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Research Article

Advancements in Deep Learning for Multi-Class Brain Tumor Classification: A Systematic Review

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Abstract

Brain tumors provide a huge medical challenge because of their intricacy, high mortality rate, and influence on the central nervous system. Accurate and early diagnosis is essential for developing effective treatment regimens and improving patient outcomes. Traditionally, brain cancers have been diagnosed via invasive approaches such as biopsies and radiologists manually analyzing Magnetic Resonance Imaging (MRI) data. However, these conventional procedures are time-consuming, prone to human error, and frequently lack consistency in multi-class tumor detection. Deep learning, a type of artificial intelligence, has emerged as a possible solution to these problems in recent years, automating and improving brain tumor classification accuracy.

This paper focuses on the use of deep learning approaches in the multi-class categorization of brain cancers, namely gliomas, meningiomas, and pituitary tumors. We present a thorough review of several deep learning architectures, including Convolutional Neural Networks (CNNs), ResNet, VGG, DenseNet, and others, highlighting their benefits and limits in medical imaging applications. We also look at publicly accessible datasets routinely utilized in research, as well as preprocessing methods including normalization, skull stripping, and data augmentation to increase model performance. The study also examines the assessment criteria used to measure classification accuracy, as well as the primary issues that researchers encounter, such as data imbalance, model interpretability, and generalizability. Finally, we offer future possibilities for strengthening model robustness, explainability and clinical integration to help medical practitioners make accurate and efficient tumor diagnoses.

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KEYWORDS: Brain Tumor Classification, Deep Learning, Convolutional Neural Networks (CNNs), Multi-Class Classification, MRI Imaging, Skull Stripping, Data Augmentation

INTRODUCTION

Brain tumors are classed as either benign or malignant based on their abnormal and uncontrolled development inside the brain. Accurate tumor classification is critical for successful treatment planning and better patient outcomes. Traditionally, diagnosis entails human interpretation of MRI data, which is both time-consuming and prone to inter-observer variability. With advances in artificial intelligence, deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a useful tool for medical image analysis, providing automatic and extremely accurate tumor categorization.

This study will offer a complete overview of current advances in deep learning-based techniques for multi-class brain tumor classification, with an emphasis on the detection and distinction of glioma, meningioma, and pituitary tumors. It examines the most prevalent neural network topologies, accessible datasets, preprocessing approaches, assessment measures, and the field's current issues. Finally, the paper discusses potential options for improving model dependability and clinical application.

RELATED WORK

In recent years, deep learning has improved medical image processing, notably in the classification and detection of brain tumors. Using MRI data, multiple studies have investigated the use of Convolutional Neural Networks (CNNs) and other deep learning models to categorize various types of brain malignancies, such as glioma, meningioma, and pituitary tumors.

Tandel et al. [1] suggested a non-invasive, MRI-based brain tumor grading system that employs an ensemble deep learning (EDL) technique and a majority voting algorithm. The method categorizes cancers into two to six classifications using seven deep learning and seven machine learning models, respectively. The deep learning ensemble beat machine learning models with up to 100% accuracy. Explainable AI, utilizing LIME, was used to depict model decisions, which increased trust. The approach performs well and consistently across many datasets and validation folds.

Verma et al. [2] reported DS-Net, a patch-based deep learning network for reliable multi-class brain tumor classification from MRI scans. The model uses EfficientNet MBConv blocks, a deep supervision mechanism (DSM), and dilated convolutions to collect both local and global information. When tested on Fig share, Kaggle, and Sartaj datasets using several validation procedures, the model exhibited good accuracy (up to 0.99), precision, and recall. DS-Net efficiently lowers false positives/negatives, making it a dependable and efficient method for tumor categorization.

Sachdeva et al. [3] introduced BO-DenseXGB, an AI-based hybrid system for classifying multi-class brain tumors from MRI data. The model uses Convolutional Neural Networks (CNN) for feature extraction and a Bayesian-optimized XGBoost classifier for final prediction. Tumors are classified into three types: meningioma, glioma, and pituitary. When tested on the Figshare dataset including 3064 photos, the framework obtained a high accuracy of 99.02%. The results show that the model has exceptional performance and the ability to diagnose brain tumors accurately, efficiently, and automatically.

Başarslan et al. [5] introduced M-C&M-BL, a hybrid deep learning model that combines CNN and BiLSTM to classify brain tumors using MRI data. When tested on the Br35H dataset, the model outperformed previous CNN-based models such as BMRI-Net and AlexNet, scoring 99.33% accuracy and 99.35% F1-score. It has a high potential for incorporation into clinical tools and diagnostic systems, enabling early and accurate tumor identification. The research stresses the model's performance while also addressing deployment issues such as data privacy, generalizability, and infrastructure restrictions.

Karthik et al. [6] established a unified framework for accurate brain tumor multi-classification and segmentation based on MRI data. The model includes an Attention-Augmented CNN for thorough feature extraction, a Random Forest for enhanced classification, and a U-Net for accurate tumor segmentation. This fusion draws on the strengths of attention processes, ensemble learning, and semantic segmentation. Tested on a heterogeneous MRI dataset, the model displays good accuracy, precision, and F1-score, providing a reliable solution for brain tumor analysis and assisting in effective clinical decision-making.

Hammad et al. [7] introduced a deep learning solution for multi-class brain tumor detection based on transfer learning and EfficientNet-B4. The model, which includes Global Average Pooling, batch normalization, and dropout layers, is fine-tuned and assessed on a Kaggle MRI dataset using several optimization strategies. EfficientNet-B4 with AdamW obtained the best results, with 99.24% accuracy and 99.75% specificity. The study illustrates the model's ability to provide precise, efficient brain tumor categorization, assisting clinical decision-making and enhancing treatment planning in neuro-oncology.

Khan et al. [8] introduced a new brain tumor classification model built on the Manta Ray Foraging Optimizer (MRFO) and upgraded residual blocks within the DenseNet-169 framework. The model enhances feature extraction and hyperparameter tuning to improve multiclass classification accuracy. When evaluated on four separate datasets, it achieved 99.10% accuracy, outperforming prior models. The approach, which combines MRFO with improved residual learning, shows excellent generalization and durability, making it a reliable AI-driven option for early brain tumor detection and medical decision support.

Amin et al. [9] introduced ADE_DieT, a new model for multi-class brain tumor classification that combines the DieT Transformer for feature extraction, PCA for dimensionality reduction, and the ADE method for feature selection. With a 96.09% accuracy, the model surpasses various pre-trained architectures and overcomes discrepancies in manual MRI diagnosis. ADE_DieT helps oncologists make early treatment decisions by enhancing diagnostic speed and reliability. The technique improves clinical operations by decreasing radiologists' workloads and providing consistent, reliable brain tumor detection with MRI data.

Nahiduzzaman et al. [10] suggested a hybrid, explainable model for diagnosing four kinds of brain tumors using MRI images by merging a lightweight Parallel Depthwise Separable CNN (PDSCNN) and Ridge Regression Extreme Learning Machine (RRELM). Enhanced with CLAHE for improved picture quality, the model achieves excellent accuracy (99.22%) and beats cutting-edge approaches. SHAP is used to increase explainability and transparency in model choices. The method has excellent performance, minimal complexity, and interpretability, making it appropriate for real-world clinical brain tumor detection and decision assistance.

Ramamoorthy et al. [13] proposed a hybrid AI model that combines Honey Bee Optimization (HBO) and Probabilistic U-RSNet for effective multiclass brain tumor classification from MRI data. The strategy improves prediction accuracy by utilizing advanced segmentation and optimization techniques. When tested on the BraTS 2020, BraTS 2021, and OASIS datasets, the model beats classic deep learning approaches such as CNN, LSTM, and GANs in terms of accuracy, precision, recall, F1 score, and Jaccard index. The suggested approach provides a viable, non-invasive alternative to biopsies for diagnosing brain tumors.

While these models demonstrate promising performance, issues such as dataset imbalance, lack of generalization across imaging modalities, and restricted interpretability persist. Recent research emphasizes the relevance of preprocessing procedures such as skull stripping, normalization, and data augmentation in improving model resilience.

Overall, the research indicates the efficacy of deep learning models in brain tumor categorization. However, further research is required to create models that are not only accurate, but also clinically interpretable and generalizable over a wide range of datasets.

Research Gap

Despite significant progress in applying deep learning techniques for brain tumor classification, several critical research gaps remain unaddressed, limiting the effectiveness, generalizability, and clinical integration of current models.

Limited Availability of Large and Balanced Datasets: Most existing studies rely on small or moderately sized publicly available datasets such as Fig share or BraTS. These datasets often suffer from class imbalance, with an unequal distribution of tumor types, leading to biased model performance—especially for underrepresented classes like pituitary tumors.

Lack of Standardized Preprocessing and Annotation: There is no uniform standard for preprocessing MRI images across studies. Techniques like skull stripping, normalization, and augmentation vary widely, making it difficult to compare models fairly. Additionally, manual annotations used for training often differ in quality and consistency.

Overfitting and Poor Generalization: Many deep learning models demonstrate high accuracy on specific datasets but fail to generalize well to unseen data, especially from different scanners or institutions. This restricts their real-world applicability in diverse clinical settings.

Limited Exploration of 3D MRI Data: The majority of studies utilize 2D MRI slices, ignoring the spatial continuity and volumetric information inherent in 3D brain scans. This limits the model's understanding of tumor morphology and spatial structure.

Lack of Explainability and Clinical Trust: Most deep learning models operate as black boxes, offering predictions without interpretability. This hinders trust and adoption by radiologists and clinicians, who require insight into how a decision was made.

Few End-to-End Clinical Deployments: Although many models achieve high accuracy in controlled research settings, few have been validated through real-time clinical trials or integrated into diagnostic workflows. There is a gap between research performance and practical deployment.

Insufficient Focus on Multi-Class Classification: While binary classification (tumor vs. no tumor) is common, fewer studies focus on multi-class classification involving glioma, meningioma, and pituitary tumors simultaneously. This limits clinical usefulness where differential diagnosis is critical.

Aims:

The major goal of this review article is to thoroughly assess and describe current advances in deep learning approaches used for multi-class classification of brain cancers using MRI data. The study aims to assess the efficacy of various deep learning models, datasets, preprocessing approaches, and performance assessment procedures in the area by concentrating on many tumor types—specifically glioma, meningioma, and pituitary tumors. It also seeks to highlight present problems and suggest future research options for increasing clinical acceptance and diagnostic reliability.

OBJECTIVES

To present an overview of brain tumor types and their clinical importance

Explain the distinctions between gliomas, meningiomas, and pituitary tumors. Highlight the significance of correct and timely categorization for optimal therapy.

To investigate the use of deep learning in medical imaging and brain tumor classification
Discuss how deep learning, namely Convolutional Neural Networks (CNNs), has revolutionized image-based diagnosis. Consider its advantages over standard machine learning and manual approaches.

To study cutting-edge deep learning models used for multi-class brain tumor categorization
Analyze designs like VGGNet, ResNet, DenseNet, Inception, and Capsule Networks. Evaluate their performance and applicability for MRI image analysis.

To identify the limitations and challenges in current research
Address problems including restricted data availability, class imbalance, and model interpretability. Examine the generalizability of models across various clinical settings.

To suggest future avenues for research and clinical integration
Suggestions for enhancements include explainable AI, 3D CNNs, federated learning, and interaction with healthcare systems. Radiologists must have deep learning technologies that are user-friendly, accurate, and dependable.

Experimental Methodology
The experimental technique for deep learning-based multi-class brain tumor classification generally consists of a set of methodical processes used to train, validate, and assess a neural network model on MRI data. The objective is to automatically categorize brain cancers into glioma, meningioma, and pituitary tumors with high accuracy and generalizability. The typical procedure used in most investigations is detailed below:

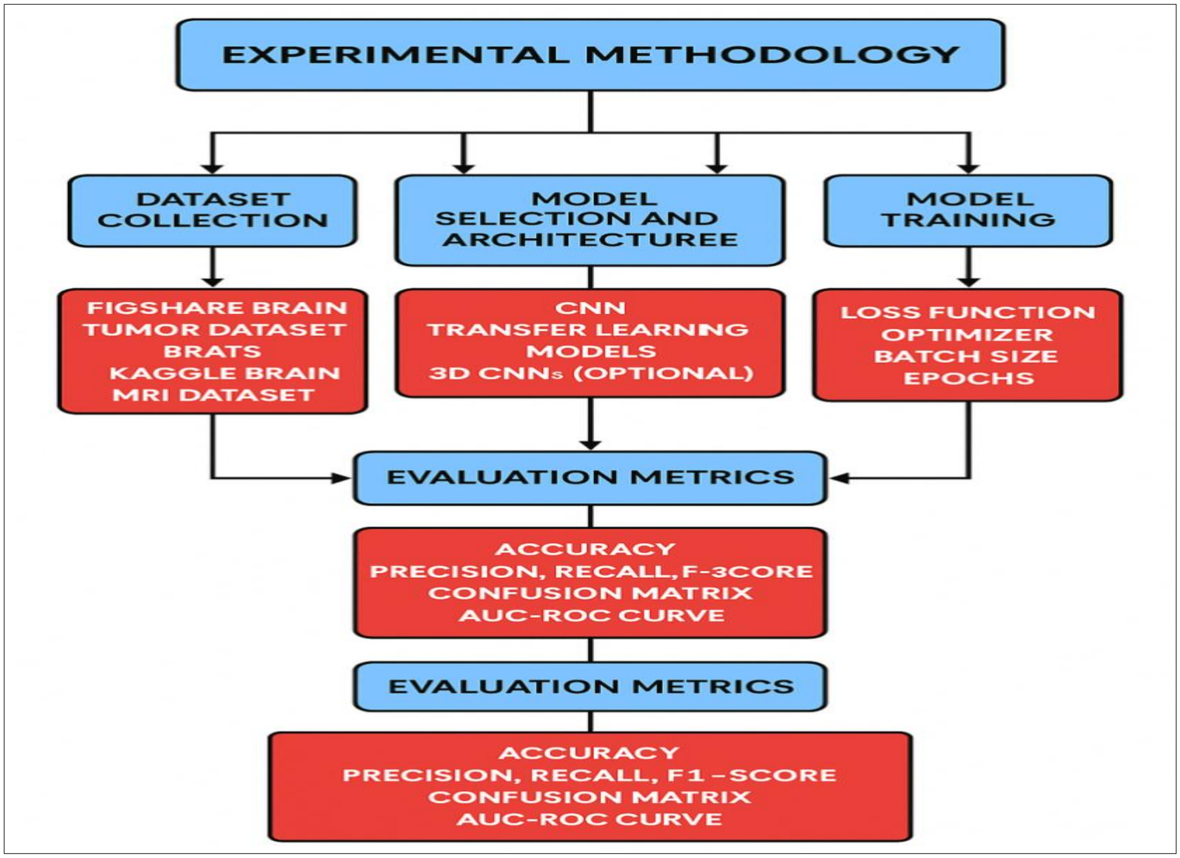

FIGURE 1: Experimental Methodology

1. Dataset collection:
For experimental analysis, publicly available MRI datasets are commonly used. Some of the most widely adopted datasets include:

Figshare Brain Tumor Dataset: Contains T1-weighted contrast-enhanced images of glioma, meningioma, and pituitary tumors.

BraTS (Brain Tumor Segmentation Challenge): Provides multimodal MRI scans (T1, T2, T1c, FLAIR) with expert-labeled segmentations.

Kaggle Brain MRI Dataset: Offers labeled brain MRI images suitable for classification tasks.

These datasets are generally divided into training, validation, and test.

2. Data Preprocessing
Preprocessing is critical for standardizing input data and improving model performance. Typical preprocessing processes are:
Skull Stripping: Skull stripping is a preprocessing technique used in medical image analysis, notably in brain imaging (such as MRI or CT scans), that removes non-brain tissues from MRI pictures.
Resizing: Standardizes image dimensions (e.g., 224×224 pixels for CNN input).
Normalization: Scales pixel values to a specific range, typically [0, 1].

3. Data Augmentation: Data augmentation is used to enhance dataset size and variability using rotation, flipping, zooming, contrast adjustments, and noise injection. It increases model generalization, prevents overfitting (particularly when training data is restricted), and strengthens the model's resilience to fluctuations in real-world data.

4. Model Selection and Architecture
Different deep learning architectures can be used for multi-class classification:

CNN (Convolutional Neural Network): Custom or pre-defined architectures (3–7 convolution layers with ReLU and max pooling).

Transfer Learning Models: Pre-trained architectures such as VGG16, ResNet50, DenseNet121, and InceptionV3 are fine-tuned using the brain tumor dataset to leverage their learned features.

3D CNNs (optional): For volumetric MRI scans, capturing spatial information across slices. The final layers typically include fully connected layers followed by a **Softmax** activation function to handle multi-class output.

5. Model Training

Loss Function: Categorical Cross-Entropy for multi-class classification.
Optimizer: Adam or SGD (Stochastic Gradient Descent) with learning rate tuning.

Batch Size: Typically ranges between 16–64 depending on memory availability.
Epochs: Models are trained for 20–100 epochs, with early stopping to prevent overfitting.

Hardware: GPU-based training using TensorFlow, Keras, or PyTorch frameworks.

6. Evaluation Metrics
A variety of categorization measures are used to evaluate model performance:
Accuracy: Accuracy measures the model's ability to correctly predict across all samples. It is calculated by dividing the number of correct predictions (including true positives and true negatives) by the entire sample size. This metric provides a broad picture of how well the model is performing, but it may be distorted by an unequal distribution of classes in the dataset.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Where:
TP: True Positives (correctly predicted positive samples)
TN: True Negatives (correctly predicted negative samples)
FP: False Positives (incorrectly predicted positive samples)
FN: False Negatives (incorrectly predicted negative samples)

Precision: Precision measures the model's positive prediction accuracy, which is shown in the ratio of properly categorized positive samples. It is calculated by dividing the number of true positives by the total of true and false positives. High accuracy indicates that the model generates few false positives and can successfully identify positive samples.

$$Precision = \frac{TP}{TP + FP}$$

Recall: Recall, also known as sensitivity, measures how well the model distinguishes between positive and non-positive samples. It's calculated by dividing the number of true positives by the sum of true positives and false negatives. A high recall value indicates that the model successfully identifies the majority of positive samples.

$$Recall = \frac{TP}{TP + FN}$$

F1-Score: The F1-Score is a statistic that offers a fair assessment of how well the model works. It is calculated by taking the harmonic mean of accuracy and recall. It provides a consistent measurement that accounts for both inaccurate positive and negative outcomes. The F1-Score is especially useful in circumstances when class distribution is unequal, as it balances accuracy and recall.

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Confusion Matrix: The Confusion Matrix is a performance evaluation tool used in classification tasks to show how well a machine learning model performs. It demonstrates the model's ability to recognize classes.

AUC-ROC Curve: It examines the trade-off between true positive and false positive rates in each class.

Future Scope

Deep learning has already shown tremendous promise in automating brain tumor categorization; nevertheless, there are several chances for additional development and clinical use. Future research should focus on overcoming present constraints and exploring improved methodologies for developing more robust, generalizable, and interpretable diagnostic systems.

Creating large and diverse datasets: There is an urgent need to develop comprehensive, multi-institutional datasets covering a wide range of MRI modalities, scanner types, and patient demographics. Incorporating longitudinal data and clinical records would help to increase model accuracy and dependability.

Integration of 3D Deep Learning Models: Most recent research use 2D slice-based categorization, which overlooks volumetric continuity. 3D CNNs or hybrid models can use spatial information across slices to provide a better understanding of tumor shape, volume, and growth trends.

Explainable and interpretable AI models: Future systems should include explainable AI (XAI) approaches as saliency maps, attention processes, or Grad-CAM, to improve trust and acceptance in clinical contexts. These technologies can give visual or written explanations of the model's conclusions, allowing radiologists to confirm the diagnosis.

Transfer and Federated Learning: Transfer learning enables models learned on huge general datasets to be fine-tuned for medical imaging applications that need restricted data. Federated learning, on the other hand, allows for collaborative training across hospitals without disclosing patient data, protecting privacy and increasing model resilience.

Multi-Modal Data Fusion: Combining MRI with other clinical information, such as pathology reports, patient history, and genetic data, can result in more precise and individualized tumor categorization systems.

Real-time clinical deployment: Future research should focus on incorporating AI models into hospital systems via user-friendly software tools or PACS (Picture Archiving and Communication System) plugins. Validation through clinical studies will be required to establish safety, effectiveness, and usefulness in real-world scenarios.

CONCLUSION

Deep learning has emerged as a game-changing tool in the field of brain tumor classification, with the potential to improve diagnostic processes through speed, precision, and automation. This research investigated numerous deep learning models, particularly Convolutional Neural Networks (CNNs), utilized in multi-class classification of brain tumors, focusing on their architectures, datasets, preprocessing methodologies, performance measures, and common problems. Despite tremendous progress, some challenges to wider clinical application remain, including restricted dataset availability, a lack of model generalization, and interpretability concerns. However, recent research and technical breakthroughs, like as 3D modeling, explainable AI, and federated learning, present hopeful alternatives to these restrictions.

As the medical world transitions to more data-driven and intelligent diagnostic systems, the future of deep learning in brain tumor classification seems bright. AI-powered techniques can play a critical role in increasing early detection, minimizing diagnostic mistakes, and improving patient care outcomes in neuro-oncology if data scientists, radiologists, and clinical researchers work together more closely.

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