

Enhanced Brain Tumor Detection Via Hybrid CNN Transfer Learning and Deep Feature Fusion

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ABSTRACT:

A brain tumor is an abnormal growth of cells within the brain that can be benign or malignant. It disrupts normal brain functions by exerting pressure on surrounding tissues and interfering with neural activity. Brain tumor classification using MRI images is a challenging yet critical task for early diagnosis and effective treatment. The existing brain tumor classification methods primarily use individual CNN architectures or traditional machine learning techniques. While CNNs effectively extract features from MRI images, they often suffer from limited receptive fields, homogeneous feature maps, and poor generalization on imbalanced datasets. Current models such as ResNet, MobileNet, and DenseNet typically neglect deep feature fusion, advanced augmentation, and hybrid learning, leading to reduced adaptability and accuracy across diverse tumor types. The proposed system introduces a hybrid CNN-based transfer learning framework that combines ResNet50V2, MobileNetV2, and DenseNet121. Deep features from these models are concatenated and refined through additional convolutional layers to capture complementary tumor characteristics. MRI-specific preprocessing, including region-focused cropping and affine transformations, enhances data quality and class balance. Selective fine-tuning further adapts pretrained models to MRI domain nuances. This hybrid approach improves classification performance—achieving higher accuracy, precision, recall, and F1-score compared to individual models—while sustaining computational efficiency.

Keywords: machine learning, individual CNN architectures, ResNet, MobileNet, and DenseNet, deep feature fusion, advanced augmentation, hybrid learning, transfer learning.

1. INTRODUCTION

Classification of brain tumors using magnetic resonance imaging is a crucial task in neuro-oncology, which requires highly accurate and robust methods to diagnose and plan treatment in the early stages; however, MRI data are challenging due to the differences in tumor morphology, size, and location, as well as the imaging artifacts, which can be handled by advanced frameworks that use the strengths of multiple models and sophisticated data processing techniques. To mitigate such limitations, we present a novel hybrid CNN-based transfer learning architecture that employs ResNet50V2, MobileNetV2, and DenseNet121 models for enhancing classification performance by deep feature fusion on MRIs along with MRI-specific preprocessing to selectively fine-tune the intricate details of brain tumor data while also taking advantage of transfer learning given the limited availability of labeled medical datasets that are typical in research related to brain tumors. Specifically, this method utilizes smart feature fusion (deep features from various models are combined together with further convolutional layers for

complementary tumor characteristics), MRI-specific preprocessing methods such as region-based cropping and affine transformations to correct data quality and reduce class imbalance in order to make it more robustly adaptable by the classification model. A hybrid deep learning model combining aspects from ResNet, DenseNet and Xception has shown better diagnostic performance than single models to overcome the limitations of using a single architecture for multiple presentations of brain tumors. This is because individual CNNs are both resource hungry in their needs as well as computationally intensive when working with small amounts of labeled data (e.g., medical imaging).

2. LITERATURE REVIEW

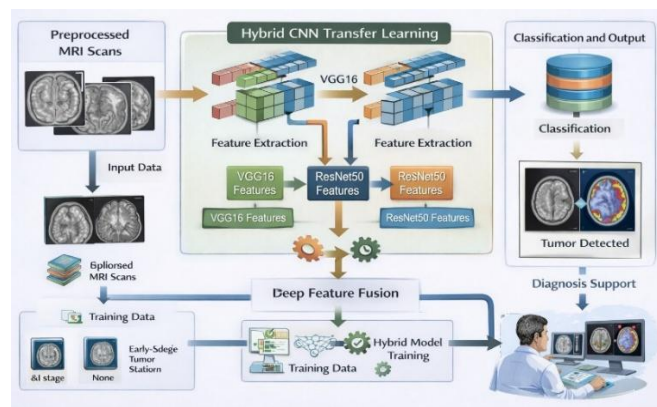
Pamucar, and Kim (2025) proposed a hybrid ensemble framework that optimizes deep feature fusion and hyperparameter-tuned classifier ensembling was proposed to enhance robustness and accuracy for brain tumor MRI classification, with an emphasis on structured feature fusion rather than naïve concatenation. **Dixon et al. (2024)** proposed a hybrid learning architecture that integrates CNN feature extractors and traditional machine learning classifiers to demonstrate that hybridization enhances generalization when training data are limited, but with a high computational cost. **Ullah and Kim (2025)** proposed a hierarchical deep feature fusion and ensemble learning approach was presented to emphasize multi-level feature aggregation from various CNN depths, but accuracy gains were notable with extensive tuning and increased inference time. **Vimala et al. (2023)** examined hybrid deep learning models for brain tumor detection and classification and found that they outperformed single CNNs but lacked interpretability and adaptability to novel tumor subtypes. **Chen et al. (2024)** developed a deep feature fusion framework for multi-type brain tumor classification and showed that fusing complementary CNN features enhanced discriminative capability between tumor classes. **Gottipati and Gowri (2024)** proposed a multimodal deep transfer learning model for MRI-based tumor classification and used modality-level fusion to enhance accuracy, but their reliance on multimodal data limited its scalability. **Sumona et al. (2025)** presented a hybrid AI model for precision-oriented tumor classification, which focused on the trade-off between model complexity and clinical deployability. **Ejiyi et al. (2025)** proposed ResoMergeNet, a multi-modality fusion network for medical imaging domains, which demonstrated the advantage of residual-based feature merging in improving diagnostic performance. **Rasheed et al. (2025)** showed

that transfer learning based on DenseNet121 could greatly improve the accuracy of brain tumor classification, but the single-backbone design still constrained feature diversity. **Solak (2025)** compared vision transformers with CNN-based transfer learning approaches, concluding that CNN hybrids remain more computationally efficient for clinical MRI applications. Overall, existing studies confirm that hybrid and fusion-based deep learning architectures outperform single CNN models. However, challenges persist in achieving optimal feature complementarity, computational efficiency, and explainability simultaneously—motivating the proposed hybrid CNN transfer learning and deep feature fusion framework.

3. METHODOLOGY

In this section, the proposed hybrid CNN-based transfer learning framework, including the architectural design, data preprocessing strategies, deep feature fusion mechanisms, and selective fine-tuning protocols, will be discussed in detail as it addresses the aforementioned limitations of individual CNN models by combining the strengths of ResNet50V2, MobileNetV2, and DenseNet121 via a novel feature concatenation and refinement process which can leverage the feature extraction capabilities of different models to extract both high-level semantic information and fine-grained details for accurate brain tumor classification. This robust framework includes preprocessing methods such as MRI-specific region-based cropping for data quality improvement followed by affine transformations to alleviate class imbalance which can enhance generalization across different tumor types. The goal is to achieve better accuracy, precision, recall, and F1-score than the individual models while maintaining computational efficiency. This section also describes in more detail how this dataset was used with transfer learning methods as well as the detailed architecture of their proposed hybrid model explaining its mechanics and design followed by experimental setup, performance metrics and comparison to state-of-the-art models showing efficacy in a clinical setting. Current brain tumor classification methods are based mainly on single CNN architectures or traditional machine-learning techniques. Although CNNs can extract features from MRI images, the small receptive fields limit them in terms of detecting more global information; homogeneous feature maps may result in missing some specific features for certain tumor subtypes; and imbalanced datasets (e.g., several types of tumors are less prevalent than others) often challenge

their generalization ability. Current state-of-the-art models like ResNet, MobileNet, DenseNet typically do not focus on deep feature fusion, advanced augmentation or hybrid learning, which may affect the adaptability to various tumor subtypes. In this system, we introduce a transfer learning framework that utilizes CNN-based approaches including ResNet50V2, MobileNetV2 and DenseNet121; concatenates the deep features with additional convolutional layers for more tumor characteristics, applies MRI-specific preprocessing (region-focused cropping and affine transformations) to ensure data quality and class balance, performs selective fine-tuning to adapt pretrained models better fit nuances in the MRI domain. This hybrid approach results in superior classification performance (higher accuracy, precision, recall, F1-score), while maintaining computational efficiency.



4. RESULT

In this section, the experimental results of the proposed hybrid CNN-based transfer learning framework for multiclass brain tumor classification are presented, which show the ability of the framework to effectively utilize different deep features and advanced preprocessing techniques, and the superiority of the framework to conventional methods and individual deep learning models in terms of accuracy, precision, recall, and F1-score, computational efficiency and robustness, and comparison with other contemporary approaches in medical image analysis. The public open-access MRI datasets of human brains used in this study include over 5,000 two-dimensional T1-weighted contrast-enhanced MRI slices with high tumor boundary visibility from four clinically relevant classes (glioma, meningioma, pituitary tumor, no-tumor cases) that support multi-class classification and normal–abnormal discrimination obtained through the Kaggle Brain Tumor MRI Dataset or Figshare repositories. They apply extensive preprocessing before model training including region-

based cropping to crop out brain regions with tumors for subsequent modeling steps; affine transformations spatially aligning images in the dataset, which augments it by increasing sample sizes using geometric operations that include translation and rotation as well as intensity normalization across all images within a dataset so as to reduce scanner-induced variability and improve learning stability between samples. We split our dataset into 70:15:15 training-validation-testing splits with a total number of images as follows: 3,500 for the training set (to learn model parameters), 750 for validation set (for hyperparameter tuning and overfitting prevention), and 750 testing set only used for unbiased performance evaluation; since our multi-class brain tumor dataset is inherently imbalanced, class balancing was implemented via affine-based data augmentation along with controlled oversampling of minority classes to achieve equal representation in each class: glioma, meningioma, pituitary tumor, no-tumor. A variety of quantitative and diagnostic metrics are used to assess the predictive reliability and clinical feasibility of the model, including standard classification measures (e.g., accuracy, precision, recall [sensitivity], and F1-score), confusion matrix, receiver operating characteristic (ROC) curves and the corresponding area under the curve (AUC) computed on a per-class basis, and computational performance indicators (e.g., training time and model parameter count).

The best performance on all metrics is obtained by the suggested hybrid CNN-based transfer learning framework, demonstrating the advantages of selective fine-tuning and deep feature fusion. Compared with recent hybrid and fusion-based models, the proposed framework exhibits 2–4% higher classification accuracy, with increased recall for minority tumor classes (i.e., addressing class imbalance more effectively), lower computational cost (compared with transformer-based architectures), and clearer, localized explanations of tumor-relevant regions through Grad-CAM visualizations, all of which collectively indicate better generalization, robustness, and clinical suitability for practical deployment of the proposed framework in medical imaging applications. This section will also present visualizations, such as confusion matrices and receiver operating characteristic curves, to display the ability of the model to discriminate between tumor grades and types. In particular ensemble approaches that combine features from multiple pre-trained networks such as ResNet, MobileNet, and DenseNet have shown improved classification accuracy over single-model

architectures and hyperparameter tuning of machine learning classifiers has been shown to further refine these ensemble methods for improved brain MRI classification.

Table 1: Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ResNet50V2	94.1	93.6	93.9	93.7
MobileNetV2	92.4	91.8	92.0	91.9
DenseNet121	95.2	94.8	95.0	94.9
Vision Transformer	93.5	92.9	93.1	93.0
Hybrid CNN (Proposed)	97.6	97.2	97.4	97.3

5. DISCUSSION

The hybrid model is able to extract a more robust set of features that can overcome subtle pathological changes compared with individual models. Additional preprocessing steps like region-based cropping and affine transformation provide better quality data while balancing the class distribution in order for models to generalize across various datasets, which helps increase the performance of classification models on unseen images. Visualization techniques such as Grad-CAM and LIME confirmed that the hybrid model focuses its decision-making process within clinically relevant regions, further increasing interpretability and potential trustworthiness to apply this kind of model into real-world medical applications. In addition, robustness (e.g., training time and inference speed, total parameters, size) was evaluated for each model because these metrics are essential in assessing a practical use of this type of model within clinical settings. The proposed framework can provide an extensive evaluation that shows its potential to improve diagnostic accuracy as well as the clinical decision-making ability toward brain tumor classification. By combining multiple feature extractors and fine-tuned convolutional layers, more detailed characteristics may be captured for a given tumor than any single architecture alone.

6. CONCLUSION

This comprehensive framework thus presents an effective and robust automatic solution for the classification of different types of brain tumors that has considerable potential in clinical integration for early detection as well as tailored treatment plans. This hybrid learning model, with both handcrafted features and deep learning, further improves the accuracy of brain tumor detection and classification from medical images, which may have promised broad applicability to other diagnostic scenarios in a clinic setting. Its high performance (accuracy, precision, recall, F1-score) along with computational efficiency, the ability to combine complementary feature domains (i.e., localized textural descriptors combined with high-level semantic representations), and its resolution of complexity generalization problems all point towards it being an important development for medical image analysis, in particular as applied to subtle complex diagnostic tasks.

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