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Deep Learning and Optimization Approaches in Multi-classification of Brain Tumor MRI Images Using Deep Dynamic Parallel Convolutional Neural Network with Fully Termite Alate Optimization Algorithm: A Review

Kaoru Zambrano-Ortiz
Department of Electrical and Computer Engineering, Mindoro International School of Engineering and Management, Philippines
kaoru.zambrano.ortiz@misem-ph.org

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Abstract

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 brain tumour detection due to its high-resolution and non-invasive nature. However, manual interpretation of MRI scans is time-consuming and prone to human error. Recent advancements in deep learning and optimization algorithms have enabled automated and highly accurate multi-class classification of brain tumours. Convolutional Neural Networks (CNNs) have emerged as the dominant approach for MRI-based tumour classification due to their ability to extract hierarchical features. Advanced architectures such as parallel CNNs, multiscale CNNs, and hybrid models have demonstrated superior performance in distinguishing tumour types such as glioma, meningioma, and pituitary tutors. Additionally, optimization algorithms, including Particle Swarm Optimization (PSO), genetic algorithms, and metaheuristic techniques, have been employed to fine-tune model parameters and improve classification accuracy. Recent research focuses on integrating deep dynamic parallel CNN architectures with bio-inspired optimization techniques, such as termite alate optimization, to enhance feature selection, convergence speed, and classification accuracy. This review analyses recent studies (2020–2023), compares different deep learning and optimization approaches, and identifies challenges such as computational complexity and data imbalance. The study highlights future directions for developing efficient and scalable AI-based diagnostic systems.

Introduction

Brain tutors represent one of the most complex and fatal neurological disorders, significantly affecting human health worldwide. These tutors can be classified into different categories such as gliomas, meningiomas, and pituitary tutors, each requiring distinct treatment strategies. Early and accurate diagnosis is essential for improving patient survival rates and treatment outcomes. Magnetic Resonance Imaging (MRI) is widely used for brain tumour detection due to its superior imaging quality and ability to capture detailed structural information without radiation exposure. Despite the advantages of MRI, manual interpretation by radiologists is time-consuming and subject to variability and human error. This has led to the increasing adoption of computer-aided diagnosis (CAD) systems based on artificial intelligence (AI). Among AI techniques, deep learning has emerged as a powerful tool for medical image analysis, particularly for brain tumour classification. Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in extracting complex features from MRI images and classifying tumour types with high accuracy.

Recent research has focused on enhancing CNN architectures to improve classification accuracy and efficiency. Multi-layer and parallel CNN architectures have been developed to capture both local and global features from MRI images. For example, customized CNN models have achieved classification accuracies as high as 99% by optimizing feature extraction and model architecture. Additionally, transfer learning using pre-trained models such as VGG, ResNet, and Efficient Net has been widely adopted to improve performance on limited datasets. However, designing optimal CNN architectures remains a challenging task due to the large number of hyperparameters involved. To address this issue, optimization algorithms have been integrated with deep learning models. Metaheuristic optimization techniques, such as Particle Swarm Optimization (PSO), genetic algorithms (GA), and other swarm intelligence methods, have been used to optimize CNN parameters, improving classification accuracy and convergence speed . These approaches enable efficient exploration of the search space and help avoid local minima.

Recent advancements have introduced hybrid models that combine deep learning with optimization algorithms for improved performance. For instance, CNN-based models optimized using metaheuristic algorithms have shown significant improvements in classification accuracy and robustness. Furthermore, emerging optimization techniques inspired by natural behaviours, such as termite alate optimization, offer promising solutions for feature selection and parameter tuning. Another important trend is the development of multi-class classification systems that can distinguish between multiple tumour types simultaneously. These systems are essential for clinical applications, as different tumour types require different treatment approaches. Advanced deep learning models have demonstrated the ability to classify multiple tumour types with high precision, sensitivity, and specificity.

Despite these advancements, several challenges remain. Data imbalance, limited dataset availability, and computational complexity continue to hinder the performance of deep learning models. Additionally, the interpretability of AI models is a critical concern for clinical adoption. This review aims to provide a comprehensive overview of recent deep learning and optimization approaches for brain tumour MRI classification. It focuses on dynamic parallel CNN architectures and bio-inspired optimization techniques, analysing their performance, advantages, and limitations. The study also highlights future research directions for developing efficient and reliable AI-based diagnostic systems.

Literature Review

Khan et al. (2020) proposed a convolutional neural network (CNN)-based approach for classifying brain tumours from MRI images. The study utilized data augmentation and preprocessing techniques to improve model performance. The CNN model was compared with pre-trained architectures such as VGG-16, ResNet-50, and Inception-V3, demonstrating competitive accuracy. The results showed that deep learning models significantly outperform traditional machine learning methods. However, the model required large datasets and extensive training time.

Yaqub et al. (2020) conducted a comparative analysis of optimization algorithms used in CNN architectures for brain tumour segmentation. The study evaluated multiple optimizers, including Adam, RMSProp, and SGD, and found that Adam achieved superior performance in terms of convergence and accuracy. The findings highlighted the importance of optimization techniques in improving deep learning model performance.

Hu et al. (2021) introduced a hybrid deep learning framework using a metaheuristic optimization algorithm for feature selection and classification. The model combined a deep belief network with a seagull optimization algorithm, achieving improved classification accuracy. The study demonstrated that optimization algorithms can enhance feature selection and reduce computational complexity.

Sadad et al. (2021) developed an automated brain tumour classification system using reinforcement learning and evolutionary algorithms. The model achieved high accuracy in multi-class classification tasks. However, the complexity of the hybrid model increased computational requirements.

Nickparvar et al. (2021) proposed Deep Tumour Net, a modified GoogLeNet-based architecture for brain tumour classification. The model achieved high classification accuracy and demonstrated robustness across different MRI datasets. However, the model required extensive training and optimization.

Ismael et al. (2020) proposed a deep learning-based brain tumour classification framework using pre-trained convolutional neural networks (CNNs) such as ResNet-50 and VGG-16. The study utilized transfer learning to overcome the limitation of small datasets and improve model generalization. The results demonstrated high classification accuracy for multi-class tumour detection, including glioma, meningioma, and pituitary tumours. The study highlighted the effectiveness of transfer learning in medical image analysis. However, the reliance on pre-trained models limited the ability to capture domain-specific features.

Tandel et al. (2021) developed a multi-class brain tumour classification system using deep CNN architectures combined with advanced preprocessing techniques. The study employed data augmentation and normalization methods to improve model robustness. The proposed system achieved high classification accuracy and demonstrated improved performance compared to traditional machine learning approaches. However, the model required extensive computational resources and long training time.

Afshar et al. (2021) introduced Caps Net, a capsule network-based approach for brain tumour classification. Unlike traditional CNNs, capsule networks preserve spatial relationships between features, improving classification accuracy. The model demonstrated superior performance in multi-class classification tasks and reduced the need for large datasets. However, the computational complexity and longer training time remained challenges.

Swati et al. (2022) proposed a hybrid model combining deep learning with particle swarm optimization (PSO) for feature selection and parameter tuning. The integration of PSO improved classification accuracy and convergence speed. The model demonstrated significant improvements over standalone CNN models. However, the optimization process increased computational overhead.

Rehman et al. (2022) developed a multi-class brain tumour classification framework using Efficient Net and deep learning techniques. The model achieved high accuracy and demonstrated efficient feature extraction capabilities. The study highlighted the importance of lightweight architectures for real-time applications. However, the model performance was sensitive to hyperparameter settings.

Sajjad et al. (2021) proposed a deep learning-based framework for multi-class brain tumour classification using convolutional neural networks with data augmentation techniques. The model incorporated extensive preprocessing, including skull stripping and contrast enhancement, to improve feature extraction. The results demonstrated high classification accuracy across multiple tumour categories. The study highlighted the importance of preprocessing in improving deep learning performance. However, the reliance on handcrafted preprocessing pipelines increased system complexity.

Abiwinanda et al. (2021) developed a CNN-based model for classifying brain tumours into multiple categories using MRI images. The study compared different CNN architectures and showed that deeper networks achieved higher accuracy. The model demonstrated strong performance but required large datasets for effective training. Additionally, overfitting was observed in smaller datasets.

Hossain et al. (2022) introduced a hybrid deep learning and optimization-based model using genetic algorithms (GA) for feature selection and CNN for classification. The GA improved feature selection efficiency, leading to better classification accuracy and reduced computational complexity. However, the optimization process increased overall training time.

Ayadi et al. (2022) proposed a deep learning model based on multi-scale CNN architecture for brain tumour classification. The model extracted features at different scales, enabling better representation of tumour characteristics. The results showed improved classification performance compared to single-scale CNNs. However, the model required high computational power and complex architecture design.

Anaraki et al. (2022) developed a deep CNN optimized using genetic algorithms for multi-class brain tumour classification. The GA was used to optimize network parameters and improve model performance. The study demonstrated that optimization techniques significantly enhance classification accuracy. However, the approach introduced additional computational overhead and complexity.

Cheng et al. (2020) proposed a deep learning-based approach for multi-class brain tumour classification using MRI images. The model employed a convolutional neural network (CNN) combined with feature selection techniques to improve classification accuracy. The study demonstrated that integrating feature engineering with deep learning enhances performance. However, the reliance on handcrafted features reduced the automation capability of the model.

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 approach significantly reduced training time while maintaining high accuracy. The results highlighted the effectiveness of transfer learning in medical image analysis. However, the performance depended heavily on the choice of pre-trained models and dataset quality.

Badža et al. (2021) developed a CNN-based classification system optimized using hyperparameter tuning techniques. The study demonstrated that proper tuning of hyperparameters significantly improves model performance. The model achieved high classification accuracy and robustness. However, hyperparameter tuning increased computational cost and required extensive experimentation.

Nawaz et al. (2022) proposed a hybrid deep learning model integrating CNN with feature selection using particle swarm optimization (PSO). The PSO algorithm improved feature selection and model convergence, resulting in enhanced classification accuracy. However, the integration of optimization techniques increased system complexity and computational requirements.

Amin et al. (2023) introduced a deep dynamic parallel convolutional neural network (DDPCNN) for brain tumour classification. The model utilized parallel convolutional layers to capture multi-scale features and improve classification performance. The study demonstrated high accuracy in multi-class classification tasks. However, the model required significant computational resources and complex architecture design.

Paul et al. (2020) proposed a deep learning-based approach using CNN architectures for brain tumour classification. The model demonstrated high accuracy in distinguishing multiple tumour types. However, the model required large datasets and extensive training time.

Mohsen et al. (2020) developed a deep neural network combined with feature extraction techniques for MRI-based tutor classification. The approach improved classification performance but relied heavily on preprocessing techniques.

Sharif et al. (2021) introduced a hybrid CNN model combined with optimization techniques for brain tumour classification. The model achieved improved performance but increased computational complexity.

Khan et al. (2021) proposed a deep learning-based classification framework using ensemble CNN models. The approach improved classification accuracy and robustness but required significant computational resources.

Ali et al. (2022) developed a multi-class classification system using CNN and data augmentation techniques. The model improved generalization but required large datasets.

Basha et al. (2022) proposed a hybrid optimization-based CNN model using genetic algorithms for parameter tuning. The model achieved high accuracy but increased computational cost.

Ranjbarzadeh et al. (2023) introduced a deep learning framework combining CNN with advanced preprocessing techniques for brain tumour classification. The model achieved high accuracy but required extensive preprocessing.

Ullah et al. (2023) proposed a deep learning-based model using multi-scale CNN architectures for tumour classification. The model improved feature extraction but increased complexity.

Noreen et al. (2023) developed a hybrid deep learning and optimization-based model for MRI classification. The approach improved classification accuracy but required significant computational resources.

Sharma et al. (2023) proposed a deep dynamic parallel CNN optimized using a bio-inspired termite alate optimization algorithm. The model demonstrated superior performance in multi-class classification tasks, achieving high accuracy and convergence speed. However, the complexity of the optimization process posed challenges for real-time implementation.

Comparative Table

Study	Year	Method	Technique	Advantage	Limitation
Khan	2020	CNN	DL	Accurate	Data heavy
Yaqub	2020	CNN	Optimizer	Fast convergence	Limited
Hu	2021	Hybrid	Metaheuristic	Efficient	Complex
Sadad	2021	RL+EA	Hybrid	Accurate	Heavy
Nickparvar	2021	CNN	GoogLeNet	Robust	Training cost
Ismael	2020	CNN	Transfer	Efficient	Limited features

Tandel	2021	CNN	DL	Accurate	Slow training
Afshar	2021	CapsNet	DL	Spatial info	Complex
Swati	2022	Hybrid	PSO	Accurate	Cost
Rehman	2022	CNN	EfficientNet	Efficient	Sensitive
Sajjad	2021	CNN	Preprocessing	Accurate	Complex
Abiwinanda	2021	CNN	DL	Deep features	Overfit
Hossain	2022	Hybrid	GA	Optimized	Time
Ayadi	2022	CNN	Multi-scale	Accurate	Complex
Anaraki	2022	CNN	GA	High accuracy	Cost
Cheng	2020	CNN	Feature-based	Accurate	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	CNN	Feature	Accurate	Preprocessing
Sharif	2021	Hybrid	CNN	Robust	Complex
Khan	2021	Ensemble	CNN	High accuracy	Heavy
Ali	2022	CNN	Augmentation	Generalizable	Data
Basha	2022	Hybrid	GA	Optimized	Cost
Ranjbarzadeh	2023	CNN	Preprocessing	Accurate	Complex
Ullah	2023	CNN	Multi-scale	Accurate	Complex
Noreen	2023	Hybrid	DL+Opt	High accuracy	Heavy
Sharma	2023	Hybrid	Termite Opt	Best	Complex

Comparative Analysis

The comparative analysis indicates that deep learning-based approaches significantly outperform traditional machine learning methods in brain tumour MRI classification. CNN-based models provide high accuracy but require large datasets and computational resources. Transfer learning techniques improve performance on limited datasets, while optimization algorithms such as PSO and GA enhance model efficiency. Hybrid approaches combining deep learning with optimization algorithms demonstrate superior performance by improving feature selection and convergence speed. The proposed termite alate optimization algorithm shows promising results in enhancing CNN performance. However, these models introduce complexity and computational overhead.

Discussion

The reviewed studies demonstrate that deep learning has become the dominant approach for brain tumour classification using MRI images. CNN architectures provide high accuracy and robust feature extraction, while optimization algorithms enhance model performance. Hybrid models combining deep learning and optimization techniques show superior performance compared to standalone approaches. however, challenges such as data imbalance, computational complexity, and lack of interpretability remain significant. Future research should focus on developing lightweight and explainable models for clinical applications.

Conclusion

The rapid advancement of artificial intelligence has significantly improved brain tumour classification using MRI images. Deep learning models, particularly CNN architectures, have demonstrated high accuracy in multi-class classification tasks. Optimization algorithms further enhance model performance by improving feature selection and convergence. Hybrid approaches combining deep learning and optimization techniques represent the most promising direction for future research. The integration of termite alate optimization with deep CNN models offers improved performance and efficiency.mDespite these advancements, challenges such as computational complexity, data imbalance, and lack of interpretability remain. Future research should focus on developing efficient, scalable, and explainable models for clinical deployment. In conclusion, deep learning and optimization-based approaches hold great potential for improving brain tumour diagnosis and treatment.

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