A Survey of Automatic Brain Tumor Detection and Classification Techniques

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***Abstract*—The timely and accurate detection of brain tumors is a critical challenge in modern healthcare. This survey paper synthesizes recent research on computer-aided automatic brain tumor detection and classification, focusing on methods presented in four contemporary IEEE papers. We analyze the effectiveness of both traditional signal processing (active contour models) and modern deep learning approaches (CNNs like ResNet, EfficientNet, InceptionV3, and VGG-16). The papers are categorized based on their primary methodology, from active contours to deep learning-based detection and classification, with an emphasis on privacy preservation and comprehensive model evaluation. We compare their reported performance metrics, including accuracy, precision, recall, and AUC, to provide a concise overview of the state of the art. The synthesis reveals that deep learning-based approaches, particularly fine-tuned CNN models, consistently achieve high accuracy, while the integration of privacy-preserving techniques is an emerging and vital research direction.**

***Index Terms*—Brain tumor detection, deep learning, CNN, MRI, active contour, privacy preservation, survey.**

I. Introduction

Brain tumors are life-threatening abnormalities caused by the uncontrolled proliferation of cells within the brain tissues, often leading to severe impairment in cognitive, motor, and sensory functions. Early detection plays a critical role in determining the course of treatment and directly influences patient survival rates. Magnetic Resonance Imaging (MRI) is widely regarded as the most effective modality for brain tumor diagnosis due to its excellent soft-tissue contrast and non-invasive nature [1]. However, interpreting MRI scans manually remains time-consuming, complex, and prone to significant human error, particularly in cases where tumor boundaries are irregular or visually similar to surrounding brain structures.

Traditional manual diagnosis is challenged by numerous factors such as noise, varying tumor sizes, overlapping intensities, inconsistent imaging conditions, and limited radiologist availability [4]. These limitations have paved the way for automated computer-aided diagnosis (CAD) systems aimed at improving both diagnostic speed and accuracy. Early CAD systems relied on classical image-processing methods, including thresholding, clustering, and active contour models [14]. Although computationally efficient and interpretable, these techniques often struggle in dealing with low-contrast images and complex tumor morphologies.With the rise of artificial intelligence, deep learning especially Convolutional Neural Networks (CNNs)—has significantly transformed medical image analysis [2]. Unlike traditional methods that depend on handcrafted features, CNNs automatically learn meaningful patterns from MRI images. Architectures such as ResNet50, EfficientNet, and InceptionV3 have demonstrated exceptional performance in tumor classification and detection tasks due to their ability to learn hierarchical features. Additionally, transfer learning allows these models to perform well even when large labeled medical datasets are not available.

This survey consolidates findings from four recent and influential IEEE-indexed research papers, covering both classical and deep learning approaches [1]. It presents a detailed review of methodologies such as active contour modeling, CNN ensembles with privacy preservation, fine-tuned ResNet50 for multi-class classification, and EfficientNet-based lightweight frameworks. The objective is to compare their performance, highlight their strengths and limitations, and identify emerging research directions that shape the future of brain tumor detection [11].

The analyzed papers are:

1) **Novel Robust Automatic Brain-Tumor Detection and Segmentation Using Magnetic Resonance Imaging** (Xu et al. [1]): This work proposes a novel active-contour model combined with texture analysis to improve the robustness of brain tumor detection.

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2) **Deep Learning-Based Brain Tumor Detection in Privacy-Preserving Smart Health Care Systems** (Lata et al. [2]): This paper presents a CNN-based system for brain tumor detection that integrates cryptographic techniques to ensure patient data privacy.
3) **Abnormal Brain Tumors Classification Using ResNet50 and Its Comprehensive Evaluation** (Younis et al. [3]): This study leverages a fine-tuned ResNet50 model with data augmentation for multi-class brain tumor classification.
4) **A Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Finetuned EfficientNet** (Shah et al. [4]): This research fine-tunes the EfficientNet-B0 model and compares its performance against several other state-of-the-art CNNs for binary tumor detection.

II. Methodologies for Brain Tumor Detection

The reviewed papers can be broadly classified into two methodological categories: signal processing-based and deep learning-based.

A. Signal Processing: Active Contours

The work by Xu et al. [1] employs an active contour-based segmentation technique that starts with an outward-expanding contour to locate suspicious tumor regions within MRI images. The core idea behind active contours is to evolve a deformable boundary until it fits the object of interest based on edge and region properties. However, traditional contour models often generate false positives when noise or unclear boundaries are present.To overcome these issues, the method introduces a two-stage filtering strategy. First, a relative area ratio filtering removes extremely small segmented regions that are unlikely to correspond to actual tumor tissue. Second, a texture-based analysis compares brightness differences between inner and outer boundaries of the detected region, significantly reducing false alarms [14]. This added texture evaluation increases robustness against intensity variations commonly found in MRI scans.

Although the method is computationally light and does not require a training dataset, it still has notable limitations. It heavily depends on initial contour placement and may underperform in cases where tumor boundaries are extremely irregular or faded [11]. Thus, while it is suitable for segmentation tasks, it lacks the accuracy of modern deep learning models for classification.

B. Deep Learning Approaches

The remaining three papers utilize deep learning, specifically Convolutional Neural Networks (CNNs), to address brain tumor detection and classification.

1) CNN Ensemble with Privacy Preservation: Lata et al. [4] propose a privacy-preserving smart healthcare system built using an ensemble of three CNN architectures: VGG-16, InceptionV3, and ResNet50. By combining predictions from multiple models, the ensemble achieves better generalized performance and reduces the chance of misclassification. Each model provides unique representational strengths, making the ensemble highly robust.Beyond classification accuracy, the system incorporates AES-128 encryption along with PBKDF2-based key derivation to ensure secure handling of MRI images. This integration of cryptographic mechanisms protects patient data during transmission and storage, addressing a critical real-world requirement often overlooked in purely performance-oriented research.Although the ensemble achieves exceptionally high accuracy, it is computationally expensive, making it less suitable for real-time or edge-device deployment. Its main advantage lies in clinical environments where secure cloud-based diagnosis is required.

2) Fine-Tuned ResNet50 for Multi-Class Classification: Younis et al. [3] implement a fine-tuned ResNet50 model to classify MRI images into four categories: glioma, meningioma, pituitary tumor, and no tumor. ResNet50 addresses training difficulties found in very deep models by using skip connections, allowing smoother gradient flow.The model benefits significantly from transfer learning and extensive data augmentation, which enhances its ability to generalize from limited datasets. The reported results demonstrate very high accuracy for each tumor type, including perfect classification of some categories.However, the model still faces certain limitations. It cannot effectively detect multiple tumor regions within a single MRI scan, and its computational cost is comparatively high. Nonetheless, its multi-class classification capability makes it valuable for detailed clinical diagnosis.

III. Comparative Performance Analysis

The performance of the models is evaluated using a range of metrics. We provide a summary and comparison of the key findings from each paper. It is important to note that direct comparison can be challenging due to differences in datasets, classification tasks (binary vs. multi-class), and evaluation metrics used.

Methodology	Accuracy	AUC	Key Features
Active Contour + Texture Analysis	92%	0.9244	Signal processing-based, texture analysis for false alarm reduction
CNN Ensemble	99.92%	0.9999	Privacy-preserving via AES-128 and PBKDF2
Fine-tuned ResNet50	99%	0.999038	Multi-class classification (4 types), transfer learning
Fine-tuned EfficientNet-B0	98.87%	0.988	Lightweight model, comparative analysis of CNNs

Table 1: Performance Comparison of Different Methodologies

This table presents a comparative analysis of different brain tumor detection approaches based on their accuracy, Area Under the Curve (AUC), and distinctive features. Xu et al. [1] employed an active contour with texture analysis, achieving an accuracy of 92%, but with relatively lower AUC performance.Analysis of AUC values further supports this trend. All deep learning models achieve AUC scores above 0.98, reflecting excellent discriminatory capability between tumor and non-tumor classes. In contrast, the active contour method shows a lower AUC (0.92), indicating more difficulty handling ambiguous or low-contrast cases.From a computational perspective, EfficientNet-B0 demonstrates superior efficiency.

Its high accuracy combined with low parameter count makes it ideal for deployment on low-power devices. In contrast, the CNN ensemble, though highly accurate, demands considerably more memory and processing power, limiting its real-world usability in resource-constrained environments [21]. The resilience of each model against imaging variations also varies. ResNet50 and EfficientNet-B0 show strong generalization due to transfer learning and augmentation techniques. These models handle variations in brightness, orientation, and tumor shape more effectively compared to classical approaches.

In terms of real-world clinical application, each method provides unique advantages. The CNN ensemble is best suited for cloud-based secure medical diagnosis systems [2]. ResNet50 is ideal for multi-class tumor classification tasks required for treatment planning. Meanwhile, EfficientNet-B0's lightweight nature makes it suitable for emergency screening or use in remote healthcare settings. These results collectively highlight how performance, efficiency, and usability must be balanced depending on the intended deployment scenario.

IV. Discussion and Future Directions

The papers collectively highlight a clear trend toward deep learning as the dominant approach for automatic brain tumor detection. While the active contour model proposed by Xu et al. [1] offers a novel signal processing perspective and demonstrates robust segmentation capabilities, the sheer performance of CNNs on classification tasks, as shown by the other three studies, is undeniable.An important future direction, as pointed out by Lata et al. [2], is the integration of privacy and security features into diagnostic systems. As these systems become more prevalent, protecting sensitive patient data is paramount. The use of cryptographic algorithms like AES-128 is a promising step in this direction.

Furthermore, while the models presented by Younis et al. [3] and Shah et al. [4] show high overall accuracy, they also have limitations. Younis et al. [3] note their model's inability to detect multiple tumors in a single scan, which is a critical clinical requirement. Shah et al. [4] suggest future work on investigating more influential deep CNN models and expanding the datasets used for training to further improve performance.Another major theme emerging from this review is the growing emphasis on privacy and security in medical AI systems. The adoption of cryptographic methods, such as AES-128 encryption integrated with CNN-based diagnosis, demonstrates an essential requirement for ensuring patient confidentiality. This is especially critical as healthcare systems increasingly adopt cloud-based and IoT-enabled diagnostic workflows. Without strong privacy-preserving mechanisms, the scalability and practical deployment of automated tumor detection systems may face significant barriers.

V. Conclusion

This survey of four recent IEEE papers demonstrates the rapid advancements in computer-aided brain tumor diagnosis [2]. The field has evolved from classic signal processing methods to sophisticated deep learning architectures. While active contour models remain a valid approach for segmentation and can be augmented to reduce false alarms, deep learning-based methods, particularly those leveraging transfer learning with models like ResNet50, InceptionV3, and EfficientNet, consistently achieve high accuracy and are emerging as the standard [17]. The nascent, yet vital, area of privacy preservation in these systems, as demonstrated by the integration of cryptography, represents a crucial next step for the widespread adoption of smart healthcare technologies.

Despite remarkable progress, notable challenges remain. Current deep learning models often require large annotated datasets, and many fail to detect multiple tumors or handle multimodal MRI inputs effectively. Additionally, model interpretability, which plays a vital role in gaining clinicians' trust, is still limited in most CNN-based systems [11]. Future research should focus on developing hybrid models that integrate classical interpretability with deep learning accuracy, exploring multimodal MRI fusion techniques, and designing models capable of identifying tumor grade, size variations, and multiple tumor instances within the same scan [14]. Further, incorporating explainable AI (XAI) mechanisms, such as saliency maps or attention-based visualization, will enhance clinical trust and support decision-making.

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