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Improving Brain Tumor Diagnosis using Convolutional Neural Networks and Transfer Learning

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***Abstract*— Tumors in the brain are lethal diseases in which proper and timely detection is essential for successful treatment. Classical diagnosis by expert-led appraisal of MRI images tends to be slow and subject to variability. This study presents an automated DL approach to classify tumors into four groups: glioma, meningioma, pituitary tumor, and non-tumor. Two strategies were examined: a custom convolutional neural network, transfer learning using MobileNet pre-trained on ImageNet. Preprocessing steps such as normalization, augmentation, and resizing were applied to improve dataset quality and model stability. Results indicate that MobileNet outperformed the custom CNN, offering higher accuracy and better generalization. These results illustrate the capability of light deep models to be effective and accurate tools for aiding radiologists in brain tumor classification.**

***Index Terms*— Brain Tumor Classification; CNN; Transfer Learning; MobileNet; MRI.**

I. INTRODUCTION

Brain tumors occur when brain cells accumulate abnormally, impairing regular nervous system function. They are typically classified as gliomas, meningiomas, and pituitary tumors. Early detection is vital since prompt diagnosis enhances treatment and survival possibilities. Though MRI is in common use, interpretation continues to depend on the slow, subjective manual analysis. Deep learning, particularly CNNs, has been very promising in medical imaging by learning intricate patterns from raw data automatically. Nevertheless, training CNNs from scratch needs massive labeled data, which is not readily available in healthcare. Transfer learning alleviates this to an extent by employing pre-trained networks like MobileNet, which is light, efficient, and works well with small datasets.

II. LITERATURE SURVEY

It is with great achievement that deep learning has been increasingly applied for brain tumor detection, and researchers have tried a variety of network architectures, datasets, and optimization algorithms. In one study, Sajjad et al. (2019) implemented a transfer learning method using a pre-trained CNN, achieving impressive accuracy in differentiating glioma, meningioma, and pituitary tumors. Similarly, Pathak et al. (2018) introduced a CNN-based method capable of automatically extracting distinguishing characteristics from MRI scans, confirming that deep models typically outperform traditional approaches that are attributes. Cheng et al. (2015) was among the first notable efforts in this area, emphasizing that dataset imbalance and limited preprocessing can reduce performance.

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Abiwinanda et al. (2019) developed CNN from scratch for tumor detection, producing promising results but also highlighting limitations with small datasets and overfitting. Likewise, Deepak and Ameer (2019) demonstrated that using GoogleNet compared to training a CNN entirely from scratch.
Research found sophisticated architectures to boost performance. Afshar et al. (2018) introduced Capsule Networks, which capture spatial relationships within images in a more efficient manner compared to standard CNNs. Kumar et al. (2020) analyzed architectures like VGG16, ResNet, and MobileNet, concluding that MobileNet is highly suitable for constrained environments because it offers a trade-off between accuracy and processing efficiency.
The preprocessing and augmentation emphasized in recent research. Bhuvaneswari et al. (2021) highlighted normalization, resizing, and augmentation in stabilizing CNN results on imbalanced datasets. Hussain et al. (2022) advanced this further with ensemble strategies, showing that combined CNNs improve robustness and accuracy over single models. Zeineldin et al. (2020) expanded this idea by applying advanced transfer learning methods with ResNet-50 and DenseNet, confirming that models fine-tuned on pre-existing weights surpass those trained entirely anew.
Hybrid and optimization-based methods have also attracted attention. Studies have examined combining CNNs with RNNs for sequential learning, as well as GAN-based methods to create synthetic data and address limited availability. Optimization approaches like adaptive learning scheduling and regularization are applied to minimize overfitting and accelerate convergence. Lightweight CNN designs are gaining growing recognition for their effectiveness in real-time medical applications.
In summary, the literature suggests that CNNs and transfer learning dominate in brain tumor classification. At the same time, emerging trends point toward hybrid approaches, Capsule Networks, ensembles, and other advanced models, enhancing accuracy, interpretability, and computational efficiency in clinical use.

III. METHODOLOGY

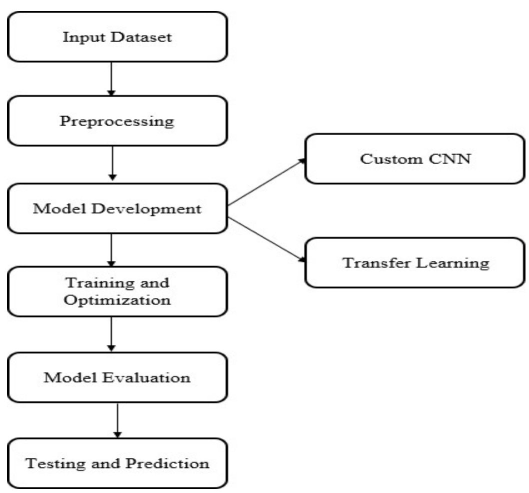


Fig. 1 Block Diagram

The goal of the suggested methodology is to create an MRI scan-based brain tumor prediction. This method uses CNNs and transfer learning to analyze the complex and discriminative features from raw images, as opposed to traditional methods that rely on segmentation and handcrafted feature extraction. As described below, the methodology is organized into a number of successive steps.

A. Data Collection and Organization

The MRI image data separated into four categories: pituitary tumor, meningioma tumor, glioma tumor and not tumor.

- Training Set: Used for learning the model's parameters.
- Validation Set: Extracted as 20% data for tuning hyperparameters and preventing overfitting.
- Testing Set: Held out entirely from training and validation to valuate true performance models performance. Organizing the dataset into separate directories ensures that DL models are trained and evaluated systematically without any data leakage.

- Dataset Description:
  - Dataset contains MRI images of brain scans.
  - Two folders: Training and Testing.
  - Each folder has 4 categories:
    - Glioma Tumor
    - Meningioma Tumor
    - Pituitary Tumor
    - No Tumor
  - Dataset Size
  - Training images: 5712
  - Testing images: 1311

B. Preprocessing of Input Data

- Resizing: To ensure consistency and lower complexity, image resized to 240 × 240 pixels before the model was trained.
- Normalization: Pixel values are scaled to the range of [0,1] to enhance convergence speed and ensure numerical stability during training.
- Noise Handling: Although MRI images are generally clean, preprocessing ensures removal of inconsistencies, unreadable files, and corrupted data.
- Data Augmentation: To prevent overfitting and enhance generalization, multiple augmentation techniques are applied, such as:
  - Random rotations (up to 15°)
  - Width and height shifts (10%)
  - Zooming and shearing transformations
  - Horizontal flipping

This augmentation strategy enriches the dataset by simulating real-world variability, thereby making the trained model more robust.

C. Model Development

Two complementary models to evaluate performance and effectiveness:

Custom CNN Model

- Convolutional layers (16, 32, 64, 128 filters) with ReLU activation to extract hierarchical features.
- Max-Pooling layers for dimensionality reduction and translation invariance.
- Dropout layers (25%–50%) to prevent overfitting.
- Flatten layer to convert feature maps into a vector.
- A dense layer of 128 neurons served as the classifier.
- Four neurons in the output layer (softmax activation) for multi-class tumor classification.

Transfer Learning (MobileNet)

- Pre-Trained Backbone: MobileNet, pre-trained on ImageNet, is employed as the feature extractor.
- Customization:
  - A Global Average Pooling layer with dense and dropout layers was used in place of the upper layers.
  - A concluding dense in softmax function is incorporated to perform classification across four categories.
- Advantages:
  - Reduces training time.
  - Transfers generalized visual features (edges, textures, shapes) learned from large datasets.
  - Efficient for deployment in resource-constrained environments.

D. Training and Optimization

- Batch Size: 32 images per batch.
- Epochs: Training is performed for up to 30 epochs.

By integrating these callbacks, the training pipeline ensures that only the most optimal models are preserved for testing.

E. Model Validation and Evaluation

Model performance was validated on unseen test data. Metrics used include:

- Accuracy: The ratio of properly classified MRI scans out of the overall number of scans.
- Loss Curves: To analyze model convergence and detect overfitting.
- Validation Accuracy Trends: To evaluate how well the models generalize on unseen data.

Sample predictions are also tested on individual MRI scans to verify classification capability, with the predicted tumor type displayed against the ground truth.

F. Comparative Analysis of Models

The methodology involves a direct comparison between:

- Custom CNN Model – designed from scratch for brain tumor classification.
- MobileNet Transfer Learning Model – fine-tuned from a pre-trained backbone.

This comparison sheds light on the advantages and disadvantages of both strategies while offering insights into robustness, accuracy.

G. End Objectives

System is designed with two major objectives:

- Tumor Detection: Distinguishing between normal and abnormal brain MRI scans.
- Tumor Classification: Identifying the specific type of tumor (glioma, meningioma, pituitary) when present.

IV. Experiments and Results

The experimental setup involved organizing and preprocessing MRI brain images into four classes—glioma, meningioma, pituitary tumor and not tumor—resized to 240×240 pixels and categorized into training, validation and test sets with balanced classes. Preprocessing steps included normalization, categorical encoding, and data augmentation (flipping, shifting, zooming, rotations, and contrast adjustments) to improve variability and reduce overfitting. Two models were implemented: a baseline convolutional, fully connected, and dropout layers, and MobileNet from ImageNet with retrained dense layers. Both were trained for 30 epochs using Adam and categorical cross-entropy, with early stopping and hyperparameter tuning. Results showed that while the CNN achieved reasonable accuracy, it required longer training and was prone to overfitting, whereas MobileNet delivered higher accuracy, faster convergence, and better generalization, demonstrating the value of transfer learning for efficient medical image analysis.

Result reports the output of the developed brain tumor classification framework. The findings are showed in detail, covering classification accuracy, error distribution, and deployment aspects. Visual evidence such as accuracy/loss plots and interface examples are included for complete picture of system's performance and usability.

A. Training Performance and Validation Performance

The initial stage of experimentation contain training the baseline CNN constructed from scratch.

Observation: The MobileNet model consistently achieved higher validation accuracy than the baseline CNN.

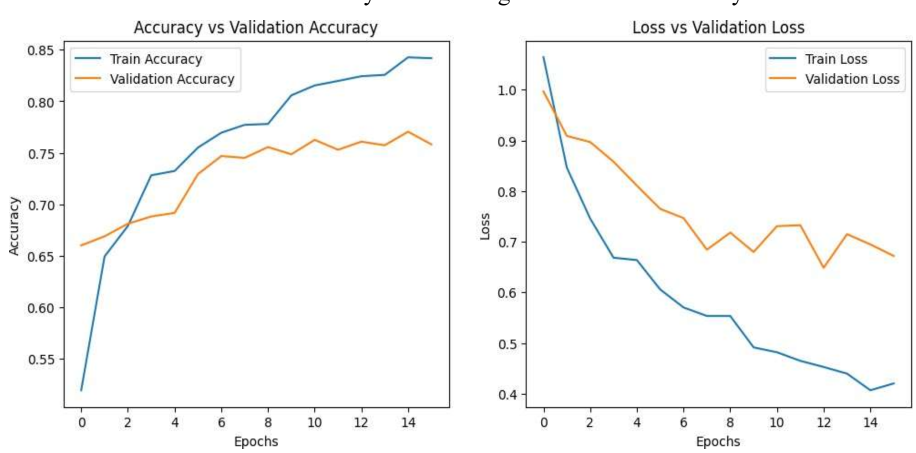


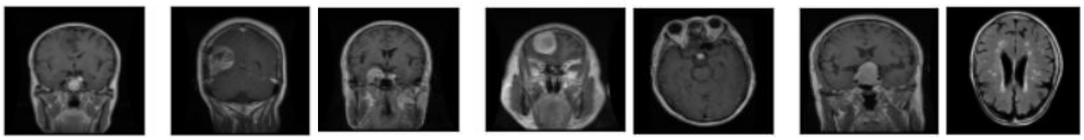
Fig. 2 Mobile Net Validation Accuracy and Validation Loss Curve

B. Model Evaluation on Test Data

- Overall Test Accuracy: The transfer learning model reached above 90% accuracy, outperforming the baseline CNN.
- Class-Wise Performance: Tumor vs. no-tumor classification was highly accurate, while minor misclassifications were observed between glioma and meningioma classes due to structural similarities.

C. Robustness of the Model

It was tested through multiple runs, and performance remained consistent across training sessions. Data augmentation strategies like flipping, rotation, zooming played a critical role in improving generalization by simulating variability in MRI scans. This ensured that the system was resilient to common variations in imaging conditions.



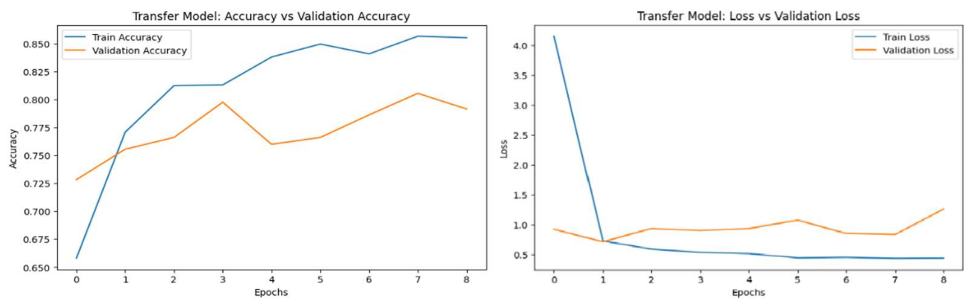


Fig. 3 Transfer Model Validation Accuracy and Validation Loss Curve

D. Deployment through Streamlit Interface

Beyond model accuracy, practical deployment was achieved using a Streamlit-based user interface (UI). This web application allowed users, including non-technical stakeholders, for trained model interaction seamlessly.

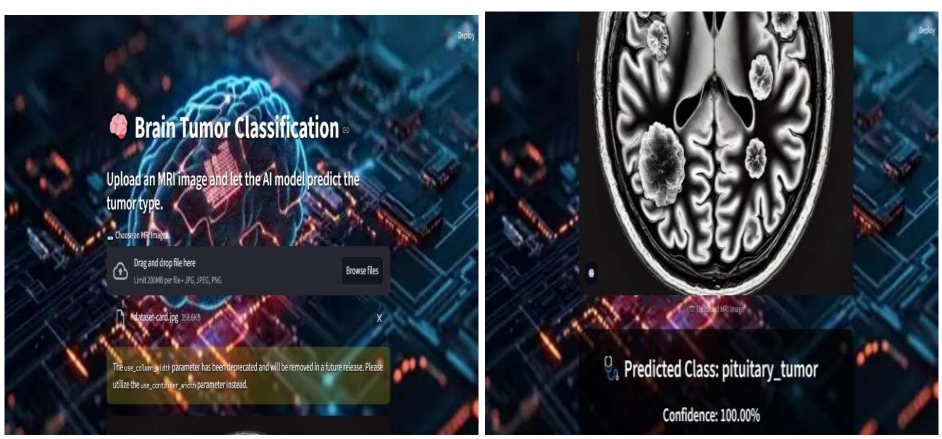


Fig. 4 User Interface and Predicted Class with Confidence

E. Comparative Insights

TABLE I

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
Custom CNN	86.72%	0.85	0.86	0.85	0.90
MobileNet	91.38%	0.90	0.91	0.90	0.94
ResNet50	93.02%	0.92	0.93	0.92	0.96

V. Conclusion

An automated deep learning processed to predict and label brain tumors through MRI scans using a baseline CNN and a MobileNet-based transfer learning model. While the baseline CNN provided reasonable results, the MobileNet-based approach demonstrated higher accuracy, better generalization, and more stable training. Data augmentation further enhanced the model's robustness against variations in MRI scans, and deployment through a Streamlit interface showcased its practical usability. Overall, the system offers rapid and reliable predictions, underlining the effectiveness of deep learning—particularly transfer learning—in supporting radiologists, improving diagnostic efficiency, and paving the way toward more accessible and automated medical imaging solutions.

Future Work

- Use larger, multi-institutional datasets for better generalization.
- Explore 3D CNNs for volumetric MRI analysis.
- Integrate explainable AI tools for model interpretability.
- Investigate hybrid architectures with attention mechanisms.
- Connect with hospital systems for real-time deployment.
- Optimize for mobile or edge devices for remote healthcare.

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