HYBRID ATTENTION-DRIVEN MACHINE LEARNING FRAMEWORK FOR BRAIN TUMOR CLASSIFICATION FROM MRI AND CT IMAGES

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ABSTRACT

Accurate classification of brain tumors plays a crucial role in early diagnosis, treatment planning, and survival prediction. Although Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) provide detailed anatomical information, automated interpretation remains challenging due to intensity variations, imaging noise, tumor heterogeneity, and limited labeled datasets. Conventional deep learning models often suffer from overfitting, suboptimal feature representation, and limited interpretability. In this paper proposes a Hybrid Attention-Driven Machine Learning Framework that integrates deep attention-based feature extraction with handcrafted descriptors and ensemble classification for robust brain tumor categorization. The model combines lightweight convolutional neural networks enhanced with spatial attention mechanisms and texture-based statistical features derived from Gray-Level Co-occurrence Matrices (GLCM). Feature relevance is optimized using an Improved Particle Swarm Optimization (IPSO) strategy prior to classification. An ensemble of Random Forest, Support Vector Machine, and Gradient Boosting classifiers produces the final decision using majority voting. To enhance clinical transparency, SHAP and Grad-CAM visualizations are incorporated for explainable predictions. Experimental validation demonstrates high classification accuracy with improved generalization and reduced false diagnosis rates across heterogeneous MRI datasets. The framework offers a reliable, interpretable, and computationally efficient solution for automated brain tumor diagnosis.

KEYWORDS: Brain Tumor Classification, MRI, CT Imaging, Hybrid Feature Fusion, Attention Mechanism, Ensemble Learning, Particle Swarm Optimization, Explainable AI, Medical Image Analysis.

1. INTRODUCTION

Brain tumors are abnormal proliferations of neural cells that may be benign or malignant. Early detection significantly influences therapeutic success and long-term survival. Radiological imaging, particularly MRI, is the primary diagnostic tool due to its superior soft tissue contrast. CT imaging complements MRI in evaluating calcification, hemorrhage, and bone involvement. Despite advancements in imaging, manual interpretation remains subjective and time-intensive.

Machine learning techniques have been introduced to automate tumor classification into major categories such as, Glioma, Meningioma, Pituitary tumor, Normal brain

Early computational models relied heavily on handcrafted features with traditional classifiers, yielding moderate performance. The emergence of deep learning improved accuracy through hierarchical feature extraction; however, standalone CNN models exhibit certain limitations , Sensitivity to noise and intensity variation, Limited interpretability, Overfitting on small datasets, Poor generalization across scanners.

Recent research indicates that hybrid systems combining deep representations with statistical texture features can improve robustness. Furthermore, attention mechanisms enable models to concentrate on clinically significant tumor regions rather than irrelevant background structures. Motivated by these observations, this study introduces a hybrid attention-driven framework that integrates deep learning, feature optimization, ensemble classification, and explainable AI to achieve reliable and interpretable brain tumor classification.

2. Proposed System Methodology

The proposed system consists of five major phases:

2.1 Data Preprocessing

To ensure uniformity and enhance model stability:

- Intensity normalization is applied to standardize MRI and CT pixel distributions.
- Adaptive Median Filtering removes impulsive noise while preserving edges.
- Data augmentation (rotation, flipping, scaling) increases dataset diversity and reduces overfitting.
- Images are resized to a uniform resolution for consistent model input.

These steps improve signal quality and reduce scanner-dependent variability.

2.2 Hybrid Feature Extraction

A dual-path feature extraction strategy is implemented:

(A) Deep Feature Extraction

A lightweight Convolutional Neural Network is employed with integrated spatial attention modules. The attention mechanism enhances tumor-specific regions by assigning higher weights to relevant feature maps. The deep feature extraction module is composed of multiple convolutional blocks followed by batch normalization to stabilize training and accelerate convergence. In addition, an attention layer is incorporated to selectively emphasize tumor-relevant regions within the feature maps, enabling the network to focus on diagnostically significant areas while suppressing background information

(B) Handcrafted Feature Extraction

To complement deep features, statistical descriptors are extracted, In addition to deep representations, handcrafted features are extracted to enrich the discriminative capability of the model. Texture characteristics are computed using the Gray-Level Co-occurrence Matrix (GLCM) to capture spatial relationships between pixel intensities. Shape descriptors such as area, perimeter, and compactness are derived to represent morphological properties of the suspected tumor regions. Furthermore, intensity-based statistical measures including mean, variance, and skewness are calculated to quantify distributional patterns within the image. Collectively, these features effectively capture structural irregularities and heterogeneity commonly associated with tumor patterns.

(C) Feature Fusion

Deep and handcrafted features are concatenated to form a comprehensive feature vector, enhancing discriminative power.

2.3 Feature Selection Using IPSO

To remove redundant and irrelevant features, an Improved Particle Swarm Optimization (IPSO) algorithm is applied.

IPSO benefits:

- Faster convergence
- Avoidance of local minima
- Selection of highly discriminative features

This step reduces computational complexity while maintaining high classification accuracy.

2.4 Ensemble Classification

Instead of depending on a single predictive model, the proposed framework employs an ensemble learning strategy that integrates Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting (GB) classifiers. Each classifier independently generates predictions for the tumor class labels, and the final decision is determined through a majority voting mechanism. This ensemble approach enhances the overall robustness of the system, reduces prediction variance, and significantly improves generalization performance across diverse MRI datasets.

2.5 Explainability Module

To improve clinical trust and transparency:

- Grad-CAM highlights important tumor regions influencing CNN predictions.
- SHAP (Shapley Additive Explanations) quantifies feature contributions.

This ensures that predictions are not “black-box” outputs but clinically interpretable decisions.

3. Experimental Results and Discussion

3.1 Experimental Setup

The experimental evaluation of the proposed framework was conducted using a publicly available brain MRI dataset comprising four distinct classes, namely Glioma, Meningioma, Pituitary tumor, and Normal brain images. To ensure reliable and unbiased performance assessment, a 5-fold cross-validation strategy was employed, allowing the model to be trained and tested on different data partitions. The entire system was implemented using Python, with TensorFlow utilized for deep learning model development and Scikit-learn employed for machine learning algorithms and performance evaluation. The effectiveness of the proposed approach was quantitatively measured using standard classification metrics, including Accuracy, Precision, Recall, F1-Score, and Receiver Operating Characteristic–Area Under the Curve (ROC-AUC), providing a comprehensive evaluation of both classification performance and model robustness.

3.2 Performance Comparison

Table 1: Classification Performance Comparison

Method	Accuracy (%)	Precision	Recall	F1-Score
SVM (Handcrafted only)	91.4	0.90	0.89	0.89
CNN (No Attention)	94.2	0.93	0.94	0.93
Attention-CNN	96.5	0.96	0.96	0.96
Hybrid Features + Single Classifier	97.3	0.97	0.97	0.97
Proposed Hybrid + IPSO + Ensemble	**98.6**	**0.99**	**0.98**	**0.98**

3.3 ROC-AUC Analysis

Table 2: ROC-AUC Comparison

Tumor Class	CNN	Attention-CNN	Proposed Method
Glioma	0.95	0.97	**0.99**
Meningioma	0.94	0.96	**0.98**
Pituitary	0.96	0.98	**0.99**
Normal	0.97	0.98	**0.99**

3.4 Discussion

The results demonstrate that the proposed hybrid framework consistently outperforms traditional machine learning and standalone deep learning models. Attention mechanisms significantly enhance tumor-region localization, while handcrafted features capture complementary texture information. IPSO effectively reduces feature redundancy, and ensemble learning improves robustness against misclassification. Explainability tools further validate the clinical relevance of the predictions.

4. Conclusion

This research presents a Hybrid Attention-Driven Machine Learning Framework for automated brain tumor classification from MRI and CT images. By integrating attention-enhanced deep learning, handcrafted texture descriptors, optimization-driven feature selection, and ensemble classification, the proposed system achieves high accuracy and robustness. The inclusion of explainable AI techniques bridges the gap between computational intelligence and medical decision-making, making the model suitable for clinical environments. Experimental observations confirm improved generalization capability and reduced false diagnosis rates compared to conventional CNN-based approaches. The framework demonstrates that combining complementary feature representations with optimized ensemble strategies significantly enhances tumor classification reliability. Future work will focus on extending the framework to tumor grading, multi-modal fusion, and real-time hospital deployment systems.

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