Comparing Brain Tumour Classification Using Pre-Trained Models and Ensemble

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Introduction

Problem: The problem addressed by this project is the need for accurate and reliable classification of brain scans, which is essential for medical diagnosis and research in neuroscience. This project employs Convolutional Neural Networks (CNNs) for the segmentation and classification of brain tumors from MRI scans, crucial due to the need for high diagnostic accuracy.

Motivation: The motivation behind this project lies in enhancing the accuracy and robustness of brain scan classification, a crucial task in medical diagnosis and research. By comparing the effectiveness of pre-trained models versus ensemble methods, we aim to identify the most reliable approach for accurately classifying brain scans. This research addresses the pressing need for more precise diagnostic tools in neuroscience and neuroimaging, potentially leading to improved patient outcomes and deeper insights into brain-related disorders.

Challenges:

Data Variability and Volume: The high variability in MRI scans, due to different equipment and protocols, complicates the training process and necessitates robust models that generalize well on new, unseen images.

Class Imbalance: The prevalence of non-tumor images over tumor images in datasets can skew the training of models, requiring careful balance and tuning of the model.

High Dimensionality: The high resolution and depth of MRI scans mean that models must handle a large input size, which can impede training efficiency and require significant computational power.

Data

The dataset utilized for this research work was gotten from Kaggle [1], an open community for Machine Learning repository. Dataset contains an image folder with a total of 3762 images. Also present is a CSV file containing image features and target class (0 and 1), indicating if the image has a tumor or not. A total of 2079 images has no tumor while 1683 images has tumor.

Data Prepossessing: All images were resized to 224x224 pixels to fit the input layer of the CNNs, ensuring consistency across all inputs. We then applied Normalization and Augmentation techniques such as scaling pixel values, rotating, zooming and image flipping. These steps helps to prevent overfitting and promote model generalizability across MRI scans. After denoising, we smoothened the images using median filtering, and then finally we employed adaptive histogram equalization (AHE) and contrast limited adaptive histogram equalization (CLAHE) to further refine the images quality, making the features more distinct and easier for the neural network to analyse.

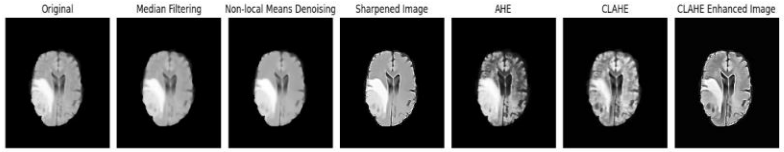


Figure 1: Image Preprocessing.

Technique	Applied by	Details
Resizing	Both	To 224x224 pixels (Our study & Ali et al.)
Normalization	Both	Standardization of pixel values
Augmentation	Both	Rotation, Zooming, Flipping (Our Study)&(Ali et al.)
M - Filtering	Ours	Reduces noise with a kernel size of 5x5
NL - Means	Ours	Reduces image, filter strength of 10, window 21x21
CLAHE	Ours	Contrast enhancement, limits noise amplification

Algorithms/Methods

Deep CNNs were used in image classification. The following models were used:

Pre-trained Models: Xception, ResNet50, InceptionV3; utilized for their powerful feature extraction capabilities in image classification tasks.

Custom CNN Architecture: Specially designed to explore the impacts of various hyperparameters on learning outcomes.

Ensemble Model: Fusion of the strengths of the three powerful pre-trained deep learning architectures: Xception, ResNet50 and InceptionV3 through a majority voting mechanism by concatenating the output of their respective final model layers.

Hyperparameter Tuning: To enhance our model's performance, we employ Keras Tuner for hyperparameter tuning

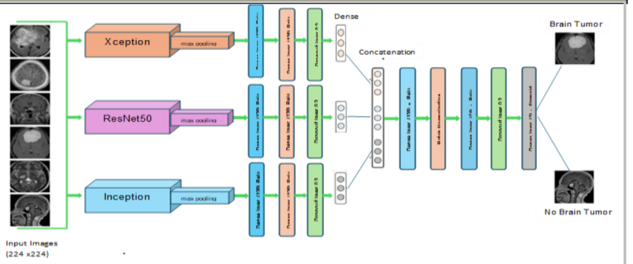
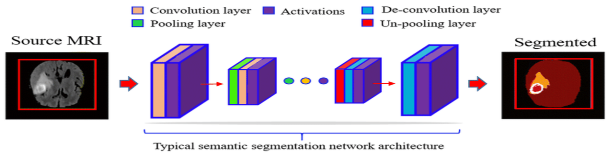
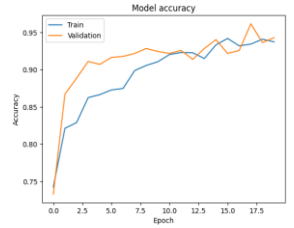


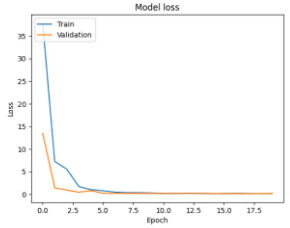
Figure 2: Ensemble model architecture.

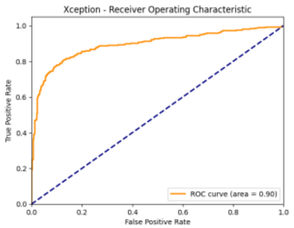


Results and Evaluation

Accuracy value increased with epochs for all models while loss decreased with epochs







Model	Test Loss	Accuracy	Precision	Recall	F1-Score	AUC	Confusion Matrix (TN, FP, FN, TP)
Xception	0.441	83.53%	83%	89%	86%	90%	371, 48, 76, 258
ResNet50	0.654	55.64%	78%	50%	36%	83%	419, 0, 334, 0
InceptionV3	0.460	80.74%	80%	81%	80%	89%	341, 78, 67, 267
VGG16	0.675	66.93%	71%	64%	62%	79%	388, 31, 218, 116

Model	Source	Acc	Prec	Recall	F1-Score	Notes
Xception	Our Study	84%	83%	89%	86%	Results after Keras hyperparameter tuning
ResNet50	Our Study	83%	88%	85%	88%	Results after Keras hyperparameter tuning
Custom CNN	Our Study	Best: 92%	Best: 92%	Best: 90%	Best: 91%	Results after Keras hyperparameter tuning
Ensemble Model	Our Study	93%	90%	89%	90%	Using ResNet50, InceptionV3, Xception after H. tuning
ResNet18	Ali et al.	98%	N/A	N/A	N/A	Fine-tuned model
Ensemble Model	Ali et al.	99%	N/A	N/A	N/A	Using ResNet18, ResNet101, ConvNet

Model Deployment

The deployment of the model on was executed using "Streamlit". This innovation represents a pivotal advancement in supporting medical professionals in diagnosing brain tumors effectively.

Through this streamlined interface, healthcare experts can access accurate insights swiftly, enhancing diagnostic accuracy and patient care.

Relevant Risks and Privacy Issues

Ethical Concerns: Ensuring compliance with ethical standards for handling sensitive patient data, including informed consent, data anonymization, and protection of privacy.

Legal Issues: Adhering to regulatory requirements, such as HIPAA in the United States and GDPR in the European Union, to safeguard patient rights and data security.

Security Risks: Implementing robust cybersecurity measures to prevent unauthorized access, data breaches, and potential exploitation of medical information.

Social Implications: Addressing concerns about the impact of automated diagnosis on healthcare professionals, patient-doctor relationships, and healthcare disparities.

Mitigation Strategies: Employing encryption techniques, access controls, and audit trails to secure medical data; fostering transparency and accountability in algorithm development and deployment; and promoting interdisciplinary collaboration to address societal and ethical considerations.

Conclusion

This comprehensive approach, combining pre-trained models with a custom-tuned CNN and employing ensemble techniques such as majority voting, not only improved accuracy but also offered insights into the model's diagnostic processes, pushing the boundaries of medical imaging AI towards better clinical applicability and reliability in brain tumor detection.

References

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2. Du, G., Cao, X., Liang, J., Chen, X. and Zhan, Y., 2020. Medical Image Segmentation based on U-Net: A Review. Journal of Imaging Science & Technology, 64(2).

3. Arora, A., Jayal, A., Gupta, M., Mittal, P. and Satapathy, S.C., 2021. Brain tumor segmentation of mri images using processed image driven u-net architecture. *Computers*, *10*(11), p.139.

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