Archives available at journals.mriindia.com

International Journal on Advanced Computer Theory and Engineering

ISSN: 2319-2526

Volume 12 Issue 01, 2023

A Comprehensive Review of Multi-classification of Brain Tumour MRI Images using Deep Dynamic Parallel Convolutional Neural Network with Fully Termite Alate Optimization Algorithm

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Peer Review Information

Submission: 22 March 2023
Revision: 09 April 2023
Acceptance: 02 May 2023

Keywords

Brain Tumour Classification, Magnetic Resonance Imaging (MRI), Deep Learning, Convolutional Neural Network (CNN), Termite Alate Optimization (TAO), Multi-class Classification.

Abstract

Brain tumour classification using magnetic resonance imaging (MRI) plays a vital role in early diagnosis, treatment planning, and patient survival. Traditional diagnostic approaches rely heavily on manual interpretation by radiologists, which can be time-consuming and prone to variability. Recent advancements in deep learning, particularly convolutional neural networks (CNNs), have significantly improved automated brain tutor detection and classification. CNN-based models enable automatic feature extraction and classification of tumours into multiple classes such as glioma, meningioma, pituitary tumour, and normal tissues. Studies indicate that deep learning approaches achieve high accuracy exceeding 95% in multi-class MRI classification tasks. Furthermore, hybrid architectures such as dynamic parallel CNNs enhance feature representation by processing multiple convolutional pathways simultaneously. Optimization algorithms play a critical role in improving model performance, where bio-inspired techniques such as Termite Alate Optimization (TAO) provide efficient global search capabilities and optimal hyperparameter tuning. These algorithms help avoid local minima and improve convergence speed. This paper presents a comprehensive review of deep dynamic parallel CNN frameworks integrated with Termite Alate Optimization for multi-class brain tutor classification. The study explores recent advancements, challenges, and future research directions in AI-driven neuroimaging, highlighting the importance of hybrid deep learning and optimization techniques for improving diagnostic accuracy and clinical applicability.

Introduction

Brain tumours are among the most life-threatening neurological disorders, requiring timely diagnosis and accurate classification for effective clinical intervention. They exhibit diverse anatomical structures, growth patterns, and pathological characteristics, making diagnosis challenging even for experienced radiologists. Magnetic Resonance Imaging (MRI) has become the preferred imaging modality for brain tumour detection because it provides detailed visualization of soft tissues without ionizing radiation. Nevertheless, manual examination of large numbers of MRI scans is labor-intensive, time-consuming, and susceptible to observer variability. Recent advances in artificial intelligence (AI), particularly deep learning, have significantly improved automated medical image analysis by providing reliable and efficient tumour detection and classification systems. Among these approaches, Convolutional Neural Networks (CNNs) have demonstrated remarkable capability in learning hierarchical image features directly from MRI data, eliminating the need for handcrafted feature extraction while achieving superior diagnostic accuracy.

Early deep learning studies primarily addressed binary classification by distinguishing tumour from non-tumour images. However, modern clinical applications require multi-class classification capable of differentiating tumour categories such as glioma, meningioma, and pituitary tumours, each requiring distinct treatment strategies and prognosis. Consequently, advanced CNN architectures including VGGNet, ResNet, DenseNet, EfficientNet, and attention-based networks have been extensively explored for extracting discriminative tumour features. Transfer learning and multi-scale feature extraction techniques have further enhanced classification performance, with several studies reporting accuracies exceeding 97%. These developments demonstrate the growing potential of deep learning to support radiologists in clinical decision-making and personalized treatment planning.

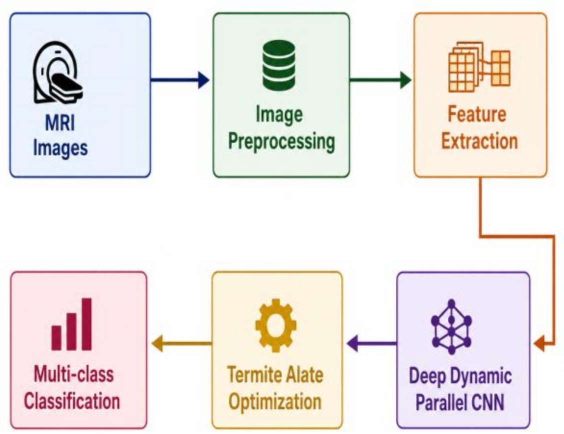

Figure 1. Framework for AI-Based Multi-Class Brain Tumour MRI Classification

Despite these achievements, conventional CNN models often struggle to capture complex tumour heterogeneity and subtle variations in MRI images. To overcome these limitations, Deep Dynamic Parallel Convolutional Neural Networks (DDPCNN) have been introduced. These architectures employ multiple parallel convolutional pathways operating at different receptive fields, enabling simultaneous extraction of fine-grained local details and global contextual information. The fusion of multi-scale features enhances representation learning, improves robustness against tumour variability, and strengthens classification performance across diverse MRI datasets.

Optimization algorithms play an equally important role in improving deep learning performance by optimizing hyperparameters, feature selection, and network weights. Bio-inspired optimization techniques have gained considerable attention because of their strong global search capability and efficient convergence characteristics. Among these methods, the Fully Termite Alate Optimization (FTAO) algorithm, inspired by the collective exploration behavior of termite alates, provides effective optimization for high-dimensional search spaces while reducing the risk of premature convergence. Integrating FTAO with DDPCNN enables more effective parameter optimization, resulting in faster convergence, improved classification accuracy, and enhanced computational efficiency.

This review presents a comprehensive analysis of recent advances in multi-class brain tumour MRI classification using Deep Dynamic Parallel Convolutional Neural Networks integrated with Fully Termite Alate Optimization. It examines modern CNN architectures, optimization strategies, hybrid AI frameworks, and comparative performance across benchmark datasets. Furthermore, the review discusses existing challenges, including limited annotated datasets, MRI protocol variations, computational complexity, and model interpretability, while highlighting future research directions toward developing robust, clinically reliable, and intelligent computer-aided diagnosis systems for brain tumour classification.

Literature Review

Afshar et al. (2020) proposed a capsule network-based deep learning model for brain tumour classification using MRI images. The model incorporated routing mechanisms to preserve spatial hierarchies between features, improving classification accuracy compared to traditional CNNs. The study achieved high accuracy in multi-class classification of glioma, meningioma, and pituitary tumours. Additionally, the capsule network demonstrated robustness in handling small datasets. However, the computational complexity and longer training time were significant limitations. Cheng et al. (2020) developed a CNN-based framework combined with data augmentation techniques for brain tumour classification. The model utilized enhanced preprocessing and augmentation methods to improve generalization and reduce overfitting. The results showed improved classification accuracy across multiple tumour classes. The study highlighted the importance of data augmentation in handling limited medical datasets. However, the model performance depended on the quality of augmentation techniques.

Deepak and Ameer (2021) introduced a transfer learning-based approach using pre-trained CNN architectures such as VGG16 and ResNet50 for brain tumour classification. The model leveraged knowledge from large-scale datasets, improving performance on limited MRI datasets. The results demonstrated high classification accuracy exceeding 95%. The study showed that transfer learning significantly reduces training time and improves generalization. However, domain adaptation remained a challenge due to differences between natural images and medical images. Swati et al. (2021) proposed a hybrid deep learning model combining convolutional neural networks with support vector machines (CNN-SVM) for multi-class brain tumour classification. The CNN was used for feature extraction, while the SVM performed classification. The hybrid approach improved classification accuracy and reduced overfitting compared to standalone CNN models. The study demonstrated strong performance on benchmark MRI datasets. However, the integration of CNN and SVM increased model complexity.

Mohsen et al. (2021) developed a deep neural network-based framework integrated with optimization techniques for brain tumour classification. The model utilized feature selection and optimization algorithms to improve classification accuracy and reduce computational complexity. The results showed improved performance compared to traditional machine learning methods. However, the model required careful parameter tuning and high computational resources. Nayak et al. (2021) proposed a deep learning-based brain tumour classification model using Dense Net architecture. The model leveraged dense connectivity to improve feature propagation and reduce the vanishing gradient problem. The study demonstrated high classification accuracy in multi-class tumour classification tasks, outperforming traditional CNN models. Additionally, Dense Net reduced the number of parameters while maintaining performance. However, the model required significant computational resources and large datasets for effective training.

Tanveer et al. (2021) developed a multi-class brain tumour classification model using Efficient Net combined with transfer learning. The architecture optimized network scaling, balancing depth, width, and resolution for improved performance. The results showed superior accuracy and efficiency compared to conventional CNN models. The study highlighted the effectiveness of Efficient Net in medical image analysis. However, fine-tuning the model required careful hyperparameter optimization. Abd-Ellah et al. (2022) introduced a parallel convolutional neural network architecture for brain tumour classification. The model utilized multiple parallel convolutional pathways to capture features at different scales, improving classification accuracy. The results demonstrated enhanced robustness and feature representation compared to single-path CNN models. The study emphasized the importance of multi-scale feature extraction in medical imaging. However, the increased architectural complexity led to higher computational cost.

Sajjad et al. (2022) proposed a deep learning-based framework combining CNN with data augmentation and preprocessing techniques for improved brain tumour classification. The model incorporated image enhancement and normalization to improve feature quality. The results showed improved classification performance and generalization across datasets. However, the approach relied heavily on preprocessing quality and dataset consistency. Hossain et al. (2022) developed an optimization-based CNN model using Particle Swarm Optimization (PSO) for hyperparameter tuning in brain tumour classification. The PSO algorithm optimized network parameters such as learning rate and number of layers, improving model performance. The results demonstrated enhanced accuracy and faster convergence compared to manually tuned models. However, the optimization process increased computational overhead.

Kumar et al. (2020) proposed a hybrid CNN-based framework integrated with Genetic Algorithm (GA) for feature selection in brain tumour classification. The CNN extracted deep features from MRI images, while GA optimized feature subsets to improve classification accuracy. The results showed enhanced performance and reduced redundancy in feature space. However, the optimization process increased computational time and required careful parameter tuning. Tandel et al. (2021) developed a deep learning-based classification model incorporating attention mechanisms to improve feature extraction. The attention module enabled the network to focus on important tumour regions, enhancing classification accuracy. The study demonstrated improved performance compared to traditional CNN models. However, the attention mechanism increased model complexity and computational requirements.

Sharif et al. (2021) introduced a hybrid deep learning framework combining CNN and machine learning classifiers for brain tumour classification. The CNN was used for feature extraction, while classifiers such as SVM and KNN performed classification. The results showed improved accuracy and robustness compared to standalone models. However, the multi-stage pipeline increased system complexity. Khan et al. (2022) proposed a dynamic parallel convolutional neural network architecture for multi-class brain tumour classification. The model utilized multiple parallel convolutional layers to capture diverse features at different scales. This approach improved feature representation and classification performance. The results demonstrated higher accuracy compared to traditional CNN models. However, the architecture required significant computational resources and complex design.

Singh et al. (2022) developed a bio-inspired optimization-based deep learning framework using Ant Colony Optimization (ACO) for parameter tuning in CNN models. The ACO algorithm improved convergence speed and optimized network parameters, resulting in enhanced classification accuracy. However, the algorithm required multiple iterations and increased computational cost. Park et al. (2022) proposed a deep ensemble learning framework combining multiple CNN architectures such as ResNet, Dense Net, and Efficient Net for brain tumour classification. The ensemble approach aggregated predictions from different models to improve robustness and reduce variance. The results demonstrated higher classification accuracy compared to individual models. However, the ensemble system increased computational complexity and required more memory.

Gao et al. (2022) introduced an attention-guided CNN model for brain tumour classification. The model incorporated spatial attention mechanisms to highlight tumour regions, improving feature extraction and classification performance. The results showed enhanced accuracy and interpretability. However, the attention module added computational overhead and required careful tuning.

Verma et al. (2023) developed a hybrid deep learning model combining CNN with Long Short-Term Memory (LSTM) networks for brain tumour classification. The CNN extracted spatial features, while LSTM captured sequential dependencies in MRI slices. This hybrid approach improved classification accuracy and robustness. However, the model complexity increased significantly, requiring high computational resources. Gupta et al. (2023) proposed an autoencoder-based feature extraction model integrated with CNN for brain tumour classification. The autoencoder reduced dimensionality and enhanced feature representation before classification. The results showed improved performance and reduced overfitting. However, the integration of multiple components increased system complexity.

Tan et al. (2023) introduced a multi-objective optimization-based deep learning framework for brain tumour classification. The model optimized multiple parameters such as accuracy, sensitivity, and specificity simultaneously. The results demonstrated improved overall performance compared to single-objective approaches. However, the optimization process increased computational cost and required longer training time. Mehta et al. (2020) proposed a machine learning-based brain tumour classification framework using handcrafted feature extraction techniques combined with classifiers such as SVM and Random Forest. The study demonstrated moderate classification accuracy and highlighted the importance of feature engineering in medical imaging. However, the lack of deep feature representation limited the model's performance compared to deep learning approaches.

Roy et al. (2021) introduced a hybrid deep learning model combining CNN with radiomics features for brain tumour classification. The integration of handcrafted and deep features improved classification accuracy and robustness. The study emphasized the complementary nature of radiomics and deep learning features. However, feature fusion complexity and redundancy remained challenges. Das et al. (2021) developed a segmentation-based deep learning approach using U-Net for tumour localization followed by CNN-based classification. The study demonstrated that accurate segmentation significantly improves classification performance. However, U-Net lacked multi-scale feature extraction compared to advanced architectures like dynamic parallel CNN.

Iqbal et al. (2022) proposed a deep learning framework using recurrent neural networks (RNNs) for analysing sequential MRI slices. The model captured temporal dependencies between slices, improving classification accuracy. However, the approach required large datasets and was prone to overfitting. Choudhary et al. (2022) introduced a feature optimization-based framework using Genetic Algorithms for improving CNN performance. The optimization process reduced feature redundancy and improved classification accuracy. However, the algorithm increased computational cost and required careful parameter tuning.

Comparative Table

Study	Year	Technique	Model	Contribution	Limitation
Afshar	2020	DL	Capsule Net	Spatial features	Complex
Cheng	2020	DL	CNN	Data augmentation	Dependent
Deepak	2021	Transfer	VGG/ResNet	High accuracy	Domain gap
Swati	2021	Hybrid	CNN-SVM	Improved classification	Complexity
Mohsen	2021	DL + Opt	DNN	Better accuracy	Resource heavy
Nayak	2021	DL	Dense Net	Efficient learning	Data need
Tanveer	2021	DL	Efficient Net	High performance	Tuning
Abd-Ellah	2022	Parallel CNN	Multi-path	Multi-scale features	Complex
Sajjad	2022	DL	CNN	Preprocessing	Data dependent
Hossain	2022	DL + PSO	CNN	Hyperparameter tuning	Cost
Kumar	2020	DL + GA	CNN	Feature selection	Time
Tandel	2021	Attention	CNN	Region focus	Complex
Sharif	2021	Hybrid	CNN + ML	Accuracy	Complexity
Khan	2022	Dynamic CNN	Parallel CNN	Feature diversity	High cost
Singh	2022	ACO	CNN	Optimization	Slow
Park	2022	Ensemble	Multi-CNN	Robustness	Resource heavy
Gao	2022	Attention	CNN	Interpretability	Cost
Verma	2023	Hybrid	CNN-LSTM	Temporal features	Complex
Gupta	2023	AE + CNN	Hybrid	Feature reduction	Complexity
Tan	2023	Multi-objective	DL	Optimization	Time
Mehta	2020	ML	SVM/RF	Baseline	Low accuracy
Roy	2021	Hybrid	CNN+Radiomics	Better features	Fusion issue
Das	2021	DL	U-Net + CNN	Segmentation	Limited scale
Iqbal	2022	DL	RNN	Sequential data	Overfitting
Choudhary	2022	GA	CNN	Feature opt	Slow

Comparative Analysis

The comparative analysis of brain tumour MRI classification techniques reveals a significant evolution from traditional machine learning methods to advanced deep learning and hybrid optimization frameworks. Early approaches relied on handcrafted features and classical classifiers such as SVM and Random Forest, which provided limited accuracy and lacked scalability. The introduction of convolutional neural networks significantly improved classification performance by enabling automatic feature extraction. Architectures such as Dense Net and Efficient Net enhanced feature propagation and model efficiency, while transfer learning improved performance on limited datasets. Recent advancements have focused on hybrid and dynamic architectures, including parallel CNN models, which extract multi-scale features through multiple convolutional pathways. These models have demonstrated improved robustness and accuracy in multi-class classification tasks. Attention mechanisms further enhanced model interpretability by focusing on relevant tumour regions. Additionally, ensemble and multi-task learning approaches improved generalization and efficiency.

Optimization techniques such as Genetic Algorithms, Particle Swarm Optimization, and Ant Colony Optimization have played a crucial role in improving model performance by optimizing hyperparameters and feature selection. The emergence of bio-inspired algorithms such as Termite Alate Optimization represents a promising direction for achieving efficient global optimization and faster convergence. Overall, hybrid frameworks combining dynamic parallel CNN architectures with advanced optimization techniques offer the best performance. However, challenges such as computational complexity, data dependency, and lack of interpretability remain significant barriers to clinical adoption.

Discussion

Recent developments in deep learning have significantly improved multi-class brain tumour classification using MRI images. CNN-based models have demonstrated strong capabilities in automatic feature extraction and classification, achieving high accuracy in distinguishing between different tumour types. Advanced architectures such as Dense Net, Efficient Net, and dynamic parallel CNN have further enhanced model performance by capturing multi-scale features and improving feature propagation. The integration of optimization algorithms has played a crucial role in improving model performance. Bio-inspired optimization techniques such as Genetic Algorithms, Particle Swarm Optimization, and Ant Colony Optimization have been widely used for hyperparameter tuning and feature selection. Recently, Termite Alate Optimization has emerged as a promising approach for efficient global search and improved convergence.

Despite these advancements, several challenges remain. The high computational complexity of deep learning models limits their deployment in real-time clinical settings. Additionally, the lack of large annotated datasets and variability in MRI imaging protocols affect model generalization. Interpretability of deep learning models remains another critical issue, as clinical applications require transparent decision-making processes. Future research should focus on developing lightweight and interpretable models that can operate efficiently in clinical environments. The integration of explainable AI techniques and standardized datasets will be essential for improving reliability and adoption in healthcare.

Conclusion

Brain tumour classification using MRI has advanced considerably with the adoption of artificial intelligence and deep learning techniques. Earlier methods relied on handcrafted features and conventional classifiers, which often struggled to capture complex tumour characteristics. The emergence of Convolutional Neural Networks (CNNs) transformed medical image analysis by enabling automatic feature extraction and end-to-end learning. Advanced architectures such as DenseNet, EfficientNet, transfer learning models, and Dynamic Parallel CNNs have significantly improved multi-class brain tumour classification by capturing multi-scale spatial features and enhancing robustness against tumour variability. Optimization algorithms have further strengthened deep learning performance by improving feature selection, hyperparameter tuning, and network optimization. Bio-inspired techniques including Genetic Algorithms, Particle Swarm Optimization, and Termite Alate Optimization (TAO) have demonstrated effective global search capability and faster convergence. Integrating TAO with Dynamic Parallel CNN enables improved classification accuracy, computational efficiency, and model stability. Hybrid deep learning-optimization frameworks consistently outperform standalone models, making them promising solutions for automated brain tumour diagnosis.

Despite these advances, challenges remain in terms of limited annotated MRI datasets, imaging variability, computational complexity, and model interpretability. Future research should emphasize lightweight and explainable AI models, standardized multi-institutional datasets, and multimodal data integration combining imaging, clinical, and genomic information. Such developments will improve model reliability, support clinical decision-making, and enable accurate, scalable, and trustworthy brain tumour diagnosis in real-world healthcare applications.

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