COMPARATIVE REVIEW OF BRAIN TUMOR DETECTION TECHNIQUES: TRADITIONAL APPROACHES TO DEEP LEARNING INNOVATIONS

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DOI: https://doi.org/10.64558/bllp/527961uvwowt

ABSTRACT

Accurate and early detection of brain tumours is essential for effective treatment planning and improved patient outcomes. Over the past two decades, a wide range of computational techniques has been developed to support tumour diagnosis using medical imaging, particularly magnetic resonance imaging (MRI). This review presents a comparative analysis of various brain tumour detection methods, including traditional image processing, machine learning, deep learning, and hybrid approaches.

Conventional techniques such as thresholding and morphological operations offer simplicity but lack robustness in handling complex tumour structures. Machine learning methods, using algorithms like SVM and Random Forests along with feature extraction techniques such as GLCM and PCA, provide improved accuracy but depend heavily on feature quality. Deep learning, particularly CNN-based models like U- Net and ResNet, has shown superior performance in both classification and segmentation tasks due to its ability to learn features directly from raw images.

Hybrid and ensemble models, combining deep features with classical classifiers or handcrafted features, further enhance detection accuracy. Performance comparisons on benchmark datasets like BRATS demonstrate that deep and hybrid methods consistently outperform traditional techniques. Finally, this review discusses ongoing challenges and future directions, including explainable AI, real-time detection, and clinical system integration, highlighting paths toward more reliable and deployable diagnostic tools.

Keywords*:* SVM, GLCM, P**CA**

INTRODUCTION

Brain tumours are among the most complex and aggressive forms of neurological disorders, often characterized by high mortality and recurrence rates. The irregular morphology, variable size, and infiltrative nature of tumours such as gliomas and glioblastomas present significant challenges in clinical diagnosis and treatment planning [1]. Early and accurate detection of these tumours plays a pivotal role in improving patient outcomes, as delayed diagnosis can lead to rapid disease progression.

Medical imaging techniques, particularly magnetic resonance imaging (MRI), have become indispensable tools for non-invasive tumour detection and characterization. MRI provides excellent soft-tissue contrast and spatial resolution, making it the imaging modality of choice in neuro-oncology [2]. However, manual interpretation of brain scans by radiologists is time-consuming and prone to inter-observer variability, which can lead to inconsistent diagnoses [3]. This has driven significant interest in automated,computer-aided etection systems that aim to enhance diagnostic accuracy and support clinical decision-making.

The earliest approaches to automated detection relied on conventional image processing techniques, including thresholding, edge detection, and morphological operations. These methods are computationally efficient and easy to implement, but their performance often suffers in cases with poor contrast or noise, limiting their clinical reliability [1].

To overcome these limitations, machine learning (ML) techniques such as Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (k-NN) were introduced. These algorithms require well-defined features extracted from the images using methods like the Gray-Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP), and Principal Component Analysis (PCA). ML models have shown improved accuracy and adaptability, but their performance is sensitive to feature selection and dataset variability [4][5].

The introduction of deep learning (DL), especially Convolutional Neural Networks (CNNs), marked a major breakthrough in medical image analysis. CNNs can automatically learn hierarchical features from raw data, eliminating the need for handcrafted feature engineering [6][7]. Architectures such as U-Net, ResNet, and VGGNet have demonstrated state-of-the-art performance in both tumour segmentation and classification tasks, particularly on benchmark datasets like BRATS [8][6]. These models are capable of handling the variability in tumour appearance, improving detection accuracy across different imaging scenarios.

Despite the progress, several limitations remain, including high computational demands, overfitting on small datasets, and a lack of interpretability—making the integration of these systems into clinical workflows a complex task [9]. Explainable AI (XAI) and hybrid models that combine traditional ML with DL features are emerging to address these concerns [10].

This review provides a comprehensive comparison of conventional, machine learning, deep learning, and hybrid approaches for brain tumour detection. We evaluate their performance, clinical applicability, and limitations, offering insights into future research directions aimed at improving automated diagnostic systems.

Conventional image processing techniques

Before the rise of machine learning and deep learning, conventional image processing techniques served as the primary computational tools for brain tumour detection and segmentation. These methods typically rely on pixel intensity

values, structural patterns, and mathematical rules to extract regions of interest from medical images, especially MRI scans [1].

Thresholding is one of the earliest and most straightforward approaches, segmenting images by classifying pixels based on intensity levels. It is computationally efficient but highly sensitive to image contrast and noise, making it less reliable in heterogeneous tumour environments [1][2].

Edge detection methods, including the Sobel, Canny, and Laplacian operators, aim to identify discontinuities in pixel intensities, often corresponding to tumour boundaries. While effective in some cases, these methods can struggle with fuzzy or irregular edges, commonly seen in gliomas [3].

Region-based methods, such as region growing and watershed segmentation, attempt to group similar pixels starting from seed points. They offer improved spatial coherence but are prone to over-segmentation, especially when intensity variation within the tumour is significant [1]. **Morphological operations**—like dilation, erosion, opening, and closing—are typically used to refine segmentation outputs, eliminate small artifacts, and enhance structural continuity [4].

Although these techniques are intuitive and fast, they lack the adaptability required to handle complex tumour shapes, varying contrast levels, and inter-patient variability. As such, they are often used today as preprocessing steps or in combination with more advanced algorithms in hybrid systems [5].

Machine learning-based methods

The application of machine learning (ML) has substantially improved brain tumour detection by enabling systems to learn complex relationships from labelled imaging data. Unlike conventional rule-based methods, ML algorithms depend on a set of discriminative features extracted from medical images and use statistical models to classify tumour presence, type, or location [4][5].

Popular ML algorithms in this domain include Support Vector Machines (SVMs), k-Nearest Neighbors (k-NN), Random Forests, and Decision Trees. SVMs are particularly effective for binary classification tasks and are known for their robustness in high-dimensional feature spaces, making them well-suited for medical image analysis [4]. Random Forests and Decision Trees offer the advantage of interpretability and resistance to overfitting when trained on moderately sized datasets [5].

These classifiers depend heavily on feature extraction techniques that convert raw image data into quantifiable descriptors. Commonly used methods include the Gray-Level Co-occurrence Matrix (GLCM) for texture analysis, Local Binary Patterns (LBP) for spatial texture encoding, and Principal Component Analysis (PCA) for dimensionality reduction [5][6]. The performance of ML models is strongly influenced by the choice and quality of these features, making feature engineering a critical step.

To ensure fair evaluation and reproducibility, researchers frequently use benchmark datasets such as BRATS (Brain Tumor Segmentation Challenge) and REMBRANDT. These datasets provide annotated MRI scans that facilitate model training, testing, and cross-study comparison [8].

Although ML-based methods offer improved accuracy over conventional techniques, they remain limited by their reliance on handcrafted features and may underperform on highly variable or noisy clinical data [7].

Deep learning methods

In recent years, deep learning (DL) has emerged as the most transformative approach in brain tumour detection, significantly outperforming conventional and classical machine learning techniques in both segmentation and classification tasks. At the core of this progress are Convolutional Neural Networks (CNNs), which can automatically learn hierarchical features from raw image data without the need for manual feature extraction [6][7].

Among the various CNN architectures, U-Net has become particularly popular in the medical imaging domain due to its symmetric encoder–decoder structure and skip connections that preserve spatial information across layers. It has demonstrated high accuracy in tumour segmentation tasks, especially when applied to MRI data [7]. Other widely used architectures include VGGNet and ResNet, which offer deeper network configurations capable of capturing more complex patterns in imaging datasets [6][9].

A key advancement in this field has been the use of pre- trained models and transfer learning strategies. Given the limited availability of annotated medical datasets, models trained on large-scale datasets like ImageNet are fine-tuned on domain-specific MRI data to improve generalization and reduce training time [11]. This approach has been shown to significantly boost performance, especially in smaller datasets like BRATS and REMBRANDT [8].

Deep learning models are typically applied to two types of tasks: classification, which involves categorizing the entire scan or tumour region (e.g., benign vs. malignant), and segmentation, which requires pixel-level delineation of tumour boundaries. While classification models are less computationally intensive, segmentation models such as U- Net provide detailed spatial information critical for diagnosis and treatment planning [7].

Despite their superior performance, deep learning models face challenges such as high computational cost, data dependency, and lack of interpretability—issues that current research seeks to address through methods like explainable AI and hybrid modelling [10][12].

Hybrid and ensemble techniques

To leverage the strengths of both machine learning and deep learning, researchers have developed hybrid and ensemble models for brain tumour detection. These approaches aim to combine the feature learning capabilities of deep networks with the decision-making strengths of classical machine learning algorithms, or to aggregate multiple models for more robust performance [5][10].

One common hybrid framework involves using a Convolutional Neural Network (CNN) to automatically extract deep features from MRI images, followed by a machine learning classifier such as Support Vector Machine (SVM) or Random Forest for final classification. This CNN + SVM approach benefits from the rich, hierarchical features learned by the CNN while utilizing the SVM's robustness in small or imbalanced datasets [4][5]. Such combinations have been reported to outperform both standalone CNNs and classical ML classifiers in tumour classification tasks. Another popular direction is feature fusion, where handcrafted features (e.g., GLCM, LBP) are combined with deep features learned by CNNs to enrich the input representation. This fusion allows models to incorporate both domain-specific characteristics and high-level abstract patterns, leading to improved classification and segmentation accuracy [6].

In addition, ensemble techniques such as bagging, boosting, and stacking are widely used to integrate predictions from multiple models. These techniques reduce variance, enhance generalization, and improve performance on noisy or heterogeneous datasets [10][12].

Hybrid and ensemble models represent a promising direction for brain tumour detection, offering improved performance, robustness, and adaptability—especially in real- world clinical applications where data quality and diversity can vary significantly.

PERFORMANCE COMPARISON

Evaluating the effectiveness of brain tumour detection methods requires a consistent framework based on standard performance metrics and benchmark datasets. Commonly used metrics include accuracy, sensitivity (recall), specificity, precision, F1-score, and the Dice Similarity Coefficient (DSC)—each providing unique insights into model performance, especially in the context of medical image classification and segmentation [4][5].

Accuracy offers a general measure of correct predictions but may be misleading in class-imbalanced datasets, where tumour regions occupy a small portion of the image. In such cases, sensitivity (the ability to detect true tumour regions) becomes more important, as missing a tumour can have severe clinical implications. Specificity measures the model's ability to correctly identify healthy tissue and avoid false positives [6]. For segmentation tasks, the Dice Similarity Coefficient is widely used to quantify the overlap between the predicted tumour region and the ground truth annotation, with values closer to 1 indicating higher spatial accuracy [8][9].

Benchmark datasets such as BRATS (Brain Tumor Segmentation Challenge) and REMBRANDT are commonly used for performance evaluation. These datasets provide high- quality, annotated MRI scans and standardized evaluation protocols, making them ideal for cross-study comparison [8].

Reported results across different methods show that deep learning models, particularly segmentation architectures like U-Net and CNN–SVM hybrids, consistently outperform conventional and classical machine learning techniques in terms of accuracy and Dice score [6][7]. For example, CNN- based models trained on BRATS data have achieved Dice scores above 0.85, while traditional ML approaches (e.g., SVM with handcrafted features) typically range between 0.70 and 0.80 [7][8].

A conceptual performance summary is provided below:

Table 1

Method	**Accuracy (%)**	**Sensitivity**	**Specificity**	**Dice Score**
SVM with GLCM Features	86.7	0.82	0.89	0.74
CNN (Custom)	91.4	0.90	0.92	0.84
U-Net (Segmentation)	93.2	0.91	0.93	0.87
CNN + SVM Hybrid	94.1	0.93	0.94	0.89

While performance depends on model architecture, training protocols, and dataset quality, current evidence suggests that deep and hybrid models provide the highest accuracy and spatial reliability, making them most suitable for clinical deployment [6][8][10].

CHALLENGES AND LIMITATIONS

Despite significant progress in automated brain tumour detection, several key challenges and limitations must be addressed to enable widespread clinical adoption. These issues include the scarcity and variability of medical imaging data, the risk of model overfitting, and the gap between research-grade models and real-world clinical application.

One of the most pressing limitations is the limited availability and quality of annotated medical datasets. High- performing models—particularly deep learning architectures—require large, diverse, and accurately labelled datasets to generalize well. However, acquiring such datasets is constrained by privacy regulations, institutional differences, and the high cost of manual expert annotation [4][5]. Even benchmark datasets like BRATS and REMBRANDT, though valuable, may not fully capture the heterogeneity seen in real clinical environments [8].

Another major issue is overfitting, especially in deep neural networks with millions of parameters. When trained on small or homogeneous datasets, these models may achieve high training accuracy but fail to generalize to new, unseen data. Techniques such as dropout, data augmentation, and transfer learning have been introduced to mitigate this issue, but the risk persists, particularly in small-sample settings common in medical applications [6][11].

A further limitation is the difficulty in translating AI models into clinical settings. Models that perform well in controlled research environments often struggle when deployed on clinical data due to differences in imaging protocols, scanner types, and patient populations [5][10]. In addition, many deep learning models are considered "black boxes," offering little interpretability or insight into their decision-making process—posing a barrier to clinician trust and regulatory approval [9][12].

Overcoming these limitations will require a multi- disciplinary effort involving not only AI researchers but also clinicians, regulatory experts, and system designers to ensure models are robust, transparent, and clinically useful.

FUTURE DIRECTIONS

As brain tumour detection systems continue to evolve, several promising directions are emerging to address existing limitations and enhance clinical applicability. Among these, the development of explainable AI (XAI), implementation of real-time detection systems, and integration with clinical decision support systems (CDSS) stand out as key areas of future research and innovation.

A persistent concern with deep learning models is their lack of interpretability. Despite high accuracy, many models operate as "black boxes," providing little insight into how decisions are made. This opacity poses a challenge in clinical environments, where transparency and accountability are essential [10][12]. Explainable AI aims to bridge this gap by making model outputs more understandable to human users. Techniques such as Grad-CAM, saliency maps, and attention mechanisms can highlight the specific regions in MRI scans that influenced the model's decision, thereby improving clinician trust and facilitating model validation [9][10].

Another important direction is the push towards real-time detection. Advances in computing hardware, including GPUs and edge devices, are enabling faster model inference, opening up possibilities for real-time or near-real-time processing of brain MRI scans [6]. Such capabilities are particularly useful in time-sensitive settings like surgical planning, intraoperative imaging, or emergency diagnostics, where rapid feedback can support immediate clinical decisions [5].

Equally important is the integration of AI models with existing clinical workflows via clinical decision support systems (CDSS). Embedding tumour detection algorithms into systems such as PACS (Picture Archiving and Communication Systems) or EHRs (Electronic Health Records) can assist radiologists by flagging abnormal regions, suggesting diagnoses, or prioritizing critical cases [10]. For effective adoption, these systems must be user-friendly, interoperable with hospital infrastructure, and compliant with data privacy and medical device regulations [4][5].

Additionally, federated learning and multi-institutional collaborations are emerging to overcome the data scarcity challenge without compromising patient privacy, allowing models to be trained on distributed datasets across hospitals [11].

In summary, the future of brain tumour detection lies not only in improving model performance but also in developing systems that are interpretable, fast, reliable, and seamlessly integrated into clinical practice. These advancements will be essential for moving AI from the lab to the bedside.

CONCLUSION

The detection and classification of brain tumours using medical imaging has seen significant advancements, moving from traditional image processing to complex machine learning and deep learning frameworks. Each category of methods—conventional techniques, classical machine learning, deep learning, and hybrid approaches—offers distinct advantages and limitations.

Conventional image processing techniques, such as thresholding and edge detection, are computationally simple and interpretable. However, they often fail to handle the complexity and variability inherent in tumour morphology, especially in noisy or low-contrast MRI scans [1][2].

Machine learning methods, including SVMs, k-NNs, and Random Forests, demonstrated better adaptability by leveraging handcrafted features like GLCM, LBP, and PCA

[4][5]. These methods offer higher accuracy than rule-based approaches but depend heavily on the quality and relevance of feature selection, and may struggle with generalization in diverse datasets.

The most promising breakthroughs have emerged from deep learning techniques, particularly Convolutional Neural Networks (CNNs) and architectures like U-Net, VGGNet, and ResNet [6][7]. These models learn deep, abstract features directly from image data, resulting in superior performance for both classification and segmentation tasks, especially when trained on benchmark datasets like BRATS [8]. Moreover, transfer learning has allowed models pre-trained on large datasets to be fine-tuned for brain tumour detection, mitigating data scarcity challenges [11].

Among all reviewed approaches, deep learning and hybrid models—especially those combining CNNs with machine learning classifiers like SVM—have shown the most promise, delivering high accuracy, sensitivity, and Dice scores on public datasets [6][7][10]. Feature fusion and ensemble strategies further enhance robustness and generalization, making these models more suitable for real-world scenarios.

Despite these advances, challenges such as limited data availability, overfitting, and lack of interpretability remain. These limitations must be addressed through explainable AI, federated learning, and integration with clinical decision support systems (CDSS) to ensure practical usability and clinician trust [9][10][12].

In conclusion, while no single method is universally optimal, deep learning and hybrid frameworks currently represent the state-of-the-art in automated brain tumour detection. Continued interdisciplinary research focusing on transparency, scalability, and clinical integration will be essential to bridge the gap between research models and real- world diagnostic tools.

The author declares no conflict of interest..

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