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NeuroVisionNet: A Custom Transfer Learning with VGG16 for Brain Tumor Recognition

Aishwarya S Gamanagatti
Dept. ECE
KLS Vishwanatharao Deshpande Institute of Technology, Haliyal 581329,India
aishu1647@gmail.com

Shruthi Bagi
Dept. ECE
KLS Vishwanatharao Deshpande Institute of Technology, Haliyal 581329,India
shruthibagi15@gmail.com

Vaishnavi G H
—Dept. ECE
KLS Vishwanatharao Deshpande Institute of Technology, Haliyal 581329,India
vaishnaviharchilkar@gmail.com

Prof. Suraj Kadli
Supervising Author, Dept. of Electronics and Communication Engineering
KLS Vishwanatharao Deshpande Institute of Technology, Haliyal 581329,India
sbk@klsvdit.edu.in

Abstract*— Brain tumors are among the most Life-threating and complicated diseases to improve treatment outcomes. Conventional diagnostic approaches radiologists' expertise. This research introduces an automated framework for detecting brain tumors, utilizing the capabilities of VGG16, a predefined convolutional neural network model, variability and delays in decision-making, fine-tuned via transfer learning on MRI brain scan images. Our methodology emphasizes efficient data preprocessing, robust feature extraction, and a lightweight classification head tailored for binary classification. Experimental results reveal exceptional classification accuracy, validating the model's applicability in prediction effectiveness. This research highlights the transformative power of deep learning in augmenting diagnostic workflows and enabling scalable, real-time medical support.

Keywords- *Brain tumor, Deep learning, VGG16, MRI, Image based neural network, Cross - domain learning, Biomedical image analysis.*

INTRODUCTION

Brain tumors, whether malignant or benign, are life-threatening due to their location and the sensitivity of surrounding tissues. Globally, brain tumors affect hundreds of thousands annually, with prognosis significantly dependent on the stage at which they are diagnosed. MRI technology remains the leading approach to detect brain tumors imaging, offering high-resolution, contrast-rich scans. However, interpreting these images is inherently complex, time consuming, and subject to inter-radiologist variability. Breakthroughs in AI-driven learning have redefined image-based diagnostic solutions, offering high accuracy and consistency. CNN models, notably, have proven highly effective feature extraction and classification tasks within medical imaging. VGG16, an advance neural architecture created by oxford's visual geometry group is renowned for its simplicity and depth. This work integrates VGG16 into an end-to-end framework for two-class categorization of MRI brain scan as tumor or non-tumor, reducing dependence on handcrafted features and domain-specific preprocessing.

LITERATURE REVIEW

The implementation of deep learning in neuroimaging has garnered widespread attention in recent years. Early implementations relied on shallow CNNs or conventional ML using manually engineered features features, yielding moderate performance. With the advent of transfer learning and availability of large-scale image repositories like ImageNet, deeper models like VGG16, ResNet, and InceptionNet became applicable to medical domains. Lakkimsetti et al. [1] employed a CNN framework that demonstrated good classification accuracy on limited datasets. Selvarani and Sharmila [2] proposed a hybrid approach combining image partioning and classification, resulting to enhanced precision. Afshar et al. [5] explored capsule networks that preserve spatial hierarchies and

relationships in MRI data, producing state-of-the-art results. Additionally, Prastawa et al. [6] proposed an outlier detection-based segmentation method, which enabled advancements in enabled advancements in identifying tumor regions techniques. These studies underscore the importance of architecture selection and preprocessing in performance optimization. Despite progress, challenges persist around dataset size, class imbalance, model interpretability, and clinical trust. This study addresses some of these issues through a carefully tuned transfer learning pipeline that achieves high accuracy on a balanced MRI dataset with a simplified training regime.

METHODOLOGY

Our system architecture encompasses the following stages:

A. Dataset Acquisition: The dataset comprises T1-weighted contrast-enhanced MRI images classified into two categories: 'tumor' and 'no tumor'. The images are sourced from a publicly available repository and manually verified to ensure labelling accuracy.

B. Pre-Processing Image: were resized to 128x128 pixels for faster computation, pixel values were adjusted to fall between 0 and 1. A range of image enhancement techniques, including random rotations, horizontal/vertical flips, zooming, and brightness shifts were applied to enhance model generalization and mitigate overfitting.

C. VGG16 Architecture: The pre-trained VGG16 model was imported excluding the final dense layer. We appended a custom classification head with a Flatten layer, a Dense layer (256 units, ReLU), a Dropout layer (0.5), and a final Dense sigmoid function-based layer used for binary outcome prediction. All convolutional layers of VGG16 were frozen during training to retain pre-trained features.

D.Training Configuration: The model was optimized with the Adam algorithm (learning rate = 0.0001), binary cross-entropy loss, and data was processed in batches of 32 samples for 20 epochs. Early stopping and model checkpointing were implemented to prevent overfitting and retain the best performing weights.

Fig.no.1: Epoch

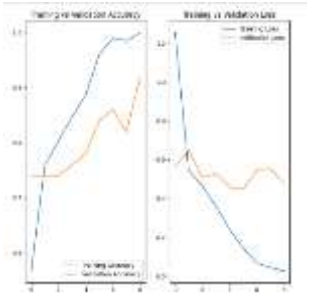

Fig.no.2 : Training and Validation Loss

E. Model Validation Tools The predicitive capability of the model was assessed via accuracy, loss curves, precision, recall, F1 score, and the confusion matrix to ensure comprehensive validation.

EXPERIMENTAL RESULTS

The model delivered outstanding outcomes with consistent performance across training and validation:

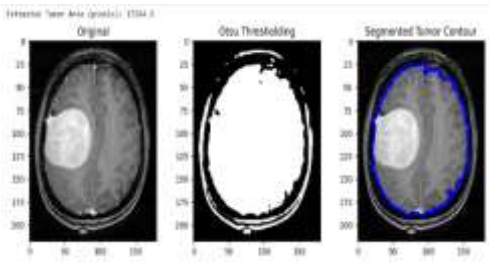

Fig.no.3: Estimated Tumor Area

Fig.no.4: Training and Validation loss

Training Accuracy: 99.60%

Validation Accuracy: 98.00%

Training Loss: 0.0240

Validation Loss: 0.0982

The confusion matrix revealed high sensitivity and specificity, with minimal false negatives — a crucial metric in medical diagnostics. ROC and precision recall curves further confirmed the reliability and strength of the system. The visualizations below show the training behavior:

Accuracy Curve: Stable and consistently increasing over epochs.

Loss Curve: Steadily decreasing, indicating successful convergence. This high performance, despite limited training data,demonstrates the effectiveness of transfer learning combined with advanced regularization methods.

Real-time Deployment: Optimizing the model for real-time use in embedded systems and mobile applications.

Clinical Trials: Validating the model in collaboration with hospitals to ensure clinical reliability and ethical compliance.

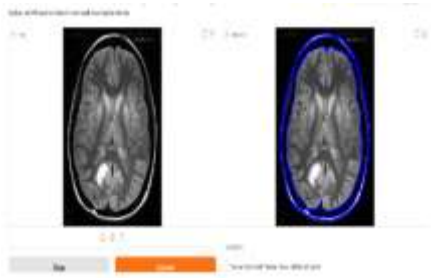

Fig.no.5: Final Result

APPLICATIONS

The developed framework can be implemented in the following domains:

Clinical Decision Support: Assists radiologists by highlighting suspicious scans and reducing human workload.

Telemedicine: Enables remote diagnosis in rural or resource-limited regions.

Medical Education: Serves as an smart assistant for educating medical trainees and researchers.

Edge Deployment: Adaptable for integration in mobile apps or embedded systems in hospitals or ambulances.

Multi-modal Integration: Can be extended to fuse textual reports and MRI images for comprehensive diagnostic aid.

FUTURE SCOPE

To improve the real-world usability of the model and support its integration into medical practice, upcoming efforts will concentrate on:

Multiclass Classification: Identifying and categorizing tumor types, includingglioma, meningioma, and pituitary tumors.

Tumor Segmentation: Using U-Net or Mask R-CNN to localize tumors and quantify tumor size.

Explainable AI: Incorporating Grad-CAM or LIME to highlight regions influencing model decisions.

Larger Datasets: Training on multi institutional datasets to improve generalization. Real-time

Deployment: Optimizing the model for real-time use in embedded systems and mobile applications.

Clinical Trials: Validating the model in collaboration with hospitals to ensure clinical reliability and ethical compliance.

CONCLUSION

This research introduces a robust, scalable, and high-performing deep learning-based system designed to detect brain tumors using the VGG16 architecture. Through effective transfer learning, preprocessing, and regularization, the model achieves near-expert accuracy while remaining lightweight and easy to deploy. By reducing diagnostic variability and enabling faster clinical workflows, this system marks a significant step toward democratizing medical AI. Future work will push boundaries toward localization, explainability, and deployment to bring AI assisted diagnostics closer to mainstream healthcare.

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