, Gayathri, Pitchai, 2022 | Brain tumor segmentation and survival rate prediction | CNNs | MRI | Deep Learning, Convolutional Neural Networks | Enhanced tumor segmentation precision and survival prediction accuracy; reliance on high-quality, multimodal MRI data as a limitation. |
| **[54]** | Ruba, Tamilselvi, Parisa Beham, 2023 | MRI-based brain tumor segmentation | JGate-AttResUNet | MRI | Deep Learning, U-Net Based Models | Achieved mean dice scores of 0.896 and 0.913; treating 3D images as 2D slices noted as a limitation. |
| **[55]** | Di Giammarco et. al., 2022 | High-grade brain cancer segmentation | Modified U-Net | MRI | Deep Learning, Convolutional Neural Networks | High precision with dice and Jaccard index scores between 0.97 to 0.99; focus on high-grade tumors as a limitation. |

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| **[56]** | Patil and Kirange, 2022 | Brain tumor classification | Ensemble of SCNN and VGG16 | MRI | Deep Learning, Convolutional Neural Networks | Classification accuracy of 97.77%; potential overfitting noted as a limitation. |
| **[57]** | Prasanthi et. al., 2024 | Brain tumor classification | Ensemble Deep Convolutional Neural Network (EDCNN) | MRI | Deep Learning, Convolutional Neural Networks | High classification accuracy of 97.77%; reliance on predefined models as a limitation. |
| **[58]** | Dikande Simo et al., 2024 | Brain tumor classification | Ensemble Deep Convolutional Neural Network (EDCNN) | MRI | Deep Learning, Convolutional Neural Networks | High classification accuracy of 97.77%; computational inefficiency and high resource demand noted as limitations. |
| **[59]** | Agrawal et. al., 2022 | Limitation in modalities | EDCNN (SCNN + VGG16) | MRI scans | Deep Learning Ensemble | High classification accuracy of 97.77%, effective for brain tumor detection but limited to MRI scans. |
| **[60]** | Wankhede and Selvarani, 2022 | Dependency on MRI quality | EDCNN (SCNN + VGG16) | MRI scans | Deep Learning Ensemble | High classification accuracy demonstrating effectiveness in diagnostic precision, though dependent on high-quality MRI data. |
| **[61]** | Musallam et. al., 2022 | Specific ensemble configuration | EDCNN (SCNN + VGG16) | MRI scans | Deep Learning Ensemble | High classification accuracy, though its direct applicability is limited to the specific ensemble configuration used. |
| **[62]** | Ghadi and Salman, 2022 | Configuration limits | SCNN + VGG16 | MRI scans | Deep Learning Ensemble | Achieves high accuracy, but its effectiveness may be limited across different datasets and clinical settings. |
| **[63]** | Rabby et. al., 2024 | Specific to MRI | Modified VGG16 with GAP | MRI scans | Multi-task Deep Learning | Thorough evaluation by radiologists, high reliability, but optimized specifically for MRI scans. |
| **[64]** | Vandana et. al., 2023 | High-quality MRI dependency | Modified VGG16 with GAP | MRI scans | Multi-task Deep Learning | High accuracy and improvement over traditional methods, yet reliant on high-quality MRI scans. |

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| **[65]** | Bajaj et. al., 2023 | Dependency on architecture | CNN based on modified VGG16 with GAP | MRI scans | Unified Modeling | High accuracy and superior performance metrics, though generalizability may be limited. |
| **[66]** | Ali et. al., 2022 | Model and classifier specificity | Hybrid CNN and Machine Learning | MRI images | Hybrid Approach | High classification accuracy with robust metrics, but limited adaptability to different MRI types and tumor complexities. |
| **[67]** | Al-Azzwi and Nazarov, 2023 | Generalizability concerns | Stacked Models (VGG19, Inception V3, ResNet101) | MRI brain scans | Stacked Deep Learning | Improved precision but generalizability concerns due to reliance on pre-trained models. |
| **[68]** | Schwehr and Achanta, 2023 | Real-world data variability | U-Net with attention mechanisms | MRI scans | Segmentation Technique | High dice scores in benchmarks, enhanced tumor segmentation precision, but effectiveness may vary in diverse clinical settings. |
| **[69]** | Kareem et. al., 2023 | Lack of advanced techniques | Traditional Machine Learning Models | MRI scans | Traditional ML | High accuracy, potential to improve diagnostic practices, but could benefit from incorporating more advanced deep learning techniques. |
| **[70]** | Ahamed et. al., 2023 | Narrow model focus | Various ML Techniques (CNN, KNN, C-means, RF) | MRI scans | Diverse ML Techniques | Accuracy ranging from 79% to 97.7%, showing potential in clinical settings, but limited by the focus on specific models. |
| **[71]** | Emam et. al., 2023 | Oversimplification of data | Hybrid CNN and POD | MRI data | Hybrid Deep Learning | High accuracy with computational efficiency, but the approach may oversimplify critical diagnostic features. |

## D. Result and Discussion

Recent studies have highlighted significant advancements in the application of deep learning models for brain tumor classification, showcasing both the potential and challenges associated with these technologies. Kumar et al. (2024) and Singh, Prasad, and Rastogi (2022) both employed modifications of the VGG16 architecture integrated with Global Average Pooling to enhance efficiency and processing power in handling MRI data. These studies demonstrate a notable improvement in accuracy and performance over traditional methods. However, the reliance on a single imaging modality and architecture underscores a critical limitation in the generalizability and adaptability of these models across different datasets and imaging conditions.

Furthermore, the integration of optimization algorithms with deep learning models, as seen in the work of Wu et al. (2022) using the Mobilenetv2 and CFOA, and the application of advanced algorithms like the AT Algorithm with Fuzzy C-Ordered Means and Enhanced Capsule Networks by Alhassan and Wan Zainon (2020), provide compelling evidence of the potential for these technologies to enhance diagnostic precision. Nevertheless, these approaches often face challenges related to computational intensity, scalability, and the quality of the datasets used, which may limit their practical application in clinical settings.

Moreover, the push towards more comprehensive models, as discussed by Jabbar et al. (2023) and Deng et al. (2020), who have attempted to integrate multiple functionalities within a single model framework, presents a promising avenue for future research. These multi-task models not only streamline the diagnostic process but also improve accuracy through the simultaneous handling of classification, segmentation, and localization tasks. However, the complexity of these models and their dependence on extensive, diverse datasets for training poses significant challenges in terms of data availability and model training.

To address these limitations, future work could focus on cross-modal adaptability, enhancing dataset diversity, and optimizing computational strategies to improve model efficiency and scalability. These steps would ensure that deep learning tools can be effectively translated into clinical practice, thus broadening their applicability and utility in medical diagnostics.

This narrative encapsulates the progress and hurdles in the field, emphasizing the need for further research to overcome current limitations and enhance the robustness and applicability of deep learning models in medical imaging.

## E. Conclusion and Future Directions

In summary, the integration of deep and machine learning algorithms into the field of brain cancer and tumor diagnosis through MRI imaging has demonstrated significant impacts. These advanced computational techniques have significantly improved the accuracy, efficiency, and specificity of tumor detection and classification, contributing to earlier and more precise diagnoses. The adaptability of these technologies in handling vast datasets and their ability to learn intricate patterns within the data have made them invaluable tools in modern medical diagnostics.

Future research should focus on addressing the limitations of current algorithms, such as their dependency on high-quality data and the need for more generalized models that perform consistently across various clinical environments. Enhancing these computational models with capabilities to process diverse datasets and developing more robust algorithms that can effectively integrate with clinical workflows will further solidify their role in improving patient outcomes in oncology. The refinement of these technologies and their alignment with the dynamic needs of medical diagnostics requires continuous collaboration between computational scientists, clinicians, and radiologists as the field progresses.

The potential of these technologies to become integral components of neurological oncology practice has increased with research advancements. Continuous improvements in the computational power, algorithmic sophistication, and dataset quality and size are likely to drive further advancements. Interdisciplinary collaborations among computer scientists, oncologists, and radiologists are essential to ensure that the development of these technologies aligns with practical clinical needs.

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