Efficient and Explainable Brain MRI Tumor Classification: A Lightweight MobileNetV2-SVM Pipeline with External Validation and Domain Adaptation

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Abstract

Background/Objectives: Magnetic Resonance Imaging (MRI) plays a vital role in brain tumor diagnosis by providing clear visualization of soft tissues without the use of ionizing radiation. Given the increasing incidence of brain tumors, there is an urgent need for reliable diagnostic tools, as misdiagnoses can lead to harmful treatment decisions and poor outcomes. While machine learning has significantly advanced medical diagnostics, achieving both high accuracy and computational efficiency remains challenging, particularly when external validation and calibration assessment are required for clinical translation. **Methods:** We developed a lightweight pipeline combining MobileNetV2 feature extraction with classical machine learning classifiers (Logistic Regression, SVM). The pipeline includes rigorous calibration analysis, Grad-CAM explainability, external validation on a separate dataset, and domain adaptation strategies. Efficiency profiling was conducted on standard CPU hardware to assess deployment readiness. **Results:** Internal validation achieved 96.0% accuracy, 95.8% macro-F1 score, and 99.0% ROC-AUC. External validation revealed significant domain shift with performance dropping to 72.3% accuracy and 67.5% macro-F1, particularly affecting glioma detection (23% recall). Simple domain adaptation via external recalibration and threshold optimization improved external performance to 78.4% macro-F1 and 58% glioma recall. The pipeline demonstrates real-time capability with 45.7 images/second throughput, 2.22M parameters, and 8.52 MB model size. **Conclusions:** Our lightweight pipeline provides clinically relevant performance with transparent external validation, practical domain adaptation, and deployment-ready efficiency. The approach addresses key gaps in medical AI validation while maintaining computational efficiency suitable for real-world deployment. The combination of high accuracy, explainability, and efficiency makes this pipeline suitable for clinical evaluation studies and radiologist assistance tools. **Keywords:** MR images; brain tumor; classification; machine and deep learning; MobileNetV2; SVM; external validation; domain adaptation; explainable AI

1. Introduction

Brain tumors represent a significant global health burden, with approximately 18.1 million new cancer cases diagnosed worldwide annually. Magnetic Resonance Imaging (MRI) has become the gold standard for brain tumor diagnosis due to its superior soft tissue contrast and non-invasive nature. However, the increasing complexity of brain tumor classification and the growing demand for accurate diagnostic tools have created an urgent need for automated systems that can assist radiologists in clinical decision-making. Recent advances in deep learning have demonstrated remarkable success in medical image analysis, with many studies reporting accuracies exceeding 95% on internal validation sets. However, several critical limitations persist in the current literature

that hinder clinical translation and real-world deployment.

1.1. Related Work and Current Limitations

External Validation Gaps: The majority of existing studies report performance only on internal datasets, with limited external validation on independent datasets from different institutions or imaging protocols. This creates an overoptimistic view of real-world performance, as models often exhibit significant performance degradation when applied to external data due to domain shift, scanner differences, and population variations. **Calibration Assessment:** While classification accuracy is widely reported, the reliability of predicted probabilities—crucial for clinical decision-making—is rarely assessed. Poorly calibrated models can lead to overconfident predictions that misguide clinical decisions, particularly in high-stakes scenarios such as brain tumor diagnosis. **Computational Efficiency:** Many state-of-the-art models require substantial computational resources, limiting their deployment in resource-constrained clinical environments. The lack of comprehensive efficiency profiling in existing literature makes it difficult to assess real-world deployment feasibility. **Explainability and Trust:** The "black box" nature of deep learning models limits clinical adoption, as radiologists require interpretable explanations for AI-assisted decisions. While some studies incorporate explainability methods, quantitative assessment of explanation faithfulness is often missing.

1.2. Our Contributions

To address these limitations, we present a comprehensive brain MRI tumor classification pipeline with the following key contributions: • **Lightweight Architecture:** A MobileNetV2-based feature extractor combined with classical machine learning classifiers, achieving competitive performance with minimal computational requirements (2.22M parameters, 8.52 MB model size). • **Rigorous External Validation:** Systematic evaluation on an independent external dataset, quantifying performance degradation and identifying class-specific vulnerabilities, with transparent reporting of domain shift effects. • **Comprehensive Calibration Analysis:** Assessment of prediction reliability using Expected Calibration Error (ECE), Maximum Calibration Error (MCE), and reliability diagrams, with domain-specific calibration strategies. • **Practical Domain Adaptation:** Simple, safe adaptation strategies including external recalibration and threshold optimization that improve external performance without catastrophic forgetting. • **Explainable AI with Quantitative Metrics:** Grad-CAM visualization of attention patterns combined with perturbation-based robustness assessment to quantify explanation quality and clinical plausibility. • **Deployment-Ready Efficiency Profiling:** Detailed computational analysis including parameters, FLOPs, latency, throughput, and memory requirements on standard hardware.

2. Materials and Methods

2.1. Dataset Description and Preprocessing

Primary Dataset: We utilized a publicly available brain MRI dataset containing 14,046 images across four classes: glioma (1,621 images), meningioma (1,645 images), pituitary tumors (1,757 images), and no tumor (2,000 images). The dataset was split into training (10,281 images), validation (1,143 images), and test (2,622 images) sets using stratified sampling to maintain class distribution and ensure representative evaluation. **External Dataset:** For external validation, we used a separate public dataset containing 394 images with the same four-class structure: glioma (100 images), meningioma (115 images), pituitary tumors (74 images), and no tumor (105 images). This dataset was kept entirely separate from the primary dataset to ensure unbiased external validation and realistic assessment of generalization performance. **Preprocessing Pipeline:** All images were preprocessed consistently across datasets to ensure reproducibility: resized to 224×224 pixels using bilinear interpolation, converted to RGB format, and normalized using ImageNet statistics (mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]). No data augmentation was applied during feature extraction to ensure consistent evaluation conditions.

2.2. Model Architecture and Training

Feature Extraction: We employed MobileNetV2-1.0 as the feature extractor, utilizing pretrained weights from ImageNet. The model was modified to remove the classification head, outputting 1280-dimensional feature vectors from the global average pooling layer. This approach leverages transfer learning to extract rich, generalizable features while maintaining computational efficiency. **Classification Heads:** Three classical machine learning classifiers were trained on the extracted features: (1) Logistic Regression with multinomial loss and L2 regularization (C=10), (2) Linear SVM with balanced class weights, and (3) RBF SVM with balanced class weights and probability estimation. Features were standardized using StandardScaler fitted on the training set to improve convergence and performance. **Hyperparameter Optimization:** Model selection was performed using 5-fold cross-validation on the validation set, optimizing for macro-F1 score to ensure balanced performance across all classes. The best-performing model (Logistic Regression) was selected for further analysis and external validation.

2.3. External Validation and Domain Adaptation

Baseline External Evaluation: The best-performing model from internal validation was applied directly to the external dataset without any adaptation, measuring performance degradation due to domain shift and quantifying the gap between internal and external performance. **Domain Adaptation Strategies:** Two approaches were evaluated: (1) Simple Adaptation using domain-specific recalibration and per-class threshold optimization, and (2) Partial Fine-tuning of the last two MobileNetV2 blocks with strong regularization (negative ablation). The simple adaptation approach was found to be more effective and safer for deployment. **Calibration Assessment:** Probability calibration was assessed using Expected Calibration Error (ECE), Maximum Calibration Error (MCE), Brier Score, and Log Loss. Temperature scaling was applied for calibration improvement, with separate calibration models fitted for internal and external domains.

2.4. Explainability and Faithfulness Assessment

Grad-CAM Visualization: Gradient-weighted Class Activation Mapping (Grad-CAM) was applied to the MobileNetV2 feature extractor to visualize attention patterns and identify regions that influenced classification decisions. Both Grad-CAM and Grad-CAM++ variants were evaluated for comprehensive analysis. **Faithfulness Metrics:** Explanation faithfulness was quantified using perturbation-based robustness assessment. High-importance pixels were progressively masked, and the resulting probability drop was measured to assess how well the explanations align with model behavior. Average deletion AUC was computed for each class to provide quantitative faithfulness scores.

3. Results

3.1. Internal Validation Performance

The pipeline achieved excellent performance on the internal test set with 96.0% accuracy, 95.8% macro-F1 score, and 99.0% ROC-AUC. Per-class performance demonstrated balanced results across all tumor types: Glioma (93.9% F1-score, 90.6% recall, 97.4% precision), Meningioma (92.8% F1-score, 95.4% recall, 90.3% precision), Pituitary (96.9% F1-score, 97.7% recall, 96.1% precision), and No Tumor (99.9% F1-score, 99.8% recall, 100.0% precision). Calibration analysis revealed good initial calibration with ECE = 0.048 after temperature scaling, indicating reliable probability estimates for clinical decision-making. The reliability diagrams showed well-calibrated predictions across all confidence levels, with minimal deviation from the diagonal reference line.

3.2. External Validation and Domain Shift Analysis

External validation revealed significant performance degradation, with accuracy dropping from 96.0% to 72.3% (-23.7%), macro-F1 from 95.8% to 67.5% (-28.3%), and ROC-AUC from 99.0% to 89.8% (-9.2%). The domain shift affected classes differentially, with glioma showing severe degradation (F1: 93.9% $\rightarrow$ 29.0%, Recall: 90.6% $\rightarrow$ 23.0%), while meningioma and no tumor maintained relatively good performance. External validation also revealed severe calibration degradation, with ECE increasing from 0.048 to 0.130 (+171%) and log loss from 0.168 to 1.959 (+1066%), highlighting the critical need for domain-specific calibration strategies in real-world deployment.

3.3. Domain Adaptation Outcomes

Domain-specific recalibration and threshold optimization significantly improved external performance: macro-F1 improved from 67.5% to 78.4% (+10.9%), accuracy from 72.3% to 78.4% (+6.1%), and glioma recall from 23.0% to 58.0% (+35.0%). Per-class performance after adaptation showed balanced results: Glioma (60.1% F1-score, 58.0% recall, 62.4% precision), Meningioma (80.2% F1-score, 88.7% recall, 72.8% precision), Pituitary (89.3% F1-score, 85.1% recall, 93.9% precision), and No Tumor (83.6% F1-score, 80.0% recall, 87.5% precision). Partial fine-tuning resulted in performance degradation (macro-F1: 67.5% $\rightarrow$ 16.3%), highlighting the risks of fine-tuning on small external datasets and supporting the use of simpler, safer adaptation strategies.

3.4. Efficiency Profiling and Deployment Analysis

The pipeline demonstrates exceptional efficiency characteristics suitable for real-world deployment: 2,223,872 parameters (2.22M), 305.73 MMac FLOPs, 8.52 MB model size, 21.88 ± 2.36 ms CPU latency per image, and 45.7 images/second throughput. Memory requirements are minimal with <10 MB for the model and <100 MB total footprint including feature caches. Input size analysis showed minimal latency improvement with smaller inputs (160×160: 22.27 ms vs 224×224: 20.96 ms), indicating CPU memory access bottlenecks rather than computation limitations. The pipeline achieves real-time performance on standard CPU hardware, making it suitable for deployment in resource-constrained clinical environments.

4. Discussion

4.1. Clinical Implications and Performance Analysis

Our pipeline demonstrates that lightweight architectures can achieve competitive performance while maintaining computational efficiency. The 96% internal accuracy and 78% external accuracy (after adaptation) provide clinically relevant performance for brain tumor classification, particularly with the significant improvement in glioma detection (23% $\rightarrow$ 58% recall). The calibration analysis reveals important insights for clinical deployment. While internal calibration is good (ECE: 0.048), external calibration degrades significantly (ECE: 0.130), highlighting the need for domain-specific calibration in real-world deployment. The simple adaptation approach effectively addresses this through external recalibration and threshold optimization. Grad-CAM visualizations provide clinically interpretable explanations that can enhance radiologist confidence in AI-assisted decisions. The high faithfulness scores (78-98%) indicate reliable explanations that align with clinical reasoning and can support clinical decision-making processes.

4.2. Comparison with Existing Literature

Our results compare favorably with existing literature while addressing critical gaps. The 96% internal accuracy is competitive with state-of-the-art approaches, while the 78% external accuracy (after adaptation) represents a more realistic assessment of real-world performance. The combination of high accuracy, computational efficiency, and external validation represents a significant advancement over existing approaches. The domain adaptation results demonstrate that simple strategies can be highly effective, achieving 35% improvement in glioma recall without requiring extensive computational resources or risking catastrophic forgetting. This approach is more practical for clinical deployment than complex fine-tuning strategies.

4.3. Limitations and Future Work

Dataset Limitations: Our approach classifies individual MRI slices rather than complete volumes, and the external validation set (394 images) is relatively small. Both datasets may share similar imaging characteristics, and individual patient information was not available for analysis. **Technical Limitations:** Significant performance drops indicate substantial domain differences, glioma detection remains challenging (58% recall), analysis is limited to single MRI sequences, and external calibration remains suboptimal. **Clinical Readiness:** While the pipeline demonstrates strong performance and efficiency, it is not yet ready for unsupervised clinical use. It is suitable for clinical evaluation studies, radiologist assistance tools, and prospective validation. **Future Directions:** Multi-center validation studies, 3D volume analysis, multi-sequence integration, and prospective clinical trials are needed to fully assess clinical utility and regulatory approval potential.

5. Conclusions

We present a comprehensive brain MRI tumor classification pipeline that addresses critical gaps in medical AI validation and deployment. Our lightweight MobileNetV2-based approach achieves competitive performance (96% internal accuracy) while maintaining exceptional computational efficiency (45+ images/second, 8.52 MB model). The rigorous external validation reveals significant domain shift challenges (28% macro-F1 drop), particularly affecting glioma detection. However, our simple domain adaptation strategy—combining external recalibration and threshold optimization—effectively addresses these challenges, improving external performance to 78.4% macro-F1 and dramatically enhancing glioma recall from 23% to 58%. Key contributions include transparent reporting of external validation with domain shift analysis, practical domain adaptation strategies that avoid catastrophic forgetting, comprehensive calibration assessment with domain-specific solutions, explainable AI with quantitative faithfulness metrics, and detailed efficiency profiling demonstrating deployment readiness. The pipeline demonstrates that reliable, explainable, and efficient brain tumor classification is achievable with careful attention to validation, calibration, and adaptation strategies. While not yet ready for unsupervised clinical use, the approach provides a solid foundation for real-world evaluation and clinical integration studies. The combination of scientific rigor, practical adaptation strategies, and deployment efficiency makes this work particularly relevant for the medical AI community, addressing the critical need for clinically translatable AI systems that are both accurate and trustworthy.

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