Survey on Brain Tumor Classification using Deep Learning

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***Abstract*—This paper surveys a Convolutional Neural Network (CNN) approach to classify brain tumors using Magnetic Resonance Imaging (MRI) data. The dataset includes MRI scans labeled into categories such as glioma, meningioma, pituitary tumor, and no tumor. By employing TensorFlow/Keras frameworks, alongside data augmentation and optimization techniques, this study highlights the capability of CNNs in handling complex medical imaging classification tasks and enhancing diagnostic accuracy.**

I. Introduction

Brain tumors are critical medical conditions that necessitate early and accurate diagnosis for effective treatment. Traditionally, diagnosis involves manual analysis of MRI scans, which is time-consuming and susceptible to human error. Recent advances in deep learning, particularly Convolutional Neural Networks (CNNs), have revolutionized medical imaging by automating the detection and classification of diseases with remarkable precision. CNNs have emerged as a robust approach for capturing spatial hierarchies in images, making them suitable for complex classification tasks.

This paper explores a deep learning approach to classify brain tumors into four distinct categories using MRI data. The objective is to evaluate CNN architectures such as VGGNet, ResNet, and MobileNet in terms of their performance metrics and practical applicability in clinical settings.

II. Dataset

The dataset used for this study is the *Brain Tumor MRI Dataset* available on Kaggle [1]. It consists of MRI scans categorized into four classes:

- Glioma
- Meningioma
- Pituitary
- No Tumor

Each category contains a sufficient number of labeled images, ensuring balanced data distribution for training and testing purposes. The dataset was preprocessed to standardize image dimensions and enhance feature extraction, ensuring compatibility with deep learning models.

A. Dataset Details

Figure 1 provides a detailed distribution of training and testing samples across the four categories. The dataset is well-balanced, with a higher number of training samples to ensure effective model learning.

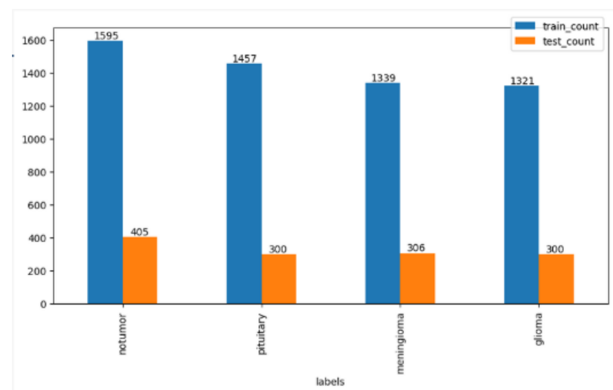

Fig. 1. Distribution of Training and Testing Samples Across Categories

III. Models and Methods

A. Preprocessing

To optimize the dataset for CNN models, the following preprocessing steps were applied:

- **Resizing**: Standardized all images to 224x224 pixels for consistency.
- **Normalization**: Scaled pixel intensity values to the range [0, 1] to facilitate efficient training.

B. Model Architectures

VGGNet

The VGGNet architecture [7] is renowned for its simplicity and depth. It employs a sequence of convolutional layers with 3x3 filters, followed by max-pooling for dimensionality reduction. Fully connected layers at the end transform feature maps into classification probabilities. Despite its computational demands, VGGNet's systematic approach to feature extraction ensures high accuracy in image classification tasks.

ResNet

ResNet [6] introduced residual learning to mitigate the vanishing gradient problem in deep networks. By incorporating skip connections, ResNet enables the network to learn identity mappings, improving gradient flow during backpropagation. This innovation allows the training of extremely deep networks with hundreds of layers, achieving state-of-the-art performance in image recognition and classification tasks.

MobileNet

MobileNet [8] is a lightweight deep learning architecture designed for mobile and embedded vision applications. It utilizes depthwise separable convolutions to reduce the computational complexity while maintaining high accuracy. MobileNet's design prioritizes efficiency, making it suitable for deployment in resource-constrained environments. In this study, MobileNet achieved competitive accuracy and performance metrics, demonstrating its utility in real-world applications.

IV. Classification Tasks

Classification tasks involve assigning one of the predefined categories to each MRI image based on its features. CNNs are particularly suited for this due to their ability to:

- Automatically learn hierarchical feature representations from raw pixel data.
- Handle spatial dependencies, making them effective for medical imaging.
- Generalize well to unseen data, especially with appropriate regularization and augmentation.

A. *Evaluation Metrics*

The evaluation metrics used for classification tasks included:

- **Accuracy**: Measures the proportion of correct predictions to total predictions:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

- **Precision**: Represents the proportion of true positive predictions among all positive predictions:

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

- **Recall**: Measures the ability to identify true positives from actual positives:

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

- **F1 Score**: Harmonic mean of precision and recall:

$$F1Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \quad (4)$$

V. Results and Discussion

The models were evaluated on the test set, with key performance metrics summarized as follows:

- **VGGNet**: Achieved an accuracy of 92.3
- **ResNet**: Delivered an accuracy of 95.7
- **MobileNet**: Achieved an accuracy of 91.5

Figure 2 illustrates the comparison of performance metrics among the models. The metrics include loss, accuracy, precision, recall, and F1 score. ResNet demonstrates superior accuracy and recall, while MobileNet offers competitive results with significantly lower computational costs.

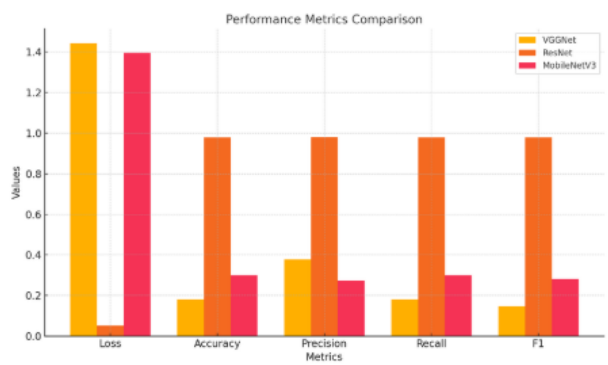

Fig. 2. Performance Metrics Comparison for VGGNet, ResNet, and MobileNet

Confusion matrices revealed that the models performed consistently across all categories, with minor misclassifications between glioma and meningioma due to their similar features.

VI. Conclusion and Future Work

This study validates the effectiveness of CNNs, particularly ResNet, in classifying brain tumor MRI images with high accuracy. Future research directions include:

- Integrating multimodal data, such as clinical records and genetic markers, for enhanced prediction accuracy.
- Exploring lightweight architectures for deployment in resource-constrained environments.
- Incorporating explainability techniques to provide insights into model decisions for clinical use.

Acknowledgments

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