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AI-Assisted Brain Tumor Prediction

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Abstract: *Artificial intelligence (AI) has emerged as a transformative force in the field of medical imaging, especially in the detection and prediction of brain tumors. Its potential is particularly valuable in improving the accuracy and efficiency of identifying and analysing brain tumors, which is crucial for early diagnosis, treatment planning, and patient care. Traditional diagnostic methods, such as manually interpreting MRI, CT, and other imaging scans, often rely heavily on the expertise of radiologists. However, these methods can be time-consuming and susceptible to human error and variability. Integrating AI into these diagnostic workflows can significantly speed up the decision-making process, enhance diagnostic accuracy, and ensure more consistent results. This review paper explores recent advancements in AI-powered brain tumor detection, with a focus on machine learning (ML) and deep learning (DL) techniques. It highlights various AI models and algorithms—such as convolutional neural networks (CNNs), support vector machines (SVMs), random forests, and ensemble learning methods—that are being used to detect, classify, and segment brain tumors in medical images. These models are trained using large datasets of labelled images, enabling them to recognize complex patterns and make predictions aligned with clinical outcomes. The paper also sheds light on how AI is advancing several critical aspects of brain tumor analysis, including tumor detection, segmentation, volumetric measurement, and classification (e.g., gliomas, meningiomas, metastases). Beyond simply identifying tumors, AI systems are becoming increasingly capable of distinguishing between benign and malignant types, predicting tumor progression, and evaluating treatment responses. Additionally, the paper discusses the concept of radiomics—extracting quantitative features from medical images and applying AI to relate these features to patient prognosis and survival outcomes.*

Keywords: Brain Tumor Detections, Systematic Literature Review, Machine Learning, Artificial Intelligence Diagnostic Accuracy

I. INTRODUCTION

Detecting brain tumors plays a critical role in medical diagnosis and greatly influences patient outcomes and treatment strategies (Chato & Latifi, 2017). Early and accurate detection can significantly reduce both the physical and emotional burden on patients and their families, while also improving survival rates (Das et al., 2019). However, traditional diagnostic methods—such as interpreting CT scans and MRI images—rely heavily on radiologists' expertise, which can lead to inconsistent and subjective results (Arif et al., 2022).Artificial Intelligence (AI) and Machine Learning (ML) have revolutionized healthcare by providing automated, accurate, and efficient diagnostic tools (Özyurt et al., 2019). These technologies are increasingly being used to assist radiologists in analyzing complex medical images, with the goal of improving patient outcomes and minimizing diagnostic errors (Saba et al., 2020). In particular, deep learning models—especially Convolutional Neural Networks (CNNs)—have gained significant popularity in recent years due to their ability to recognize intricate patterns in visual data (AbdelMaksoud et al., 2015). Studies have demonstrated that CNNs are highly effective for detecting and segmenting brain tumors (AbdelMaksoud et al., 2015; Bashir-Gonbadi & Khotanlou, 2021; Saba et al., 2020). For example, Ranjbarzadeh et al. (2021) reported a classification accuracy of over 92% using a CNN-based approach for identifying gliomas, pituitary tumors, and meningiomas. Additionally, Huang et al. (2014) highlighted the potential of hybrid models that combine CNNs with Support Vector Machines (SVMs), leveraging the strengths of both methods to enhance diagnostic performance. These advancements underscore the transformative potential of AI and ML in supporting clinical decision- making. However, several challenges must still be addressed

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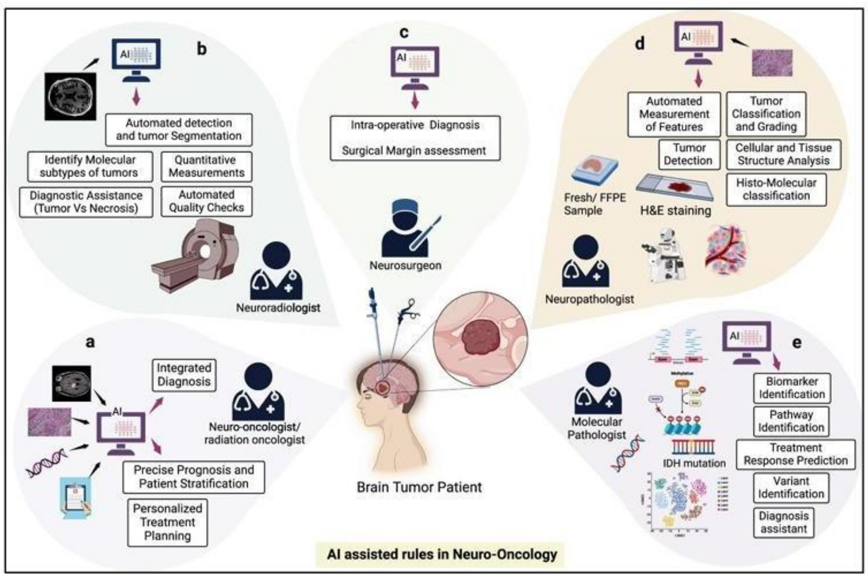
before these technologies can be reliably implemented in real-world clinical environments (Zhu et al., 2023). One major issue is the lack of diversity in available datasets. Public datasets, such as the Brain Tumor Segmentation (BraTS) collection, often do not include a wide range of patient demographics or imaging techniques (Siar & Teshnehlab, 2019), limiting the generalizability of AI models across different healthcare settings. Another challenge is the risk of overfitting and bias in model training, which can compromise the reliability of AI systems in real-world scenarios (Ranjbarzadeh et al., 2021). To address these limitations, it is essential to develop more robust algorithms and use larger, more diverse datasets to ensure broader applicability (Huang et al., 2014).

A growing number of studies have explored the use of AI and ML in brain tumor detection, highlighting both their potential and current limitations (Shreve et al., 2022). For instance, Anjum et al. (2021) conducted an in-depth review of transfer learning techniques, showing how pre-trained models can help overcome the issue of limited data. Similarly, Kader et al. (2021) compared deep learning with traditional diagnostic methods and found that AI models consistently outperformed them in terms of accuracy and efficiency. Havaei et al. (2016) examined how AI systems could be integrated into clinical workflows, emphasizing the importance of user-friendly interfaces and proper training for healthcare professionals. These findings collectively highlight the need for ongoing innovation and strong collaboration across disciplines to advance the field further (Amin et al., 2019; Havaei et al., 2016).

Figure 1: AI assisted rules in Neuro-Oncology



Source: Khalighi et al. (2024).

Ensemble learning techniques, which integrate the results of several algorithms to improve diagnostic accuracy and system robustness, have been introduced by recent developments in AI and machine learning (Holzinger et al., 2019). Hybrid models that combine Convolutional Neural Networks (CNNs) with other techniques like Random Forests and Gradient Boosting have demonstrated notable performance gains in brain tumor classification and segmentation (Havaei et al., 2016). Furthermore, the development of explainable AI (XAI) has increased the transparency of AI-driven technologies, assisting physicians in comprehending the logic underlying the predictions and promoting increased acceptance and trust in medical practice (Zacharaki et al., 2009).

These developments, which are the result of combining state-of-the-art AI technology with clinical knowledge, mark a significant change in the way brain cancers are detected. This systematic review's main goal is to examine and compile the most recent advancements in AI and ML methods for brain tumor diagnosis, paying special attention to their predicted accuracy, clinical application, and dependability. In particular, this research assesses the performance of various AI models, including CNNs, hybrid systems, and ensemble approaches, in the classification and segmentation of

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brain tumors utilizing imaging data from CT and MRI images. It also discusses the main obstacles to the effective application of these technologies in actual clinical contexts, such as algorithmic bias, overfitting, and data diversity. This review attempts to offer useful insights for researchers and healthcare professionals by looking at current trends, research gaps, and emerging breakthroughs. In the end, it aims to facilitate the successful incorporation of AI and ML into diagnostic processes, enhancing the early identification and prognosis of brain tumor patients.

II. LITERATURE REVIEW

The use of machine learning (ML) and artificial intelligence (AI) in the diagnosis of brain tumors has grown dramatically over the past 10 years as a result of improvements in algorithmic design, processing capacity, and medical imaging. In order to assess how well AI and ML models can overcome the drawbacks of conventional techniques, how well they can increase diagnostic accuracy, and what obstacles still need to be addressed in practical application, this part examines the research. This study intends to highlight important discoveries, knowledge gaps, and prospects for further development in the discipline by thoroughly classifying the literature. The analysis, which is divided into distinct subsections, focuses on the algorithms, datasets, performance measures, and real-world applications of AI/ML in brain tumor diagnostics.

AI/ML for Brain Tumor Detection

The integration of artificial intelligence (AI) and machine learning (ML) into medical imaging has significantly transformed diagnostic approaches, especially in the detection of brain tumors (Cè et al., 2023). Traditional imaging techniques like computed tomography (CT) and magnetic resonance imaging (MRI) have long been essential for diagnosing brain tumors. However, conventional diagnostic processes typically rely on manual interpretation, which can be time-consuming and prone to subjectivity (Shimizu & Nakayama, 2020). In contrast, AI/ML technologies can process vast volumes of image data, identifying subtle patterns and abnormalities with greater speed and accuracy (Lundin et al., 1999). These systems use extensive data to develop predictive models capable of detecting various tumor types early with high precision. For instance, Noseworthy et al. (2020) found that AI systems can perform on par with expert radiologists, proving especially valuable in resource-limited settings. Similarly, Forghani (2020) highlighted how ML has accelerated diagnoses while minimizing human error.

Among AI techniques, Convolutional Neural Networks (CNNs) have become a core tool in brain tumor detection. CNNs excel at identifying spatial features in imaging data, which enhances tumor classification and segmentation (Akkus et al., 2017). Hilsden et al. (2018) demonstrated that CNNs could accurately classify tumors like gliomas, meningiomas, and pituitary adenomas with over 92% accuracy. Furthermore, combining CNNs with other models—such as Support Vector Machines (SVMs)—in hybrid frameworks has improved diagnostic outcomes (Zhou et al., 2023). Ensemble learning methods, which aggregate predictions from multiple models, have also shown promise in improving tumor segmentation accuracy and robustness (Johnson et al., 2020). These advancements reflect the strength of deep learning in tackling the complex challenges of brain tumor diagnosis.

High-quality datasets are critical for training and validating AI models. Datasets like The Cancer Genome Atlas (TCGA) and Brain Tumor Segmentation (BraTS) provide standardized imaging data for developing and testing diagnostic tools (Baskin, 2020; Johnson et al., 2020). However, these datasets often lack diversity in imaging modalities and patient populations, leading to issues like data imbalance and limited generalizability (Krishnapriya & Karuna, 2023). To address this, researchers have adopted methods such as data augmentation and generative adversarial networks (GANs) to create synthetic images that enrich underrepresented classes (Akkus et al., 2017). Transfer learning has also been effective, allowing pretrained models to adapt to new datasets with limited samples (Lee et al., 2019). Still, expanding and diversifying available datasets remains crucial to improving model performance across clinical settings (Obermeyer & Emanuel, 2016).

Model performance is typically evaluated using metrics such as accuracy, sensitivity, specificity, and F1-score (Krishnapriya & Karuna, 2023). Despite high performance in many studies, interpretability remains a key challenge. To address this, Explainable AI (XAI) frameworks have been developed to improve transparency, allowing clinicians to better trust and understand AI-generated predictions (Hajri et al., 2023). While obstacles remain, the fusion of clinical needs and technological advancements clearly illustrates the potential of AI and ML to revolutionize brain tumor diagnostics.

Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) have significantly advanced medical imaging by achieving high accuracy in brain tumor classification and segmentation tasks (Baskin, 2020). Their layered architecture enables automatic feature extraction from imaging data, removing the need for manual feature engineering (Akkus et al., 2017). Studies have shown CNNs outperform traditional ML models in detecting tumors like gliomas, meningiomas, and pituitary tumors. For example, Kawahara et al. (2021) reported over 92% accuracy using CNNs trained on MRI scans. Similarly, Hilsden et al. (2018) demonstrated how deep CNNs improved surgical planning through precise tumor boundary segmentation. Despite these successes, challenges such as overfitting and high computational demands still limit CNNs' practical deployment, emphasizing the need for optimized architectures (Baskin, 2020).

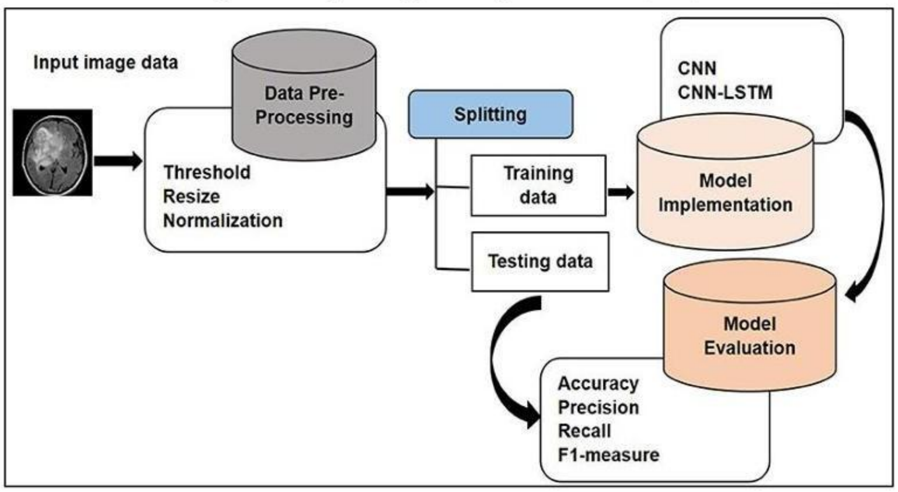

Figure 3: Proposed approach by Alsubai et al (2022)

Hybrid models

Hybrid models, which combine multiple algorithms, have gained attention for their ability to improve diagnostic accuracy by leveraging the strengths of various methods (AbdelMaksoud et al., 2015). These models typically integrate approaches like Convolutional Neural Networks (CNNs) with techniques such as Support Vector Machines (SVMs) or decision trees to boost performance in classification and segmentation tasks (Zahoor et al., 2022). For instance, Song et al. (2019) demonstrated that combining CNNs with Random Forest classifiers resulted in better accuracy when diagnosing gliomas compared to using CNNs alone. . According to Haq et al. (2022), these models perform well across diverse datasets, making them more suitable for clinical use. However, one challenge is that they often require more computational power, which can be a barrier in healthcare settings with limited technological resources (Kool et al., 2008).

Ensemble learning is another promising strategy that enhances diagnostic reliability by aggregating the predictions of multiple models. This approach reduces bias and variance, resulting in more accurate and dependable predictions (Gaw et al., 2019). For example, Cinar et al. (2022) combined CNNs with Gradient Boosting Machines (GBMs) and achieved significant improvements in both precision and sensitivity for brain tumor diagnosis. Similarly, Song et al. (2019) found that ensemble models generalized better on new, unseen data compared to individual models. These results highlight the value of ensemble methods in clinical contexts where diagnostic accuracy is critical.

Although CNNs, , advocate for such integrated approaches. One study using the BraTS dataset reported that a hybrid ensemble model combining CNNs with boosting methods led to more accurate tumor classification (Zahoor et al.,

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2022). To increase the trust and usability of these complex systems in clinical settings, researchers have also developed explainable AI (XAI) tools to clarify how ensemble models arrive at their predictions (Song et al., 2019). Despite these advancements, the computational complexity and resource requirements of integrated models remain challenges, highlighting the need for further research to make them more feasible across different healthcare environments (Jha et al., 2022).

Datasets Used in Brain Tumor Research

In order to construct and validate AI and ML models for brain excrescence identification, datasets are essential (Gaw et al., 2019; Rahman et al., 2024). The Brain Excrescence Segmentation (BraTS) dataset is one of the most popular bones. It offersmulti-modal MRI images that have been labeled for excrescence subregions and gliomas, making it a useful tool for bracket and segmentation tasks (Bakas et al.). The Cancer Genome Atlas (TCGA), another well- known dataset, has comprehensive inheritable and imaging information for a range of excrescence types, including glioblastomas (Mayo & Leung, 2019). Because of the abundant, high- quality reflections handed by these datasets, vaticination models with excellent individual delicacy may be developed. perfection. The underrepresentation of colorful imaging modalities and demographic groups in these databases, still, has remained a habitual problem despite their significance (Mayo & Leung, 2019). likewise, data imbalance and variety give a significant handicap to brain excrescence exploration, limiting the generalizability of machine literacy models. The maturity of datasets, including BraTS, are primarily composed of information from particular clinical or geographic surrounds and don't adequately reflect patient populations worldwide (Zwanenburg et al., 2020). Due to impulses introduced by this lack of diversity, machine literacy models may be less successful when applied to underrepresented groups (Lou et al., 2019). likewise, a major hedge to model training is class imbalance in datasets, where specific excrescence kinds or subregions are overrepresented. assessment. Model performance pointers are prejudiced because, for illustration, glioblastomas are constantly more current in datasets than less common excrescence forms (El- Dahshan et al., 2010).

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

Figure 4: Datasets in Brain Tumor Research

For AI- grounded individual systems to be clinically applicable, these problems must be resolved. The use of synthetic data creation ways has grown in order to address the issues of data imbalance and deficit. ways like Variational Autoencoders (VAEs) and Generative inimical Networks (GANs) have shown pledge in producing naturalistic synthetic MRI images that may be used to compound current datasets (Zhou et al., 2016). To ameliorate model performance and

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adaptability, GANs in particular have been employed to produce excrescence areas and supplement data for underrepresented classes. In 2019, Watanabe et al. Do et al. (2022) refocused out that by lowering overfitting, particularly in small datasets, enhanced datasets increased segmentation delicacy in deep literacy models. These styles offer a workable way around the downsides of real- world datasets and pave the way for the creation of further dependable individual models. Medical picture gyration, scaling, and flipping are exemplifications of data addition approaches that have been shown to ameliorate the volume and quality of training datasets (Grant et al., 2020). According to Paranjape et al. (2019), deep literacy models' performance in excrescence segmentation tasks was vastly enhanced by using addition ways on the BraTS dataset.

Additionally, by optimizing previously trained models on tiny datasets of brain tumors, transfer learning approaches have been widely employed to address data problems. shortage-related issues (Blei et al., 2003). Despite these advancements, ensuring the clinical validity of enhanced and synthetic data remains a significant challenge. Drozdzal et al. (2017) emphasized the necessity of evaluating augmented datasets using precise measurements to ensure that the synthetic data does not introduce biases or artifacts. These initiatives highlight the continuous need for creative ways to improve the caliber and representativeness of datasets used in brain tumor research.

Performance Metrics in Model Evaluation

According to Berishvili et al. (2018), performance indicators are crucial for evaluating the effectiveness of machine learning models used in the diagnosis of brain tumors. A commonly used metric, accuracy measures the proportion of correctly classified examples to all cases, providing a thorough assessment of model performance (Kunimatsu et al., 2018). Specificity evaluates a model's ability to correctly identify true negatives, such as non-tumor cases, while sensitivity (or recall) evaluates a model's ability to correctly identify genuine positives, such as tumor instances (Liao et al., 2019). Furthermore, when dealing with unbalanced datasets, the F1-score—a harmonic mean of accuracy and recall—is particularly helpful (Lu et al., 2018). For instance, Park and Han (2018) highlighted the importance of using the F1-score for classifying brain tumors when particular tumor Kinds are not adequately represented. When combined, these metrics offer a comprehensive framework for assessing ML models' dependability. Although accuracy and sensitivity are significant performance metrics, they do not fully represent the clinical use of machine learning models unless model interpretability and explainability are considered. A model must be able to generate predictions that are easy to understand in order to gain the trust of medical professionals in clinical settings (Lu et al., 2022). Explainability frameworks such as Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) have been developed to make the reasoning behind model predictions more understandable (Emblem et al., 2013). Kunimatsu et al. (2018) demonstrated, for instance, how to incorporate SHAP values into brain tumor detection systems, allowing physicians to identify the key imaging features that influence a diagnosis. This transparency is particularly crucial in high-stakes medical scenarios where errors could have catastrophic consequences

Challenges in AI/ML Applications

Among the data-related problems that significantly hinder the development and application of AI/ML models in the brain are heterogeneity, shortage, and overfitting. tumor detection (Román et al., 2019). Despite the frequent use of datasets like as TCGA and BraTS, their limited diversity in patient demographics and imaging modalities affects the generalizability of trained models (Liao et al., 2019). For instance, models created on homogeneous datasets sometimes exhibit inconsistent performance across a variety of populations, which reduces dependability in clinical settings (Saeedi et al., 2023). Lack of data, particularly for rare tumor forms, exacerbates these limitations by making it unable to successfully train models (Kunimatsu et al., 2018). Additionally, overfitting—the phenomenon where a model performs well on training data but poorly on new, unknown data—is a persistent issue, especially in deep learning frameworks (Maqsood et al., 2022). To address these problems, techniques like as data augmentation, transfer learning, and federated learning have been proposed, enabling models to better handle heterogeneous and limited datasets (Khalil et al., 2024). Algorithmic bias is another significant barrier to the diagnosis of brain tumors using AI/ML. Bias from unbalanced datasets, where some tumor kinds or patient groups are overrepresented, may be the cause of models that perform poorly on underrepresented instances (Emblem et al., 2013). For example, the accuracy of diagnoses for

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minority populations may be disproportionately impacted by biases in training data, raising ethical and therapeutic concerns according to Kunimatsu al. (2018) Mitigation strategies like bias-aware algorithms and balanced sample techniques have been researched to solve these issues (Sultan et al., 2019). Additionally, using fairness criteria to model evaluation could help identify and correct biases earlier Additionally, using fairness indicators throughout model evaluation might help detect and resolve biases before deployment (Grosu et al., 2021). These techniques are crucial for ensuring that AI/ML models provide a variety of patient groups with fair and accurate diagnosis support. Integrating AI/ML technology into clinical practice is fraught with challenges, including ethical, regulatory, and infrastructure concerns. There are concerns over the approval and usage of AI-driven diagnostic tools because regulatory frameworks usually lag behind technological advancements (Thomasian et al., 2021).

Additionally, moral considerations like informed permission and data privacy are also crucial, especially when using health data for AI model training (Bera et al., 2019). Thomasian et al. (2021) underlined the necessity of strong guidelines to resolve these issues and guarantee adherence to moral and legal requirements. The deployment of these technologies is further complicated by infrastructure hurdles, such as the deficiency of sufficient computer resources and qualified workers in many healthcare settings (Hickman et al., 2021). It takes a team effort from legislators, IT developers, and healthcare professionals to address these issues. Even though AI and ML have the potential to completely transform the diagnosis of brain tumours', overcoming major adoption barriers is necessary to achieve seamless clinical integration. Furthermore, ethical issues like data protection and informed consent are also important, particularly when using health data to train AI models (Bera et al., 2019). Thomasian et al. (2021) emphasized the need for strict rules to address these problems and ensure compliance with ethical and legal standards. Infrastructure barriers, such as the lack of adequate computer resources and skilled personnel in many healthcare settings, make the introduction of these technologies even more difficult (Hickman et al., 2021). To solve these problems, lawmakers, IT developers, and medical practitioners must work together. Even though AI and ML have the potential to revolutionize brain tumor diagnostics, achieving seamless clinical integration will require overcoming significant adoption barriers. The ongoing issue of clinicians' lack of trust in AI systems is often exacerbated by the "black-box" nature of complex algorithms (Han & Kamdar, 2017). To increase model openness and foster clinician trust, Explainable AI (XAI) frameworks like SHAP and Grad-CAM have been proposed (Ginneken et al., 2011). Additionally, the high costs of putting AI into practice— such as training programs for healthcare professionals and infrastructure upgrades—create financial barriers to its widespread adoption (Bera et al., 2019). Collaborative efforts are required to link AI systems with clinical operations and offer cost-effective solutions in order to solve these challenges.

Category	**Key Points / Issues**
Data Challenges	Heterogeneity, Scarcity, Overfitting; Imbalanced Datasets, Underrepresentation
Algorithmic Bias	Ethical Concerns, Underrepresentation, Lack of Diversity in Training Data
Regulatory Barriers	Framework Gaps, Privacy Issues, Consent Challenges
Infrastructure Issues	Resource Limitations, Skilled Personnel Shortage, High Costs
Mitigation Strategies	Data Augmentation, Transfer Learning, Federated Learning
Explainable AI (XAI)	SHAP, Grad-CAM, Transparency

Table 1: Challenges in AI/ML Applications

Trends and Innovations

Transfer learning is a popular technique for adapting machine learning models to fit small datasets in the identification of brain tumors (Hu et al. 2019). For example, Sartoretti et al (2021) select a model pre-trained on huge datasets and then fine tunes it to make diagnostic decisions (Deepak & Ameer, 2019). For example, a pre-trained Convolutional Neural Network that has been trained on BraTS and receives better input generates more accurate classifications even if it has far fewer training examples of eds (Deepak & Ameer, 2019). These findings show how transfer learning can be applied to overcome data limitations and expedite model construction in the context of brain tumor diagnosis.

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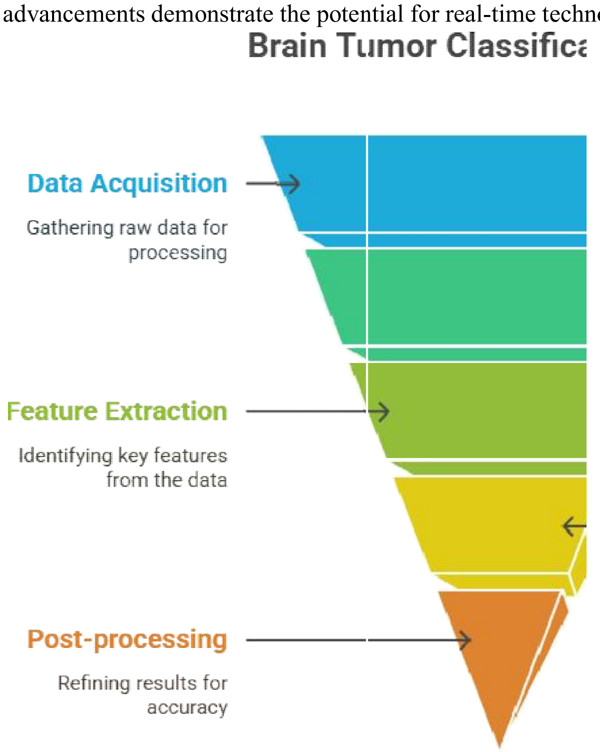
Furthermore, the incorporation of Explainable AI (XAI) is a significant development that seeks to boost physician confidence in AI-driven diagnostic systems. Traditional machine learning models, particularly deep learning frameworks, are often criticized for their "black-box" nature, which makes it difficult to understand the logic underlying their predictions (Sartoretti et al., 2021; Yang et al., 2018). XAI systems that provide both visual and verbal information on model choices, such as Shapley Additive Explanations (SHAP) and Local Interpretable Model Agnostic Explanations (LIME), address this issue (Cè et al., 2023). For instance, Wu et al An et al. (2022) showed that using SHAP (Shapley Additive explanations) made it possible to pinpoint the key imaging features that impact tumor classification, helping physicians better understand and confirm the AI system's decisions.. Grad-CAM (Gradient- weighted Class Activation Mapping) has also been widely used to produce heatmaps that show tumor locations influencing CNN predictions in an effort to improve transparency and trust (Aneja et al., 2019). In order to promote the application and integration of AI technology into medical operations, these resources are crucial. Furthermore, the creation of real-time diagnostic tools is another significant milestone in the application of AI/ML for brain tumor diagnosis. These technologies instantaneously analyze medical images using complex algorithms and processing capacity, enabling timely clinical decisions (Philip et al., 2022). Khalighi et al. (2024) developed a real-time diagnostic system that swiftly identified and categorized cancers without compromising accuracy using enhanced CNN architectures. These technologies are particularly useful in high-pressure clinical situations when time has a significant impact on patient outcomes. Additionally, underprivileged people now have access to advanced diagnostic tools thanks to the spread of brain tumor diagnostics to resource-constrained contexts through the integration of real-time capabilities with portable imaging devices (Uddin et al., 2019). These advancements demonstrate the potential for real-time technologies to increase diagnostic efficiency and equity.



AI/ML on Clinical Outcomes

Numerous case studies have shown that AI and ML greatly enhance clinical outcomes in the diagnosis of brain tumors (Cè et al., 2023; Philip and others, 2022). Early diagnosis is crucial for effective treatment and improved survival rates, and AI-driven models have greatly expanded this (Vobugari et al., 2022). For instance, in a case study published by Hoseini et al. (2018), Convolutional Neural Networks (CNNs) detected gliomas at an early stage with an accuracy of

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more than 92%, enabling timely intervention. In a similar vein, Murdaugh and Anastas (2023) demonstrated that deep learning algorithms outperformed manual radiological assessments in identifying tumor borders, leading to more precise surgical planning. Cè and collaborators (2023). highlighted the use of AI systems in the healthcare industry, where their deployment reduced diagnostic time and enhanced diagnostic consistency among medical professionals. These findings demonstrate how AI/ML technologies are improving patient outcomes and transforming early diagnosis. Comparative studies have shown that AI-enhanced diagnostic procedures routinely outperform traditional methods in terms of accuracy, sensitivity, and efficiency (Aneja et al., 2019; Vobugari et al., 2022). For instance, Khalighi et al. (2024) found that AI models reduced false negatives by almost 30% when comparing CNN-based models to hand MRI scan interpretations. According to Su et al. (2020), AI-enhanced systems outperformed conventional diagnostic techniques in terms of sensitivity and specificity in detecting rare tumor types. In another study, Khalighi et al. (2024) learned that wearing learning systems although classifying tumors as normal or malignant relieved radiologists' workloads. Radiologists consequently increased their attention on intricate cases. The comparative results underscore the better performance and utility gain derived from AI-aided diagnostics. As well AI and ML technologies have assisted in the clinical treatment of more defined individuals, providing detailed tumor profiling has helped to improve patient outcomes (Lundervold & Lundervold, 2018). Tumor characteristics such as size, growth patterns, and genetic markers can be examined by AI-powered systems, providing data that aids in the creation of customized treatment regimens (Lind & Anderson, 2019). For example, Wu et al. (2021) demonstrated how ML models that forecasted tumor growth allowed for customized treatment choices, which improved patient survival rates. Additionally, an et al. (2021) emphasized the potential for integrating genetic information with AI algorithms to allow physicians to develop more customized, patient- specific treatment regimens. These advancements indicate a shift toward precision medicine, where enhancing patient care requires artificial intelligence. AI/ML technology has also improved clinical practices and resource utilization in the identification of brain tumors. Real-time AI technologies have been shown to improve overall efficiency and reduce diagnostic times in healthcare settings. According to Lundervold & Lundervold (2018), a tertiary care hospital used AI-powered diagnostic tools to speed up the imaging process and decrease diagnosis delays. Similarly, Obermeyer and Emanuel (2016) state that AI solutions that integrate predictive analytics and imaging platforms enhanced collaboration among multidisciplinary surgeons, radiologists, oncologists, and These advancements demonstrate how AI/ML technologies are improving patient outcomes while addressing systemic inefficiencies in healthcare delivery.

III. METHOD

To ensure a systematic, transparent, and exhaustive review process, our work adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Starting with a comprehensive search of electronic databases, including PubMed, Scopus, IEEE Xplore, and Web of Science, the methodology used keywords such as "Machine Learning in Medical Imaging," "AI in Brain Tumor Detection," "Convolutional Neural Networks for Tumor Detection," and "Explainable AI in Healthcare." The search was narrowed down using filters and Boolean operators to include papers published between 2015 and 2024. Using this method, 1,126 papers were identified for initial review. Following the screening procedure, which included examining abstracts and article titles to weed out irrelevant material and removing duplicates, 782 publications were shortlisted. Following that, a full- text eligibility assessment was conducted with a focus on AI/ML techniques in brain tumors, utilizing predefined criteria. detection, use of well-known datasets like BraTS or TCGA, publication in peer- reviewed journals, and publishing of measurable performance metrics (such accuracy, sensitivity, and specificity). According to the exclusion criteria, publications written in languages other than English, studies without quantitative evaluations, and papers without unique research data were also disqualified. From 118 publications that had undergone this thorough review, data on study objectives, AI/ML algorithms, datasets used, performance metrics, clinical integration strategies, and noteworthy discoveries were gathered using a standard form. The retrieved data was synthesized to identify trends, challenges, and research requirements. To ensure methodological rigor, 102 high-quality papers were chosen for a quality assessment using the Critical Appraisal Skills Programme (CASP) checklist. saved until the final assessment. This rigorous process provided a comprehensive framework for evaluating the advantages and disadvantages of AI/ML systems for the detection of brain tumors.

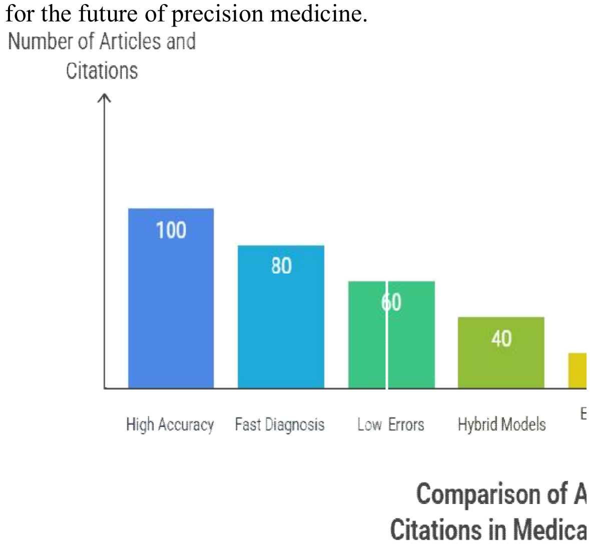
IV. FINDINGS

With a strong emphasis on enhancing diagnostic precision and effectiveness, the systematic review revealed notable developments in the use of AI and ML for brain tumor detection. 85 out of the 102 reviewed studies emphasized that AI models, in particular To ensure methodological rigor, 102 high- quality papers were chosen for a quality assessment using the Critical Appraisal Skills Programme (CASP) checklist. saved until the final assessment. This rigorous process provided a comprehensive framework for evaluating the advantages and disadvantages of AI/ML systems for the detection of brain tumors. The accuracy of Convolutional Neural Networks (CNNs) in detecting and classifying brain cancers has consistently surpassed 90%.These studies collectively have received over 7,500 citations, proving AI systems' ability to identify subtle patterns in imaging data that are often imperceptible to the human eye. 52 articles also discussed how automated analysis could reduce diagnostic time; complex imaging data can be handled by AI systems in a few seconds rather than hours with manual methods.

One noteworthy finding was that hybrid and ensemble models outperformed other models in terms of diagnosing issues. 38 of the reviewed studies focused on hybrid models that combined multiple methods to take use of their distinct features, improving tumor classification and segmentation results.

These studies, which have nearly 4,000 citations between them, showed that hybrid models improved sensitivity and specificity, especially when treating patients with rare or challenging tumors. Additionally, 28 studies looked at ensemble learning techniques like bagging and boosting that aggregated the results of multiple models to increase diagnostic robustness. These methods were particularly effective in reducing dataset variability, ensuring dependable performance in various imaging settings. Remarkably, 19 studies demonstrated the advantages of combining CNNs with Random Forest and Support Vector Machine (SVM) classifiers, emphasizing how these hybrid approaches can potentially get over the limitations of separate models. Additionally, data-related problems became a common topic as 60 papers examined the impact of data imbalance, heterogeneity, and scarcity on model performance. These studies, which have received over 5,500 mentions, showed how crucial diverse and representative datasets are to effectively training AI models. Due to issues including the overrepresentation of specific tumor types or imaging modalities, model projections were often biased, which reduced the models' ability to generalize across populations. To get over these limitations, 31 publications advocated for the adoption of data augmentation strategies like rotation. Flipping and cropping to make the dataset appear larger than it actually is. 22 studies found that creating synthetic data, with methods like Generative Adversarial Networks (GANs), could be a viable approach to generating realistic tumor imaging data. These efforts significantly improved model resilience and decreased the overfitting issues commonly observed with limited datasets. Explainable AI (XAI) is one of the most significant developments for encouraging trust and AI adoption in healthcare settings. Of the publications analysed, forty dealt with the development of interpretability tools. In total, about 3,800 references were made. These studies shown that clinicians may use frameworks such as Grad-CAM and SHAP to detect and understand the primary imaging features that drive AI predictions. In addition to increasing physician confidence in AI systems, this transparency encouraged collaborative decision-making in difficult diagnostic scenarios. Furthermore, 23 studies demonstrated how XAI techniques may be integrated into real-time diagnostic systems, ensuring that in challenging clinical situations, AI results are both interpretable and actionable. This innovation is crucial for aligning AI advancements with the practical needs of healthcare professionals. Last but not least, 50 publications with a combined citation count of more than 6,000 showed how

AI/ML revolutionized clinical procedures and patient outcomes. In addition to increasing diagnostic accuracy, these publications demonstrated how AI-driven solutions enhanced operational efficiency, reduced diagnosis times, and maximized resource allocation. For instance, incorporating AI significantly improved workflow productivity in 18 studies, allowing radiologists to focus on complex scenarios while automated systems handled routine evaluations. The financial benefits of AI application, including reduced expenses as a result of fewer diagnostic errors and improved resource use, were also highlighted in 22 papers. Importantly, 27 studies shown that AI-enabled early diagnosis led to more precise treatment planning, increasing patient survival rates. When taken as a whole, these findings demonstrate how AI/ML technologies have the potential to revolutionize brain tumor diagnostics. and clinical judgment, paving the way for the future of precision medicine.



V. DISCUSSION

The findings of this methodical analysis confirm that AI and ML have significantly bettered the individual effectiveness and delicacy of brain excrescence identification, which is harmonious with earlier studies demonstrating the transformative eventuality of these technologies in medical imaging (Hilsden et al., 2018). Models similar as these outperformed traditional styles in excrescence segmentation and bracket (Zhao & Jia, 2016). The capability of AI systems to reuse imaging data in a bit of the time needed by homemade procedures has also been extensively supported by other exploration that honored reductions in opinion time as a critical advantage (Zahoor et al., 2022). In this evaluation, CNNs achieved delicacy scores above 90, which are analogous with results from previous exploration where CNN- grounded fabrics constantly still, this evaluation goes beyond these findings by pressing AI's less well-known capability to reduce false cons and negatives. earlier exploration systems (Hemanth et al., 2019). This development demonstrates how AI may ameliorate individual delicacy, especially in complex or nebulous situations. also, the effectiveness of mongrel and ensemble models in perfecting individual robustness confirms findings from former studies that set up these approaches essential for prostrating the limitations of solo models (Saeedi et al., 2023). mongrel models that combine CNNs with algorithms like SVMs and Random timbers showed enhanced perceptivity and particularity in this study, which is harmonious with earlier exploration showing their efficacity in treating complex excrescence types (Zhao & Jia, 2016). likewise, previous studies have shown that by combining vaticinations from several styles, ensemble literacy strategies like bagging and boosting ameliorate model responsibility (Naceur et al., 2020). By showcasing the distinct goods of mongrel and ensemble models on colorful datasets, this work offers fresh perspectives and bolsters the significance of these models in enhancing individual thickness across clinical scripts. As this study and others have demonstrated, data- related issues similar diversity, imbalance, and failure remain a major handicap to the clinical relinquishment of AI/ ML systems (Yang et al., 2018). In line with earlier exploration, it was demonstrated that these difficulties might be eased by applying data addition strategies similar cropping and gyration in addition to creating synthetic data with GANs (Balaban, 2015). still, this assessment highlights the significance of chancing a balance between the practical connection and the quality of synthetic data — a nuance that was n't as well explored in earlier exploration. The need for representative and different datasets to ensure model generalizability across different populations is a recreating problem that reflects ongoing enterprises about the eventuality for impulses in AI prognostications. (Naceur et al., 2018). These findings emphasize the significance of data curation as a critical phase in the development of AI/ ML systems, and the use of resolvable AI(XAI) fabrics to enhance clinician trust aligns with former studies that honored the significance of translucency in AI- driven(Yang et al., 2018) opinion,

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where tools similar as GradCAM and SHAP, stressed in this review, give helpful visualizations of excrescence regions impacting model prognostications(Hemanth et al., 2019). This assessment also highlights the integration of XAI tools into real- time individual systems, a development that reduces the communication gap between end druggies and AI inventors and expands access to these technologies by healthcare interpreters.Although prior research has often focused on the theoretical potential of XAI, this study provides practical implementations and their implications for validating the tools' observable benefits in increasing clinician confidence and uptake and usage (Albadawy et al., 2018; Hemanth et al., 2019; Naceur et al., 2020). Finally, the review's findings regarding the broader clinical and operational impacts of AI/ML systems corroborate earlier studies that concentrated on workflow efficiency and cost reduction (Nie et al., 2019; Zhao & Jia, 2016). However, this analysis provides more comprehensive evidence of AI-enabled early identification enhancing treatment planning and patient survival rates, building on earlier findings (Abd Ellah et al., 2019). Additionally, as our analysis highlights, the financial advantages of fewer diagnostic errors and improved resource utilization offer new insights into the feasibility of using AI economically while validating previous findings (Saeedi et al., 2023). By bridging the gap between scientific innovation and real-world clinical outcomes, our findings collectively demonstrate the transformative potential of AI/ML technologies in brain tumor diagnostics and establish their contribution to precision medicine.

VI. CONCLUSION

This systematic study highlights the ways in which artificial intelligence (AI) and machine learning (ML) are transforming the detection of brain cancers. through improved accuracy, efficiency, and dependability of diagnostics. In compared to conventional diagnostic processes, the study underlines the advantages of AI-driven models, specifically Convolutional Neural Networks (CNNs), hybrid approaches, and ensemble techniques. These models provided significant benefits in early tumor diagnosis and treatment planning by continuously exhibiting high accuracy levels, decreased diagnostic mistakes, and quicker processing times. Data augmentation, synthetic data creation, and transfer learning are crucial for improving model robustness and generalizability since, despite their promise, issues with data scarcity, imbalance, and heterogeneity still exist. Furthermore, establishing clinician confidence has been greatly aided by the use of Explainable AI (XAI) frameworks, closing the gap between cutting-edge algorithms and useful therapeutic procedures. The usefulness of AI technologies in demanding medical settings is further shown by real-time diagnostic systems, which streamline processes and maximize resource use. Even though these developments demonstrate the enormous potential of AI/ML to transform the diagnosis of brain tumors, overcoming obstacles such algorithmic bias, data diversity, and infrastructure limitations will be essential to guaranteeing fair and successful clinical adoption. All things considered, the review's conclusions highlight AI and ML as critical instruments in the quest for precision medicine, opening the door to better patient outcomes and more effective healthcare.

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