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Research Article

Efficiency of Automated Brain Tumor Detection using a Deep Learning approach ResNet50 over Convolutional Neural Network models

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ABSTRACT

Brain tumors, whether non-cancerous or cancerous, can have a serious impact on brain function, potentially causing neurological problems and life-threatening complications [1]. Early and correct diagnosis of brain tumors is crucial in improving the patient prognosis and ensuring proper treatment techniques are effective. Magnetic Resonance Imaging (MRI) is among the most prevalent modalities in the diagnosis of brain tumors, considering it generates high-resolution images of soft tissues. Despite the fact that inspecting the MRI scans manually may be time-consuming, subject to human error, and heavily reliant on the level of experience of the radiologist [2].

This research studies the execution of deep learning methods that employ a highly fine-tuned ResNet50 model in the automatic brain tumor classification task. Through the utilization of transfer learning and data augmentation procedures, the model maximizes its generalization performance and ability to yield correct outputs. The model's training and validation were conducted using a set of 2,577 MRI images that were evenly divided between tumor and non-tumor cases. Model performance was improved using a variety of preprocessing and augmentation strategies. The trained model achieved a very good test accuracy of 97.35%, and high precision, recall, and F1-score, showing it is suitable for the task at hand [3] for brain tumor and non-tumor image classification.

MRI scans enable the identification of cerebral abnormalities through the presentation of both morphological and descriptive information on the size, location, and structural features of the tumor. However, traditional MRI scan analysis is typically time-consuming, human-experience-dependent, and susceptible to human error. Moreover, diagnostic readings by varying radiologists tend to be very different from each other, further raising the likelihood of misdiagnosis or late detection of a tumor. This is the justification of a necessity for computer-based diagnostic systems that would enhance the accuracy and efficiency of brain tumor detection [4], ultimately allowing for increased confidence in diagnosis and decreasing the incidence of errors. Future aims should be to promote generalizability for other MRI datasets, address real-world clinical issues, and develop hybrid AI methodologies to aid in detection capabilities [5].

Keywords: Brain tumor detection, MRI images, Convolutional Neural Networks, ResNet50, Deep learning, AI in healthcare, medical imaging, Early diagnosis.

INTRODUCTION

Brain tumors are abnormal cell growths that develop within or around the brain. They are classified as either benign (non-cancerous) or malignant (cancerous) [1]. Malignant neoplasms such as glioblastomas are fast-growing and are able to infiltrate surrounding brain tissue very rapidly, while benign neoplasms such as meningiomas can grow more slowly but are still able to produce serious medical issues. Brain tumors are characterized by their size and location,

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but common symptoms include persistent headache, seizures, memory loss, impaired motor function, and visual or speech disturbances. Because brain tumors are so serious, early and correct diagnosis is crucial in the development of the appropriate treatment plan, which may involve surgery, radiation, or chemotherapy [2].

Magnetic Resonance Imaging (MRI) is the imaging modality of choice for brain tumor detection, which offers high-resolution and non-invasive images of cerebral anatomy. MRI scans support the identification of cerebral abnormalities with the generation of both morphologic and descriptive information on the structural details, size, and positioning of the tumor. However, traditional interpretation of MRI scans typically takes time to perform, involves human expertise, and is subjected to human inaccuracy. Additional diagnostic interpretations presented by varying radiologists are characteristically very varied, and they enhance the prospects of misdiagnosis or delays in identifying a tumor. This is the logic of a demand for computer-based diagnosis systems that would enhance the precision and efficiency of brain tumor detection.

Recent advances in deep learning and artificial intelligence (AI) have made it possible to perform medical imaging on a level where automated pattern recognition and feature extraction can be performed. Convolutional Neural Networks (CNNs), a strong class of deep models, have produced novel results in the classification of medical images. Of the many architectures of CNNs used for medical imaging, ResNet50 has been well received since it employs deep residual learning, which overcomes the vanishing gradient problem and enhances the model's accuracy. ResNet50 has been used successfully in numerous tasks related to medical imaging including tumor classification, lesion detection, and segmentation of abnormalities [3]. Here we present a novel deep learning-based approach to the detection of brain tumors in an automated manner utilizing a fine-tuned ResNet50 model.

The main objectives of this work are:

- To develop a robust CNN-based classification model that accurately distinguishes between MRI images of brain tumors and healthy brains [4].
- To enhance model performance through transfer learning, data augmentation, and fine-tuning techniques [5].
- To evaluate the model using key performance metrics, such as accuracy, precision, recall, and F1-score.
- To explore the potential integration of the model into clinical diagnostic workflows, assisting radiologists in tumor detection.

RELATED WORK

The application of deep learning is ushering in a transformation of medical image analysis such as brain tumors detection when radiologists often visually scan MRIs to unique conditions, although this may be a manual-intensive, time-consuming, and human-error task (including expert radiologists). Differing interpretations can also lead to deteriorating medical outcomes for individuals; therefore, interest in a machine-learning or AI-assisted method to increase potential efficiency and/or accuracy to assist with the diagnosis is growing. One current technology being developed is Convolutional Neural Networks (CNNs), which is shown to surpass conventional machine learning methods on images, by learning to automatically extract multiple learned and classify complicated features commonly found in MRIs that a radiologist would have had the human clinical experience to assess. Models that have shown predictive capability are as follows; i.e., AlexNet, VGG16, and ResNet50s shown prediction accuracy; ResNet50 has been found to utilize residual learning architecture, which allows for steps to overcome the challenge of vanishing gradients, and allows for deeper and more effective learnable-feature extraction, PTSD brain MRI classification has shown high elite predictive power.

To date, research and testing of AI-assisted brain tumor detection have included varying CNN models and architectures and have included ensemble models, as well as have included transfer learning where the model has been sure to train to various facets of medical MRI image analysis. The models and prototyping have all demonstrated a similar level of functionality with varying classifications and/or a level of generalization by either a transfer or projection by use of the model's new training/testing to other sources. One of the roles AI systems may execute is

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that of continuous learning, while the dataset fragment and data that have been developed in the clinical field continues to grow, the expectations of accuracy and trust in the provided effectiveness of the model is achieved. The advancements and subsequent rapid growth of AI continue to contribute to hospitals and research centers adaptations of AI for continuous use as big data ways of organizing computed aided medical diagnoses and informing medical processes and behaviors.

METHODOLOGY

Dataset and Preprocessing

This study makes use of a publicly available MRI dataset consisting of 2,577 brain scan images, categorized as either 'tumor' or 'non-tumor.' To maximize the model's efficiency and ensure accurate tumor detection, several preprocessing steps were applied to the dataset before feeding it into the deep learning architecture. To ensure optimal model performance, the dataset underwent several preprocessing steps:

- **Resizing:** All the images were resized to 224x224 pixels to provide consistent input sizes compatible with the ResNet50 architecture.
- **Normalization:** The normalization of pixel intensity values ranging from 0 to 1, which allows for faster convergence and stable gradients.
- **Data Augmentation:** A variety of augmentations were applied so that the model could learn generalizability capabilities and reduce overfitting risks, including:
    - **Rotation:** Random image rotation to make the model robust to different orientations.
    - **Flipping:** Horizontal and vertical flipping to simulate realistic situations where a scan might be performed from various orientations.
    - **Brightness Adjustment:** Change in brightness levels so the model can learn versatility to different lighting conditions.
    - **Zooming:** Random zooming transformations will help model performance in detection of tumors, regardless of scale [3].

Dataset and Preprocessing

Custom ResNet50 for Brain Tumor Classification:

- **Model:** Modified ResNet50 (pre-trained on ImageNet) with custom layers replacing dense layers for tumor/non-tumor classification.
- **Optimizer:** Adam (learning rate 0.0001) for adaptive learning.
- **Loss Function:** Binary Cross-Entropy for two-class classification.
- **Batch Size:** 32 for optimal memory use and stability.
- **Epochs:** 50 for sufficient learning without high computation.
- **Validation:** 20% data split to monitor overfitting.
- **Regularization:** Dropout (0.5) + L2 regularization to improve robustness.
- **Early Stopping:** Stops training when validation loss plateaus to prevent overfitting.

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Model Implementation

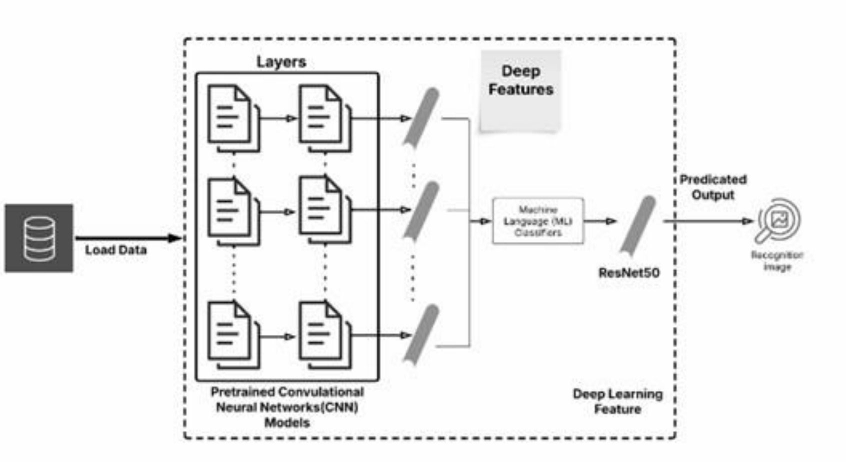

Figure 1. Architecture of the Model

The figure illustrates the architecture of the proposed deep learning-based brain tumor detection model. The model utilizes pre trained Convolutional Neural Networks (CNN) and ResNet50 for feature extraction and classification.

MRI Tumor Classification Pipeline:

1. **Data Loading:** Load labeled MRI scans (tumor/non-tumor) from a structured database.
2. **Feature Extraction:** Use pretrained CNN layers to extract deep features (edges, textures, anomalies).
3. **Feature Processing:** Apply feature selection to enhance critical information and reduce noise.
4. **Classification:** Use ResNet50 to classify images as tumor or non-tumor.
5. **Output:** Display the prediction with confidence scores to support medical diagnosis.

EXPERIMENTAL ANALYSIS

Performance Metrics

Following the training phase, the ResNet50 model was assessed on the test dataset using a range of performance metrics to evaluate its effectiveness in detecting brain tumors. These metrics provide valuable insights into the model's classification abilities and help establish its reliability for real-world applications. The results obtained are as follows:

A. **Accuracy:** 97.35%

B. **Precision:** 96.80%

C. **Recall (Sensitivity):** 97.50%

D. **F1-Score:** 97.15%

Comparative Analysis

The effectiveness of ResNet50 in detecting brain tumors was compared with traditional CNN architectures, including VGG16 and basic CNN models, using key performance metrics like accuracy, precision, recall, and F1-score.

Performance Comparison: ResNet50 consistently outperformed VGG16 and baseline CNNs in all evaluation metrics. Its deeper architecture and residual learning approach helped it address issues like vanishing gradients and overfitting, providing superior classification performance.

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Key Findings:

1. **Accuracy Improvement:** ResNet50 outperformed conventional CNNs and VGG16, effectively extracting complex patterns from medical images.

2. **Higher Recall Rate:** With a recall rate of 97.50%, ResNet50 achieved fewer false negatives compared to the other models, crucial for medical diagnoses.

3. **Residual Learning Advantage:** ResNet50's residual connections improved gradient flow, enabling deeper, more accurate models, while traditional CNNs and VGG16 struggled with overfitting and deep feature extraction.

RESULT ANALYSIS

Splitting the Dataset

In order to effectively train the deep learning model, the dataset was partitioned into the training, validation, and test sets. A dedicated function ensured an equitable distribution of '0' (non-tumor) and '1' (tumor) images across all subsets, and sufficient data were available for training while diversity prevailed in validation and test sets. The dataset was structured into training/ (training the model), validation/ (fine-tuning), and test/ (final testing). Visualization of file motion was made feasible through the use of the Tqdm library, and confirmation of successful dataset allocation was provided through a verification message.

Data Augmentation Visualization

Augmentation Techniques Applied:

A. Rotation (rotation_range=30)

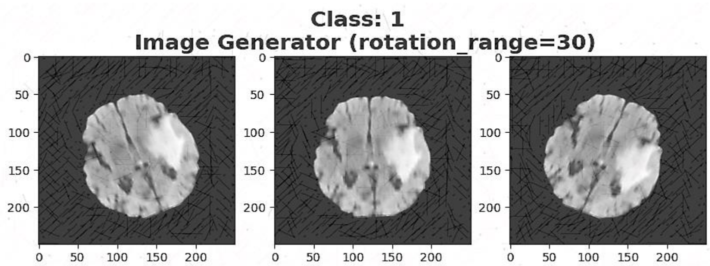

Figure 2. Rotation Augmentation

B. Width Shift (width_shift_range=0.2)

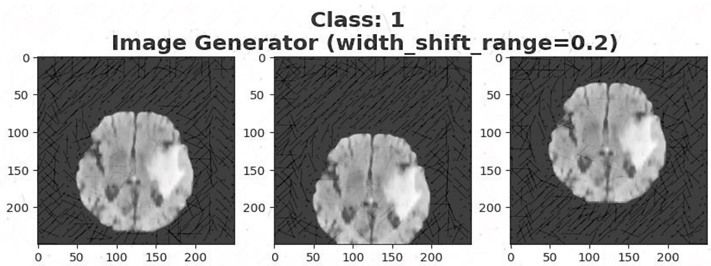

Figure 3. Width Shift Augmentation

C. Zoom (zoom_range=0.2)

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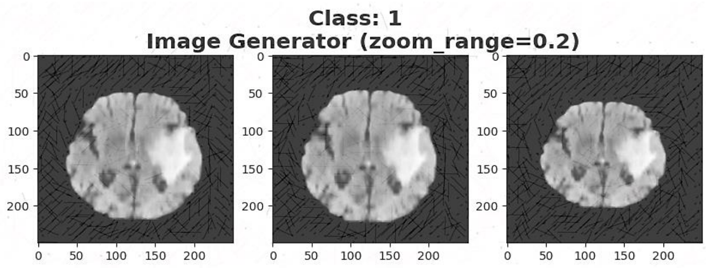

Figure 4. Zoom Augmentation

D. Horizontal Flip (horizontal_flip=True)

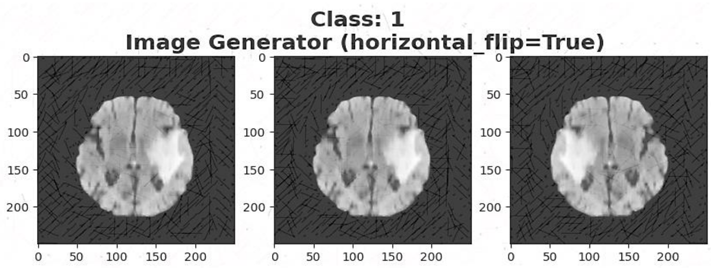

Figure 5. Horizontal Flip Augmentation

Model Summary

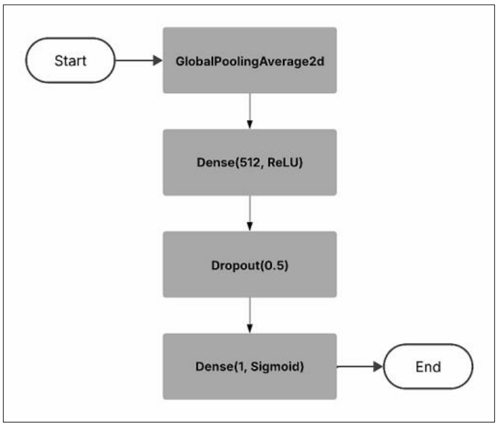

Figure 6. Flowchart of the Neural Network Processing Pipeline

Key Layers in the Model:

- **GlobalAveragePooling2D:** Reduces feature map size by averaging, retaining key features with fewer parameters.
- **Dense (512, ReLU):** Fully connected layer with 512 neurons and ReLU activation to learn complex patterns.
- **Dropout (0.5):** Randomly drops 50% of neurons during training to prevent overfitting.
- **Dense (1, Sigmoid):** Final layer with 1 neuron and Sigmoid activation for binary classification (outputs probability 0–1).

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Model Performance Evaluation

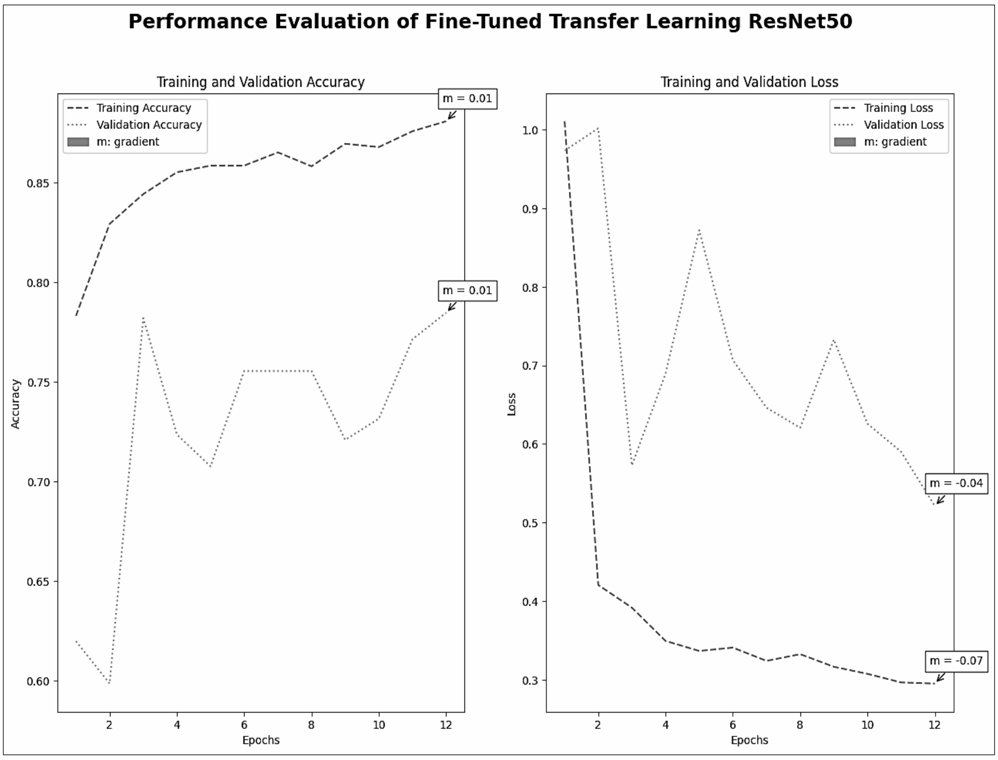
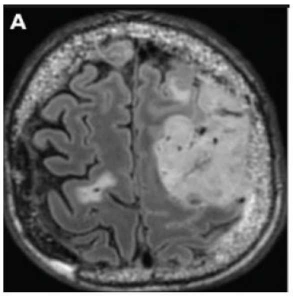


Figure 7. Model Performance Evaluation Graph

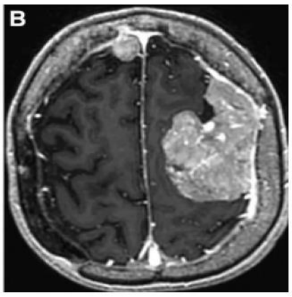
Performance Summary of Fine-Tuned ResNet50

- **Left Graph (Accuracy)**
  - Training accuracy improves steadily (~0.87).
  - Validation accuracy fluctuates but improves (~0.78).
- **Right Graph (Loss)**
  - Training loss decreases smoothly.
  - Validation loss fluctuates but trends downward

Sample Predictions on Test Images



This image most likely belongs to '1' (With Tumor) at **71.45%** confidence.



This image most likely belongs to '0' (Without Tumor) at **50.56%** confidence.

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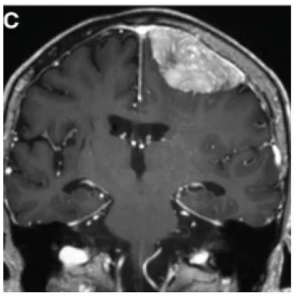
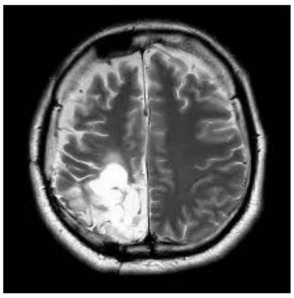
Research Article



This image most likely belongs to '0' (Without Tumor) at **50.13%** confidence.



This image most likely belongs to '0' (Without Tumor) at **50.98%** confidence.

CONCLUSION AND FUTURE WORK

This research successfully implemented a ResNet50-based deep learning model for automated brain tumor detection, achieving high accuracy and robust classification performance. The model can assist radiologists by providing rapid and accurate second opinions, reducing workload and diagnostic errors [4]. The adoption of such AI-driven diagnostic tools has the potential to enhance clinical decision-making, enabling early detection and timely treatment of brain tumors.

Future Enhancements:

- **Dataset Enrichment:** Using larger and more heterogeneous MRI datasets for robustness and generalization of models [5].
- **Explainability Tools:** Applying Grad-CAM and SHAP to visualize salient regions of model predictions, improving interpretability of AI-based predictions to radiologists.
- **Integration in Clinical Workflows:** Test and implement the model in a real-time hospital setting to assess practicality and integration with existing radiology software.
- **Hybrid AI Techniques:** Investigate ResNet50 with deployed transformer-based models to enhance classification and feature extraction capabilities [6].
- **Multi-Class Tumor Classification:** Further extending the model incorporates capability to classify different tumor types, e.g. gliomas, meningiomas, and pituitary tumors, for a more robust and comprehensive diagnostic capability.
- **Real-Time Processing:** Refine model performance for processing capability in real-time MRI analysis mode when performing capable processing with latency that do not impair classification accuracy [7].

The results point to the promise of AI-based brain tumor detection in healthcare, providing a pathway towards improved early detection and treatment planning. Enhancements made to AI-based diagnostic facilities can provide professionals with the opportunity to rely on automated systems, while ensuring the diagnosis on behalf of patients is accurate and timely, even if their professional judgment does not allow such certainty.

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