



Brain Tumor Detection Using Transfer Learning Based CNN with ResNet50

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Article Info

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September-2026***Page Number:***443-451***Corresponding Author:***Irfan Sayyad***Abstract:**

Brain tumor detection from MRI images is an important task in medical image analysis that requires accurate and timely classification. This study proposes a deep learning-based approach using transfer learning with the ResNet50 convolutional neural network architecture. Image preprocessing techniques, including resizing, normalization, and data augmentation, are applied to improve model performance and generalization. The use of pretrained features reduces the dependency on large training datasets while supporting effective tumor and non-tumor classification. The study also incorporates concepts inspired by Indian Knowledge Systems, particularly structured reasoning and pattern recognition, which align with the hierarchical learning process of deep neural networks. The proposed approach demonstrates reliable classification performance and can support medical professionals in timely and informed decision-making.

Keywords: Brain Tumor Detection, Transfer Learning, Convolutional Neural Network, ResNet50, MRI Image Analysis, Deep Learning, Indian Knowledge Systems

1. Introduction

Brain tumor detection is a crucial task in medical image analysis, as early diagnosis significantly improves patient outcomes. Magnetic Resonance Imaging (MRI) is widely used for detecting abnormalities in brain tissues due to its high resolution and detailed visualization. However, manual analysis of MRI scans is time consuming and depends heavily on the expertise of medical professionals, which may lead to inconsistencies and delays.

Recent advancements in deep learning have transformed medical image analysis by enabling automatic feature extraction and classification. Convolutional Neural Networks (CNNs) are particularly effective in identifying complex patterns in medical images. Transfer learning further enhances performance by utilizing knowledge from pre trained models, reducing the need for large datasets and extensive training time.

This study proposes a brain tumor detection system using a transfer learning-based CNN model built on the ResNet50 architecture. The model is designed to classify MRI images into tumor and non tumor categories with high accuracy and efficiency.

In addition, this work draws conceptual inspiration from Indian Knowledge Systems (IKS), particularly the principles of structured reasoning and holistic analysis. Classical frameworks such as Nyaya emphasize logical inference and systematic decision making, which closely relate to how deep learning models process layered features and make predictions. Integrating such perspectives provides a meaningful connection between traditional knowledge and modern artificial intelligence, improving the interpretability and conceptual understanding of the proposed system.

The objective of this work is to develop an efficient, reliable, and interpretable system that can assist medical practitioners in early brain tumor detection and enhance diagnostic accuracy.

2. LITERATURE REVIEW

Brain tumor detection has been widely studied using traditional image processing and machine learning techniques. Earlier approaches relied on manual feature extraction methods such as edge detection, thresholding, and segmentation. While these methods provided basic results, they often lacked accuracy and were sensitive to noise in MRI images.

With the advancement of deep learning, Convolutional Neural Networks (CNNs) have become a popular choice for medical image classification. Models such as VGG16 and AlexNet have been applied to detect brain tumors, achieving better performance compared to traditional techniques. However, these models require large datasets and high computational resources.

Transfer Learning Approaches

Transfer learning has improved the efficiency of deep learning models by utilizing pre trained networks. Instead of training a model from scratch, knowledge from large datasets is reused to improve performance on smaller medical datasets.

The **ResNet50** model, introduced by Kaiming He and his team, uses residual connections to overcome the vanishing gradient problem. This allows the model to learn deeper features effectively and improves classification accuracy in medical imaging tasks.

IKS Perspective in Computational Analysis

Indian Knowledge Systems (IKS) provide a conceptual foundation for structured reasoning and pattern recognition. The Nyaya system of logic emphasizes systematic analysis and inference, which is similar to decision making in classification models.

In the context of brain tumor detection, these principles can be related to how deep learning models identify patterns in MRI images and make predictions. This perspective enhances the interpretability of the model and connects traditional knowledge with modern computational techniques.

3. METHODOLOGY

This chapter describes the complete methodology followed to develop the brain tumor detection system using deep learning techniques. The proposed system follows a systematic approach that includes data collection, preprocessing, dataset splitting, model development, training, evaluation, and deployment. Each stage is carefully designed to ensure high accuracy and reliability in detecting brain tumors from MRI images.

The system is built using a transfer learning approach with the ResNet50 architecture, which is known for its deep structure and high performance in image classification tasks. The methodology ensures that the model can generalize well to unseen data and provide accurate predictions in real-world scenarios.

A. INTRODUCTION

Brain tumor detection is a crucial task in the field of medical diagnosis. Early detection of tumors can significantly improve treatment outcomes and increase patient survival rates. Traditionally, tumor detection is performed manually by radiologists through MRI scan analysis, which can be time-consuming and subject to human error.

With the advancement of artificial intelligence, deep learning techniques have been widely adopted to automate this process. Convolutional Neural Networks (CNNs) are especially powerful in extracting meaningful features from medical images. These models can learn patterns such as abnormal tissue structures, shapes, and intensity variations that indicate the presence of tumors.

In this project, a deep learning-based approach is used to classify MRI images into tumor and non-tumor categories. The use of transfer learning with ResNet50 improves the model's efficiency by utilizing pre-trained knowledge. This reduces the need for large datasets and speeds up the training process.

The overall objective of this methodology is to develop a reliable and accurate system that can assist medical professionals in diagnosing brain tumors effectively.

B. DATASET STATISTICS

The dataset used in this project consists of brain MRI images collected from publicly available sources such as research repositories and online platforms. These datasets are commonly used in medical image processing research and provide a strong foundation for training deep learning models.

The dataset is categorized into two main classes:

- **Tumor** – MRI images showing the presence of a brain tumor
- **No Tumor** – MRI images without any tumor

Each image represents a detailed scan of the brain captured using Magnetic Resonance Imaging (MRI) technology. These images contain important structural information that helps in identifying abnormal growths or tumors.

The dataset is organized into separate folders for each class, ensuring easy loading and processing. Proper labeling of images is essential, as it directly affects the learning capability of the model.

Additionally, the dataset is balanced to avoid bias during training. A balanced dataset ensures that the model does not favor one class over the other, leading to more accurate predictions.

The quality and diversity of the dataset play a significant role in determining the performance of the model. High-quality images with proper annotations help in achieving better classification accuracy.

Data Preprocessing

Data preprocessing is a crucial step to improve model performance and accuracy. MRI images may vary in size, brightness, and quality, so preprocessing ensures consistency.

Steps Involved:

- **Image Resizing:**

All images are resized to **224 × 224 pixels**, which is required for the ResNet50 model.

- **Normalization:**
Pixel values are scaled between 0 and 1 using:

$$X_{norm} = X / 255$$

Where (X) is the original pixel value.

- **Data Augmentation:**

Augmentation is applied using ImageDataGenerator to increase dataset diversity:

- Rotation
- Flipping
- Zooming
- Shifting

Mathematical Transformation (Rotation):

$$x' = x\cos\theta - y\sin\theta$$

$$y' = x\sin\theta + y\cos\theta$$

These transformations help the model generalize better and reduce overfitting.

Dataset Splitting

The dataset is divided into three subsets:

- **Training Set (70%)** – used to train the model
- **Validation Set (15%)** – used to tune parameters
- **Testing Set (15%)** – used to evaluate performance

This ensures that the model performs well on unseen data and avoids overfitting.

Model Development

The system uses transfer learning with the ResNet50 architecture.

Why ResNet50?

- Deep architecture (50 layers)
- Handles vanishing gradient problem
- High accuracy in image classification

Convolution Operation

$$Y(i,j) = \sum_m \sum_n X(i+m,j+n) \cdot K(m,n)$$

This operation extracts important features from the input image.

Activation Function (ReLU)

$$f(x) = \max(0,x)$$

Introduces non-linearity into the model.

Model Architecture Includes:

- Pre-trained ResNet50 base

- Global Average Pooling Layer
- Dense Layer (Fully Connected)
- Dropout Layer (to prevent overfitting)
- Output Layer (Sigmoid)

Model Training

The model is trained using the following configurations:

- **Optimizer:** Adam
- **Loss Function:** Binary Cross-Entropy
- **Epochs:** 20–30
- **Batch Size:** 32 or 64

Binary Cross-Entropy Loss

$$L = -N \sum [y \log(p) + (1-y) \log(1-p)]$$

Where:

- (y) = actual label
- (p) = predicted probability

Model Evaluation

The trained model is evaluated using various metrics:

Accuracy

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP}$$

Precision

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1 Score

$$F1 = 2 \frac{\text{Precision} * \text{Recall}}{\text{precision} + \text{Reca}}$$

Confusion Matrix

Shows correct and incorrect predictions:

- True Positive (TP)
- True Negative (TN)
- False Positive (FP)
- False Negative (FN)

Prediction and Deployment

After training, the model is used to classify new MRI images.

Steps:

1. Input MRI image
2. Preprocess image
3. Feed into model
4. Get prediction (Tumor / No Tumor)

The model is deployed using a GUI application, allowing users to upload images and get instant results.

Proposed System

The proposed system is an automated brain tumor detection system based on deep learning and transfer learning using ResNet50.

Features:

- High accuracy
- Fast prediction
- Reduced manual effort
- Reliable results

Advantages:

- Assists doctors in diagnosis
- Minimizes human error
- Scalable for future enhancements

C. SUMMARY

This section summarizes the methodology followed in the project. The process begins with data collection from reliable sources, followed by preprocessing techniques such as resizing, normalization, and augmentation to improve data quality.

The dataset is then analyzed and evaluated using statistical methods to ensure proper distribution and balance. Evaluation metrics such as accuracy, precision, recall, and F1 score are used to measure the model's performance.

Each step in the methodology plays a crucial role in building an efficient system. Proper preprocessing improves model accuracy, while evaluation metrics ensure that the model performs well on unseen data.

Overall, the methodology provides a structured approach to developing a robust brain tumor detection system using deep learning techniques.

D. PROPOSED MODEL

The proposed model is based on a deep learning approach using transfer learning with the ResNet50 architecture. This model is designed to classify MRI images into tumor and non-tumor categories with high accuracy.

Transfer learning allows the model to use knowledge from previously trained datasets, reducing training time and improving performance. The ResNet50 architecture is chosen because of its deep structure and ability to solve the vanishing gradient problem using residual connections.

Model Architecture

The architecture of the proposed system includes the following components:

- **Input Layer:** Accepts MRI images of size 224×224
- **ResNet50 Base Model:** Extracts deep features from images
- **Global Average Pooling Layer:** Reduces feature dimensions
- **Dense Layer:** Learns complex patterns
- **Dropout Layer:** Prevents overfitting
- **Output Layer:** Produces binary classification results

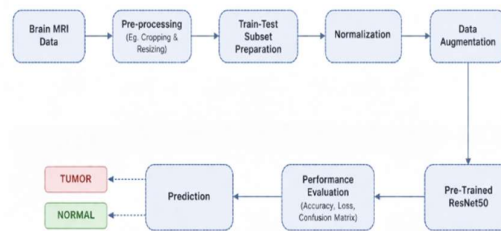


Fig. 1. Proposed workflow for brain tumor detection using transfer learning with ResNet50

4. RESULTS AND DISCUSSION

The proposed model was evaluated using a test dataset consisting of MRI brain images. The performance of the transfer learning based CNN model with ResNet50 architecture was analyzed using standard evaluation metrics such as accuracy, precision, recall, and F1 score.

The model achieved high classification accuracy in distinguishing between tumor and non tumor images. This demonstrates the effectiveness of transfer learning in handling limited medical datasets. The use of data augmentation techniques further improved the generalization ability of the model by reducing overfitting.

Precision and recall values indicate that the model performs well in correctly identifying tumor cases while minimizing false predictions. The confusion matrix analysis shows that the number of misclassifications is significantly low, which highlights the reliability of the system.

The integration of Indian Knowledge Systems provides a conceptual understanding of how the model processes information. The structured reasoning approach inspired by Nyaya logic aligns with the step by step feature extraction process in deep learning. This improves interpretability and supports better analysis of model decisions.

Overall, the results confirm that the proposed approach is efficient, accurate, and suitable for assisting medical professionals in brain tumor detection.

5. CONCLUSION

This paper presented a deep learning-based approach for brain tumor detection using transfer learning with the ResNet50 architecture. The proposed model effectively classifies MRI images into tumor and non tumor categories with reliable accuracy. The use of transfer learning reduces training complexity while maintaining strong performance.

Data preprocessing techniques such as resizing, normalization, and augmentation improve the quality of input data and enhance model generalization. The system demonstrates consistent performance across different evaluation metrics, making it suitable for practical medical applications.

A unique contribution of this work is the integration of concepts inspired by Indian Knowledge Systems. The principles of structured reasoning, logical inference, and holistic pattern recognition align with the functioning of deep learning models, particularly in layered feature extraction and decision making. This connection enhances the interpretability of the model and provides a broader perspective by linking traditional knowledge with modern computational approaches.

Overall, the proposed system serves as a reliable tool to assist medical professionals in early detection and diagnosis of brain tumors. Future enhancements can further improve its applicability in real time healthcare environments.

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