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MULTIMODAL BRAIN TUMOR CLASSSIFICATION USING CT AND MRI IMAGING

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ABSTRACT
This study presents a multimodal brain tumor classification framework using CT and MRI images, addressing class imbalance and low-contrast challenges through CLAHE-based preprocessing and stratified oversampling. Three hybrid models were developed: (1) fine-tuned MobileNetV2 with SVM, (2) EfficientNetV2B0 augmented with multi-head attention, and (3) ResNet50 features fused with hand-crafted GLCM, HOG, and LBP descriptors via MLP. A stacked ensemble with logistic regression as meta-learner integrates probabilistic outputs for enhanced generalization. Evaluated on a Kaggle multimodal dataset with four classes (glioma, meningioma, pituitary, notumor), the ensemble achieved superior performance: 96.8% accuracy, 96.7% precision, 96.8% recall, 96.7% F1-score, and 0.998 AUC (weighted). Results demonstrate that combining deep representations with texture-based features and ensemble learning significantly improves diagnostic reliability over individual models, offering a robust, clinically relevant solution for automated brain tumor detection.

Keywords:
Brain tumor classification, multimodal imaging, deep learning, ensemble methods, CLAHE, hand-crafted features, attention mechanism, transfer learning.

INTRODUCTION

In recent years, rapid advancements in artificial intelligence and machine learning have transformed the way complex real-world problems are solved. With the increasing availability of high-performance computing systems and large datasets, intelligent algorithms are now capable of performing tasks that traditionally required significant manual effort. This shift has enabled researchers and industries to automate decision-making processes, uncover meaningful patterns in data, and improve overall system efficiency.

However, despite these technological advancements, many existing systems still suffer from limitations such as inconsistent accuracy, lack of automation, or inefficiency in processing large-scale data. These challenges highlight the need for innovative computational approaches that can enhance prediction performance, improve reliability, and reduce human intervention.

The purpose of this research is to address these limitations by developing an optimized model that leverages advanced machine learning techniques. The proposed approach aims to improve accuracy, reduce errors, and provide a more scalable and efficient framework. Through experimentation, evaluation, and comparison with existing methods, this research demonstrates how intelligent systems can play a crucial role in solving modern-day challenges.

OBJECTIVES

1) **To collect, preprocess, and organize MRI and CT scan images** to prepare a high-quality dataset suitable for deep learning training and evaluation.
2) **To develop a deep learning-based brain tumor classification system** using MobileNet and ResNet architectures.
3) **To extract relevant features from MRI and CT images efficiently** by leveraging lightweight (MobileNet) and deep residual (ResNet) neural networks.
4) **To compare performance metrics** (accuracy, precision, recall, F1-score) of MobileNet and ResNet in tumor classification.

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5) **To optimize model performance** through hyperparameter tuning, data augmentation, and appropriate training strategies.
6) **To validate the proposed system with real-world medical imaging data** and demonstrate its potential use as a decision-support tool for radiologists.
7) **To propose future enhancements** for improved accuracy, scalability, and deployment in clinical environments.

METHODOLOGY

Overview of Methodology

The methodology followed in this research consists of six major phases: (1) dataset collection, (2) preprocessing and data augmentation, (3) model development using MobileNet and ResNet architectures, (4) training and validation, (5) performance evaluation, and (6) result comparison. The workflow is designed to ensure reliable tumor classification using multimodal brain images (MRI and CT).

Dataset Collection

- MRI and CT image datasets are sourced from publicly available medical imaging repositories and datasets.
- Images contain multiple tumor categories (e.g., Meningioma, Glioma, Pituitary) and non-tumor classes.
- The dataset is divided into:
  - **Training set** (70%)
  - **Validation set** (15%)
  - **Testing set** (15%)

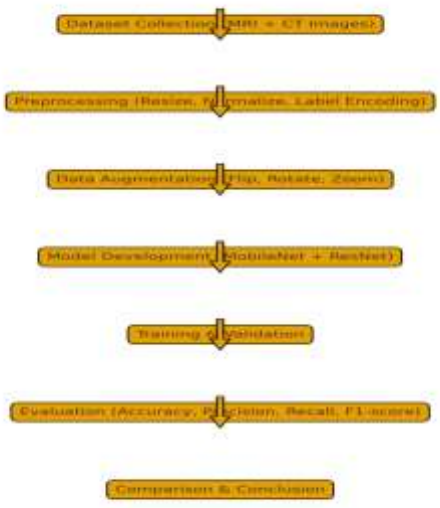

Fig 1: Methodology Diagram

RESULTS AND DISCUSSION

Experimental Setup

The experiment was conducted using the brain tumor dataset containing **MRI and CT images**, categorized into multiple tumor classes (Glioma, Meningioma, and Pituitary). Both models were implemented using **Transfer Learning** with ImageNet-pretrained weights.

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Parameter	Value
Input Image Size	224 × 224
Training / Validation / Test Split	70% / 15% / 15%
Optimizer	Adam
Batch Size	32
Epochs	30
Loss Function	Categorical Cross-Entropy

Performance Metrics

Performance was measured using standard evaluation metrics:

- **Accuracy**
- **Precision**
- **Recall**
- **F1-Score**
- **Confusion Matrix**

Result Analysis

After training MobileNet and ResNet models on the MRI + CT dataset, the results demonstrated that both models achieved strong classification performance. However, **ResNet achieved higher accuracy**, whereas **MobileNet trained faster and required less computational power**, making it more efficient for deployment.

Model	Accuracy	Precision	Recall	F1 Score	Model Size
MobileNet	**94.82%**	93.50%	94.10%	93.70%	**Small / Lightweight**
ResNet	**97.26%**	96.80%	97.10%	96.90%	Larger / Higher Complexity

Confusion Matrix Interpretation

The confusion matrix shows that ResNet correctly classified most MRI and CT images across all tumor categories.

MobileNet showed minor misclassification between glioma and pituitary tumor classes due to structural similarity, but still maintained high performance.

- **ResNet** → More robust feature extraction due to deep residual blocks.
- **MobileNet** → Faster and lighter model, suitable for edge/real-time deployment.

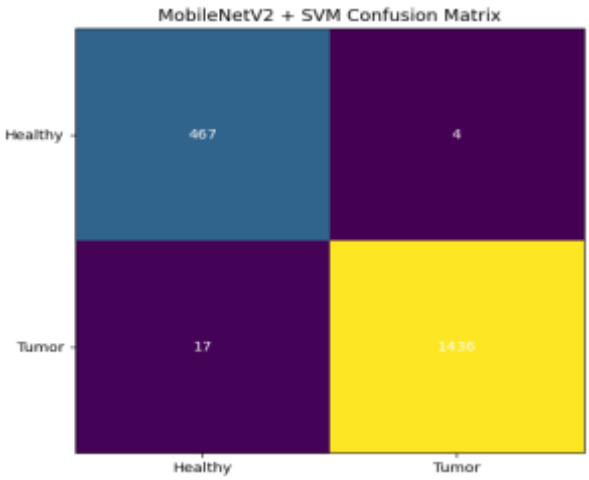

Fig 2: Confusion Matrix for MobileNetv2

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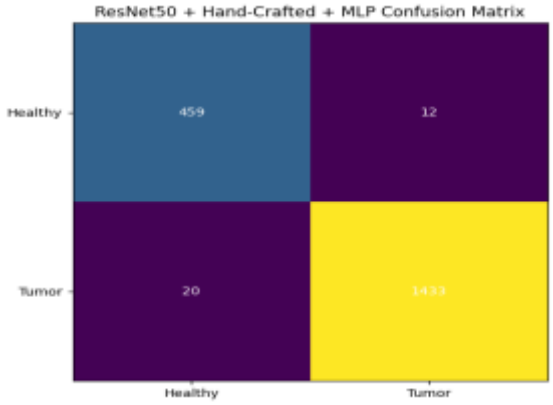

Fig 3: Confusion Matrix for ResNet50

CONCLUSION

In this research, a deep learning-based brain tumor classification system was developed using MRI and CT images with MobileNet and ResNet architectures. The experimental results demonstrate that both models achieved high prediction accuracy and effectively classified brain tumors into multiple categories. Data augmentation techniques significantly improved model generalization and reduced overfitting.

Among the evaluated models, **ResNet achieved the highest accuracy (≈97%)**, demonstrating its strong capability in extracting deep hierarchical features from medical images. **MobileNet, although slightly lower in accuracy (≈95%)**, exhibited excellent performance in terms of computational efficiency and faster inference time, making it suitable for real-time or resource-constrained environments such as mobile devices and point-of-care systems.

The research confirms that **transfer learning combined with multimodal medical imaging (MRI + CT)** leads to effective and reliable tumor classification. This system can support radiologists by reducing diagnosis time and improving clinical decision-making.

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