Archives available at journals.mriindia.com

International Journal of Electrical, Electronics and Computer Systems

ISSN: 2347-2820

Volume 14 Issue 01, 2025

A Survey of Methods and Architectures for 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 April 2025

Revision: 05 May 2025

Acceptance: 20 May 2025

Keywords

Brain Tumour, MRI Classification, Deep Learning, Convolutional Neural Network (CNN), Optimization Algorithm, Multi-class Classification.

Abstract

Brain tumour classification using Magnetic Resonance Imaging (MRI) is a critical task for early diagnosis and treatment planning. Traditional diagnostic methods rely heavily on manual interpretation, which is time-consuming and prone to errors. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have significantly improved the accuracy of automated brain tumour classification systems. Multi-class classification approaches can effectively distinguish tumour types such as glioma, meningioma, and pituitary tumours, enhancing clinical decision-making. Modern architectures such as deep dynamic parallel convolutional neural networks (DDPCNN) leverage multiple parallel pathways to capture both local and global features from MRI images, improving classification performance. Additionally, optimization algorithms play a crucial role in enhancing deep learning models by tuning hyperparameters, improving convergence, and avoiding local minima. Metaheuristic approaches, including swarm intelligence and bio-inspired algorithms, have been widely adopted for this purpose. This review presents a comprehensive analysis of recent deep learning and optimization approaches for brain tumour MRI classification. It focuses on hybrid frameworks combining CNN architectures with optimization techniques such as termite alate optimization. The study highlights key advancements, compares methodologies, and identifies challenges such as computational complexity and data imbalance, providing future research directions for intelligent diagnostic systems.

Introduction

Brain tumours are among the most dangerous neurological disorders, posing significant risks to human health due to their complexity and high mortality rates. Accurate classification of brain tumours is essential for determining appropriate treatment strategies and improving patient survival rates. Magnetic Resonance Imaging (MRI) is widely used for brain tumour diagnosis because of its ability to provide high-resolution images without radiation exposure. However, manual analysis of MRI scans is time-consuming and subject to human error, necessitating the development of automated diagnostic systems. Deep learning has revolutionized medical image analysis, particularly in brain tumour classification. Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in extracting hierarchical features from MRI images, enabling accurate classification of tumour types. Recent studies have shown that CNN-based models can achieve classification accuracies exceeding 98% in multi-class brain tumour detection tasks. These models outperform traditional machine learning approaches by automatically learning complex patterns from data.

One of the major advancements in this field is the development of multi-class classification systems capable of distinguishing between different tumour types, such as glioma, meningioma, and pituitary tumours. Multi-class classification provides a more comprehensive diagnostic framework compared to binary classification, which only identifies the presence or absence of tumours. Recent research has also focused on improving CNN architectures to enhance performance. Deep dynamic parallel convolutional neural networks (DDPCNN) have emerged as a promising approach, incorporating multiple parallel convolutional pathways to capture both global and local features. These architectures improve feature extraction and classification accuracy by processing information at different scales simultaneously.

In addition to architectural improvements, optimization techniques play a crucial role in enhancing deep learning models. CNNs involve numerous hyperparameters, including learning rates, filter sizes, and network depth, which significantly impact model performance. Metaheuristic optimization algorithms, such as Particle Swarm Optimization (PSO), genetic algorithms (GA), and bio-inspired methods, have been widely used to optimize these parameters. These algorithms improve convergence speed and help avoid local minima, leading to better classification results. The introduction of bio-inspired optimization algorithms, such as termite alate optimization, represents a new direction in this field. These algorithms mimic natural behaviours to efficiently explore the search space and optimize model parameters. When combined with deep learning architectures, they offer improved performance and robustness.

Despite these advancements, several challenges remain. Brain tumour datasets are often limited and imbalanced, affecting model generalization. Additionally, deep learning models require high computational resources, making real-time implementation challenging. The interpretability of AI models is another critical concern for clinical adoption. This survey aims to provide a comprehensive overview of recent deep learning and optimization approaches for brain tumour MRI classification. It focuses on DDPCNN architectures and termite alate optimization, analysing their effectiveness, advantages, and limitations. The study also identifies research gaps and suggests future directions for developing efficient and reliable AI-based diagnostic systems.

Literature Review

Khan et al. (2020) presented a deep convolutional neural network (CNN)-based framework for multi-class classification of brain tumours using MRI images. The model architecture consisted of multiple convolutional and pooling layers designed to automatically extract hierarchical features from input images. To enhance performance, the authors incorporated data augmentation techniques such as rotation, flipping, and scaling, which helped mitigate overfitting and improve generalization. The study compared the proposed CNN with traditional machine learning classifiers, including support vector machines (SVM) and k-nearest neighbours (KNN), and reported significantly higher classification accuracy for the deep learning approach. The results demonstrated that CNNs are capable of capturing complex spatial patterns in MRI data, enabling accurate differentiation between glioma, meningioma, and pituitary tumours. However, the model required a large labelled dataset and extensive computational resources, which may limit its application in resource-constrained environments.

Yaqub et al. (2020) investigated the impact of optimization algorithms on the performance of CNN-based brain tumour classification systems. The study evaluated widely used optimizers such as Stochastic Gradient Descent (SGD), Root Mean Square Propagation (RMSProp), and Adaptive Moment Estimation (Adam). The results showed that Adam provided faster convergence and better classification accuracy due to its adaptive learning rate mechanism. The authors emphasized that optimization algorithms play a crucial role in improving deep learning model performance by accelerating training and reducing the risk of getting trapped in local minima. Additionally, the study highlighted that improper selection of optimizers can lead to unstable training and poor generalization. Despite its advantages, the Adam optimizer required careful hyperparameter tuning to achieve optimal results.

Hu et al. (2021) proposed a hybrid deep learning framework that integrates CNN with a metaheuristic optimization algorithm for feature selection. The model utilized a deep belief network combined with a nature-inspired optimization technique to identify the most relevant features from MRI images. This approach reduced feature redundancy and improved classification accuracy. The study demonstrated that optimization algorithms can effectively enhance feature selection and improve model efficiency by reducing computational complexity. Experimental results showed that the hybrid model outperformed standalone CNN models in terms of accuracy and robustness. However, the integration of optimization algorithms increased computational overhead and required additional processing time.

Sadad et al. (2021) developed a hybrid brain tumour classification system combining reinforcement learning (RL) with evolutionary algorithms. The model used RL to learn optimal classification policies and evolutionary algorithms to optimize network parameters. This combination enabled the system to adapt dynamically to different data distributions and improve classification performance. The study reported high accuracy in multi-class tumour classification tasks, demonstrating the effectiveness of combining learning-based and optimization-based approaches. However, the complexity of the hybrid model resulted in increased training time and computational requirements, making real-time implementation challenging.

Nickparvar et al. (2021) introduced Deep Tumour Net, a modified Google Net architecture designed specifically for brain tumour classification. The model incorporated inception modules to capture multi-scale features from MRI images, improving classification accuracy and robustness. The study demonstrated that deep architectures with multi-scale feature extraction capabilities can significantly enhance tumour classification performance. The model achieved high accuracy across multiple tumour types, indicating strong generalization capability. However, the complexity of the network architecture required extensive training time and high computational resources.

Ismael et al. (2020) proposed a transfer learning-based approach using pre-trained CNN models such as ResNet-50 and VGG-16 for brain tumour classification. The use of transfer learning allowed the model to leverage knowledge from large-scale datasets, improving performance on smaller medical datasets. The study demonstrated that transfer learning significantly reduces training time and enhances classification accuracy. However, the reliance on pre-trained models limited the ability to capture domain-specific features unique to brain tumour MRI images.

Tandel et al. (2021) developed a deep CNN-based classification system incorporating advanced preprocessing techniques such as noise reduction and contrast enhancement. These preprocessing steps improved image quality and facilitated better feature extraction. The model achieved high classification accuracy and demonstrated robustness across different MRI datasets. However, the preprocessing pipeline increased system complexity and required additional computational resources.

Afshar et al. (2021) introduced a capsule network (Caps Net)-based approach for brain tumour classification. Unlike traditional CNNs, Caps Net preserves spatial relationships between features, enabling better representation of tumour structures. The study demonstrated improved classification accuracy compared to CNN-based models, particularly in small datasets. However, the computational complexity and longer training time of capsule networks limited their practical application.

Swati et al. (2022) proposed a hybrid model combining CNN with Particle Swarm Optimization (PSO) for feature selection and hyperparameter tuning. The PSO algorithm improved the efficiency of feature selection and enhanced model convergence. The study reported significant improvements in classification accuracy compared to standalone CNN models. However, the integration of PSO increased computational overhead and required careful parameter tuning.

Rehman et al. (2022) developed a brain tumour classification framework using Efficient Net, a lightweight deep learning architecture known for its efficiency and scalability. The model achieved high classification accuracy while reducing computational complexity compared to traditional CNN models. The study highlighted the importance of efficient architectures for real-time medical applications. However, the model performance was sensitive to hyperparameter settings and required careful tuning.

Sajjad et al. (2021) proposed a deep learning-based multi-grade brain tumour classification framework that integrates convolutional neural networks with extensive preprocessing techniques. The preprocessing pipeline included skull stripping, noise removal, and contrast enhancement to improve image quality before feeding the data into the CNN model. The authors also employed data augmentation strategies to address dataset imbalance and improve generalization. The model demonstrated high classification accuracy across multiple tumour types and grades, indicating the effectiveness of combining preprocessing with deep learning. However, the reliance on handcrafted preprocessing steps increased system complexity and reduced the level of automation.

Abiwinanda et al. (2021) developed a CNN-based approach for multi-class brain tumour classification using MRI images. The study evaluated different CNN architectures with varying depths and configurations to determine their impact on classification performance. The results indicated that deeper networks achieved higher accuracy due to their ability to learn complex hierarchical features. However, the study also observed overfitting issues when training deep networks on limited datasets. This highlighted the need for regularization techniques and larger datasets to improve model robustness.

Hossain et al. (2022) introduced a hybrid deep learning model combining convolutional neural networks with a genetic algorithm (GA) for feature selection. The GA was used to identify the most relevant features, reducing dimensionality and improving classification efficiency. The proposed model achieved higher accuracy compared to conventional CNN models, demonstrating the effectiveness of optimization techniques in enhancing deep learning performance. However, the integration of GA increased computational complexity and extended training time. Ayadi et al. (2022) proposed a multi-scale convolutional neural network architecture for brain tumour classification. The model utilized multiple convolutional filters of different sizes to capture features at various scales, enabling better representation of tumour characteristics. The multi-scale approach improved classification accuracy compared to single-scale CNN models. However, the increased architectural complexity required more computational resources and careful tuning of model parameters.

Anaraki et al. (2022) developed a CNN-based classification model optimized using genetic algorithms for hyperparameter tuning. The GA was employed to optimize parameters such as learning rate, number of layers, and filter sizes, resulting in improved classification performance. The study demonstrated that optimization techniques can significantly enhance deep learning models. However, the optimization process increased computational cost and required extensive experimentation. Cheng et al. (2020) proposed a hybrid approach combining deep learning with traditional feature extraction methods for brain tumour classification. The model used CNNs for feature extraction and integrated handcrafted features to improve classification accuracy. The results showed that combining deep learning with feature engineering can enhance performance. However, the reliance on manual feature extraction reduced the automation and scalability of the system.

Deepak et al. (2021) introduced a transfer learning-based framework using pre-trained CNN models such as VGG19 and ResNet50 for brain tumour classification. The model leveraged knowledge from large datasets to improve performance on smaller MRI datasets. The study demonstrated that transfer learning significantly reduces training time while maintaining high accuracy. However, the performance depended heavily on the choice of pre-trained models and domain similarity. Badža et al. (2021) developed a CNN-based brain tumour classification system optimized through hyperparameter tuning. The study explored different combinations of hyperparameters, including batch size, learning rate, and optimizer selection, to identify optimal configurations. The results showed that proper tuning significantly improves model performance and stability. However, hyperparameter tuning required extensive experimentation and increased computational cost.

Nawaz et al. (2022) proposed a hybrid deep learning model integrating CNN with particle swarm optimization (PSO) for feature selection and parameter tuning. The PSO algorithm improved feature selection efficiency and enhanced model convergence, resulting in better classification accuracy. However, the integration of PSO increased system complexity and computational requirements. Amin et al. (2023) introduced a deep dynamic parallel convolutional neural network (DDPCNN) for multi-class brain tumour classification. The model utilized parallel convolutional layers to extract features at different scales simultaneously, improving classification accuracy. The study demonstrated that parallel architectures can effectively capture complex patterns in MRI images. However, the increased architectural complexity required high computational resources and careful optimization.

Paul et al. (2020) proposed a deep learning-based CNN framework for multi-class brain tumour classification using MRI images. The model utilized multiple convolutional and pooling layers to extract features and achieved high classification accuracy. The study demonstrated that deep CNNs outperform traditional classifiers due to their ability to learn complex patterns. However, the approach required large training datasets and high computational resources. Mohsen et al. (2020) developed a deep neural network combined with feature extraction techniques for MRI-based brain tumour classification. The study integrated handcrafted features with deep learning to improve classification performance. The results showed enhanced accuracy, but the dependence on preprocessing reduced automation.

Sharif et al. (2021) introduced a hybrid CNN model combined with optimization techniques for brain tumour classification. The model achieved improved accuracy by optimizing feature selection and network parameters. However, the hybrid approach increased system complexity and computational cost. Khan et al. (2021) proposed an ensemble deep learning model combining multiple CNN architectures. The ensemble approach improved classification accuracy and robustness by leveraging the strengths of different models. However, it required significant computational resources and longer training time.

Ali et al. (2022) developed a CNN-based multi-class classification system with data augmentation techniques. The model improved generalization and achieved high accuracy across different tumour types. However, the model required large datasets for optimal performance. Basha et al. (2022) proposed a hybrid CNN model optimized using genetic algorithms. The GA improved hyperparameter tuning and feature selection, resulting in enhanced classification performance. However, the optimization process increased computational overhead.

Ranjbarzadeh et al. (2023) introduced a deep learning framework with advanced preprocessing techniques for brain tumour classification. The model achieved high accuracy but required extensive preprocessing, increasing system complexity. Ullah et al. (2023) proposed a multi-scale CNN architecture for tumour classification. The model captured features at different scales, improving classification performance. However, the complexity of the architecture required significant computational resources.

Noreen et al. (2023) developed a hybrid model combining deep learning and optimization techniques for MRI classification. The approach improved classification accuracy but introduced additional computational complexity. Sharma et al. (2023) proposed a deep dynamic parallel CNN optimized using a termite alate optimization algorithm. The model demonstrated superior classification performance by efficiently tuning hyperparameters and improving convergence speed. However, the complexity of the optimization algorithm posed challenges for real-time implementation.

Comparative Table

Study	Year	Method	Technique	Advantage	Limitation
Khan	2020	CNN	DL	High accuracy	Data heavy
Yaqub	2020	CNN	Optimizer	Fast	Tuning
Hu	2021	Hybrid	Metaheuristic	Efficient	Complex
Sadad	2021	Hybrid	RL+EA	Adaptive	Heavy
Nickparvar	2021	CNN	GoogLeNet	Robust	Cost
Ismael	2020	CNN	Transfer	Efficient	Limited
Tandel	2021	CNN	DL	Accurate	Slow
Afshar	2021	CapsNet	DL	Spatial	Complex
Swati	2022	Hybrid	PSO	Accurate	Cost
Rehman	2022	CNN	EfficientNet	Efficient	Sensitive
Sajjad	2021	CNN	Preprocess	Accurate	Complex
Abiwinanda	2021	CNN	Deep	High accuracy	Overfit
Hossain	2022	Hybrid	GA	Optimized	Time
Ayadi	2022	CNN	Multi-scale	Accurate	Complex
Anaraki	2022	CNN	GA	High accuracy	Cost
Cheng	2020	CNN	Hybrid	Improved	Manual
Deepak	2021	CNN	Transfer	Efficient	Dependent

Badža	2021	CNN	Tuning	Accurate	Cost
Nawaz	2022	Hybrid	PSO	Efficient	Complex
Amin	2023	CNN	Parallel	High accuracy	Heavy
Paul	2020	CNN	DL	Accurate	Data
Mohsen	2020	Hybrid	Feature	Accurate	Preprocess
Sharif	2021	Hybrid	CNN	Robust	Complex
Khan	2021	Ensemble	CNN	High accuracy	Heavy
Ali	2022	CNN	Augment	Generalizable	Data
Basha	2022	Hybrid	GA	Optimized	Cost
Ranjbarzadeh	2023	CNN	Preprocess	Accurate	Complex
Ullah	2023	CNN	Multi-scale	Accurate	Complex
Noreen	2023	Hybrid	DL+Opt	High accuracy	Heavy
Sharma	2023	Hybrid	Termite	Best	Complex

Comparative Analysis

The comparative analysis reveals that CNN-based approaches dominate brain tumor classification due to their superior feature extraction capabilities. Transfer learning improves performance on small datasets, while optimization algorithms such as PSO and GA enhance model efficiency. Hybrid models combining deep learning with optimization techniques achieve the best performance. The termite alate optimization algorithm demonstrates promising results in improving convergence and accuracy. However, these advanced models introduce computational complexity and require high resources.

Discussion

The reviewed studies highlight the effectiveness of deep learning in brain tumour classification using MRI images. CNN architectures provide high accuracy, while optimization algorithms enhance performance by improving feature selection and parameter tuning. Hybrid approaches combining deep learning and optimization techniques outperform standalone models. Despite these advancements, challenges such as data imbalance, computational complexity, and lack of interpretability remain. Future research should focus on developing efficient and explainable models for clinical deployment.

Conclusion

The integration of deep learning and optimization techniques has significantly improved brain tumour classification using MRI images. CNN architectures have demonstrated high accuracy in multi-class classification tasks, while optimization algorithms enhance model performance by improving convergence and feature selection. Hybrid approaches, particularly those combining deep dynamic parallel CNN architectures with bio-inspired optimization algorithms such as termite alate optimization, represent the most promising direction for future research. These models achieve superior accuracy and robustness by leveraging the strengths of both deep learning and optimization techniques.

However, challenges such as computational complexity, data imbalance, and lack of interpretability remain. Future research should focus on developing scalable, efficient, and explainable models for real-world applications.

In conclusion, deep learning and optimization-based approaches hold great potential for improving brain tumour diagnosis and treatment, contributing to better patient outcomes.

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