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A Literature Review on Brain Tumour Detection Approaches Using MRIs

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ABSTRACT

Brain tumours are among the most common malignant tumours, making their accurate detection and precise evaluation crucial for effective treatment planning and strategic regimens. Recent advancements in machine learning (ML) and deep learning (DL) have significantly increased tumour identification precision, enabling the automatic pro cessing of complex imaging data and substantially reducing the needfor time-consuming manual intervention. However, persistent challenges in automated detection approaches stem from pervasive imaging artifacts, variations in image quality, and diverse tumor appearances. This comprehensive review addresses these challenges by highlighting key innovations and their clinical relevance across various automated approaches, including clustering, soft computing, and deep learning techniques for the classification and segmentation of brain tumours using magnetic resonance imaging (MRI). Furthermore, we synthesize the quantitative results of state-of-the-art models, summarizing performance measures such as the Dice Score and Sensitivity. Ultimately, this review outlines the critical future research pathways necessary to effectively address remaining obstacles and enhance the precision of automated segmentation and classification

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1. INTRODUCTION

Brain tumour detection and treatment have evolved significantly over the last few decades, shifting from labour-intensive manual imaging techniques to sophisticated machine-learning-driven approaches [1]. Historically, manual review of magnetic resonance data has been a significant component of brain tumour analysis [2]. This process is characterized by time-consuming and error-prone operations, as well as variability across evaluators [3]. The development of computer technologies, automated image processing, and data analysis has notably improved the precision and effectiveness of tumour identification and characteristics [4]. Modern methodologies integrate clustering, soft computing, deep learning, and thresholding techniques to achieve precise tumour seg mentation, classification, severity assessment, and outcome prediction [5][6]. These advancements provide a comprehensive understanding of tumour characteristics, allowing for more personalized treatment approaches and improved patient care outcomes [7]. The central nervous system, an intricate network comprising both the brain and the spinal cord, serves as the command center of the human body, orchestrating and regulating fundamental motor and sensory functions [8]. Abnormal and uncontrolled cell growth in the brain can manifest as non-cancerous or cancerous tumours [9]. If untreated, these can lead to severe health repercussions, including neurological impairments and even death [10]. Although substantial progress has been made in visual representation and computational tools and innovations, precise segmentation and classification of brain tumours continue to pose challenges [11]. Detection and analysis have become complicated because brain tumours exhibit various attributes, including location, dimensions, and structural forms, as well as diverse imaging patterns [12]. The brain is divided into three primary components the cerebrum, cerebellum, and brain stemeach playing a pivotal and distinct role in the brain's functional symphony [13][14]. While the integration of deep learning has revolutionized brain tumour analysis by increasing precision and reducing manual

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intervention [15], accurately detecting and segmenting brain neoplasms from MRI scans still faces significant challenges that necessitate intelligent, automated systems [16]. These persistent issues stem from several sources: Image Preprocessing is complex and time-consuming due to noise and intensity variations that obscure tumour boundaries in raw MR images [17][18]. Tumour Heterogeneity remains a formidable barrier, as the variability in tumour shape, size, location, and intensity, combined with fuzzy boundaries, makes precise delineation difficult for both automated systems and human experts [19][20]. Furthermore, Manual Interpretation is subjective, labor-intensive, and prone to variation in error between different experts [21][22]. Finally, Data Scarcity complicates the training of robust AI models, leading to class imbalance, where non-tumour pixels vastly outnumber tumour pixels [23][24]. These challenges underscore the critical need for comprehensive reviews that synthesize current solutions and clarify future research directions in automated, highly accurate brain tumour detection approaches.

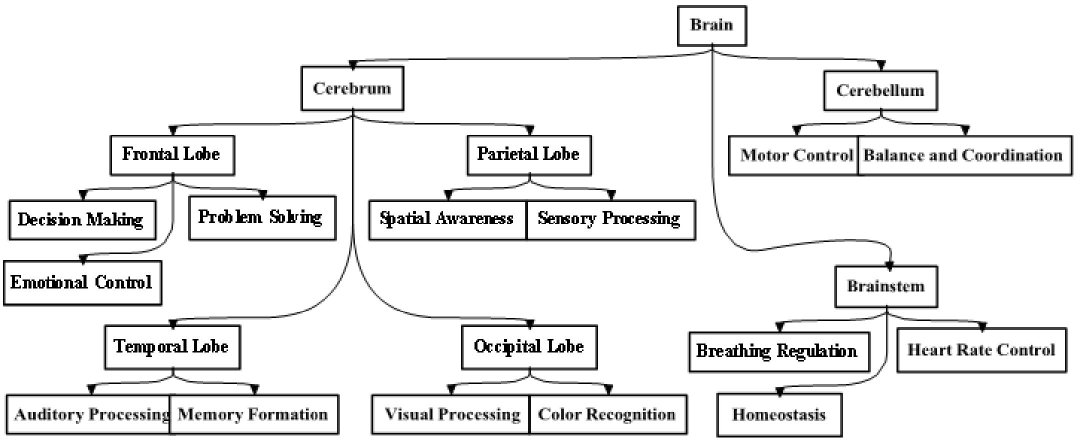

Figure 1. Brain parts and their functions. The diagram illustrates the major anatomical regions of the human brain and summarizes their primary physiological functions.

Although substantial progress has been made in visual representation and computational tools and innovations, precise segmentation and classification of brain tumours continue to pose challenges. Detection and analysis have become complicated because brain tumours exhibit various attributes, including location, dimensions, and structural forms, as well as diverse imaging patterns. The complex anatomy of the central nervous system is crucial to understand. This is because the brain is divided into three primary components. The central nervous system is an intricate and sophisticated marvel, comprising the cerebrum, cerebellum, and brain stem Figure 3. These integral components come together to form the command centre of the human body, each playing a pivotal and distinct role in its functional symphony Figure 2. Each playing distinct functional roles [9][10][21] Table 1.

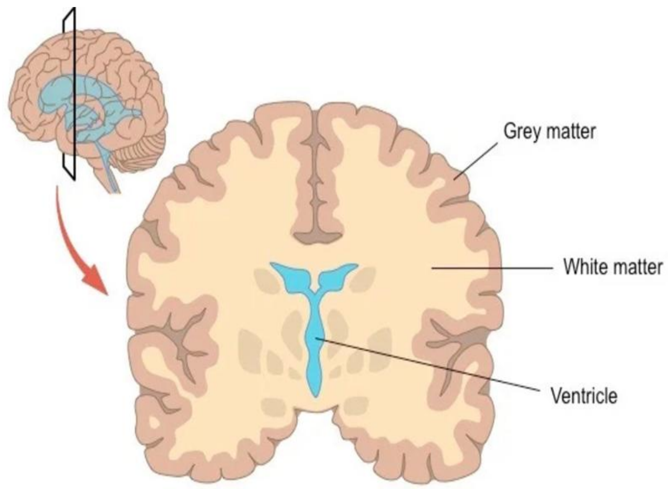

Figure 2. White vs. Grey areas.

Table 1. Key brain tissue components and their functions.

Component	Function	Description
Grey matter (GM)	Regulates of brain activity	Consists of neurons and supporting glial cells.
White matter (WM)	Connects different brain re- gions	Comprises myelinated axons. The corpus callosum connects the hemispheres.
Cerebrospinal fluid (CSF)	Not explicitly mentioned	One of the three major tissue components of the brain.

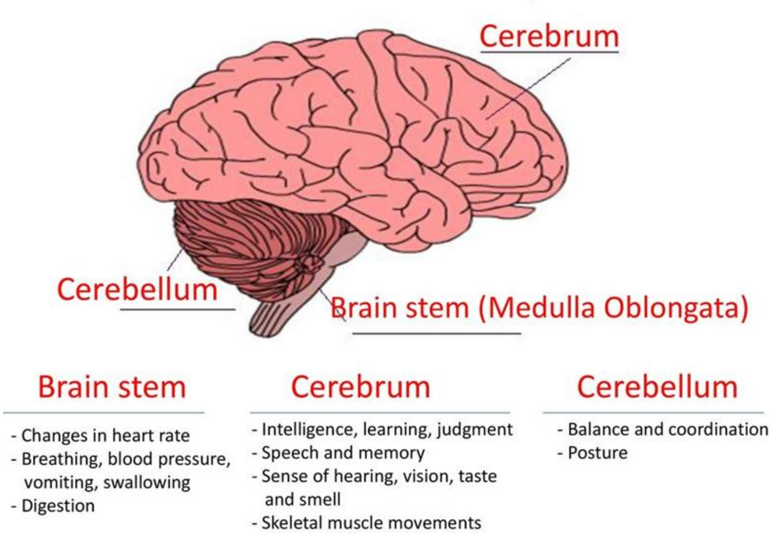

Figure 3. Anatomical regions of the human brain.

Brain tumours are powerfully categorised into two distinct and significant classes Table 3 primary and secondary, each unveiling a unique and compelling journey of origin and impact. Primary tumours originate within the brain and include gliomas, meningiomas, and pituitary tumours [25]. Secondary tumours, or brain metastases, originate from neoplasms in different regions of the body, such as lung cancer, breast cancer, and melanoma metastases, and are invariably malignant (Section 1.1.1.).

1.1. Brain Tumor Phenotypes, Imaging Modalities and MRI Issues

Brain neoplasms are classified according to their nature, origin, grade, and stage of progression. Benign neoplasms grow slowly and are less harmful, while malignant neoplasms grow aggressively and pose greater health threats. Primary neoplasms originate in the brain, whereas secondary neoplasms spread from other regions of the body, including the breast or lungs [26][27]. The grading system helps describe the neoplasm's characteristics. Grade I neoplasms generally grow slowly and have a uniform structure, whereas grade IV neoplasms exhibit rapid growth and spread. Stages of progression begin with confined malignancies at stage 0, progressing to stage 4, where the disease has spread widely throughout the body. Table 2 classifies brain neoplasms by nature (benign or malignant), origin (primary or secondary), classification (I-IV), and stage of progression (0-4).

1.1.1. Categories of Brain Tumours

- **Primary brain tumours**: Brain tumours that originate in the brain tissue itself. These can be benign or cancerous.
  - Gliomas: They are the most common primary brain tumours that originate from glial cells.
  - Meningiomas: Developing from the meninges, they are generally benign and slow-growing.
  - Pituitary tumours: Developing in the pituitary gland can affect hormonal function.

- **Secondary brain tumours**: These are invariably malignant and originate from other forms of cancer that have metastasised to the brain.

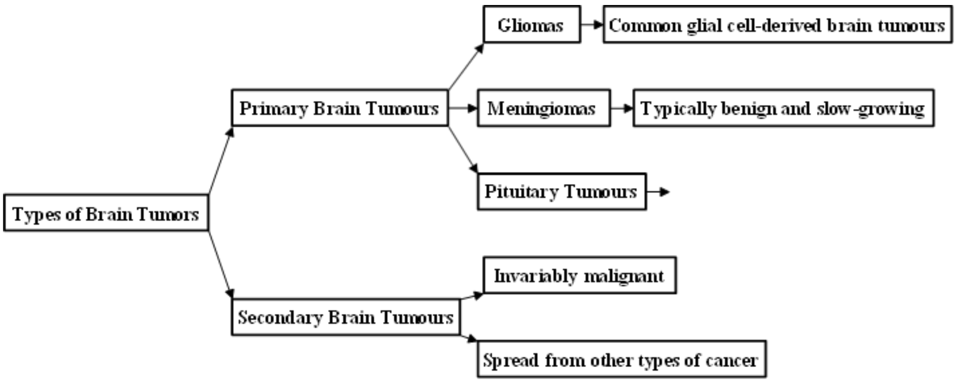

Figure 4. A schematic representation of brain tumor taxonomy: A schematic representation of brain tumor classification, highlighting the dichotomy between originating within the brain and metastasizing from extracranial primary sites.

Table 2. Classification of brain tumours based on various criteria [8].

Classification	**Type**	**Description**
Nature	Benign	Tumours that grow slowly and are less harmful.
	Malignant	Tumours that are aggressive, life-threatening, and spread rapidly.
Origin	Primary	Tumour that develops directly in brain tissue
	Secondary	Tumour that spreads to the brain from other regions of the body, such as the breast or
Grading	Grade I	Tumour with slow growth and minimal abnormalities, often is less harmful
	Grade II	Tumour with some irregular structure, growing more slowly compared to higher
	Grade III	Tumour that grows faster and exhibits more aggressive behavior than Grade II
	Grade IV	Highly invasive and fast-growing tumors that spread rapidly
Stage of Progression	Stage 0	Localized tumors that have not invaded nearby tissues.
	Stage 1	Early-stage tumors with limited growth and low spread
	Stage 2	Tumour spreads more rapidly compared to Stage 1.
	Stage 3	Tumour that has spread significantly within the local or regional area.
	Stage 4	Advanced tumour that has metastasized to distant organs or areas of the body.

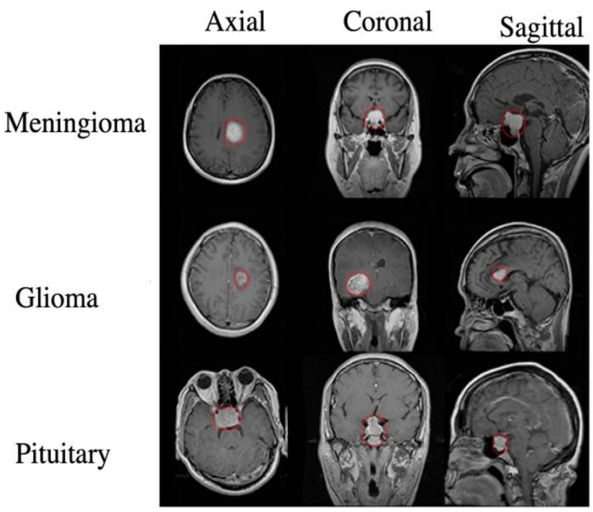

Figure 5. Brain tumour type MRI.

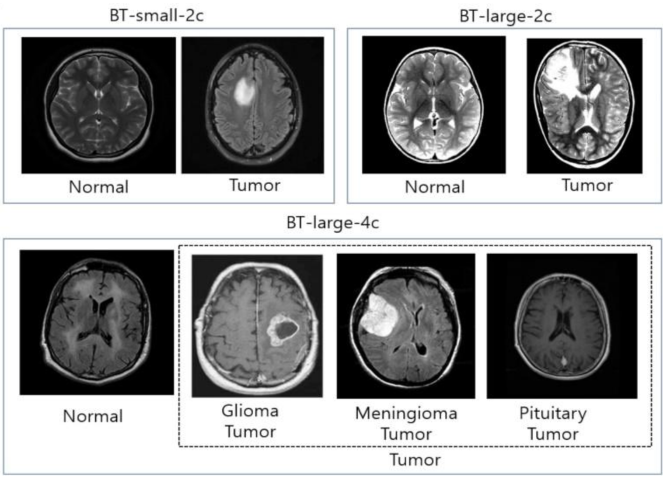

Figure 6. Brain tumour MRI example.

1.1.2. Imaging Modality: Magnetic Resonance Imaging (MRI)

Magnetic resonance imaging is highly effective in providing detailed images of soft tissues, making it excellent for identifying complex tumour structures, as well as associated conditions such as swelling, bleeding, and minor calcium build-ups. A key advantage of these techniques is that they do not expose patients to harmful radiation, making them safer than many traditional imaging methods. However, the text also highlights significant challenges: implementing these advanced methods requires considerable time and resources, posing a barrier. In addition, the techniques are not suitable for patients with metal implants, underscoring the need to exercise caution when selecting candidates for this imaging technology. Let us consider how different imaging methods can help detect brain tumours Table 3.

- MRI: the benchmark for soft-tissue imaging. It can depict the architecture of tumours, swelling, hemorrhaging, and even calcium deposits. A significant advantage? It does not involve radiation. Despite this, it is costly and time-consuming. Furthermore, it is not suitable for patients with metal implants [28].
- CT scan: This is useful for emergencies and for imaging of the bone and blood. It is fast and widely available, making it helpful for treating bleeding or trauma. However, it does not show as much detail in soft tissues. However, it also uses radiation [29].
- PET scan: This scan measures how tumours use glucose, which can help detect recurrence and active tumours. It can also indicate the difference between recurrence and scarring [30]. However, it has low spatial resolution and is expensive. It is usually combined with CT or magnetic resonance imaging (MRI).
- X-rays: This is the least common method used for brain imaging. It only shows the skull bone and is fast and inexpensive. However, it cannot image brain tissue; therefore, it is not very useful [31].

Table 3. Comparative analysis of imaging modalities.

Modality	Usefulness	What It Shows	Strengths	Limitations
MRI	Excellent gold standard	• Soft tissues • Tumor structure • Edema (swelling) • Bleeding	• Best soft tissue detail • No radiation • Multiple types (fMRI, MRS)	• Expensive • Slower • Not for patients with metal implants
CT scan	Good for emergency use	• Bone and blood • Large tumors • Calcifications	• Fast and widely available • Good for bleeding or trauma	• Lower soft tissue contrast • Ionizing radiation
PET scan	Good for tumor metabolism	• Glucose uptake • Recurrence detection	• Detects active tumors • Distinguishes recurrence vs. scan	• Low spatial resolution • Expensive • Usually combined with CT/MRI
X-ray	Limited, rarely used	• Skull bone only	• Fast • Less expensive	• Cannot image brain tissue • Ionizing radiation

Magnetic resonance imaging (MRI) plays a crucial role in the diagnosis and treatment planning of brain tumours. Provides high-resolution images of soft tissues, enabling detailed visualisation of tumours. The key MRI sequences used to evaluate brain tumours were as follows:

- **T1-weighted imaging**: Offers a detailed anatomical visualisation; fat appears bright. White matter appears bright, grey matter appears intermediate, and CSF appears dark.
- **T2-weighted imaging**: Highlights edema and necrosis; fluids appear bright. The white matter appears dark, the grey matter appears dark, the CSF appears bright, and the abnormal growth appears bright [8].
- **Contrast-enhanced T1-weighted imaging/FLAIR MRI**: Delineates tumour margins and highlights areas of improvement. The white matter appears dark, the grey matter appears dark, the CSF appears dark, and the abnormal growth appears bright [8].

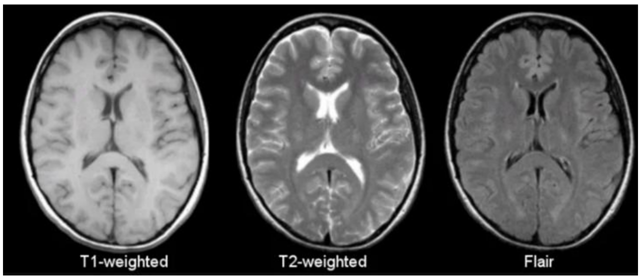

Figure 7. Types of brain MRI imaging.

In Figure 8, we compare different MRI sequences and their visualisation characteristics. In T1-weighted images, white matter appears bright, grey matter appears intermediate, CSF appears dark, and abnormal growth appears dark. In T2-weighted images, white matter appears dark, grey matter appears dark, CSF appears bright, and abnormal growth appears bright [18]. In FLAIR sequences, the white matter appears dark, the grey matter appears dark, the CSF appears dark, and the abnormal growth appears bright [8].

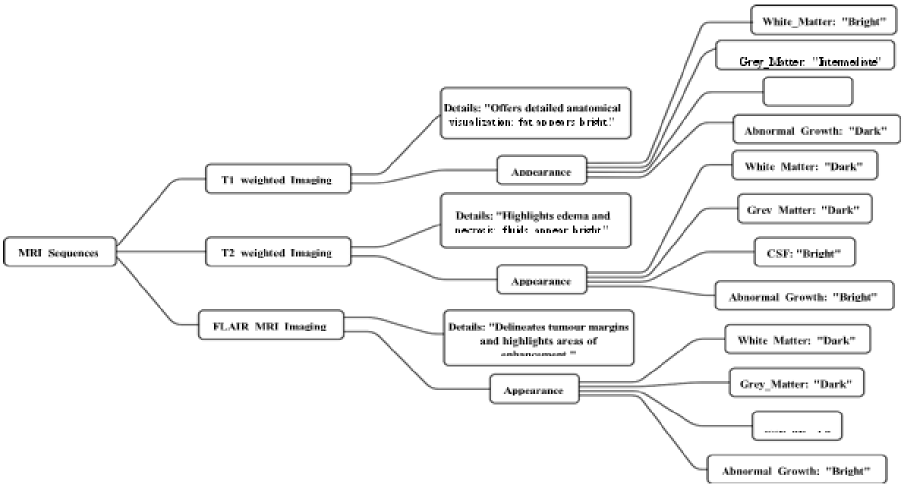

Figure 8. MRI sequence characteristics. Comparison of different magnetic resonance imaging (MRI) sequences showing their distinctive tissue contrast properties and clinical applications.

1.1.3. Issues in MRI

The process of detecting brain tumours from MRI scans presents several challenges that necessitate the development of intelligent, automated systems. Although magnetic resonance imaging is the gold standard for this task, several issues make accurate and efficient diagnosis difficult.

- **Image Preprocessing**: Raw magnetic resonance images often contain noise, artefacts, and intensity variations that can obscure tumour boundaries. Before analysis, these images require extensive preprocessing, including noise reduction and intensity normalization, which can be complex and time-consuming.

- **Tumor Heterogeneity**: Brain tumours vary widely in shape, size, location, and intensity. The fuzzy and ill-defined boundaries of many tumours make it difficult for both human experts and automated systems to accurately delineate them.
- **Manual Interpretation**: The traditional method of manual tumor segmentation by radiologists is subjective and can be prone to human error. This process is labour-intensive and time-consuming, and the results can differ between experts.
- **Data Scarcity**: Acquiring large, high-quality, and well-annotated medical image datasets for training AI models is difficult. This leads to data scarcity and class imbalance issues, where there are far more non-tumour pixels than tumour pixels, which can hinder model performance.
- **Model Constraints**: Traditional machine learning models often rely on handcrafted features, such as texture or shape, which may not fully capture the complexity and non-linear patterns of tumours in MRI images.
- **Interoperability**: Automated systems need to be robust enough to handle variations from different MRI machines and scan protocols. Differences in subsequent scans can make it difficult to determine whether a change in the image is due to a real change in the tumour or simply a technical variation.
- **Consequences of Prediction**: The consequences of a false diagnosis are severe. A false negative (missed tumour) could delay life-saving treatment, while a false positive (healthy tissue mistaken for a tumor) could lead to unnecessary and stressful follow-up procedures for the patient. This highlights the need for models with extremely high accuracy and low false-negative rates.

The classification of tumours involves categorising them into gliomas, meningiomas, and pituitary tumours [17]. The use of machine learning and deep learning models, specifically Convolutional Neural Networks (CNNs), facilitates the identification and classification of tumours by analysing features derived from medical images [7][9]. Table 4 presents a review of articles on brain tumour analysis, highlighting the development and evolution of methods and techniques used in this field. The surveys cover various aspects of brain tumour analysis, including submissions to the BraTS Challenge, healthcare deep learning applications, MRI segmentation evolution, traditional detection methods, segmentation classification pipelines, MRI image processing, SOTA segmentation models, and the medical imaging deep learning landscape.

Table 4. Survey papers on brain tumour analysis.

Ref.	Survey Focus	Key Coverage	Methodological Emphasis
[19]	BraTS Challenge Submissions Analysis	2012-2018 model architectures	Multimodal segmentation trends
[15]	Healthcare DL Applications	Cross-domain implementations	General deep learning
[20]	MRI Segmentation Evolution	Early DL adoption analysis	Neuroimaging-specific DL
[21]	Segmentation- Classification Pipelines	Hybrid system architectures	Integrated frameworks
[22]	MR Image Processing	Preprocessing-detection chain	Clinical workflow analysis
[23]	SOTA Segmentation Models	Latest DL architectures	Advanced network designs
[24]	Medical Imaging DL Landscape	Foundational techniques	General medical DL

Where BraTS = Multimodal Brain Tumor Segmentation Challenge, Chronological analysis of survey literature showing methodological progression in brain tumor analysis research.

1.2. Research Progress and Challenges

Intelligent computational strategies are imperative due to this paradigm shift, encompassing artificial intelligence techniques such as machine learning for pattern recognition and deep learning for the extraction of intricate features [1][7][33][34]. This article offers a comprehensive overview of the latest developments and advanced methods for analyzing brain neoplasms. It also identifies current challenges. The focus is on clustering, soft computing, deep learning, and thresholding methods for segmenting and classifying brain neoplasms [6].

- **Trends in brain neoplasm research**: A comprehensive analysis of research trends, classifying studies based on applications such as segmentation of neoplasms, growth prediction, and prediction of treatment outcome [35].
- **Challenges in clinical deployment**: Thorough investigation into the inherent constraints of deploying machine learning methodologies in clinical environments reveals crucial challenges, including serious concerns about data confidentiality, substantial computational resource requirements, and the imperative for

transparent, easily interpretable outcomes. [36].

- **Prospective pathways**: Recommendations for developing more robust, interpretable, and clinically viable ML models are provided. These models should focus on the diagnosis and prognosis of brain neoplasms. [37].

2. METHOD

As neuro-oncology evolves, the volume of imaging data from the advanced MRI modality (Section 1.1.2.) has grown exponentially. Traditional manual analysis methods are no longer sufficient to handle such large datasets. Machine learning and deep learning have become highly effective methods for handling large datasets, providing rapid and accurate results. The rapid advancement of neuro-oncological research and clinical diagnostics has led to the unprecedented accumulation of medical imaging data. Specifically, this collection of data comes primarily from magnetic resonance imaging (MRI) techniques. Conventional manual interpretation methods face critical limitations regarding scalability and precision when processing large datasets. Accurate identification of brain tumours is crucial for diagnosis and the development of treatment strategies. Historically, manual classification techniques have tended to be sluggish and error-prone; however, advances in machine learning and deep learning have significantly improved the precision of tumour detection. Automated analysis of raw imaging data is now possible with advanced algorithms, reducing the need for human involvement. Recent advances in tumour boundary detection techniques improve precision and improve diagnostic accuracy, ensuring that patients receive optimal treatment strategies.

2.1. Clustering Approach

MRI clustering Table 5 pixels with similar properties, such as shape, texture, and intensity, using techniques such as K-means and fuzzy C-means (FCM) Table 6. The central challenge with K-means clustering is its pronounced sensitivity to initial starting values, which can dramatically influence the outcome and effectiveness of the clustering process. In contrast, fuzzy C-means clustering [38] emerges as a more flexible and robust alternative, offering a soft yet robust approach to cluster analysis. K-means algorithms excel in scenarios where distinct, well-defined boundary segmentation is required, providing precise, unequivocal results. On the other hand, the fuzzy C-means technique shines in contexts characterised by ambiguous boundaries, deftly navigating the intricacies of such datasets.

Table 5. Clustering approaches.

Reference	Year	Data Source	Techniques	Merits	Demerits
[39]	1997	Multispectral MR images (T1- weighted, PD, T2-weighted)	Unsupervised clustering with knowledge-based techniques	Showed close correspondence with ground truth and enabled tumour volume tracking over time.	Restricted to early datasets: scalability to modern large datasets not demonstrated.
[40]	2015	Multispectral MR images (BraTS)	Hybrid clustering technique	Provide effective tumour segmentation by combining clustering strategies.	Quantitative evaluation not fully detailed; possible dependency on initialization parameters.
[41]	2013	MRI brain tumour segmentation	State-of-the-art survey	Delivered a comprehensive overview of clustering-based segmentation approaches.	No experimental validation; findings limited to qualitative insights.
[42]	2016	Brain MR Images	Rough set based intuitionistic fuzzy clustering	Demonstrated accurate segmentation through fuzzy clustering integration.	High computational complexity and sensitivity to noise not addressed.
[43]	2018	Brain MRI	Segmentation and clustering	Validated the applicability of clustering techniques in MRI segmentation.	Lack of benchmarking against advanced deep learning methods.
[44]	2022	Resting state fMRI data	AECA-MF (ambiguous entropy clustering multifactor)	Captures complex Multifactor relationships in fMRI signals	Needs validation on larger datasets; sensitivity to noise
[45]	2023	BraTS 2018 dataset	Comparative study of segmentation methods	Offered broad analysis of clustering -based segmentation approaches.	General comparative study without specific experimental out comes; effectiveness difficult to assess.

Table 6. Fuzzy logic approaches.

Reference	Year	Data Source	Techniques	Merits	Demerits
[47]	1999	Multispectral MR images (T1, T2, PD)	Fuzzy clustering with domain knowledge	Effectively detected non enhancing tumours and provided tumour correspondence across volumes.	Limited performance range; segmentation consistency issues across datasets.
[48]	2005	Non-contrasted T1/T2-weighted MR images	Fuzzy-c-means clustering + region growing	Successfully localized midline tumours with high accuracy.	Focused only on midline tumours; generalizability to all tumour types not established.
[49]	2018	BraTS dataset	Type-II fuzzy logic + ANFIS	Provided robust tumour classification and effective grade recognition.	Computationally intensive; requires large training data for ANFIS.
[50]	2020	Simulated BraTS database	Fuzzy Bayesian segmentation with denoising	Demonstrated strong segmentation capability and noise resilience.	Evaluation limited to simulated data; clinical robustness not validated.
[51]	2020	MRI images of Parkinson's dis- ease	Fuzzy information gain + K-means clustering	Recognizes changes in MRI regions, good segmentation	Performance dependent on parameter tuning, limited to Parkinson's MRI data
[52]	2021	MRI data sets (Set I, II, III)	Type-2 neutrosophic entropy fusion thresholding	Showed superior segmentation quality compared to traditional fuzzy approaches.	Complex entropy fusion model; may be computationally demanding for large datasets.
[44]	2022	fMRI time series data	Neutrosophic-entropy clustering	Captured activation differences between task/rest states	Needs validation on larger diverse datasets
[53]	2024	MR images for multiple sclero-sis detection	Fuzzy entropy-based segmentation algorithm	Automatedsegmentation of white matter lesions with improved robustness for MS detection.	Focused mainly on MS; applicability to broader brain tumour segmentation not addressed.

2.2. Sementation Approaches

Brain tumour analysis is heavily dependent on segmentation, which disaggregates the tumour into smaller components and makes it easier [21]. This process allows medical professionals to have a better understanding of the dimensions, structure, and location of the tumour. Although manual segmentation is possible, it is often labour-intensive and prone to errors due to the complexity of brain scans [54]. However, manual segmentation is both time-consuming and challenging due to the complexity of brain images and imaging artefacts that can compromise data quality. To address these issues, a variety of automated brain tumour segmentation methodologies have been developed, providing radiologists with advanced tools to improve both accuracy and efficiency Table 7. In contrast, automated segmentation employs computer algorithms to segment the tumour, delivering a remarkably swift, precision-driven, and highly efficient solution that minimises time expenditure while maximising accuracy. Among the numerous medical image segmentation methods, U-Net and the fully convolutional network (FCN) are the most prevalent and effective deep learning techniques. They excel in analysing complex imaging data with high efficiency and accuracy.

2.3. Deep Learning Approaches

Imagine having a super-smart computer that can look at brain scans and identify brain tumours. This is what deep learning is all about. It is a type of artificial intelligence that leverages sophisticated algorithms to analyse images and generate predictions. This model is trained on a large dataset of brain scan images and learns to recognise the unique characteristics of brain tumours, such as CNN-based [59], U-Net [60], U-Net variants [61], advanced loss functions [62], to detect and segment brain tumours effectively [16]. These models are trained in large datasets of brain tumour images and learn to recognise the unique characteristics of brain tumours, including their morphology, texture, and intensity distribution. As demonstrated in Table 8, deep learning-based segmentation offers improved accuracy and operational efficiency compared to traditional manual segmentation methods, making it a valuable tool for radiologists in the diagnosis and treatment of brain tumours.

Table 7. Segmentation approaches.

Reference	Year	Data Source	Techniques	Merits	Demerits
[55]	2013	Multichannel MR images	Spatial accuracy-weighted HMRF	Improved segmen tation robustness for low resolution images.	Performance may degrade for high resolution or noisy data.
[56]	2015	Multichannel MRI	Bayesian model classification	Provided faster processing compared to contemporary approaches.	May be sensitive to parameter priors; scalability to large datasets not fully tested.
[57]	2015	Brain MRI images	Improved edge detection algorithm	Enhanced tumor boundary detection using refined edge detection techniques.	Sensitive to noise and intensity variations in MRI images.
[58]	2022	BRATS 2018 and private MRI dataset	Cascade multiscale residual attention CNN with adaptive ROI	Improved segmentation accuracy using residual attention modules and adaptive ROI selection.	Complex network; higher computational cost and longer training time.
[59]	2023	BRATS and private MRI datasets	Deep hybrid representation learning (combining CNN and feature fusion)	Achieves high segmentation accuracy and better tumor boundary delineation.	Computationally intensive; requires careful parameter tuning.

Table 8. Deep learning approaches.

Reference	Year	Data Source	Techniques	Merits	Demerits
[11]	2017	BraTS 2017/2018 datasets	AResU-Net	Improved local feature extraction with attention and residuals.	Sensitive to hyper parameter tuning.
[12]	2018	BraTS dataset 2018	U-Net + VGG16	Strong segmentation capability for different tumour regions.	High memory usage due to VGG backbone.
[63]	2019	3D scans MRI	3D CNN with Euclidean similarity	Accurate tumour segmentation with volumetric estimation.	Limited testing on small datasets.
[64]	2019	BraTS dataset	FCNN with DMDF	Fast segmentation with competitive accuracy.	May struggle with irregular tumour boundaries.
[65]	2019	–	Review of CNN + radiomics	Highlights predictive biomarkers for survival and therapy response.	Mostly theoretical; lacks direct segmentation results.
[14]	2018	BraTS 2017/2018 datasets	BU-Net residual nections	Improved segmentation of tumour subregions.	Complex architecture; training instability possible.
[66]	2019	–	DNNs for segmentation/ classification	Provides detailed overview of techniques and datasets.	Review only; no novel method or quantitative validation.
[67]	2020	3064 public slices	Multiscale deep CNN	Effective classification using multiscale representation.	May not scale well to 3D volumetric data.
[68]	2020	Multisequence MRI	GoogLeNet-based CNN	Effective for multi-sequence MRI-based segmentation.	Limited validation on clinical multi centre datasets.
[69]	2020	BraTS dataset	Hybrid U-Net, Seg-Net, ResNet	Enhanced accuracy through hybrid design.	Increased architectural complexity.
[70]	2020	TCIA and BraTS datasets	2D Mask R-CNN + 3DConvNet	Effective integration of 2D and 3D models.	Requires both 2D and 3D models; computationally heavy.

2.4. Classification

Classification involves the meticulous organization of data into distinct groups, meticulously based on shared attributes, with a potent classifier tasked with expertly determining the precise group for each individual data point. When it comes to the intricate analysis of medical images, particularly for the detection and analysis of brain tumours, cutting-edge technologies such as machine learning and deep learning come into play. Machine learning, while robust, relies on predefined features and structured data, whereas deep learning transcends these limitations by autonomously extracting essential and significant features from raw data, establishing itself as an unquestionably more powerful, efficient, and seamless method, propelling the realm of medical imaging into a new era Table 9.

Table 9. Classification approaches.

Reference	Year	Data Source	Techniques	Merits	Demerits
[71]	2017	BRATS 2016	Extremely randomized trees	Proposed a novel CNN architecture enabling faster and more efficient brain tumor segmentation.	The evaluation dataset size was relatively small.
[72]	2020	Figshare brain MRI dataset	Convolutional Neural Network (CNN) for tumor classification	Achieved high accuracy with an end-to-end CNN model without manual feature extraction.	Limited dataset diversity may affect model generalization to unseen data.
[73]	2020	Brain MRI dataset (collected and preprocessed)	Hybrid image enhancement with CNN-based classification	Improved feature visibility and classification accuracy through enhanced image preprocessing.	High computational cost due to hybrid processing and deep learning stages.
[74]	2021	BRATS 2018 and private MRI dataset	Ensemble of deep CNN features with traditional ML classifiers (SVM, RF, k-NN)	Achieved higher classification accuracy by combining multiple deep feature extractors and classical classifiers.	Ensemble architecture increases model complexity and inference time.
[75]	2021	Brain MRI dataset (collected and annotated)	Transfer learning–based active learning framework	Reduced annotation cost and improved classification performance by integrating active learning with transfer learning.	Performance depends on the selection strategy and pretrained model choice.
[21]	2021	Various public MRI datasets (e.g., BRATS, TCGA)	Comprehensive survey of brain tumor segmentationand classification algorithms	Provides an extensive overview of state-of-the-art methods and challenges in brain tumor analysis.	Does not propose a new model; mainly descriptive without experimental validation.
[76]	2022	Brain MRI dataset (collected and augmented)	Transfer deep-learning model with isolated and developed layers	Achieved robust performance through customized transfer learning and optimized feature extraction.	Computationally expensive and sensitive to hyperparameter tuning.
[77]	2022	Basal ganglia MRI dataset (gliomas and germinomas)	Transfer learning using pretrained CNN models	Enhanced classification performance on limited medical datasets through knowledge transfer from large-scale models.	Model generalization may be limited due to domain-specific variations in MRI data.
[78]	2023	Brain MRI datasets (BRATS and private datasets)	Hybrid optimization algorithm combined with deep learning for segmentation and classification	Improved segmentation accuracy and tumor classification by integrating optimization with deep learning.	Computationally intensive; requires careful tuning of hybrid optimization parameters.

3. DATA COLLECTION AND DATA PRE-PROCESSING FOR BRAIN MR IMAGE

Healthcare professionals have identified biomedical image processing as a fundamental and changing discipline in biomedical practice. Medical professionals use various imaging technologies, such as magnetic resonance imaging (MRI), X-rays, and computed tomography (CT) scans [79]-[81], to detect subtle structural changes in the patient's anatomy. Medical imaging extracts diagnostic precision from visual data sets through an error-reduction strategy. Healthcare providers often opt for magnetic resonance imaging as their initial imaging modality due to its ability to provide a thorough anatomical assessment. It uses a noninvasive method that eliminates the need for radiation exposure. Medical professionals use computational tools to analyse magnetic resonance images by applying pre-processing before segmentation to identify tumour areas in the image stream [82][83]. This process proceeds through optimisation and feature extraction to locate important clinical data patterns. A review study analysed previous research to provide a complete guide on brain tumour detection by magnetic resonance imaging, its methodological progress, and its major research developments [84]-[86].

This study selected magnetic resonance imaging as the primary method of identifying, evaluating, and monitoring brain tumours. Magnetic resonance imaging is considered the gold standard in brain imaging because it can produce high-resolution images of soft tissues without using ionising radiation. This is particularly crucial in the brain, where accurate imaging of tumours, surrounding edema, bleeding, and understanding typical anatomical structures are crucial for diagnosis, developing treatment plans, and assessing prognosis. Compared to other imaging techniques Table 3. Magnetic resonance imaging is the gold standard for brain tumour detection, as it provides excellent soft-tissue detail without radiation. CT scans are fast and widely available but have lower soft tissue contrast. PET scans detect active tumours and recurrence but have low spatial resolution.

Deep neural networks have seen notable improvements in their generalisation capabilities due to data augmentation, which acts as an inherent form of regularisation. This approach becomes crucial when access to large, accurate datasets is limited, while creating new labelled data demands significant time and effort. This issue is prevalent in medical imaging applications, particularly in magnetic resonance imaging, which is essential for accurately delineating tumour boundaries. This research examines novel data augmentation techniques [87] that target brain tumour segmentation from MRI scans [88].

3.1. Public Datasets

Publicly accessible MRI datasets, such as the ICancer imaging Archive (TCIA), BraTS, and RSNA, play an essential role in brain tumour detection research Table 10. These collections provide a variety of magnetic resonance sequences and labels, helping to create and validate algorithms. Publicly available data sets are fundamental to evaluate and contrasting the efficacy of novel approaches in brain tumour detection studies. Some of the most popular and demanding datasets include:

Table 10. An overview of frequently used MRI databases for brain tumors

Datasets	Description
TCIA Dataset	• Provides a variety of MRI datasets specifically for brain tumor studies • Contains T1-weighted, T2-weighted, and FLAIR scan sequences • Ideal for overall tumor examination and segmentation
MICCAI Dataset	• Provides datasets of multimodal MRI scans • Contains T1, T2, FLAIR, and post-contrast T1-weighted images • Commonly utilized in segmentation benchmarking contests
RSNA Dataset	• Created to facilitate research on brain tumors in children • Comprises annotated MRI images of diverse tumor types in the pediatric population • Aids in creating age-specific diagnostic frameworks

The Brain Tumour Segmentation dataset, initiated in 2012, is the largest collection of multisequence brain MRI images for tumour segmentation, featuring T1, T1 contrast, T2, and FLAIR images of gliomas and meningiomas from diverse sources. Annual updates present new challenges; the 2023 edition addresses treatment disparities in childhood brain tumours and sub-Saharan African gliomas. This dataset is vital for brain tumour image analysis [32]. BRATS datasets from MICCAI conferences (2012-2024) [32] with various imaging modes [84] are crucial for tumour analysis. The 2018 MICCAI Challenge highlighted the significance of data augmentation in supervised learning.

Future research aims to improve the synthesis of synthetic tumour data for deep learning adaptation. Brain tumours are typically detected with MRI or CT. Pre-processing methods like noise reduction, normalization, and data augmentation [17] including rotation and flipping—enhance data quality and model robustness [89]. MRI enhancements include affine transformations, elastic deformations, pixel adjustments, and GAN-based synthetic data, all of which boost model performance in clinical settings. The Summary of data-augmentation techniques can be seen in Table 11.

Table 11. Summary of data-augmentation techniques.

Section	Details
Key Techniques	Affine Transformation • Basic geometric changes (flip, rotate, scale) • Example: Flipping MRI left-to-right • Pros: Easy • Cons: Unrealistic if overdone
	Elastic Deformations: • Stretching/bending images • *Example*: Tumor growth simulation • Pros: Realistic shapes • Cons: Risk of unnatural artifacts
	Pixel Adjustments: • Alter brightness/contrast • *Example*: Adjust MRI intensity • Pros: Mimics scanner variance • Cons: No shape changes
	Synthetic Data (GANs): • AI-generated fake MRIs • *Example*: GAN-generated tumors • Pros: Generates rare examples • Cons: Requires expertise

4. PERFORMANCE MEASURES

To ascertain the efficacy of software designed to detect brain tumours on medical images, it is imperative to perform a thorough evaluation of its performance. In Figure 9, the performance metrics used to evaluate the classification models are presented. Comprehending evaluation metrics is essential for reliable and effective real-world applications and diagnostic advances. Herein, we examine pivotal metrics that influence the progression of brain tumour detection software. In Table 12, we provide a summary of the confusion matrix, a tabular representation that juxtaposes the actual results with the predictions of a classification model, illustrating the model's performance and helping to understand its effectiveness. This notation is selected to maintain consistency with the standard mathematical notation and to prevent confusion with other variables. The use of Greek letters (α, β, γ, δ) is a common practice in mathematics and statistics to signify variables or constants. A detailed breakdown of the various metrics used in the classification process is provided. The alpha (α) metric denotes true positives (TP), representing the number of cases of tumour that have been accurately identified. Similarly, the beta (β) metric refers to true negatives (TN), illustrating the correct classification of non-tumour cases. Conversely, the gamma (γ) metric indicates false positives (FP), which represent cases erroneously identified as tumours. Finally, the delta (δ) metric corresponds to false negatives (FN), representing tumour cases that have been incorrectly classified as non-tumour.

	+ve	-ve
+ve	α	γ
-ve	δ	β

Figure 9. Confusion Matrix.

5. CONCLUSION

Accurate recognition and thorough evaluation of brain tumours are crucial for the precise assessment and strategic planning of effective treatment regimens. Recent breakthroughs in machine learning and deep learning have dramatically elevated tumour identification precision, enabled automatic processing of raw and complex imaging data while significantly reduced the need for labour-intensive manual intervention. Techniques such as advanced thresholding and sophisticated region-based approaches have significantly improved tumour boundary determination, thereby considerably enhancing diagnostic accuracy. However, while these strides are transformative, there is a pressing need for further research into automated segmentation techniques to effectively address persistent challenges related to image quality, tumour appearance variability, and pervasive imaging artefacts. There are some other approaches discussed in [90]-[97] that can be applied in the analysis of brain tumours using MRI.

Table 12. Performance measure parameters and their statistical significance.

Parameter	Formula	Statistical Significance
Accuracy	$\alpha+\beta+\gamma+\delta$	A higher accuracy indicates the model's overall correctness. However, it may be misleading for imbalanced datasets.
Precision	$\alpha+\delta$	Higher precision indicates fewer false positives, which is useful when false alarms are costly
Sensitivity	$\alpha+\gamma$	A higher recall indicates fewer false negatives, useful when missing actual positives is critical
Specificity	$\beta+\delta$	A higher specificity shows the model's ability to correctly identify negatives and avoid false alarms
F1 Score	$2\times Precision\times Recall$ $Precision+Recall$	A higher F1 score balances precision and recall, especially useful in imbalanced datasets.
α rate	$\alpha+\delta$	The proportion of actual tumors that were correctly identified. A value closer to 1.0 is better, as it indicates a high sensitivity to tumors.
β rate	$\beta+\gamma$	The proportion of healthy brain images that were correctly identified as such. A value closer to 1.0 is better, as it indicates the model is not prone to false alarms.
γ rate	$\gamma+\beta$	The proportion of healthy brain images incorrectly identified as tumors. The closer to 0.0, the better, as this reduces unnecessary patient stress and follow-up procedures.
δ rate	$\delta+\alpha$	The proportion of actual tumors that were missed by the model. The closer to 0.0, the better, as this is critical for ensuring no tumors are overlooked.
Dice Score	$2\alpha+\gamma+\delta$	The Dice coefficient (equivalent to the F1-score in binary classification).
Jaccard Similarity	$\alpha+\gamma+\delta$	The Jaccard Index (IoU) measures the overlap between predicted and true masks. A value closer to 1.0 indicates stronger agreement.
Hausdorff Distance (HD95)	$HD95=95th\ percentile$ $\{d(BPred,Btrue)\}$	Measures the maximum boundary error (95th percentile) between predicted and true segmentation contours. A lower HD95 indicates better spatial alignment and robustness against outliers.

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