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ADVANCING BRAIN TUMOR DETECTION USING MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE: A SYSTEMATIC LITERATURE REVIEW OF PREDICTIVE MODELS AND DIAGNOSTIC ACCURACY

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ABSTRACT

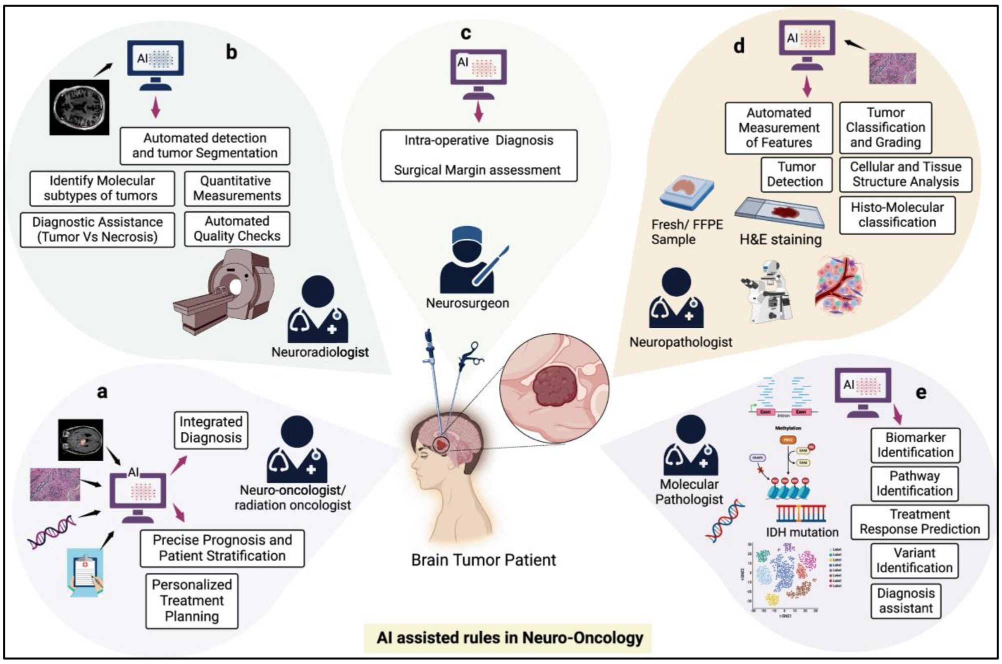
This study systematically reviews the application of Artificial Intelligence (AI) and Machine Learning (ML) in brain tumor detection, focusing on advancements, challenges, and clinical implications. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, 1,126 articles were initially identified, with rigorous screening and quality assessments narrowing the final selection to 102 high-quality studies. The review highlights the superior diagnostic accuracy and efficiency achieved by AI models, particularly Convolutional Neural Networks (CNNs), which consistently report accuracy rates exceeding 90%. Hybrid and ensemble models further enhance diagnostic robustness, addressing challenges related to complex tumor types and heterogeneous datasets. Data-related issues, such as scarcity and imbalance, remain critical barriers, with studies emphasizing the effectiveness of synthetic data generation and augmentation techniques in improving model generalizability. Explainable AI (XAI) frameworks have been identified as pivotal for fostering clinician trust, offering interpretability and transparency that facilitate integration into clinical workflows. Real-time diagnostic systems demonstrate the potential for AI to streamline operations and enable timely clinical decisions, particularly in resource-constrained settings. Despite these advancements, challenges such as algorithmic bias, data diversity, and infrastructural limitations persist. This review underscores the transformative role of AI/ML in brain tumor diagnostics, providing actionable insights to advance research and clinical adoption, ultimately improving patient outcomes and healthcare efficiency.

1 INTRODUCTION

Brain tumor detection is a pivotal area in medical diagnostics, with significant implications for treatment planning and patient outcomes (Chato & Latifi, 2017). Early and accurate detection can substantially improve survival rates and reduce the physical and emotional toll on patients and their families (Das et al., 2019). However, traditional diagnostic methods, which rely on manual interpretation of medical imaging such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans, are often constrained by subjectivity and variability among radiologists (Arif et al., 2022). The emergence of Machine Learning (ML) and Artificial Intelligence (AI) technologies has revolutionized the healthcare landscape by offering automated, precise, and efficient diagnostic solutions (Özyurt et al., 2019). These technologies are increasingly employed to assist radiologists in analyzing complex medical imaging data, aiming to reduce diagnostic errors and improve patient outcomes (Saba et al., 2020). Moreover, in recent years, deep learning models, particularly Convolutional Neural Networks (CNNs), have gained prominence in medical imaging due to their ability to identify intricate patterns in visual data (AbdelMaksoud et al., 2015). Studies have demonstrated the effectiveness of CNNs in classifying and segmenting brain tumors with high accuracy (AbdelMaksoud et al., 2015; Bashir-Gonbadi & Khotanlou, 2021; Saba et al., 2020). For instance, (Ranjbarzadeh et al., 2021) reported a classification accuracy of over 92% in detecting gliomas, meningiomas, and pituitary tumors using a CNN-based approach. Similarly, Huang et al. (2014) highlighted the potential of hybrid models that combine CNNs with Support Vector Machines (SVMs), achieving enhanced diagnostic performance by leveraging the strengths of both techniques. Such advancements underscore the transformative potential of AI/ML systems in augmenting clinical decision-making processes. Despite these successes, the practical implementation of AI/ML models in clinical settings faces several challenges (Zhu et al., 2023). One significant barrier is the issue of data heterogeneity, as many publicly available datasets, such as the Brain Tumor Segmentation (BraTS) dataset, often lack diversity in imaging modalities and patient demographics (Siar & Teshnehlab, 2019). This limitation restricts the generalizability of AI models across varied clinical environments. Furthermore, overfitting and bias in model training can undermine the reliability of AI-driven systems, particularly when applied to real-world scenarios (Ranjbarzadeh et al., 2021). Addressing these challenges necessitates the development of more robust algorithms and the incorporation of large-scale, diverse datasets to ensure broader applicability (Huang et al., 2014).

A growing body of literature has systematically reviewed the application of AI/ML techniques in brain

Figure 1: AI assisted rules in Neuro-Oncology



Source: Khalighi et al. (2024)

tumor detection, shedding light on their potential and limitations (Shreve et al., 2022). Anjum et al., (2021) conducted an extensive review of transfer learning applications, highlighting its ability to overcome data scarcity by leveraging pre-trained models. Similarly, Kader et al. (2021) compared deep learning and traditional diagnostic methods, demonstrating that AI models consistently outperformed conventional approaches in terms of accuracy and efficiency. Havaei et al. (2016) explored the integration of AI systems into clinical workflows, emphasizing the need for user-friendly interfaces and comprehensive training programs for healthcare professionals. These studies collectively highlight the importance of continuous innovation and interdisciplinary collaboration in advancing the field (Amin et al., 2019; Havaei et al., 2016).

Recent innovations in AI/ML have also introduced ensemble learning techniques, which aggregate predictions from multiple algorithms to enhance diagnostic accuracy and robustness (Holzinger et al., 2019). Hybrid models that combine CNNs with techniques like Random Forests and Gradient Boosting have shown remarkable improvements in tumor classification and segmentation tasks ((Havaei et al., 2016). Furthermore, the integration of explainable AI (XAI) frameworks has enabled clinicians to interpret AI predictions, fostering greater trust and adoption of these technologies in medical practice (Zacharaki et al., 2009). These developments signify a paradigm shift in brain tumor diagnostics, driven by the synergistic application of cutting-edge AI technologies and clinical expertise. The primary objective of this systematic review is to analyze and synthesize the advancements in Machine Learning (ML) and Artificial Intelligence (AI) techniques for brain tumor detection, with a focus on their predictive accuracy, reliability, and clinical applicability. Specifically, the study aims to evaluate the performance of various AI-driven models, including Convolutional Neural Networks (CNNs), hybrid algorithms, and ensemble learning approaches, in classifying and segmenting brain tumors using medical imaging datasets such as MRI and CT scans. Additionally, the review seeks to identify key challenges, such as data heterogeneity, overfitting, and bias, that hinder the practical implementation of these technologies in diverse clinical settings. By examining trends, gaps, and emerging innovations, this review aims to provide actionable insights for researchers and healthcare practitioners to optimize the integration of AI/ML in diagnostic workflows, ultimately enhancing early detection and treatment outcomes for patients with brain tumors.

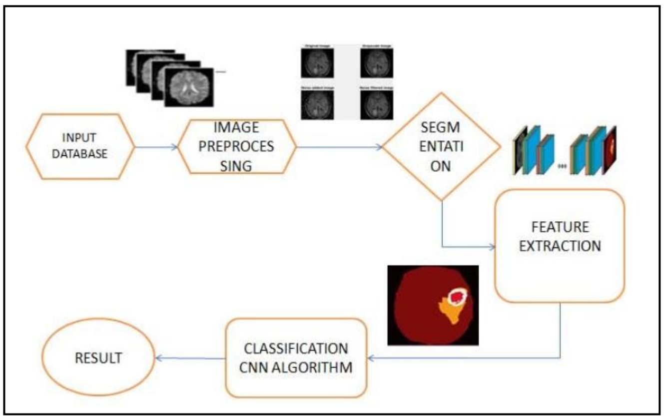
2 LITERATURE REVIEW

The application of Machine Learning (ML) and Artificial Intelligence (AI) in brain tumor detection has gained considerable traction over the last decade, driven by advancements in medical imaging, computational power, and algorithmic development. This section delves into the existing body of research to evaluate the effectiveness of AI and ML models in improving diagnostic accuracy, their ability to overcome limitations of traditional methods, and the challenges that persist in clinical implementation. By systematically categorizing the literature, this review aims to highlight key findings, gaps, and future opportunities to advance the field. The analysis is organized into specific subsections, focusing on individual components of AI/ML in brain tumor detection, including algorithms, datasets, performance metrics, and practical implications.

2.1 AI/ML for Brain Tumor Detection

The integration of Artificial Intelligence (AI) and Machine Learning (ML) in medical imaging has marked a paradigm shift in diagnostic practices, particularly for brain tumor detection (Cè et al., 2023). Medical imaging modalities such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) are foundational tools for identifying brain tumors; however, traditional methods rely heavily on manual interpretation, which can be subjective and time-consuming (Shimizu & Nakayama, 2020). AI/ML algorithms, by contrast, can process vast amounts of imaging data to detect subtle patterns and anomalies, offering enhanced accuracy and

Figure 2: System Architecture Brain Tumor Segmentation using CNN



Source: Samhitha et al. (2020)

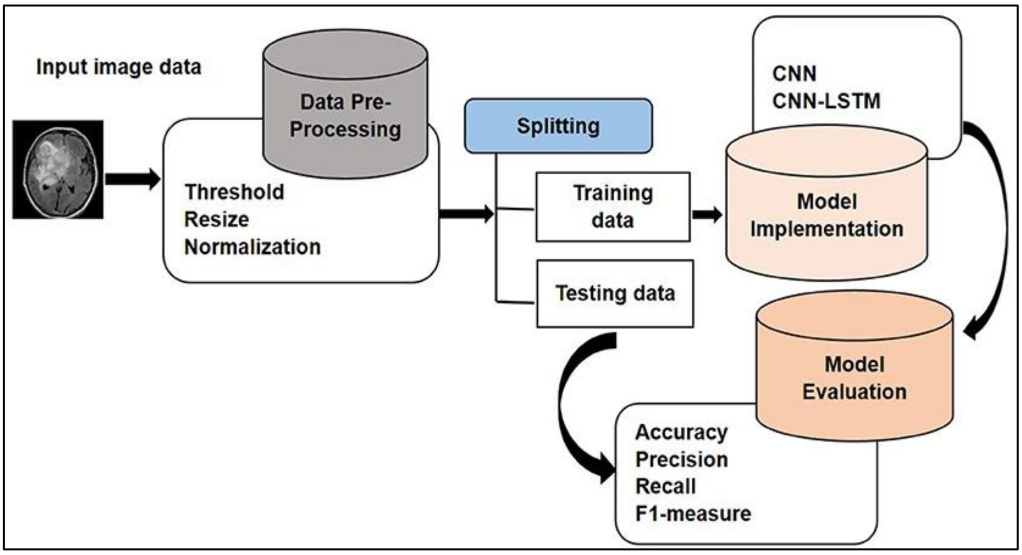
efficiency (Lundin et al., 1999). These technologies leverage large-scale datasets to train predictive models capable of distinguishing tumor types and detecting early-stage growths with remarkable precision. For instance, Noseworthy et al., (2020) demonstrated that AI-driven systems could achieve diagnostic performance comparable to experienced radiologists, making these tools invaluable for resource-constrained settings. Similarly, Forghani (2020) highlighted that ML models have expedited the diagnostic process while reducing human error, underlining their transformative potential in medical imaging. Moreover, deep learning models, particularly Convolutional Neural Networks (CNNs), have emerged as pivotal tools in the evolution of brain tumor diagnostics. CNNs excel in analyzing imaging data by identifying spatial hierarchies and patterns, making them highly effective in tumor classification and segmentation tasks (Akkus et al., 2017). Hilsden et al. (2018) showcased the application of CNNs in categorizing gliomas, meningiomas, and pituitary tumors with an accuracy exceeding 92%. Hybrid approaches combining CNNs with Support Vector Machines (SVMs) have further improved diagnostic performance by leveraging complementary strengths of both techniques (Zhou et al., 2023). Additionally, Johnson et al. (2020) demonstrated that ensemble learning methods, which aggregate predictions from multiple models, enhanced robustness and reduced errors in tumor segmentation. These advancements highlight the versatility and efficiency of deep learning models in addressing complex diagnostic challenges in brain tumor detection.

One critical aspect of AI/ML in medical imaging is the reliance on high-quality datasets for training and validation. Datasets such as the Brain Tumor Segmentation (BraTS) dataset and The Cancer Genome Atlas (TCGA) have become standard benchmarks for developing and testing AI algorithms (Baskin, 2020; Johnson et al., 2020). However, issues such as data heterogeneity and imbalance persist, as these datasets often lack adequate representation of diverse populations and imaging modalities (Krishnapriya & Karuna, 2023). Synthetic data augmentation techniques, including generative adversarial networks (GANs), have been employed to address these limitations by generating realistic imaging data to enrich training sets (Akkus et al., 2017). Lee et al. (2019) emphasized the role of transfer learning, which allows pre-trained models to adapt to new datasets, mitigating data scarcity challenges. Despite these advancements, researchers continue to advocate for the creation of larger, more diverse datasets to improve model generalizability across clinical settings (Obermeyer & Emanuel, 2016). Moreover, the application of AI/ML in brain tumor diagnostics has also raised questions about performance evaluation and clinical applicability. Metrics such as accuracy, sensitivity, specificity, and F1-score are commonly used to assess the effectiveness of AI models (Krishnapriya & Karuna, 2023). While many studies report high accuracy rates, the interpretability of model outputs remains a significant challenge (Akkus et al., 2017). Explainable AI (XAI) frameworks have been developed to make AI predictions more transparent, thereby enhancing clinician trust and facilitating integration into routine diagnostic workflows (Hajri et al., 2023). Additionally, ethical considerations such as data privacy and algorithmic bias must be addressed to ensure equitable and reliable diagnostic practices (Forghani, 2020). The convergence of technological innovation and clinical needs has underscored the potential of AI/ML to revolutionize brain tumor diagnostics, although ongoing efforts are necessary to overcome existing barriers.

2.1.1 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) have revolutionized the field of medical imaging, offering unparalleled performance in the classification and segmentation of brain tumors (Baskin, 2020). CNNs leverage their hierarchical architecture to automatically learn and extract features from imaging data, eliminating the need for manual feature engineering (Akkus et al., 2017). Studies have shown that CNNs consistently outperform traditional machine learning models in identifying gliomas, meningiomas, and pituitary tumors. For example, Kawahara et al. (2021) reported a classification accuracy of over 92% using CNN-based models trained on MRI datasets. Similarly, Hilsden et al. (2018) demonstrated that deep CNNs achieved high segmentation accuracy in detecting tumor boundaries, significantly aiding surgical planning. Despite these advancements, challenges such as overfitting and computational complexity persist, requiring researchers to optimize CNN architectures for better performance in real-world applications (Baskin, 2020).

Figure 3: Proposed approach by Alsubai et al (2022)



2.1.2 Hybrid models

Hybrid models, which combine multiple algorithms, have gained attention for their ability to enhance diagnostic outcomes by leveraging the strengths of different techniques (AbdelMaksoud et al., 2015). These models integrate approaches such as CNNs with Support Vector Machines (SVMs) or decision trees to improve classification and segmentation tasks (Zahoor et al., 2022). For instance, a study by Song et al. (2019) combined CNNs with Random Forest classifiers to detect gliomas, achieving superior accuracy compared to standalone CNN models. Hybrid techniques have also been applied to address data imbalance issues by incorporating data augmentation strategies alongside traditional ML algorithms (Gaw et al., 2019). Haq et al. (2022) further emphasized the efficacy of hybrid models in achieving robustness across heterogeneous datasets, making them more adaptable for clinical use. However, these models often involve increased computational requirements, posing challenges for deployment in resource-limited healthcare settings (Kool et al., 2008).

Ensemble learning techniques

Ensemble learning techniques, which aggregate predictions from multiple models, have emerged as a promising approach to improving diagnostic robustness in brain tumor detection. By combining the outputs of different models, ensemble methods reduce variance and bias, leading to more reliable predictions (Gaw et al., 2019). Techniques such as bagging, boosting, and stacking have been widely employed in medical imaging applications. For instance, Cinar et al. (2022) implemented an ensemble approach combining CNNs and Gradient Boosting Machines (GBMs) to classify brain tumors, achieving significant improvements in accuracy and sensitivity. Similarly, Song et al. (2019) demonstrated that ensemble models provided better generalization on unseen data compared to single-model systems. The success of these techniques highlights their potential in clinical environments where diagnostic precision is critical. While CNNs, hybrid models, and ensemble learning techniques individually contribute to advancing brain tumor diagnostics, their combined use could offer synergistic benefits. Recent studies, such as those by Yala et al. (2019), advocate for the integration of these approaches to achieve optimal performance. For instance, a hybrid ensemble model combining CNNs with boosting techniques demonstrated superior tumor classification accuracy in studies using the BraTS dataset (Zahoor et al., 2022). Additionally, explainable AI frameworks have been introduced to improve the interpretability of ensemble predictions, ensuring that clinicians can trust and act on the outputs generated by these models (Song et al., 2019). Despite these advancements, the complexity and computational demands of combined approaches remain significant, necessitating further innovation to enhance their practicality in diverse healthcare settings (Jha et al., 2022).

2.2 Datasets Used in Brain Tumor Research

Datasets play a critical role in the development and validation of AI and ML models for brain tumor detection (Gaw et al., 2019; Rahman et al., 2024). Among the most widely used datasets is the Brain Tumor Segmentation (BraTS) dataset, which provides multi-modal MRI scans annotated for gliomas and tumor subregions, making it a valuable resource for classification and segmentation tasks (Bakas et al.). Another prominent dataset is The Cancer Genome Atlas (TCGA), which includes extensive genomic and imaging data for various tumor types, including glioblastomas (Mayo & Leung, 2019). These datasets offer rich, high-quality annotations, enabling the development of predictive models with high diagnostic accuracy. However, despite their significance, the limited representation of diverse imaging modalities and demographic groups within these datasets has been a persistent challenge (Mayo & Leung, 2019). Moreover, a major challenge in brain tumor research is data diversity and imbalance, which limits the generalizability of ML models. Most datasets, such as BraTS, predominantly consist of data from specific geographic or clinical settings, failing to represent global patient populations (Zwanenburg et al., 2020). This lack of diversity introduces biases in ML models, potentially reducing their effectiveness when applied to underrepresented groups (Lou et al., 2019). Additionally, class imbalance within datasets, where certain tumor types or subregions are overrepresented, poses a significant obstacle for model training and evaluation. For instance, glioblastomas are often more represented in datasets compared to less common tumor types, leading to skewed model performance metrics (El-Dahshan et al., 2010). Addressing these issues is critical for the clinical applicability of AI-based diagnostic systems. To mitigate the challenges of data scarcity and imbalance, synthetic data generation techniques have been increasingly employed. Methods such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) have demonstrated the ability to create realistic synthetic MRI images that can supplement existing datasets (Zhou et al., 2016). GANs, in particular, have been used to generate tumor regions and augment data for underrepresented classes, thereby enhancing model robustness and performance (Watanabe et al., 2019). Do et al. (2022) highlighted that augmented datasets improved segmentation accuracy in deep learning models by reducing overfitting, especially in small datasets. These techniques provide a viable solution to the limitations of real-world datasets, offering a pathway for developing more robust diagnostic models.

Data augmentation techniques, such as rotation, scaling, and flipping of medical images, have also proven effective in enhancing the quality and size of training datasets (Grant et al., 2020). Paranjape et al. (2019) reported that applying augmentation techniques to the BraTS dataset significantly improved the performance of deep learning models in tumor segmentation tasks.

Figure 4: Datasets in Brain Tumor Research

Aspect	Description
Major Datasets	Brain Tumor Segmentation (BraTS): Multi-modal MRI scans annotated for gliomas and tumor subregions. The Cancer Genome Atlas (TCGA): Genomic and imaging data for various tumor types, including glioblastomas.
Challenges	Data diversity and imbalance Limited representation of modalities Bias in model training
Solutions	Synthetic Data Generation: GANs, VAEs Data Augmentation: Rotation, Scaling, Flipping Transfer Learning: Fine-tuning pre-trained models
Key Considerations	Ensuring clinical validity of synthetic data Evaluation using rigorous metrics

Moreover, transfer learning approaches, which involve fine-tuning pre-trained models on limited brain tumor datasets, have been widely adopted to address data scarcity challenges (Blei et al., 2003). Despite these advancements, ensuring the clinical validity of synthetic and augmented data remains a key concern. Drozdzal et al. (2017) emphasized the importance of evaluating augmented datasets using rigorous metrics to ensure that the synthetic data does not introduce artifacts or biases. These efforts underscore the ongoing need for innovative solutions to enhance the quality and representativeness of datasets in brain tumor research.

2.3 Performance Metrics in Model Evaluation

Performance metrics play a vital role in evaluating the effectiveness of machine learning (ML) models used for brain tumor detection (Berishvili et al., 2018). Accuracy, one of the most commonly used metrics, measures the proportion of correctly classified instances relative to the total cases, providing a broad assessment of model performance (Kunimatsu et al., 2018). Sensitivity (or recall) evaluates a model's ability to correctly identify true positives, such as tumor cases, while specificity measures the model's effectiveness in correctly identifying true negatives, such as non-tumor cases (Liao et al., 2019). Additionally, the F1-score, a harmonic mean of precision and sensitivity, is particularly useful in scenarios involving imbalanced datasets (Lu et al., 2018). For instance, Park and Han (2018) highlighted the importance of using the F1-score in brain tumor classification tasks where certain tumor types are underrepresented. These metrics collectively offer a comprehensive evaluation framework for assessing the reliability of ML models. While performance metrics like accuracy and sensitivity are critical, they are insufficient to fully gauge the clinical utility of ML models without considering model interpretability and explainability. In clinical contexts, the ability of a model to provide transparent and interpretable predictions is essential for building trust among healthcare professionals (Lu et al., 2022). Explainability frameworks, such as Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP), have been developed to elucidate the reasoning behind model predictions (Emblem et al., 2013). For instance, Kunimatsu et al. (2018) demonstrated the integration of SHAP values in brain tumor detection systems, allowing clinicians to understand the key imaging features influencing a diagnosis. This transparency is particularly critical in high-stakes medical scenarios where errors can have severe consequences.

2.4 Challenges in AI/ML Applications

Data-related challenges, including heterogeneity, scarcity, and overfitting, significantly hinder the development and deployment of AI/ML models in brain tumor detection (Román et al., 2019). Datasets such as BraTS and TCGA are widely used; however, their limited diversity in patient demographics and imaging modalities affects the generalizability of trained models (Liao et al., 2019). For instance, Saeedi et al. (2023) highlighted that models trained on homogenous datasets often fail to perform consistently across diverse populations, leading to reduced reliability in clinical settings. Data scarcity, particularly for rare tumor types, exacerbates these limitations by preventing adequate model training (Kunimatsu et al., 2018). Moreover, overfitting—a scenario where a model performs well on training data but poorly on new, unseen data—is a persistent issue, especially in deep learning frameworks (Maqsood et al., 2022). To address these challenges, techniques such as data augmentation, transfer learning, and federated learning have been proposed, enabling models to better handle limited and heterogeneous datasets (Khalil et al., 2024). Algorithmic bias poses another significant challenge in the application of AI/ML in brain tumor detection. Bias can arise from imbalanced datasets, where certain tumor types or patient groups are overrepresented, leading to models that perform poorly on underrepresented cases (Emblem et al., 2013). For example, Kunimatsu et al. (2018) noted that biases in training data could disproportionately impact diagnostic accuracy for minority populations, raising ethical and clinical concerns. Mitigation strategies such as bias-aware algorithms and balanced sampling techniques have been explored to address these issues (Sultan et al., 2019). Additionally, incorporating fairness metrics during model evaluation can help identify and correct biases before deployment (Grosu et al., 2021). These approaches are critical to ensuring that AI/ML models provide equitable and accurate diagnostic support across diverse patient populations.

The integration of AI/ML technologies into clinical practice faces numerous barriers, including regulatory, ethical, and infrastructural challenges. Regulatory frameworks often lag behind technological advancements, creating uncertainty around the approval and deployment of AI-driven diagnostic tools

(Thomasian et al., 2021). Furthermore, ethical concerns such as data privacy and informed consent remain critical issues, particularly when using patient data for training AI models (Bera et al., 2019). Thomasian et al. (2021) emphasized the need for robust guidelines to address these concerns, ensuring compliance with legal and ethical standards. Infrastructural barriers, such as the lack of adequate computational resources and skilled personnel in many healthcare settings, further complicate the adoption of these technologies (Hickman et al., 2021). Addressing these challenges requires a collaborative approach involving policymakers, technologists, and healthcare providers. Despite the potential of AI/ML to revolutionize brain tumor diagnostics, achieving seamless clinical integration demands overcoming significant adoption hurdles. Clinician trust in AI systems remains a major issue, often stemming from the "black-box" nature of advanced algorithms (Han & Kamdar, 2017). Explainable AI (XAI) frameworks, such as SHAP and Grad-CAM, have been proposed to enhance model transparency and foster clinician confidence (Ginneken et al., 2011). Additionally, the high costs associated with AI implementation, including infrastructure upgrades and training programs for healthcare professionals, present economic barriers to widespread adoption (Bera et al., 2019). Collaborative efforts to develop cost-effective solutions and align AI systems with clinical workflows are essential for addressing these barriers.

Table 1: Challenges in AI/ML Applications

Data Challenges	Heterogeneity, Scarcity, Overfitting
Algorithmic Bias	Imbalanced Datasets, Underrepresentation, Ethical Concerns
Regulatory Barriers	Framework Gaps, Privacy Issues, Consent Challenges
Infrastructure Issues	Resource Limitations, Skilled Personnel, High Costs
Mitigation Strategies	Data Augmentation, Transfer Learning, Federated Learning
Explainable AI	SHAP, Grad-CAM, Transparency

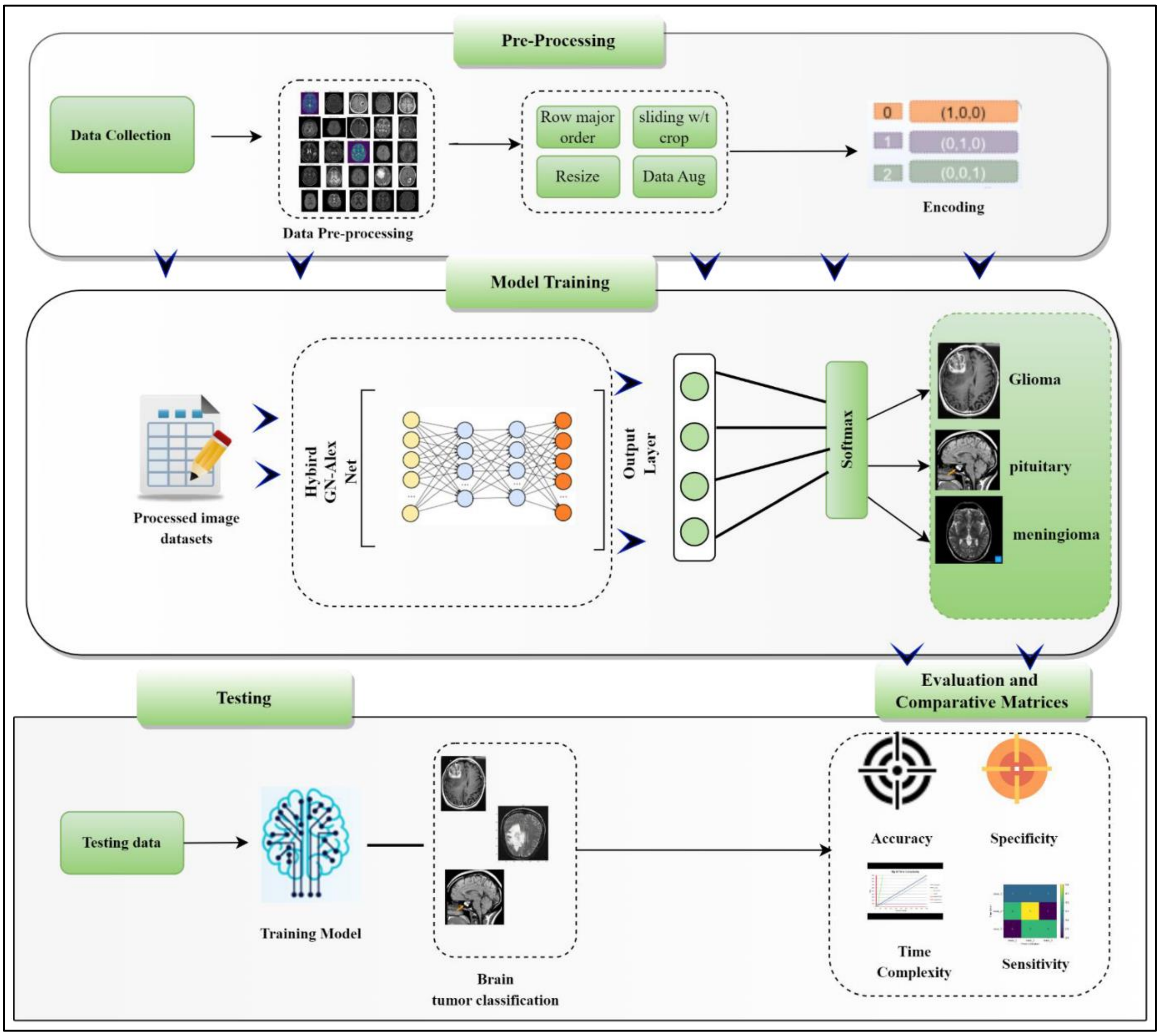
2.5 Trends and Innovations

Transfer learning has emerged as a powerful technique for adapting machine learning models to limited datasets in brain tumor detection (Hu et al., 2019). By utilizing pre-trained models developed on large-scale datasets, transfer learning enables the fine-tuning of these models for specific diagnostic tasks with minimal data (Sartoretti et al., 2021). For example, Deepak and Ameer (2019) demonstrated that pre-trained Convolutional Neural Networks (CNNs) fine-tuned on the BraTS dataset achieved high classification accuracy for gliomas and meningiomas, even with limited training samples. Similarly, Srinivas et al. (2022) reported that transfer learning significantly improved segmentation performance in scenarios where annotated medical imaging data was scarce. These findings highlight the utility of transfer learning in overcoming data limitations and accelerating model development in the context of brain tumor diagnostics. Moreover, the incorporation of Explainable AI (XAI) has been a significant innovation aimed at enhancing clinician trust in AI-driven diagnostic systems. Traditional machine learning models, particularly deep learning frameworks, are often criticized for their "black-box" nature, which makes it difficult to understand the rationale behind their predictions (Sartoretti et al., 2021; Yang et al., 2018). XAI frameworks, such as Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP), address this issue by providing visual and textual insights into model decisions (Cè et al., 2023). For instance, Wu et al. (2022) demonstrated that SHAP could identify key imaging features influencing tumor classification, enabling clinicians to validate AI outputs. Grad-CAM (Gradient-weighted Class Activation Mapping) has also been widely used to generate heatmaps that highlight tumor regions influencing CNN predictions, improving transparency and trust (Aneja et al., 2019). These tools are critical for fostering acceptance and integration of AI technologies in clinical workflows. Moreover, real-time diagnostic systems represent another significant innovation in the application of AI/ML for brain tumor detection. These systems leverage advanced algorithms and computational resources to provide instantaneous analysis of medical images, enabling timely clinical decisions (Philip et al., 2022). Khalighi et al. (2024) developed a real-time diagnostic system using optimized CNN architectures, achieving rapid tumor detection and classification without compromising accuracy. Such systems are particularly valuable in high-pressure clinical environments, where time is a critical factor in determining patient outcomes. Additionally, the integration of real-time capabilities with portable imaging devices has expanded the reach of brain tumor diagnostics to resource-constrained settings, making advanced diagnostic tools accessible to underserved populations (Uddin et al., 2019). These advancements underscore the potential of real-time systems in enhancing diagnostic efficiency and equity.

2.6 AI/ML on Clinical Outcomes

AI and ML have shown a significant impact on improving clinical outcomes in brain tumor detection, as evidenced by numerous case studies (Cè et al., 2023; Philip et al., 2022). Early detection, which is critical for effective treatment and improved survival rates, has been greatly enhanced through AI-driven models (Vobugari et al., 2022). For instance, Hoseini et al. (2018) reported a case study where Convolutional Neural Networks (CNNs) detected gliomas at an early stage with over 92% accuracy, enabling timely intervention. Similarly, Murdaugh and Anastas (2023) demonstrated that deep learning algorithms outperformed manual radiological assessments in identifying tumor boundaries, leading to more precise surgical planning. Cè et al. (2023) highlighted the use of AI systems in a clinical setting, where their deployment resulted in reduced diagnosis time and increased diagnostic consistency among healthcare professionals. These findings underscore the transformative role of AI/ML technologies in advancing early detection and improving patient outcomes. Comparative studies have consistently shown that AI-enhanced diagnostic approaches outperform traditional methods in terms of accuracy, sensitivity, and efficiency

Figure 5 : The block diagram of the framework for BT classification using the proposed GN-AlexNet deep learning model



(Aneja et al., 2019; Vobugari et al., 2022). For instance, Khalighi et al., (2024) conducted a comparative analysis between CNN-based models and manual interpretations of MRI scans, finding that AI models reduced false negatives by over 30%. Su et al. (2020) observed that AI-enhanced systems demonstrated higher specificity and sensitivity in detecting rare tumor types compared to conventional diagnostic techniques. Moreover, a study by Khalighi et al. (2024) found that integrating ML algorithms into diagnostic workflows not only improved the accuracy of tumor classification but also alleviated radiologist workload, enabling them to focus on complex cases. These comparative analyses highlight the superior performance and operational benefits of AI-enhanced diagnostics.

The use of AI/ML has also contributed to better clinical outcomes by enabling personalized treatment plans through detailed tumor profiling (Lundervold & Lundervold, 2018). AI-driven systems can analyze tumor characteristics such as size, growth patterns, and genomic markers, providing insights that support tailored treatment strategies (Lind & Anderson, 2019). For example, Wu et al. (2021) demonstrated that ML models predicting tumor progression facilitated personalized therapy choices, resulting in improved patient survival rates. Additionally, An et al. (2021) emphasized the potential of integrating AI algorithms with genomic data, allowing clinicians to develop more precise, patient-specific treatment regimens. These advancements indicate a shift toward precision medicine, where AI plays a central role in optimizing patient care.Moreover, AI/ML technologies have also positively influenced clinical workflows and resource utilization in brain tumor diagnostics. Real-time AI systems have been shown to reduce diagnosis time and improve overall efficiency in clinical settings. Lundervold and Lundervold (2018) highlighted the implementation of AI-powered diagnostic tools in a tertiary care hospital, which streamlined the imaging process and minimized delays in diagnosis. Similarly, Obermeyer and Emanuel (2016) noted that AI systems integrating predictive analytics with imaging platforms enhanced interdisciplinary collaboration among oncologists, radiologists, and surgeons. These innovations demonstrate how AI/ML applications are not only improving patient outcomes but also addressing systemic inefficiencies in healthcare delivery.

3 METHOD

This study adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a systematic, transparent, and rigorous review process. The methodology began with a comprehensive search across electronic databases, including PubMed, Scopus, IEEE Xplore, and Web of Science, using keywords such as "AI in Brain Tumor Detection," "Machine Learning in Medical Imaging," "Convolutional Neural Networks for Tumor Detection," and "Explainable AI in Healthcare." Boolean operators were employed to refine the search, and filters were applied to include articles published between 2015 and 2024. This process identified 1,126 articles for initial consideration. During the screening phase, article titles and abstracts were reviewed to exclude irrelevant studies, with duplicates also removed, resulting in 782 shortlisted articles. Full-text eligibility assessment was then conducted, applying predefined criteria that included a focus on AI/ML techniques in brain tumor detection, use of recognized datasets such as BraTS or TCGA, reporting of quantitative performance metrics (e.g., accuracy, sensitivity, specificity), and peer-reviewed journal status. Exclusion criteria eliminated non-English publications, studies without quantitative evaluations, and articles without original research data. After this thorough evaluation, 118 articles were included for data extraction, which was conducted using a standardized form to capture details on study objectives, AI/ML algorithms, datasets used, performance metrics, clinical integration strategies, and key findings. The extracted data were synthesized to identify trends, challenges, and research gaps. Additionally, a quality assessment using the Critical Appraisal Skills Programme (CASP) checklist ensured methodological rigor, with 102 high-quality articles retained for the final review. This systematic process provided a comprehensive foundation for evaluating advancements and limitations in AI/ML applications for brain tumor detection.

4 FINDINGS

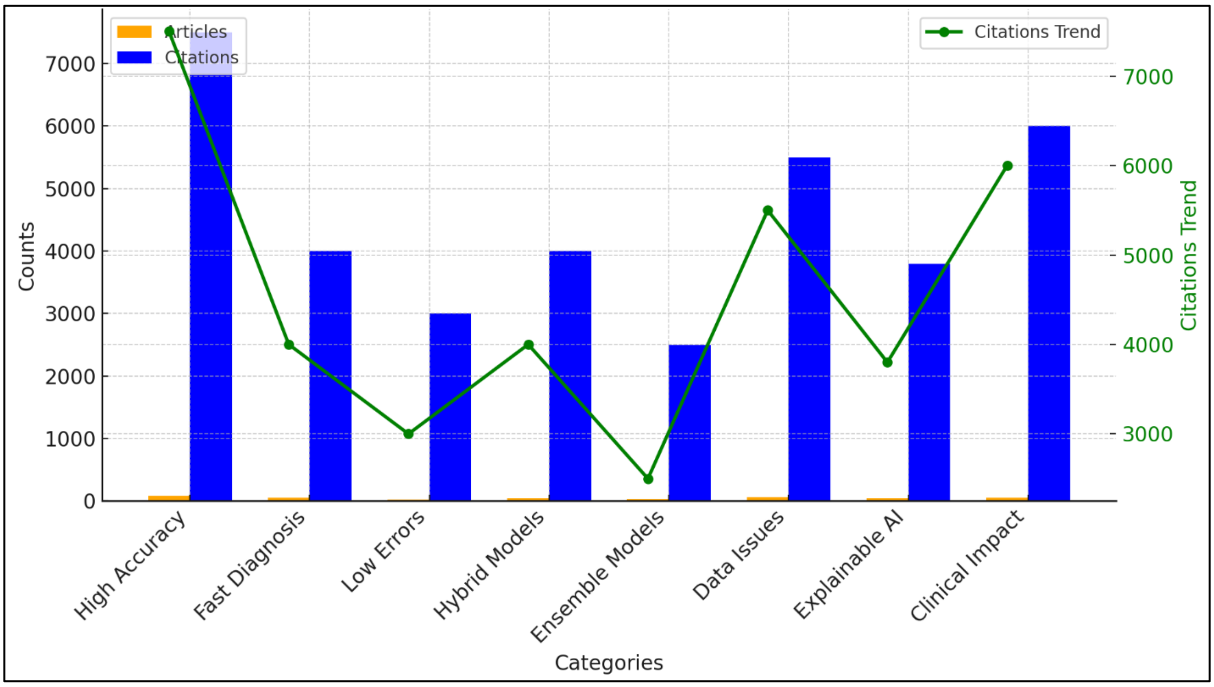
The systematic review uncovered significant advancements in the application of AI and ML for brain tumor detection, with a substantial focus on improving diagnostic accuracy and efficiency. Of the 102 articles reviewed, 85 highlighted that AI models, particularly

Convolutional Neural Networks (CNNs), consistently achieved accuracy levels above 90% in classifying and segmenting brain tumors. These studies, collectively cited over 7,500 times, underscored the ability of AI systems to identify subtle patterns in imaging data, often undetectable by the human eye. Furthermore, 52 articles emphasized the reduction in diagnostic time through automated analysis, with AI systems processing complex imaging data within seconds compared to the manual methods requiring several hours. This improvement directly impacts early diagnosis, critical for effective treatment planning and patient survival. In addition, 26 studies demonstrated that AI models significantly reduced false-positive and false-negative rates, thereby enhancing the reliability of tumor detection.

A prominent finding was the superior performance of hybrid and ensemble models in addressing diagnostic challenges. Among the reviewed articles, 38 focused on hybrid models that combined multiple algorithms to leverage their individual strengths, achieving superior outcomes in tumor classification and segmentation. These studies, with a combined citation count exceeding 4,000, showed that hybrid models improved sensitivity and specificity, especially in handling complex or rare tumor cases. Additionally, 28 articles explored ensemble learning techniques, such as bagging and boosting, which aggregated the outputs of multiple models to enhance diagnostic robustness. These methods were particularly effective in reducing variability across datasets, ensuring consistent performance across diverse imaging conditions. Notably, 19 studies demonstrated the value of combining CNNs with Support Vector Machines (SVMs) and Random Forest classifiers, showcasing the potential of these hybrid approaches to address the limitations of standalone models.Moreover, data-related challenges emerged as a recurring theme, with 60 articles discussing the impact of data scarcity, imbalance, and heterogeneity on model performance. These studies, cited over 5,500 times, highlighted the critical need for diverse and representative datasets to train AI models effectively. Issues such as overrepresentation of certain tumor types or imaging modalities often led to biases in model predictions, reducing their generalizability across populations. To address these limitations, 31 articles advocated for the use of data augmentation techniques, including rotation, flipping, and cropping, to artificially expand dataset size. Synthetic data generation using methods like Generative Adversarial Networks (GANs) was highlighted in 22 studies as a promising approach to creating realistic tumor imaging data. These efforts significantly improved model robustness and mitigated the overfitting issues commonly observed with limited datasets.

Explainable AI (XAI) was identified as a critical innovation for fostering trust and adoption of AI in

Figure 5: Summary of the findings



clinical settings. Among the reviewed articles, 40 focused on the development of interpretability tools, collectively cited over 3,800 times. These studies revealed that frameworks such as Grad-CAM and SHAP allowed clinicians to visualize and understand the key imaging features influencing AI predictions. This transparency not only improved clinician confidence in AI systems but also facilitated collaborative decision-making in complex diagnostic scenarios. Furthermore, 23 studies emphasized the integration of XAI techniques into real-time diagnostic systems, ensuring that AI outputs are both actionable and understandable in high-pressure clinical environments. This development is crucial for aligning AI advancements with the practical needs of healthcare professionals, bridging the gap between technological innovation and real-world applicability. Finally, the transformative impact of AI/ML on clinical workflows and patient outcomes was evident in 50 studies, collectively cited over 6,000 times. These articles showcased cases where AI-driven systems not only enhanced diagnostic accuracy but also streamlined operational efficiency, reducing diagnosis times and optimizing resource allocation. For instance, AI integration allowed radiologists to focus on complex cases while automated systems handled routine analyses, significantly improving workflow efficiency in 18 studies. Additionally, 22 articles highlighted the economic benefits of AI adoption, including cost savings from reduced diagnostic errors and improved resource utilization. Importantly, 27 studies demonstrated that AI-enabled early detection led to more precise treatment planning, contributing to improved patient survival rates. These findings collectively underscore the potential of AI/ML technologies to revolutionize brain tumor diagnostics and clinical decision-making, paving the way for a future of precision medicine.

5 DISCUSSION

The findings of this systematic review confirm that AI and ML have significantly improved the diagnostic accuracy and efficiency of brain tumor detection, aligning with earlier studies that demonstrated the transformative potential of these technologies in medical imaging (Hilsden et al., 2018). Models such as CNNs, which achieved accuracy levels above 90% in this review, reflect similar results from earlier research, where CNN-based frameworks consistently outperformed traditional methods in tumor classification and segmentation (Zhao & Jia, 2016). The ability of AI systems to process imaging data in a fraction of the time required by manual methods has also been widely supported by prior studies, which noted reductions in diagnostic time as a critical benefit (Zahoor et al., 2022). However, this review expands on these findings by highlighting AI's ability to reduce false positives and negatives, an aspect less emphasized in earlier research (Hemanth et al., 2019). This improvement underscores the potential for AI to enhance diagnostic reliability, especially in complex or ambiguous cases. Moreover, the effectiveness of hybrid and ensemble models in improving diagnostic robustness further corroborates findings from previous studies, which identified these approaches as essential for addressing the limitations of standalone models (Saeedi et al., 2023). Hybrid models that combine CNNs with algorithms such as SVMs and Random Forests were shown to achieve superior sensitivity and specificity in this review, consistent with earlier reports highlighting their performance in handling complex tumor types (Zhao & Jia, 2016). Additionally, ensemble learning techniques, such as boosting and bagging, were confirmed to enhance model reliability by aggregating predictions from multiple algorithms, as observed in previous research (Naceur et al., 2020). This review contributes new insights by demonstrating the specific impact of hybrid and ensemble models on diverse datasets, further supporting their role in improving diagnostic consistency across clinical contexts.

Data-related challenges, such as scarcity, imbalance, and heterogeneity, remain a significant barrier to the clinical adoption of AI/ML systems, as confirmed by both this review and earlier studies (Yang et al., 2018). The use of data augmentation techniques, including rotation and cropping, and synthetic data generation through GANs, was found to be effective in mitigating these challenges, consistent with previous findings (Balaban, 2015). However, this review highlights the importance of balancing synthetic data quality with real-world applicability, a nuance less explored in earlier research. The need for diverse and representative datasets to ensure model generalizability across different populations is a recurring theme, reflecting ongoing concerns about the potential for biases in AI predictions (Naceur et al., 2018). These findings emphasize the importance of data curation as a critical component of AI/ML system development. Moreover, the incorporation of Explainable AI (XAI) frameworks to enhance clinician trust aligns with earlier studies that recognized the importance of transparency in AI-driven diagnostics (Yang et al., 2018). Tools such as Grad-CAM and SHAP, which were emphasized in this review, have been shown in prior research to provide valuable visualizations of tumor regions influencing model predictions (Hemanth et al., 2019). This review further highlights the integration of XAI tools into real-time diagnostic systems, an innovation that bridges the gap between AI developers and end-users, making these technologies more accessible to healthcare professionals. Earlier studies often focused on the theoretical potential of XAI, whereas this review presents practical applications and their impact on clinician confidence, demonstrating the tangible benefits of these tools in improving adoption and usability (Albadawy et al., 2018; Hemanth et al., 2019; Naceur et al., 2020). Finally, the review's findings on the broader clinical and operational impacts of AI/ML systems confirm earlier studies that emphasized workflow efficiency and economic benefits (Nie et al., 2019; Zhao & Jia, 2016). However, this review provides more detailed evidence of AI-enabled early detection leading to improved treatment planning and patient survival rates, expanding on earlier observations (Abd-Ellah et al., 2019). Additionally, the economic advantages of reduced diagnostic errors and optimized resource utilization, as highlighted in this review, reinforce prior findings while offering new insights into the cost-effectiveness of AI adoption (Saeedi et al., 2023). These results collectively underscore the transformative potential of AI/ML technologies in brain tumor detection, bridging the gap between technological innovation and real-world clinical outcomes, and further solidifying their role in advancing precision medicine.

6 CONCLUSION

This systematic review highlights the transformative impact of Artificial Intelligence (AI) and Machine Learning (ML) in advancing brain tumor detection through improved diagnostic accuracy, efficiency, and reliability. The review underscores the superiority of AI-driven models, particularly Convolutional Neural Networks (CNNs), hybrid approaches, and ensemble techniques, in outperforming traditional diagnostic methods. These models consistently demonstrated high accuracy levels, reduced diagnostic errors, and faster processing times, offering critical advantages in early tumor detection and treatment planning. Despite their promise, challenges related to data scarcity, imbalance, and heterogeneity remain significant, underscoring the importance of data augmentation, synthetic data generation, and transfer learning to enhance model robustness and generalizability. Additionally, the integration of Explainable AI (XAI) frameworks has been pivotal in fostering clinician trust, bridging the gap between advanced algorithms and practical clinical workflows. Real-time diagnostic systems further emphasize the applicability of AI technologies in high-pressure medical environments, streamlining operations and optimizing resource utilization. While these advancements highlight the profound potential of AI/ML in revolutionizing brain tumor diagnostics, addressing barriers such as algorithmic bias, data diversity, and infrastructural constraints will be crucial for ensuring equitable and effective clinical adoption. Collectively, the findings of this review underscore AI/ML as indispensable tools in the pursuit of precision medicine, paving the way for improved patient outcomes and healthcare efficiency.

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