27th International Conference on Computer and Information Technology (ICCIT)
Long Beach Hotel, Cox's Bazar, Bangladesh
20th - 22nd December, 2024
Paper ID: 361

Analysis of Pre-trained CNN Models in MRI-Based Brain Tumor Detection

Authors:

Ashif Al Nayem Zeesan **Abrar Fahim** **Md. Mushfiqur Ahmed** **Shafi Chowdhury** **Asif Newaz**

Department of Electrical and Electronic Engineering
Islamic University of Technology, Dhaka, Bangladesh
Email- ashifalnayem@iut-dhaka.edu, abrarfahim619@gmail.com, mushfiqurahmed@iut-dhaka.edu, shafichowdhury42@gmail.com, asifnewaz@iut-dhaka.edu

Outline of Presentation:

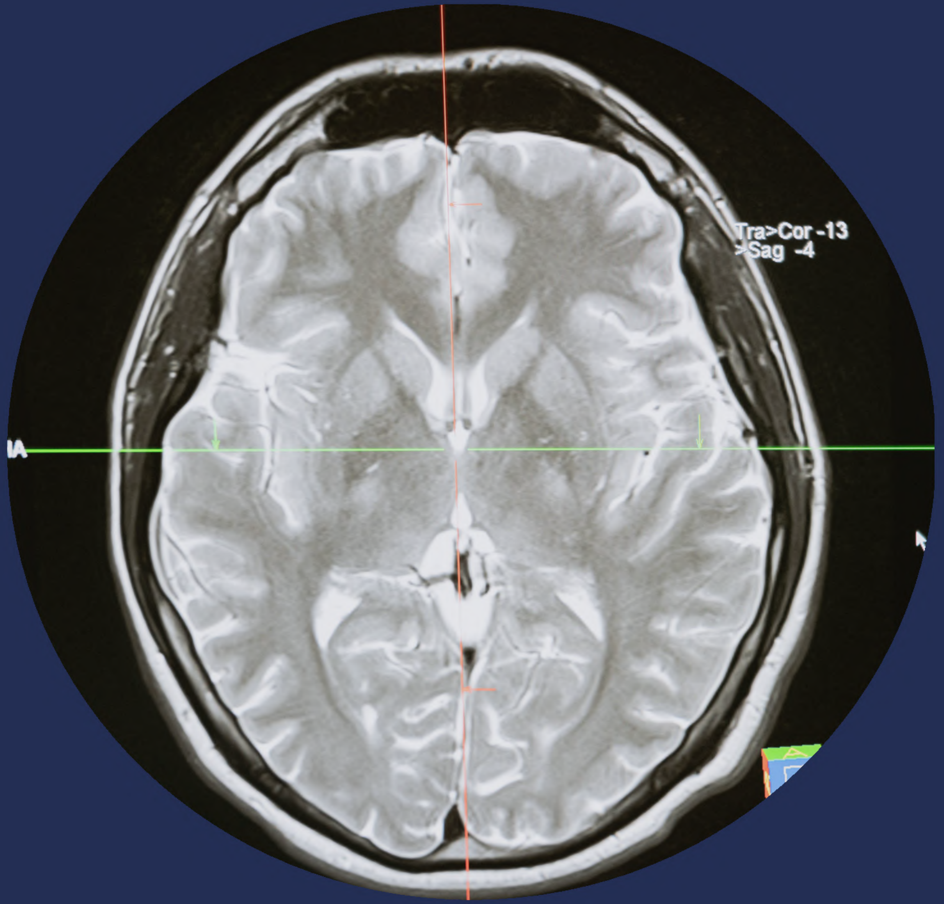
1. Abstract
2. Introduction
3. Literature Review
4. Methodology
5. Dataset
6. Preprocessing
7. Model Analysis
8. Result & Discussion
9. Conclusion

Abstract

Traditionally, brain tumor diagnosis has heavily relied on MRI or CT imaging for straightforward classification.

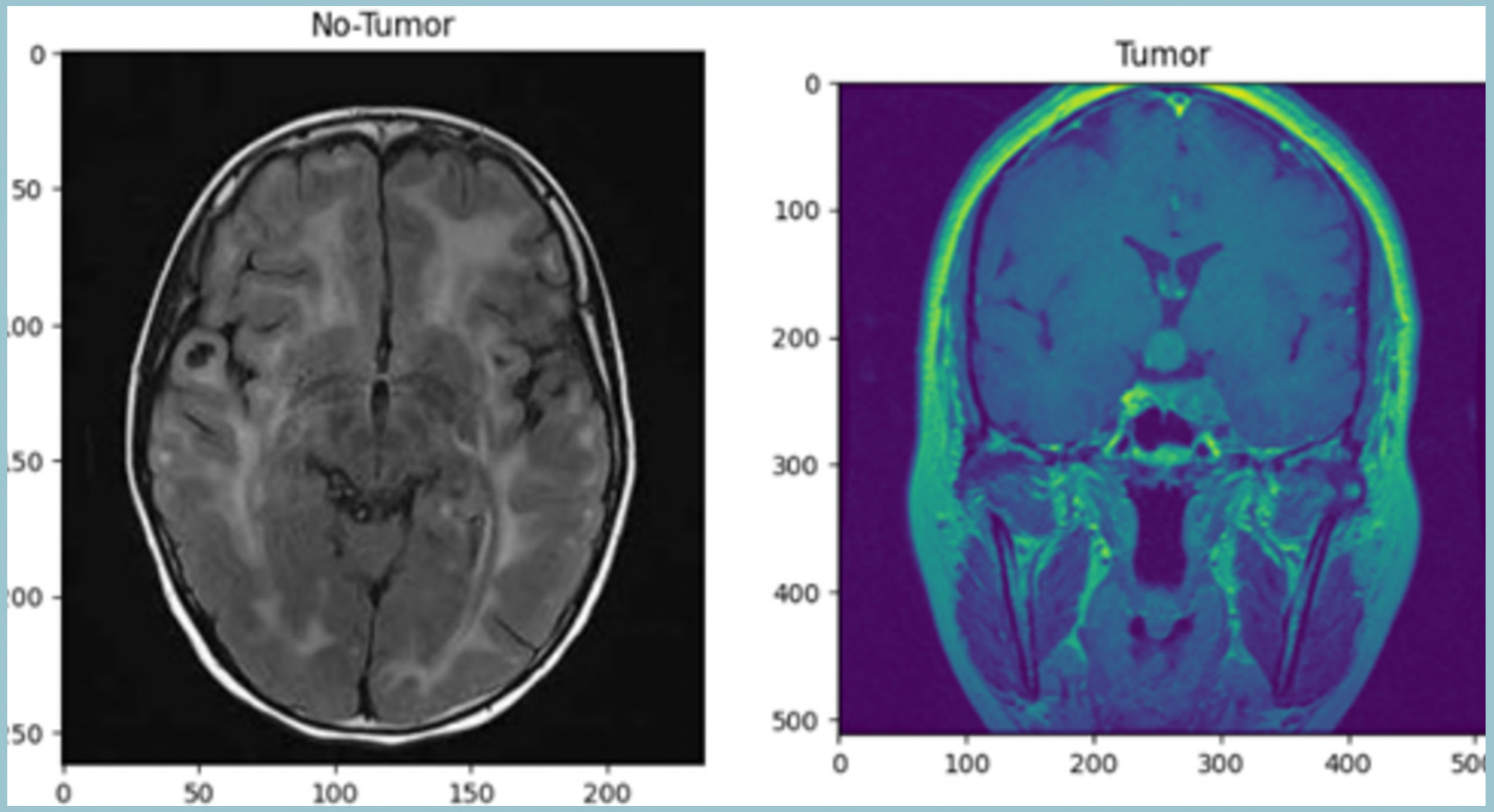
This study aims to enhance brain tumor prediction by employing deep learning techniques on MRI images.

We performed a comprehensive comparative analysis between five pre-trained models— InceptionV3, ResNet-50, VGG-16, MobileNetV2, and DenseNet121—to classify brain tumors in both binary (tumor vs. no tumor) and multi-class settings (glioma, meningioma, no tumor, and pituitary).



Introduction:

- Brain Tumors are a major global health issue, especially in developing countries like Bangladesh, which has high tumor mortality rates. Early detection using deep learning models could reduce diagnostic time and errors.
- Current tumor prediction relies heavily on manual analysis of MRI scans, which is very slow and prone to errors.
- Our objective is to leverage deep learning model and large image datasets to reduce diagnostic errors and improve the efficiency of brain tumor detection.



Literature Review:

- Kaur et al. explored the use of pre-trained CNN models like VGG16, VGG19, and InceptionV3 for classifying brain tumors from MRI images.

- Ojha et al. developed a CNN-based method for brain tumor detection using MRI data and compared it with models like InceptionV3, ResNet101, and DenseNet169.

- Deepa et al. investigated the effectiveness of ResNet models (ResNet-50, ResNet-101, and ResNet-152) for brain tumor identification. Using transfer learning, ResNet-152 outperformed the others

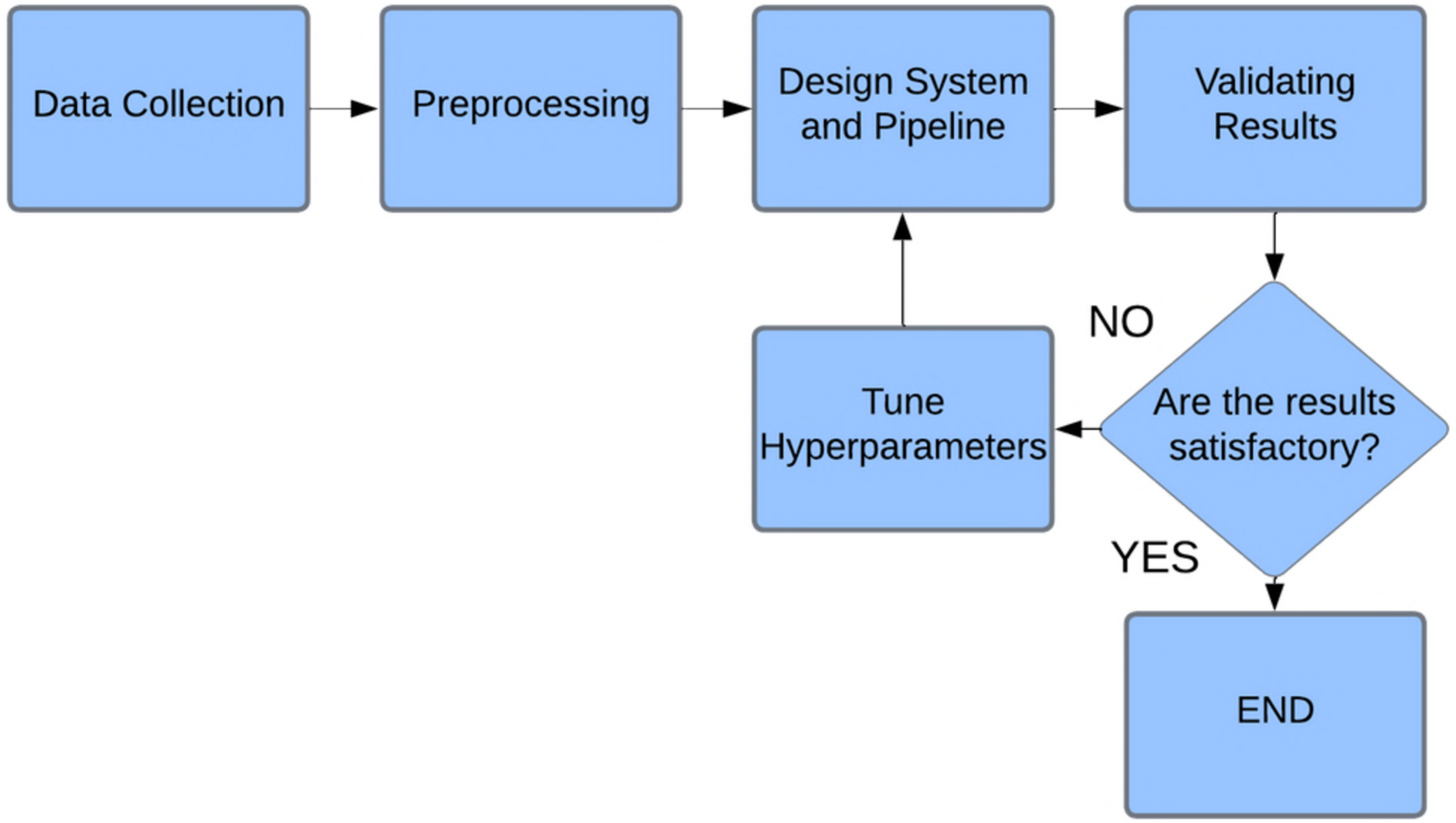
- In recent times, Özkaraca et al. introduced a dense CNN architecture for brain tumor classification, linking different layers to improve spatial spectral feature generation.

Methodology

- The system architecture processes input MRI images through resizing, enhancement, and data encoding into training, validation, and testing sets.

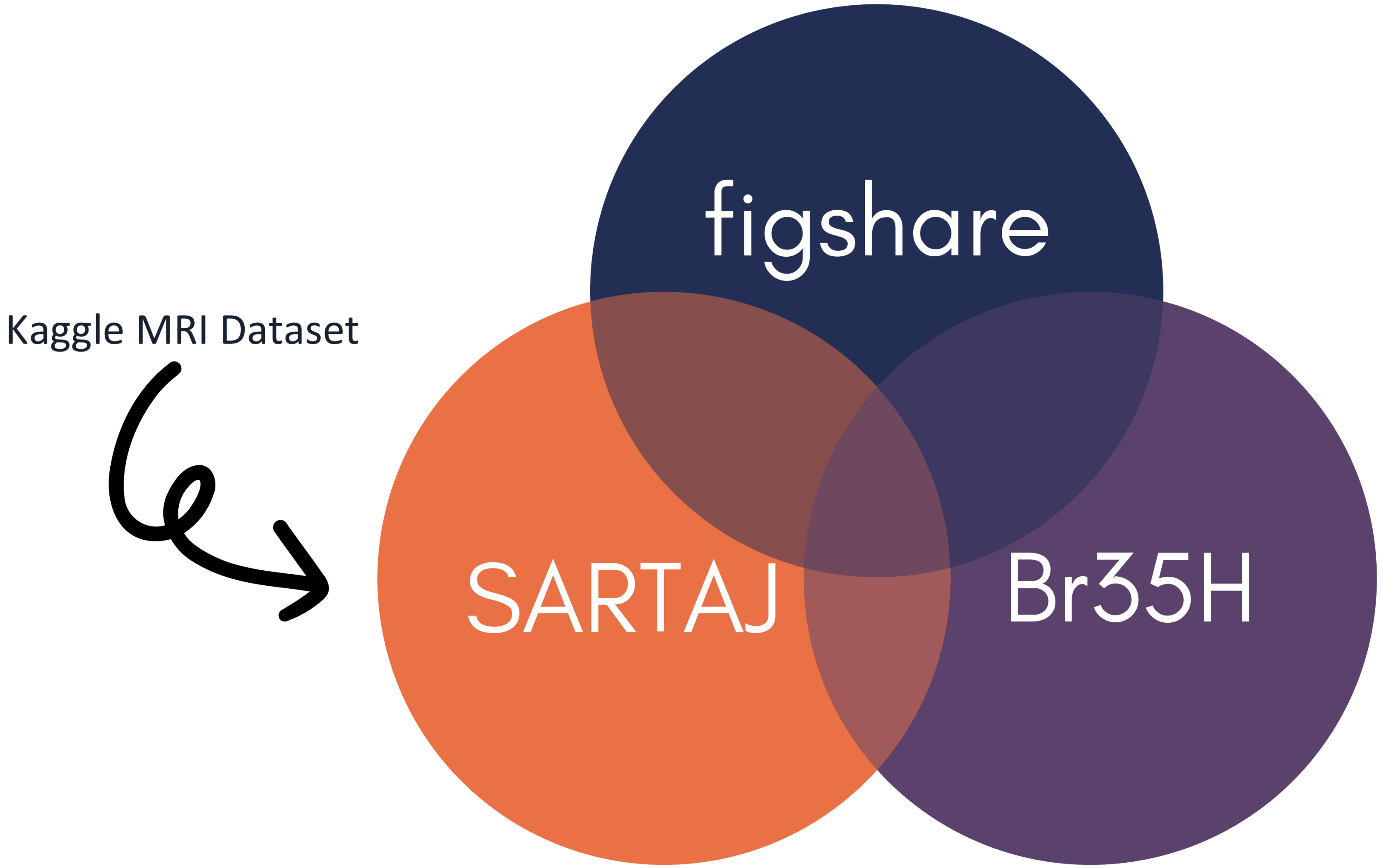
- The data is then fed into five pre-trained CNN models (InceptionV3, ResNet-50, MobileNetV2, VGG-16, and DenseNet121), which are fine-tuned for tumor detection in both binary and multi-class classification.

- Upon uploading an image, the system evaluates and outputs the presence of a tumor.



Dataset

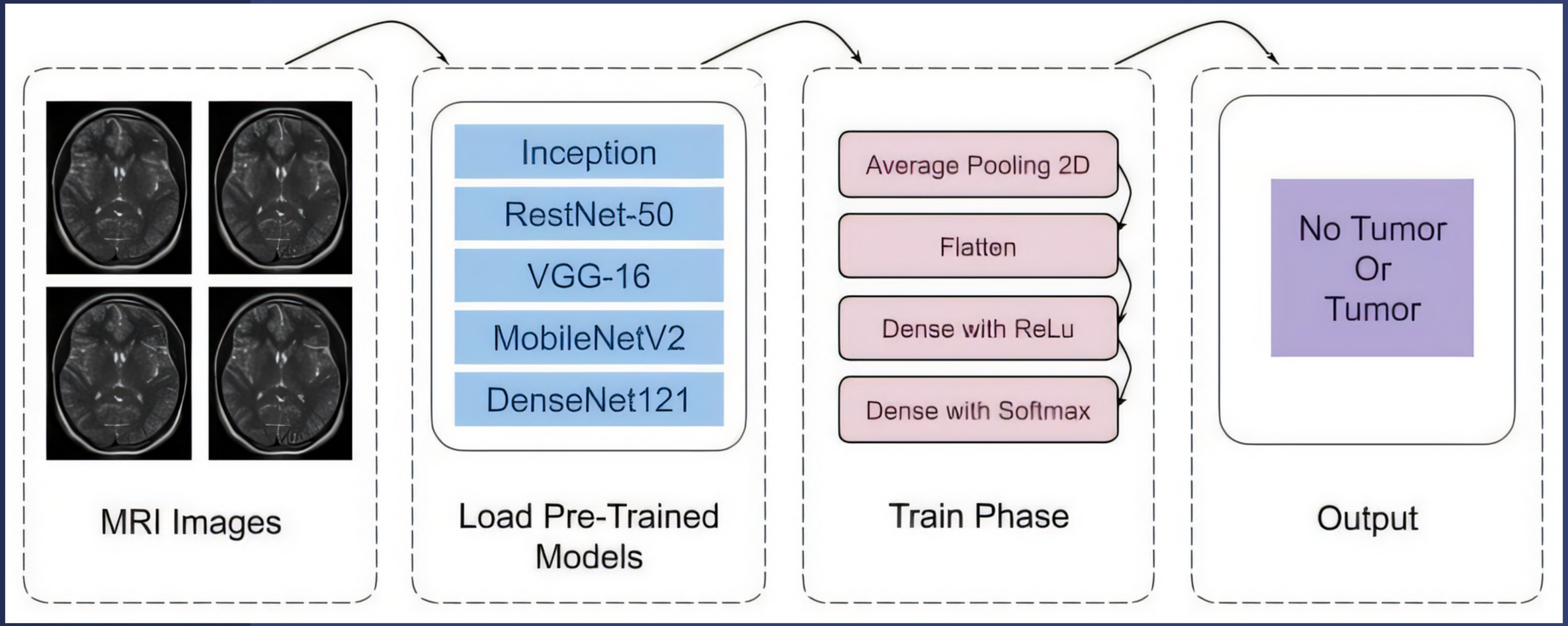
The dataset used in this study was obtained from Kaggle [19]. It is a combination of three sources: **figshare**, the **SARTAJ** dataset, and the **Br35H** dataset. It comprises a total of 7,023 human brain MRI images, categorized into four classes: **glioma** (2,262 images), **meningioma** (1,708 images), **no tumor** (1,600 images), and **pituitary** (1,453 images).



Preprocessing

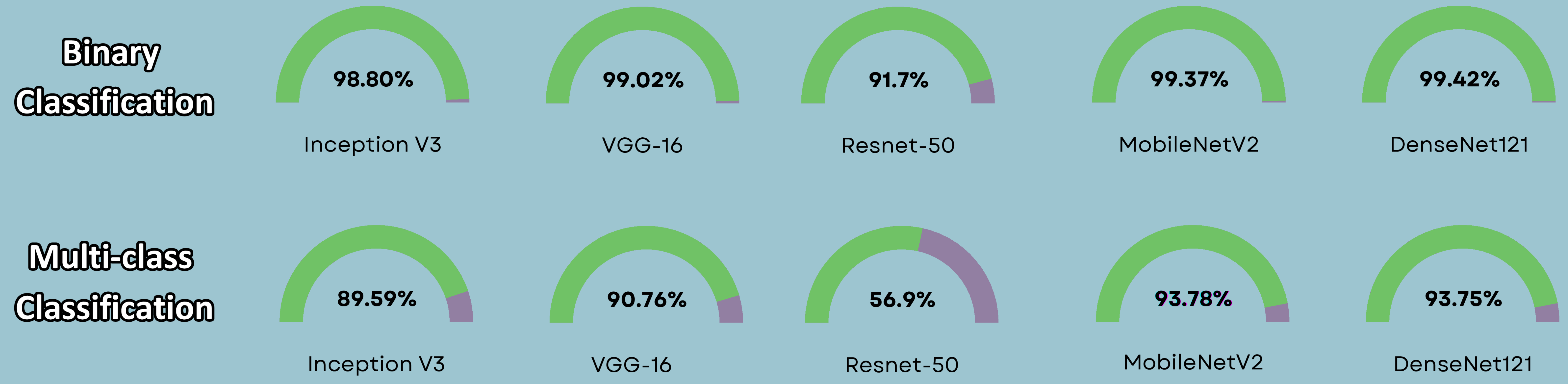
The images undergo several preprocessing steps to enhance quality and consistency, including conversion to grayscale, contrast and brightness adjustments, and sharpening. Color mapping and masking filters reduce noise, while resizing and cropping focus on the brain areas for better accuracy.

Pre-trained models are used with transfer learning (TL) to leverage knowledge from larger datasets like ImageNet. Five models—InceptionV3, ResNet-50, VGG-16, MobileNetV2, and DenseNet121—are fine-tuned for tumor detection, enhancing prediction accuracy while reducing the need for extensive retraining.



Model Analysis

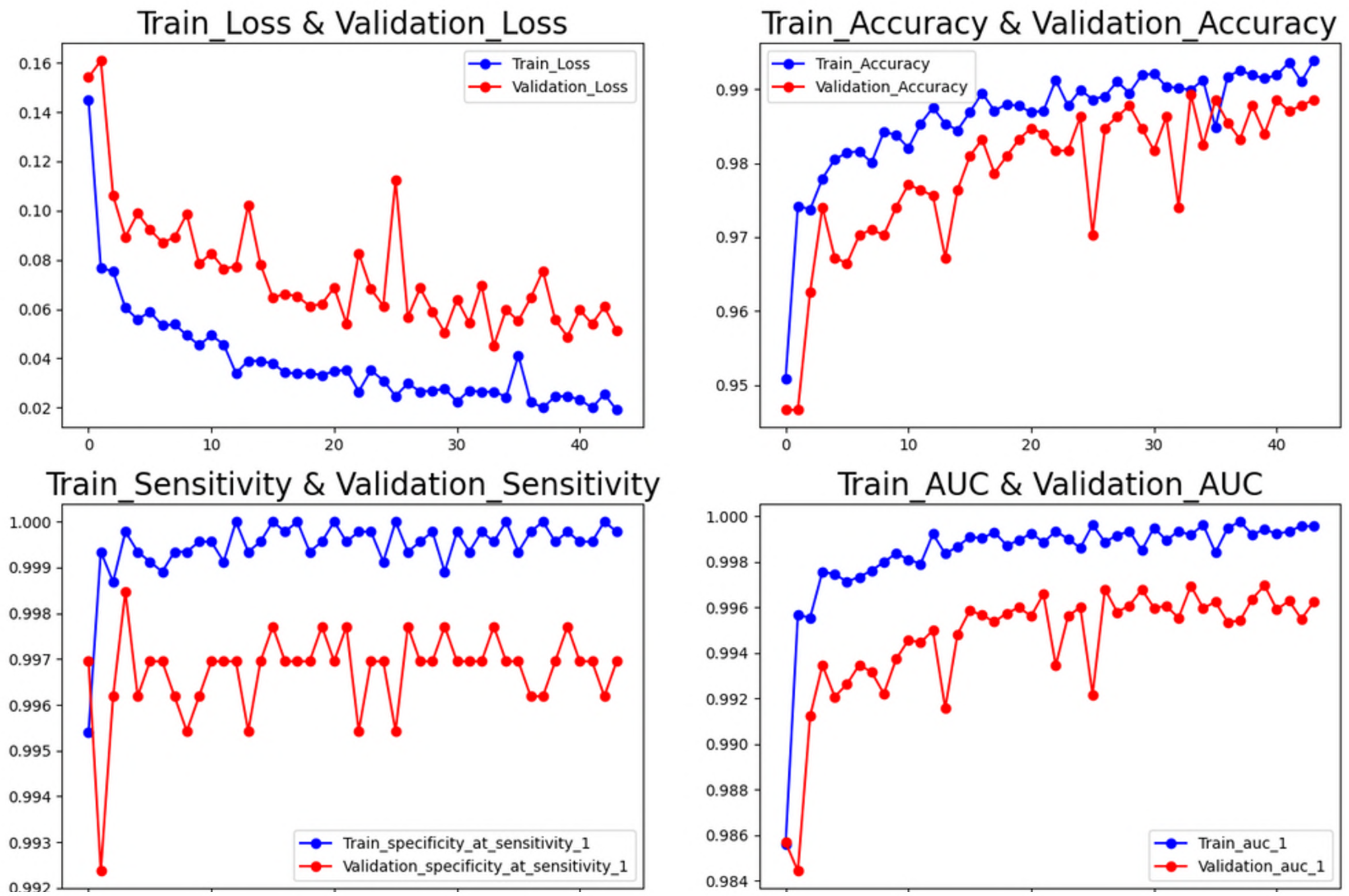
- The models were run on 150 epochs each.
- Figures show all models' accuracy over their development for binary classification and multi-class classification
- The use of callback function led to an early stopping
- A patience level of 10 was used for training

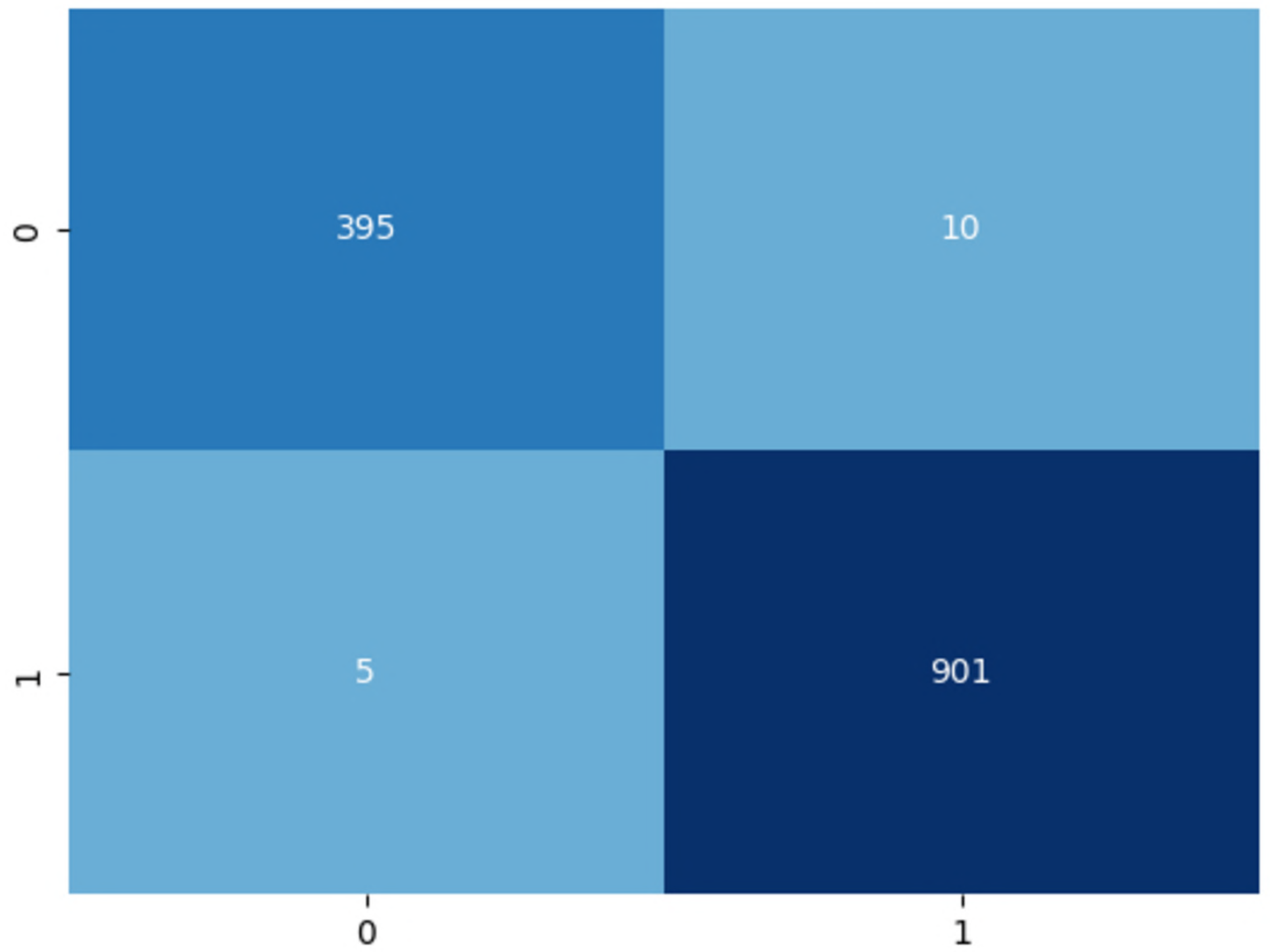


Result & Discussion

Binary Classification

Description	InceptionV3	VGG-16	ResNet-50	MobileNetV2	DenseNet121
Training Accuracy	98.80%	99.02%	91.7%	99.37%	99.42%
Validation Accuracy	97.79%	97.64%	88.7%	98.86%	98.86%
Training Loss	3.46%	3.01%	22.4%	1.39%	1.92%
Validation Loss	9.41%	10.43%	22.4%	5.30%	5.13%
Epoch Number	42	55	82	41	44

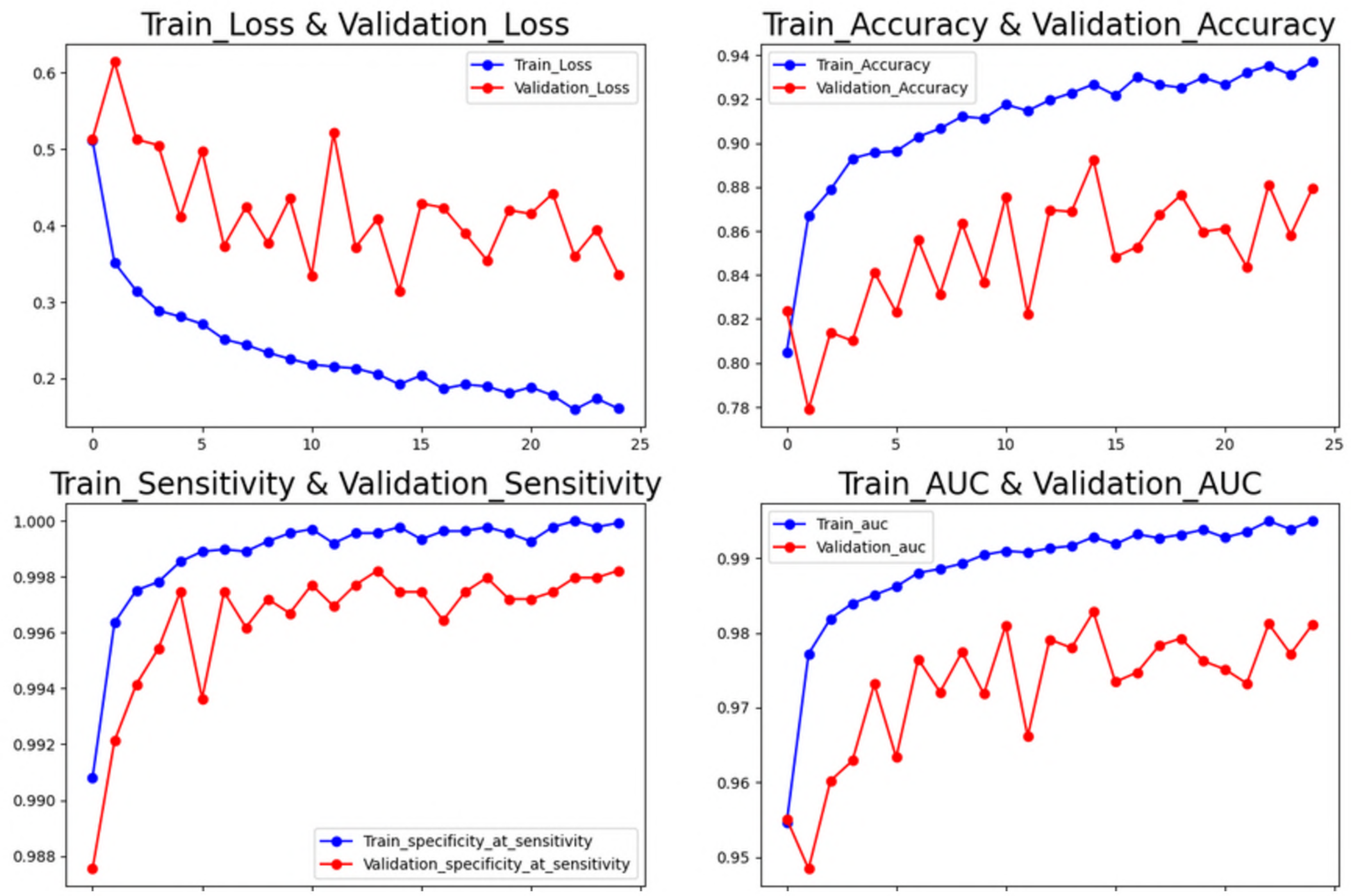


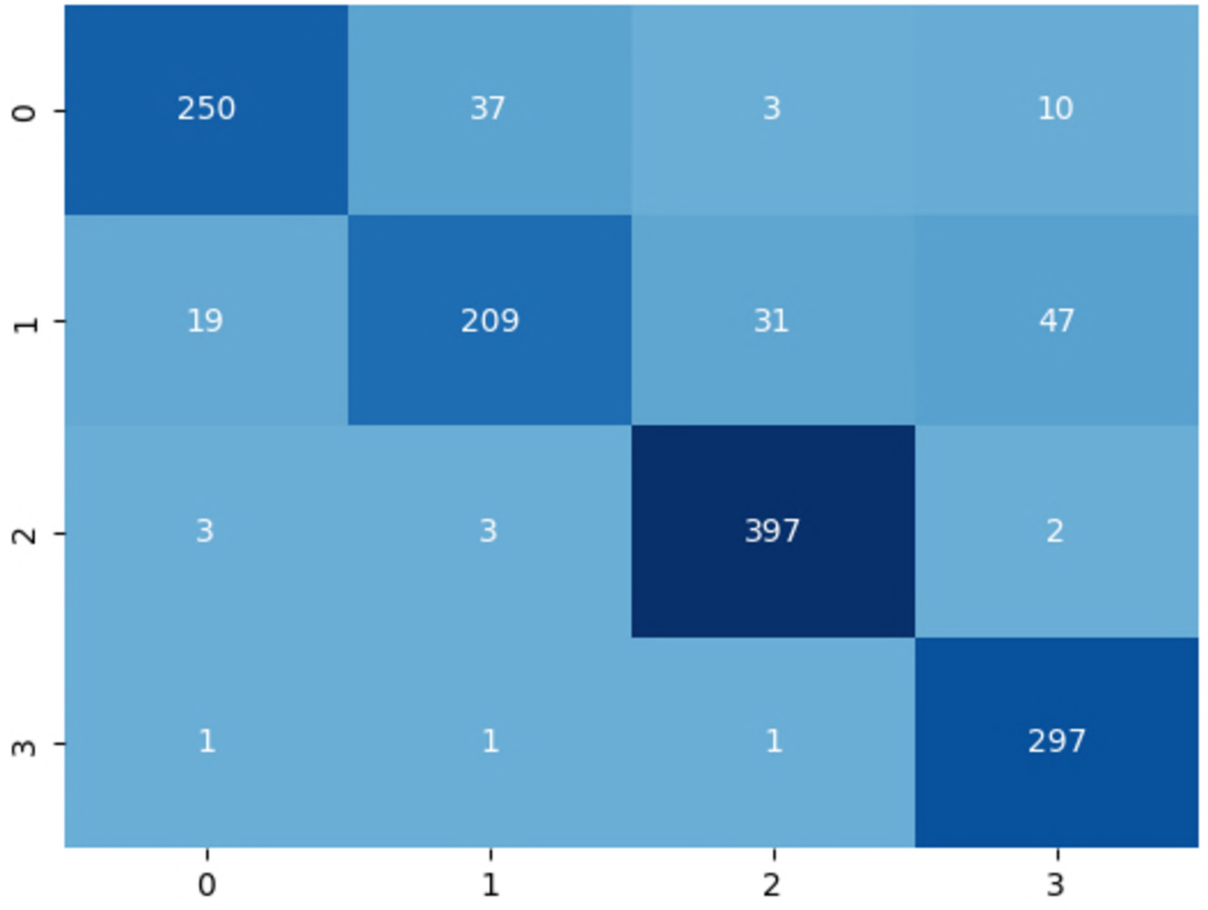


Result & Discussion

Multi-class Classification

Description	InceptionV3	VGG-16	ResNet-50	MobileNetV2	DenseNet121
Training Accuracy	89.59%	90.76%%	56.9%	93.78%	93.75%
Validation Accuracy	84.90%	85.51%	59.3%	88.10%	84.82%
Training Loss	27.54%	24.23%	92.9%	15.75%	17.20%
Validation Loss	40.70%	43.14%	99.4%	36.00%	45.07%
Epoch Number	27	31	44	23	29





Result & Discussion

CNN Architecture	Patient Condition	Precision	Recall	F-1 Score
InceptionV3	No-Tumor	0.96	0.97	0.96
InceptionV3	Tumor	0.99	0.98	0.98
VGG-16	No-Tumor	0.99	0.98	0.95
VGG-16	Tumor	0.96	0.98	0.98
ResNet-50	No-Tumor	0.81	0.98	0.82
ResNet-50	Tumor	0.93	0.98	0.92
MobileNetV2	No-Tumor	0.99	0.98	0.98
MobileNetV2	Tumor	0.99	0.98	0.99
DenseNet121	No-Tumor	0.99	0.98	0.98
DenseNet121	Tumor	0.99	0.98	0.99

Conclusion

This study evaluated five pre-trained CNN models—MobileNetV2, InceptionV3, ResNet-50, VGG-16, and DenseNet121—for brain tumor detection, with DenseNet121 and MobileNetV2 demonstrating the highest precision in both binary and multi-class classification. The results highlight the importance of model selection, as ResNet-50 showed overfitting, suggesting that larger networks may struggle with limited data. MobileNetV2's balance of efficiency and precision makes it ideal for real-time medical applications. The study also emphasizes the role of preprocessing and transfer learning to address data inaccuracies in medical imaging. Future work should focus on integrating these models into real-world healthcare settings to improve diagnostic accuracy.

References

[1] O. Özkaraca et al., “Multiple Brain Tumor Classification with Dense CNN Architecture Using Brain MRI Images,” Life, vol. 13, no. 2, p. 349, Jan. 2023, doi: 10.3390/life13020349.

[2] D. Kaur, S. Goel, R. Nijhawan, and S. Gupta, “Analysis of Brain Tumor using Pre-trained CNN Models and Machine Learning Techniques,” in 2022 IEEE International Students’ Conference on Electrical, Electronics and Computer Science, SCEECS 2022, Institute of Electrical and Electronics Engineers Inc., 2022. doi: 10.1109/SCEECS54111.2022.9741022.

[3] B. Ojha, R. Maharjan, and T. Acharya, “Brain Tumor Detection Using Convolutional Neural Networks: A Comparative Study,” International Journal on Engineering Technology, vol. 1, no. 1, pp. 11–26, Dec. 2023, doi: 10.3126/injet.v1i1.60896.

[4] A. Chattopadhyay and M. Maitra, “MRI-based brain tumor image detection using CNN based deep learning method,” Dec. 01, 2022, Elsevier B.V. doi: 10.1016/j.neuri.2022.100060.

[5] P. L. Deepa, N. Ponraj, and G. V. Sreena, “A comparative analysis of deep neural networks for brain tumor detection,” in 2021 3rd International Conference on Signal Processing and Communication, ICPSC 2021, Institute of Electrical and Electronics Engineers Inc., May 2021, pp. 36–40. doi: 10.1109/ICSPC51351.2021.9451742.


Thank You!