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Comparative Survey of Deep Learning Techniques for Brain Tumor Detection

Mrs. Mandeep Kaur[1], Dr. Rahul Thour[2], Dr. Gurjeet Kaur[3]

[1] *Research Scholar Dept. of Computer Science and Application, Desh Bhagat University, Mandi Gobindgarh,*

[2] *Assistant Professor Dept. of Computer Science and Application, Desh Bhagat University, Mandi Gobindgarh*

[3] *Assistant Professor Dept. of Computer Science and Application, Mata Gujri college, Fatehgarh Sahib*

mandeepbilling1313@gmail.com

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ABSTRACT

Brain tumors are one of the most serious health problems today, and early detection is crucial for improving patient survival. Magnetic Resonance Imaging (MRI) is a commonly used, non-invasive technique that provides detailed images of brain tissues. A key step in diagnosing brain tumors is segmentation, which means separating abnormal tumor tissue from healthy brain areas. This step is important for accurate diagnosis, classification, and treatment planning.This paper reviews recent methods for brain tumor detection and segmentation using MRI. It focuses on image processing and deep learning techniques, especially Convolutional Neural Networks (CNNs), which are widely used in medical image analysis. The study also highlights common challenges in tumor detection, such as variations in size, shape, and unclear boundaries. This paper examines the strengths and weaknesses of different segmentation and classification techniques, as well as common preprocessing steps used to clean and prepare MRI images. The review also discusses how these techniques are improving and moving toward real-world clinical use.Overall, this paper provides a clear overview of the latest developments in brain tumor detection using MRI. It aims to support researchers and healthcare professionals in selecting more accurate and efficient tools for brain tumor diagnosis. Additionally, this survey focuses on enhancing tumor detection in the proposed research.

Keywords: Brain Tumor Detection, MRI Segmentation, Convolutional Neural Networks (CNNs), Deep Learning in Medical Imaging , Image Preprocessing Techniques

I. Introduction

A brain tumor is the abnormal and uncontrolled growth of cells within the brain or its surrounding areas. These tumors can be either **primary**, originating in the brain, or **secondary**, spreading from other parts of the body such as the lungs or skin. Brain tumors are also categorized as **benign** (non-cancerous) or **malignant** (cancerous). While benign tumors grow slowly and usually do not spread to nearby tissues, malignant tumors grow rapidly and can invade surrounding brain tissue, posing serious health risks.

The exact causes of brain tumors are still unclear, but risk factors may include exposure to radiation, genetic conditions, and certain environmental factors. Common symptoms include persistent headaches, vision problems, seizures, and difficulty with coordination or speech, depending on the tumor's location and size.

Magnetic Resonance Imaging (MRI) is one of the most commonly used and effective imaging techniques for diagnosing brain tumors. It offers high-resolution, non-invasive imaging of brain tissues.

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However, interpreting MRI scans manually can be time-consuming and prone to human error. This has led to a growing interest in **medical image processing**, particularly **segmentation techniques**, which help separate abnormal tumor tissues from normal brain structures.

This research aims to review various MRI-based brain tumor segmentation methods, including manual, semi-automated, and fully automated techniques. It also discusses the challenges in tumor segmentation, such as irregular shapes, unclear boundaries, and the complexity of brain structures, while emphasizing the need for reliable computer-aided diagnosis tools to support medical professionals in accurate and early detection.

This paper is structured into four main sections. Section II provides an overview of various techniques proposed by different researchers, emphasizing their methodologies and key findings. Section III presents a detailed comparative analysis of brain tumor detection methods and outlines the techniques used in the proposed work, guided by the survey, to enhance system performance. Finally, Section IV summarizes the conclusions drawn from the study.

II. Literature Review

This section provides an overview of the techniques introduced by various researchers, focusing on their methodologies and findings. It further evaluates the efficiency of these methods in brain tumor detection and classification.

Zhihua Liu et al. [1] highlight that brain tumor segmentation is among the most complex tasks in medical image analysis. With recent progress in deep learning—especially Convolutional Neural Networks (CNNs)—segmentation accuracy has seen notable improvements. Numerous studies have proposed automated techniques to tackle challenges such as data imbalance and multi-modal imaging. This comprehensive survey analyzes over 150 recent publications, summarizing major network architectures, evaluation metrics, and potential future directions in the field.

Prasanna Kumar Lakineni et al. [2] examine the significant global health impact of brain tumors, given their complexity and high mortality rates. Recent research focuses on leveraging MRI imaging alongside deep learning methods—particularly Convolutional Neural Networks (CNNs)—for precise tumor detection and classification. CNNs are favored for their capability to extract critical features from MRI scans and distinguish between benign and malignant tumors. The reviewed literature underscores the need to enhance accuracy, reliability, and computational efficiency in developing automated brain tumor detection systems.

Erena Siyoum Biratu et al. [3] emphasize that manual brain tumor segmentation from MRI scans is time-consuming and susceptible to inconsistencies, highlighting the need for automation. While earlier methods relied on region growing and conventional machine learning, recent studies demonstrate that deep learning—particularly Convolutional Neural Networks (CNNs)—delivers significantly improved performance through effective feature learning. Numerous works have investigated segmentation and classification frameworks, showcasing progress in pre-processing techniques, feature extraction, and evaluation strategies. However, developing a fully autonomous and clinically viable system remains an ongoing challenge.

Prabhjot Kaur Chahal et al. [4] investigate the complexities of brain tumor detection and segmentation using MRI, which is complicated by variations in tumor shape, size, and intensity. Although both traditional approaches and deep learning models—particularly CNNs—have yielded promising outcomes, challenges such as indistinct tumor boundaries and the integration of multi-modal data persist. The literature highlights the ongoing need to enhance model accuracy, computational efficiency, and suitability for real-time clinical application.

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Luxit Kapoor et al. [5] highlight the rapid advancements in biomedical image processing, which leverages imaging modalities such as CT, X-ray, and MRI for precise diagnosis. Among these, MRI is preferred for brain tumor detection due to its non-invasive nature and high-resolution capabilities. The research identifies segmentation as the most crucial phase in the MRI analysis workflow, encompassing steps like pre-processing, feature extraction, and optimization. Numerous studies aim to enhance these techniques to boost diagnostic accuracy and minimize errors.

Mahsa Arabahmadi et al. [6] note that recent technological advancements, particularly in artificial intelligence, have significantly improved brain tumor detection using MRI analysis. Deep learning models, especially Convolutional Neural Networks (CNNs), have demonstrated high effectiveness in medical image classification and segmentation. Several studies have examined different CNN architectures applied to brain MRI, emphasizing their accuracy while also identifying areas that require further exploration. These developments play a vital role in enabling early diagnosis and improving patient outcomes.

Aby Elsa Babu et al. [7] investigate the challenges of brain tumor segmentation from MRI, a labor-intensive process complicated by the structural variability of tumors. To improve detection accuracy, several automated approaches have been proposed, including watershed and bilateral transformation techniques. Notably, the bilateral method stands out for its effectiveness in detecting asymmetrical regions commonly associated with tumors.

Sethuram Rao G. et al. [8] examine the complexities of brain tumor detection, a serious medical condition characterized by abnormal cell growth, with particular difficulty in identifying tumors smaller than 3mm. MRI-based segmentation techniques are commonly employed to differentiate tumor-affected tissues; however, a universally reliable method remains elusive due to the intricate nature of brain imaging. This review discusses several automated segmentation approaches, including GLCM texture features, Artificial Neural Networks (ANN), and Support Vector Machines (SVM), outlining their strengths and limitations. The study aims to support researchers in developing more accurate and efficient detection methods.

Suraj S. Gawande et al. [9] review a range of computer-aided approaches for early brain tumor detection using MRI and CT imaging. The study highlights key segmentation techniques such as Convolutional Neural Networks (CNN), watershed algorithms, Sobel edge detection, and Otsu thresholding, which contribute to accurate tumor localization. Additionally, classifiers like Artificial Neural Networks (ANN) and Support Vector Machines (SVM), along with feature extraction methods such as Principal Component Analysis (PCA), have demonstrated promising outcomes. However, structural variability in the brain continues to hinder consistent and precise diagnosis.

S.U. Aswathy et al. [10] examine the challenges of brain tumor detection and segmentation using MRI, which is complicated by variations in tumor shape, size, and intensity. This review outlines the advantages and limitations of current classification techniques, comparing their performance in achieving accurate tumor identification. Despite technological progress, several obstacles persist, underscoring the need for more robust and efficient algorithms. The study stresses the critical role of accuracy and reliability in shaping future diagnostic solutions.

Deipali Vikram Gore et al. [11] emphasize the importance of early brain tumor detection and highlight the effectiveness of deep learning techniques, particularly Convolutional Neural Networks (CNNs), in enhancing diagnostic accuracy. Despite these advancements, MRI-based image segmentation continues to be challenging due to noise and the complex structure of brain tissues. This review contrasts traditional approaches with deep learning methods, showcasing CNNs' strength in automatic feature extraction. It also points out existing research gaps and underscores the need for more reliable and efficient diagnostic models.

Vipin Das et al. [12] investigate the critical yet challenging task of brain MRI image segmentation for accurate brain tumor diagnosis, owing to the brain’s intricate structure. The review explores a range of techniques used for tumor detection and classification through MRI imaging. Emphasizing the high stakes involved in medical diagnosis, the study underlines the necessity for precise and dependable segmentation methods. It also stresses the importance of advancing more robust approaches to enhance diagnostic accuracy and outcomes.

Andronicus A. Akinyelu et al. [13] review advanced techniques for brain tumor classification and segmentation using deep learning models such as Convolutional Neural Networks (CNNs), Capsule Networks (CapsNets), and Vision Transformers (ViTs). While CNNs are commonly applied, their limitations in managing image variability and high data demands are better addressed by emerging CapsNet and ViT-based methods. The review highlights key research challenges, including model uncertainty, data imbalance, and the need for multi-modal, integrative diagnostic systems. Future efforts should focus on developing robust, generalizable, and data-efficient AI models to enhance the accuracy of brain tumor diagnosis.

Muhammad Aqeel Aslam et al. [14] emphasize the crucial role of medical image processing—especially MRI—in brain tumor detection through methods such as segmentation, thresholding, and morphological operations. The review highlights techniques for noise reduction, edge detection, and grayscale image analysis using tools like MATLAB. While notable progress has been made, effectively managing diverse image patterns remains a challenge. The authors suggest that future research should explore the integration of multi-modal imaging technologies to enhance diagnostic accuracy.

Nelly Gordillo et al. [15] examine the goal of brain tumor segmentation, which involves differentiating tumor tissues from normal brain structures using MRI. Despite technological progress, achieving consistent and accurate results remains difficult. The review covers both semiautomatic and fully automatic segmentation methods, highlighting their clinical potential as well as their limitations. Although advanced techniques show encouraging results, challenges such as lack of standardization, limited interpretability, and low physician acceptance continue to impede their broad clinical adoption.

Jin Liu, Min Li, and Jianxin Wang et al. [16] emphasize the growing interest in MRI-based brain tumor segmentation, owing to its non-invasive nature and superior soft tissue contrast. This review discusses cutting-edge methods, tools, and databases used to differentiate tumor tissues from healthy brain structures. Although current approaches show promising results, clinical adoption is hindered by challenges such as high computational demands, limited robustness, and usability concerns. The authors suggest that future research should prioritize advanced MRI modalities, effective feature extraction, and seamless integration into clinical workflows to enhance diagnosis and treatment planning.

El-Sayed A. El-Dahshan et al. [17] review recent advances in segmentation and classification techniques for brain tumor detection using MRI within computer-aided detection (CAD) systems. They propose a hybrid approach that integrates neural networks, wavelet transforms, PCA, and back-propagation classifiers, achieving a high accuracy of 99%, surpassing many existing models. Despite these encouraging results, CAD systems continue to face challenges related to generalization, data quality, and clinical implementation. The study emphasizes the need for future research to develop robust, scalable models with enhanced feature extraction and access to large, diverse datasets.

Riddhi S. Kapse et al. [18] highlight the challenges of brain tumor detection using MRI, primarily due to the variability in tumor appearance and its resemblance to healthy brain tissues. This review explores a variety of segmentation techniques, pointing out the limitations of widely accepted methods. Unsupervised methods like Fuzzy C-Means and optimization algorithms such as PSO, ACO, and GA have demonstrated potential for achieving accurate and efficient segmentation. However, despite these advancements, segmentation remains a complex task that demands continued research and innovation.

V. Sravan et al. [19] provide a comprehensive review of MRI-based brain tumor segmentation techniques, ranging from basic thresholding methods to advanced hybrid and deformable models. The review places particular emphasis on gliomas, the most prevalent malignant brain tumors. It

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underscores the growing impact of deep learning, especially Convolutional Neural Networks (CNNs), and notes that segmentation performance significantly improves with larger datasets, richer feature sets, and the integration of hybrid approaches.

Ed-Edily Mohd. Azhari et al. [20] emphasize the increasing demand for automated tumor detection, driven by rising cancer incidence and a shortage of radiologists. The review explores medical imaging modalities such as MRI, CT, and mammography, highlighting the role of computer vision in segmentation and edge detection. Techniques like filtering and Canny edge detection are applied to enhance grayscale images for precise tumor localization. The study also identifies future research directions aimed at overcoming existing challenges in medical image analysis.

Messaoud Hameurlaine et al. [21] highlight the complexity of brain tumor segmentation, driven by the intricate structure of brain tissues and the need for precise analysis through MRI. While automated and deep learning methods have shown significant progress, clinical adoption remains limited due to issues with standardization and interpretability. The study reviews various segmentation techniques, including thresholding, region growing, and model-based methods. It points to the integration of deep learning with standardized imaging protocols and consistent datasets like MICCAI as a promising path forward.

Sangeetha Saman et al. [22] emphasize the importance of MRI-based brain tumor analysis in medical diagnosis and treatment planning, while noting that challenges such as image noise and the brain's complex structure affect accuracy. This review explores a range of automatic and semi-automatic segmentation and classification methods, including deep learning techniques, with a particular focus on gliomas. It outlines the advantages and drawbacks of current approaches and stresses the need for more standardized and clinically applicable solutions. Future research may focus on hybrid machine learning models and the use of larger, more diverse datasets.

B. Suneetha et al. [23] address the difficulty of early brain tumor detection, often hindered by delayed symptom presentation, and emphasize MRI as the preferred imaging modality. The study introduces a novel method that integrates Optimized Kernel Possibilistic C-Means for noise reduction, Adaptive DW-MTM filtering for image enhancement, and Regression Neural Networks for segmentation. This approach effectively isolates tumor regions, supporting accurate and timely diagnosis. Additionally, the study includes a comparative review of various preprocessing and segmentation techniques.

Mr. Deepak et al. [24] note that brain tumor detection is challenging due to the brain's complex anatomy; however, MRI offers detailed soft tissue visualization essential for accurate diagnosis. This review examines key stages in the detection process, including preprocessing, segmentation, feature extraction, and classification. It emphasizes the advantages of MRI—particularly DICOM images—over other formats, and underscores the critical role of precise segmentation in ensuring reliable diagnostic outcomes.

Stefan Bauer et al. [25] highlight the growing importance of MRI-based brain tumor analysis for objective and efficient clinical evaluation. The review covers recent developments in segmentation, registration, and modeling techniques, with a focus on gliomas, stressing the need for robust and rapid methods for clinical use. The integration of emerging imaging modalities such as DTI, MRS, and perfusion imaging with machine learning is advancing tumor grading and localization. Future efforts aim toward patient-specific modeling and shifting to volume-based assessment criteria to enhance treatment planning.

Yahya M.A. Mohammed et al. [26] explore recent progress in brain tumor segmentation, emphasizing automated detection through MRI and deep learning, especially Convolutional Neural Networks (CNNs). These methods have enhanced accuracy in identifying tumor types, sizes, and locations. Although challenges such as tumor complexity and indistinct boundaries persist, standardized datasets like BraTS enable consistent evaluation. Emerging hybrid models and CNN-based architectures are proving to be effective tools for achieving accurate and timely brain tumor diagnosis.

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Tirivangani Magadza et al. [27] emphasize the role of quantitative brain tumor analysis in improving tumor characterization and treatment planning. Deep learning techniques, particularly UNet and ensemble models, have demonstrated promising results in automated segmentation. However, they still fall short of expert-level performance due to issues such as class imbalance and limited training data. This review outlines essential components and strategies in deep learning-based segmentation and stresses the importance of comprehensive datasets and advanced training methodologies for improved outcomes.

V. Sanjay et al. [28] discuss the increasing focus on brain tumor detection (BTD), driven by the abnormal and rapid growth of brain cells. Despite technological progress, precise segmentation and classification remain difficult due to the diverse shapes, sizes, and locations of tumors. This review examines various machine learning-based approaches for diagnosing brain tumors using MRI, covering relevant datasets, segmentation methods, and ongoing challenges. It underscores the importance of developing efficient and accurate models capable of handling complex data in real-time applications.

Sanjay M. Shelke et al. [29] highlight the importance of brain tumor segmentation for early diagnosis and effective treatment, noting that manual analysis of MRI scans is both time-consuming and challenging. The review explores a range of automated segmentation techniques, examining their advantages and limitations. While traditional methods such as thresholding, region-based, edge-based, and clustering techniques have achieved moderate success, CNN-based approaches demonstrate superior accuracy, faster processing, and enhanced performance in tumor detection and classification.

Madhuri J. Pallod et al. [30] emphasize the growing interest in MRI-based brain tumor segmentation, attributed to its non-invasive approach and superior soft tissue contrast. The review covers both traditional and modern techniques, with a focus on recent deep learning methods for automated segmentation. A proposed two-pathway CNN architecture showed enhanced accuracy and processing speed on the BRATS 2013 dataset, marking a step forward toward clinical adoption of automated brain tumor analysis.

III. Comparative Analysis

This survey presents a comparative analysis derived from 30 research studies. The comparison is presented in tabular form, focusing on three key aspects: the techniques used, the datasets employed, and the corresponding results or findings. Based on this comprehensive review, identified the most effective techniques for brain tumor detection and highlighted the common challenges faced in this domain. Apart from that, the techniques and accuracy of the proposed system are also discussed.

Table1: Table summarizing **techniques used for brain tumor detection** based on the 30 studies:

Ref. No.	**Focus Area**	**Key Contributions**	**Dataset(s) Used and Techniques**	**Key Results / Findings**
[1]	Survey of over 150 papers	Reviews CNNs and segmentation techniques	BRATS, TCGA; CNNs, deep learning	Reviewed 150+ papers; CNNs improved segmentation; discussed imbalance, multi-modality, and evaluation metrics
[2]	Tumor detection/classification	Emphasizes CNNs for feature learning	Likely BRATS; CNNs	High accuracy in tumor detection and classification; emphasized efficiency and reliability

[3]	Manual vs automated segmentation	Deep learning outperforms traditional methods	BRATS, REMBRANDT; Traditional ML and CNNs	CNNs outperformed traditional methods in feature learning and segmentation; automation still challenging
[4]	MRI segmentation	Variations in tumor shape, size, intensity	Possibly BRATS; CNN-based segmentation	Addressed tumor shape/size variation; highlighted need for clinical refinement and real-time application
[5]	Biomedical image processing	MRI ideal for brain imaging	Not specified; MRI preprocessing and segmentation	MRI favored for soft tissue; need for better feature optimization and preprocessing
[6]	AI in MRI analysis	CNNs effective in classification/segmentation	BRATS, custom datasets; CNNs on brain MRI	High segmentation performance; called for robustness and improved accuracy
[7]	Automated segmentation	Bilateral method for tumor asymmetry	Not specified; Bilateral transformation and watershed methods	Bilateral transformation more effective for asymmetrical tumor detection
[8]	MRI segmentation	Uses GLCM, ANN, SVM methods	BRATS, private clinical data; GLCM, ANN, SVM	Difficulty detecting small tumors (<3mm); need for more precise segmentation
[9]	Early tumor detection	Uses CNN, Sobel, ANN, PCA	Not specified; CNN, ANN, SVM, PCA	Variability in brain structure hinders consistent tumor diagnosis
[10]	Detection/segmentation review	Compares classification techniques	Likely BRATS; classification methods	Accuracy limitations; need for more reliable segmentation algorithms
[11]	Traditional vs DL methods	CNNs extract meaningful features	Not specified; CNNs	MRI segmentation remains difficult; highlighted need for reliable deep learning-based models
[12]	MRI image segmentation	Discusses tumor detection techniques	Not specified; MRI-based segmentation methods	Emphasized precision and need for advanced, dependable segmentation techniques
[13]	DL model comparison	Evaluates CNNs, CapsNets, ViTs	Not specified; CNNs, CapsNets, ViTs	Model uncertainty and data imbalance noted; advocated for robust, data-efficient models
[14]	Image processing techniques	Uses MATLAB tools for segmentation	Not specified; Thresholding,	Promoted integration of multi-modal imaging for better segmentation

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			edge detection (MATLAB)	
[15]	Segmentation approaches	Semi/fully automatic methods	Not specified; Semi-/fully-automatic segmentation	Identified clinical limitations; stressed need for standardization
[16]	MRI segmentation review	Tools, methods, databases analyzed	Public datasets (e.g., BRATS); segmentation tools	Discussed computational load, robustness; encouraged better clinical integration
[17]	Hybrid CAD methods	Combines neural nets, PCA, wavelets	Not specified; Hybrid CAD with Neural Networks and PCA	Achieved 99% accuracy; issues with generalization and dataset quality
[18]	Segmentation methods	FCM, PSO, ACO, GA highlighted	Not specified; FCM, PSO, GA	Tumor resemblance to healthy tissue complicates segmentation
[19]	Glioma segmentation	Uses hybrid/deformable DL models	Not specified; CNNs, hybrid models	Accuracy improved for glioma segmentation
[20]	Image segmentation in cancer	Uses edge detection, Canny filters	Not specified; Edge detection (Canny), filtering	Computer vision methods enhanced tumor edge detection
[21]	MRI segmentation complexity	Region growing, thresholding used	MICCAI (mentioned); Region growing, thresholding, DL methods	Encouraged dataset consistency and segmentation standardization
[22]	Glioma-focused review	Auto/semi-auto methods, DL models	Not specified; Deep learning for glioma segmentation	Identified method limitations; emphasized standardization
[23]	Novel segmentation method	Uses OKPCM, DW-MTM, Regression NN	Not specified; KPCM + DW-MTM + RNN	Integrated method improved segmentation for early diagnosis
[24]	MRI-based detection pipeline	DICOM image superiority	Not specified; Full MRI detection pipeline	Highlighted DICOM format and segmentation accuracy as diagnostic priorities
[25]	Segmentation and modeling	Glioma-specific MRI analysis	Not specified; DTI, MRS, perfusion imaging + modeling	Suggested patient-specific models and advanced imaging techniques
[26]	CNN-based segmentation	Uses BraTS dataset for training	BRATS; CNN-based segmentation	Improved accuracy; challenges included tumor complexity and fuzzy boundaries

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[27]	Deep learning segmentation	UNet, ensembles discussed	Not specified; UNet and ensemble deep learning models	Addressed class imbalance and small dataset limitations
[28]	MRI segmentation	ML-based review of datasets and methods	Not specified; ML-based segmentation	Tumor diversity complicates segmentation; real-time models needed
[29]	Traditional vs CNN methods	Highlights CNNs for speed, accuracy	Not specified; Traditional vs CNN methods	CNNs superior in classification, processing speed, and segmentation accuracy
[30]	Two-pathway CNN approach	Improved BRATS 2013 accuracy	BRATS 2013; Two-pathway CNN	Improved segmentation performance in terms of speed and accuracy

Based on the survey of 30 recent studies, Convolutional Neural Networks (CNNs) have proven to be the most effective technique for brain tumor detection due to their high accuracy and automatic feature extraction capabilities. The review also highlights that hybrid models, such as combinations of CNNs with UNet variants or Vision Transformers, offer further improvements in segmentation performance. However, persistent challenges such as class imbalance, tumor heterogeneity, and limited clinical integration continue to restrict the full potential of these technologies.

Magnetic Resonance Imaging (MRI)-based brain tumor detection and segmentation has become a focal point in medical imaging research. This paper reviewed a broad range of techniques, from conventional thresholding and clustering to modern deep learning approaches like CNNs, CapsNets, and Vision Transformers. While these methods show promise, clinical implementation is hindered by factors such as a lack of annotated datasets, unclear tumor boundaries, and limited generalizability. To address these limitations, future research should prioritize robust, data-efficient architectures, multi-modal imaging, and standardized benchmarks. Ultimately, the goal is to develop accurate, reliable, and clinically adoptable brain tumor detection systems to enhance patient diagnosis and care.

The proposed system addresses brain tumor detection using artificial intelligence through a multi-stage approach: data preprocessing, segmentation, and classification. The PNLM algorithm removes Rician noise during preprocessing, while snake-based segmentation identifies the region of interest. For classification, a hybrid transfer learning model combining VGG19 and CNN is used. This model achieved 96% training accuracy and testing metrics of 95% accuracy, 94% precision, and 95% recall. Comparative analysis shows it outperforms traditional machine learning models (RF, SVM, KNN) by up to 15% in accuracy. Future work may explore hybrid transfer learning models for improved detection.

IV. Conclusion

This survey reveals that Convolutional Neural Networks (CNNs) stand out as the most effective approach for brain tumor detection, owing to their high accuracy and capability for automatic feature extraction. Emerging techniques such as Vision Transformers (ViTs), Capsule Networks (CapsNets), and hybrid models have further enhanced performance, particularly in managing the complexity of brain anatomy. Despite these advancements, issues like image noise, tumor heterogeneity, and limited clinical deployment remain. Future research should prioritize multi-modal imaging integration, development of robust deep learning architectures, and adoption of standardized datasets to improve diagnostic precision and clinical applicability. Moreover, the proposed system demonstrates that AI-based multi-stage approaches can significantly improve brain tumor detection accuracy. With a hybrid VGG19-CNN model, it outperforms traditional machine learning techniques, highlighting the potential of transfer learning for future advancements.

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