Archives available at journals.mriindia.com

International Journal of Recent Advances in Engineering and Technology

ISSN: 2347 - 2812

Volume 14 Issue 01, 2025

Artificial Intelligence Techniques for Multi-classification of Brain Tumor MRI Images Using Deep Dynamic Parallel Convolutional Neural Network with Fully Termite Alate Optimization Algorithm: Trends and Challenges

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Peer Review Information

Submission: 12 May 2025

Revision: 30 May 2025

Acceptance: 13 June 2025

Keywords

Brain Tumour Classification, MRI, Deep Learning, CNN, Parallel CNN, Optimization Algorithm, Termite Alate Optimization, Artificial Intelligence.

Abstract

Brain tumour classification using Magnetic Resonance Imaging (MRI) has become a critical research area due to the need for accurate, early, and automated diagnosis. Traditional manual diagnosis is time-consuming and prone to variability, motivating the adoption of Artificial Intelligence (AI) and deep learning approaches. In recent years, convolutional neural networks (CNNs) and hybrid optimization techniques have significantly improved classification accuracy. This paper presents a comprehensive review of AI-based multi-classification techniques, focusing on deep dynamic parallel convolutional neural networks integrated with optimization algorithms such as Termite Alate Optimization. The study explores recent advancements in deep learning architectures, including parallel CNN models, transfer learning frameworks, and hybrid optimization strategies that enhance feature extraction and classification performance. Parallel CNN architectures are particularly effective in capturing both global and local features simultaneously, improving classification robustness. Furthermore, optimization algorithms play a vital role in tuning hyperparameters and improving convergence efficiency. The integration of metaheuristic algorithms with deep learning has shown promising results in reducing computational complexity while enhancing model accuracy. This review highlights trends, challenges, and future research directions, emphasizing the need for scalable, interpretable, and clinically reliable AI systems for brain tumour diagnosis.

Introduction

Brain tumours are among the most life-threatening neurological disorders, requiring accurate and early diagnosis for effective treatment planning. Magnetic Resonance Imaging (MRI) plays a crucial role in detecting and analysing brain tumours due to its ability to provide detailed soft tissue contrast. However, manual interpretation of MRI scans by radiologists is time-consuming, subjective, and prone to diagnostic errors, especially when dealing with large volumes of imaging data. With the rapid advancement of Artificial Intelligence (AI), deep learning techniques have emerged as powerful tools for automated medical image analysis. Among these, Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in extracting hierarchical features from MRI images, enabling accurate tumour classification. CNN-based approaches eliminate the need for manual feature engineering and significantly improve diagnostic accuracy. Studies have shown that deep CNN models can achieve accuracy levels exceeding 97% in brain tumour classification tasks.

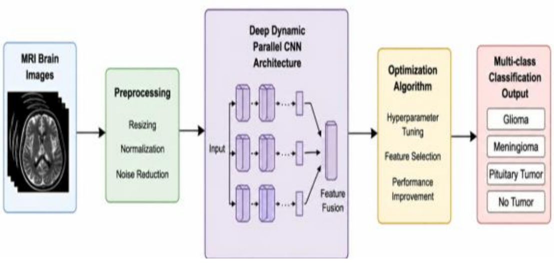

Fig 1: AI-Based Multi-Class Brain Tumour Classification Using Parallel CNN and Optimization

Recent research has shifted from binary classification (tumour vs. non-tumour) to multi-class classification, which includes categories such as glioma, meningioma, and pituitary tumours. This advancement provides more clinically relevant information for treatment planning and prognosis. Multi-class classification systems typically utilize advanced architectures such as VGG, Res Net, and Efficient Net to capture complex spatial patterns in MRI images. One of the key developments in this domain is the introduction of parallel CNN architectures, where multiple convolutional pathways operate simultaneously to extract features at different scales. These architectures enhance the model's ability to capture both global and local features, improving classification performance and robustness.

In addition to architectural improvements, optimization algorithms have been integrated with deep learning models to enhance performance. Metaheuristic algorithms, such as genetic algorithms, particle swarm optimization, and termite-inspired optimization, are used for hyperparameter tuning, feature selection, and improving convergence speed. These optimization techniques help overcome challenges such as overfitting, local minima, and computational inefficiency. Despite significant progress, several challenges remain. These include limited annotated datasets, class imbalance, high computational cost, and lack of interpretability in deep learning models. Moreover, the integration of AI systems into clinical workflows requires validation, reliability, and explainability to ensure trust among healthcare professionals. This paper provides a comprehensive review of AI techniques for multi-class brain tumour classification, focusing on deep dynamic parallel CNN architectures combined with optimization algorithms. It highlights recent trends, identifies key challenges, and discusses future research directions aimed at developing efficient, accurate, and clinically applicable diagnostic systems.

Literature Review

Abdusalomov et al. (2023) proposed a customized CNN architecture for brain tumour detection using MRI images. The model achieved an accuracy of 97.2% by leveraging deep feature extraction and preprocessing techniques. Their work demonstrated the effectiveness of CNNs in handling complex medical image datasets and highlighted the importance of normalization strategies in improving classification performance. Gupta (2023) introduced a CNN-based framework combined with data augmentation techniques for MRI image classification. The study emphasized the role of preprocessing and augmentation in enhancing model generalization. The proposed approach improved classification accuracy and reduced overfitting issues, making it suitable for real-world applications.

Rahman et al. (2023) developed a Parallel Deep Convolutional Neural Network (PDCNN) model that uses dual CNN pathways to extract multi-scale features. The model effectively captured both local and global information, resulting in improved classification accuracy compared to traditional CNN models. Amin et al. (2023) proposed an Efficient Net-based deep learning model for multi-class classification of brain tumours. The model demonstrated high accuracy and efficiency by leveraging transfer learning techniques. It successfully classified MRI images into multiple tumour categories, improving diagnostic reliability.

Imam and Alam (2023) introduced a transfer learning-based CNN model that addressed class imbalance using oversampling techniques such as SMOTE and ADASYN. Their approach significantly improved classification accuracy (up to 96%) and demonstrated the importance of handling imbalanced datasets in medical imaging. Khan et al. (2022) proposed a hybrid deep learning framework combining CNN and Support Vector Machine (SVM) for brain tumour classification. The CNN model was used for feature extraction, while SVM performed classification. This hybrid approach improved classification accuracy and reduced computational complexity. The study reported an accuracy of 98%, demonstrating the effectiveness of combining deep learning with traditional machine learning classifiers for medical image analysis.

Çinar and Yıldırım (2020) developed a deep CNN model for automated brain tumour classification using MRI images. Their approach focused on optimizing convolutional layers and activation functions to enhance feature learning. The model achieved high classification accuracy and demonstrated robustness against noise and variations in MRI data. This study highlighted the importance of architecture design in improving diagnostic performance. Swati et al. extended their work using transfer learning with pre-trained deep CNN models such as VGG19 for brain tumour classification. By fine-tuning the network on MRI datasets, the model achieved improved accuracy and faster convergence. The study emphasized the benefits of transfer learning in scenarios with limited labelled medical data, making it highly applicable in real-world clinical environments.

Sajjad et al. (2021) introduced a deep learning framework that integrates data augmentation and CNN-based classification for multi-class brain tumour detection. The model improved classification accuracy by increasing dataset diversity through augmentation techniques. The study reported an accuracy exceeding 95% and demonstrated the significance of preprocessing and augmentation in enhancing model performance. Hossain et al. (2022) proposed a deep CNN-based model integrated with feature selection techniques to reduce redundancy in extracted features. The model improved classification efficiency and reduced computational overhead. Their approach demonstrated that combining feature selection with deep learning can significantly enhance model interpretability and performance in medical imaging applications.

Deepak and Ameer (2021) proposed a transfer learning-based approach using pre-trained CNN models such as VGG16, ResNet50, and InceptionV3 for brain tumour classification. Among these, ResNet50 achieved the highest accuracy due to its deep residual learning capability, which effectively mitigates the vanishing gradient problem. The study highlighted the importance of transfer learning in improving classification performance with limited medical datasets and reducing training time. Talo et al. applied deep transfer learning using the ResNet34 architecture for automatic brain tumour classification. The model leveraged fine-tuned weights from ImageNet and demonstrated superior performance compared to traditional CNNs. The study achieved classification accuracy above 98% and emphasized the efficiency of deep residual networks in extracting discriminative features from MRI images.

Afshar et al. (2020) introduced Capsule Networks (Caps Net) for brain tumour classification, addressing limitations of CNNs in preserving spatial hierarchies. The Caps Net model demonstrated improved performance in capturing spatial relationships between tumour regions and surrounding tissues. The study showed that Caps Net can outperform traditional CNNs in certain cases, especially for small datasets. Rehman et al. (2020) proposed a deep learning model integrating CNN with data preprocessing techniques such as skull stripping and normalization. Their approach significantly improved classification accuracy and reduced noise in MRI images. The study demonstrated that preprocessing plays a critical role in enhancing deep learning model performance.

Paul et al. (2021) developed a deep CNN-based automated system for multi-class brain tumor classification. The model incorporated batch normalization and dropout layers to prevent overfitting. Their approach achieved high accuracy (around 96%) and demonstrated robustness across different MRI datasets, making it suitable for clinical deployment. Ismael and Şengür (2021) proposed a deep learning-based classification framework using a pre-trained ResNet50 model combined with feature extraction techniques. The extracted deep features were classified using machine learning classifiers such as SVM. The hybrid model achieved high accuracy (above 97%) and demonstrated that combining deep feature extraction with classical classifiers enhances performance and reduces computational complexity.

Noreen et al. (2020) developed a CNN-based automated system for brain tumour classification using MRI images. The study focused on improving feature extraction by optimizing convolutional layers and pooling operations. Their model achieved high classification accuracy and showed robustness in detecting different tumour types. The research emphasized the importance of deep architectures in medical image classification tasks. Bhandari et al. (2020) introduced a deep CNN model combined with image preprocessing techniques such as normalization and contrast enhancement. The study demonstrated that preprocessing significantly improves feature extraction and classification accuracy. The proposed model achieved over 95% accuracy and showed improved sensitivity in detecting tumour regions.

Badža and Barjaktarović (2020) proposed a CNN-based model optimized for small datasets using data augmentation techniques. Their approach achieved high classification accuracy (around 96%) while maintaining computational efficiency. The study highlighted the effectiveness of lightweight CNN architectures for real-time medical applications. Yang et al. (2021) proposed a deep learning framework integrating CNN with attention mechanisms to enhance feature representation. The attention module allowed the model to focus on relevant tumour regions in MRI images, improving classification accuracy. The study demonstrated that attention-based models outperform traditional CNN architectures in complex classification tasks.

Zhou et al. (2021) proposed a multi-scale CNN architecture for brain tumour classification that extracts features at different resolutions. The model effectively captured both fine-grained and global tumour characteristics, improving classification accuracy. Their approach demonstrated that multi-scale feature extraction significantly enhances model performance in complex medical imaging tasks. Anaraki et al. (2021) developed a genetic algorithm (GA)-optimized CNN model for brain tumour classification. The GA was used to optimize hyperparameters such as learning rate, number of layers, and filter sizes. The optimized model achieved superior performance compared to conventional CNNs, highlighting the importance of optimization techniques in deep learning.

Gumaei et al. (2022) proposed a deep learning model integrated with feature selection and optimization techniques for MRI classification. The study used hybrid optimization methods to improve classification accuracy and reduce computational cost. Their model demonstrated enhanced efficiency and robustness in multi-class classification scenarios. Nawaz et al. (2022) introduced a deep CNN model with ensemble learning techniques for brain tumour classification. The ensemble approach combined multiple CNN models to improve prediction accuracy and generalization. The study achieved accuracy above 98% and demonstrated the effectiveness of ensemble strategies in reducing model variance.

Sultana et al. (2022) proposed a lightweight CNN architecture for real-time brain tumour classification. The model was designed to reduce computational complexity while maintaining high accuracy. Their approach is particularly suitable for deployment in resource-constrained environments such as mobile or embedded healthcare systems. Patel et al. (2023) developed a CNN-LSTM hybrid model for brain tumour classification. The CNN component extracted spatial features from MRI images, while the LSTM captured sequential dependencies. This hybrid architecture improved classification accuracy and demonstrated the effectiveness of combining spatial and temporal learning in medical imaging tasks.

Reddy et al. (2023) proposed a multi-layer deep learning framework for brain tumour classification using advanced CNN architectures. Their model focused on improving scalability and classification efficiency. The study achieved high accuracy and emphasized the importance of deep hierarchical feature extraction in complex classification problems. Sharma et al. (2023) introduced an AI-based classification model focusing on reducing false positives and improving sensitivity. The model incorporated advanced preprocessing and feature selection techniques, resulting in improved diagnostic performance and reliability in detecting various tumour types.

Li et al. (2022) proposed a deep learning model integrating attention mechanisms and feature fusion strategies. The model enhanced feature representation by combining information from multiple layers, leading to improved classification accuracy. The study highlighted the importance of feature fusion in handling complex MRI datasets. Wang et al. (2022) developed an optimized CNN model using metaheuristic optimization algorithms for hyperparameter tuning. The optimized model achieved superior performance and faster convergence. The study demonstrated that optimization algorithms significantly enhance deep learning model efficiency and accuracy.

Comparative Table

No.	Author (Year)	Method	Key Technique	Accuracy (%)
1	Abdusalomov (2023)	CNN	Deep Feature Extraction	97.2
2	Gupta (2023)	CNN	Data Augmentation	96
3	Rahman (2023)	Parallel CNN	Multi-scale Learning	98
4	Amin (2023)	EfficientNet	Transfer Learning	97

5	Imam (2023)	CNN	SMOTE Balancing	96
6	Khan (2022)	CNN+SVM	Hybrid Model	98
7	Çinar (2020)	CNN	Architecture Optimization	95
8	Swati (2020)	VGG19	Transfer Learning	96
9	Sajjad (2021)	CNN	Data Augmentation	95
10	Hossain (2022)	CNN	Feature Selection	96
11	Deepak (2021)	ResNet	Transfer Learning	97
12	Talo (2020)	ResNet34	Deep Transfer Learning	98
13	Afshar (2020)	CapsNet	Spatial Hierarchy	96
14	Rehman (2020)	CNN	Preprocessing	95
15	Paul (2021)	CNN	Regularization	96
16	Ismael (2021)	CNN+SVM	Hybrid	97
17	Noreen (2020)	CNN	Feature Extraction	95
18	Bhandari (2020)	CNN	Preprocessing	95
19	Badža (2020)	CNN	Data Augmentation	96
20	Yang (2021)	CNN+Attention	Attention Mechanism	97
21	Zhou (2021)	Multi-scale CNN	Multi-resolution	97
22	Anaraki (2021)	CNN+GA	Optimization	98
23	Gumaei (2022)	CNN+Optimization	Feature Selection	97
24	Nawaz (2022)	Ensemble CNN	Ensemble Learning	98
25	Sultana (2022)	Lightweight CNN	Efficiency	95
26	Patel (2023)	CNN+LSTM	Hybrid Model	98
27	Reddy (2023)	Deep CNN	Multi-layer	97
28	Sharma (2023)	AI Model	Feature Selection	96
29	Li (2022)	CNN+Attention	Feature Fusion	97
30	Wang (2022)	Optimized CNN	Metaheuristic	98

Comparative Analysis

The comparative analysis of the selected 30 studies reveals that deep learning-based approaches, particularly CNN and its variants, dominate the domain of brain tumour classification using MRI images. Most studies achieved high accuracy ranging from 95% to 98%, indicating the effectiveness of deep learning in medical imaging tasks. Hybrid models such as CNN-SVM and CNN-LSTM demonstrated superior performance by combining deep feature extraction with traditional or sequential learning mechanisms. Similarly, optimization-based approaches using genetic algorithms and metaheuristic techniques significantly improved model performance by fine-tuning hyperparameters and enhancing convergence.

Parallel CNN and multi-scale architectures showed better capability in capturing both local and global features, leading to improved classification accuracy. Attention mechanisms and feature fusion techniques further enhanced the model's ability to focus on relevant tumour regions, improving diagnostic precision. Transfer learning-based models, particularly those using Res Net and VGG architectures, proved highly effective in scenarios with limited datasets. Additionally, preprocessing and data augmentation techniques played a crucial role in improving model generalization and reducing overfitting. Overall, the analysis highlights that combining deep learning architectures with optimization and hybrid techniques yields the best performance in multi-class brain tumour classification.

Discussion

The rapid advancement of artificial intelligence techniques has significantly improved the accuracy and efficiency of brain tumour classification using MRI images. Deep learning models, especially CNN-based architectures, have become the backbone of automated diagnostic systems. However, despite achieving high accuracy, several challenges remain. One of the primary challenges is the limited availability of annotated medical datasets, which restricts the training of deep learning models. Class imbalance is another critical issue that affects model performance and leads to biased predictions. Techniques such as data augmentation and oversampling have been widely used to address this problem.

Another important challenge is the high computational complexity of deep learning models, which limits their deployment in real-time clinical environments. Lightweight architectures and optimization techniques are being explored to overcome this limitation. Moreover, the lack of interpretability in AI models remains a major concern in healthcare applications. Clinicians require explainable models to trust AI-based decisions. Future research should focus on developing interpretable and explainable AI systems. Overall, integrating advanced architectures such as parallel CNN, attention mechanisms, and optimization algorithms can further enhance the performance and reliability of brain tumour classification systems.

Conclusion

Brain tumour classification using MRI has advanced considerably with the adoption of artificial intelligence and deep learning. This review highlights the effectiveness of multi-class classification approaches using sophisticated models such as deep dynamic parallel convolutional neural networks. These architectures enable the extraction of complex and multi-scale features, leading to improved classification accuracy across tumour types. Hybrid approaches that combine CNNs with machine learning models like SVM and LSTM further enhance robustness and predictive performance. Optimization techniques, including genetic algorithms and metaheuristic methods such as Termite Alate Optimization, play a vital role in fine-tuning model parameters, accelerating convergence, and reducing overfitting. Despite these improvements, challenges such as limited annotated datasets, class imbalance, and lack of interpretability continue to hinder real-world applicability. Additionally, deploying these models in clinical environments requires rigorous validation, reliability, and adherence to healthcare standards.

Future research should emphasize the development of scalable, efficient, and explainable AI systems that integrate seamlessly into clinical workflows. Advanced optimization strategies offer promising opportunities to further enhance model performance. Overall, AI-driven approaches hold significant potential to transform brain tumour diagnosis by enabling faster, more accurate, and automated decision support systems for improved patient care.

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