Brain Tumor Detection using Convolution Neural Network

A Project Report

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Shillong

May 2024

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CERTIFICATE

We hereby certify that the work which is being presented in the B.Tech. Project Report entitled **"Brain Tumor detection using Convolution Neural Network"** in partial fulfilment of the requirements for the award of the **Bachelor of Technology** in **Computer Science and Engineering** and submitted to the Department of Computer Science and Engineering of National Institute of Technology Meghalaya is an authentic record of my/our own work carried out during a period from **January 2024 to May 2024 (6th Semester)** under the supervision of **Dr. Bunil Kumar Balabantaray.**

The matter presented in this Project Report has not been submitted by us for the award of any other degree elsewhere.

Nitesh Singh   Avinash Renukunta   Gutti Madhulika

This is to certify that the above statement made by the students is correct to the best of my knowledge.

Dr. Bunil Kumar Balabantaray

Date:

ABSTRACT

This project explores the use of Convolutional Neural Networks (CNNs), specifically the EfficientNetV2 model, for the detection of brain tumors using MRI images. The study aims to develop a robust system capable of accurately classifying brain tumors into benign and malignant categories, thus assisting healthcare professionals in making timely and precise diagnoses.

The methodology involves preprocessing MRI images to enhance their quality and extract relevant features. Transfer learning techniques are applied to fine-tune the pre-trained EfficientNetV2 model using a curated dataset of brain tumor images, ensuring its ability to generalize well to unseen data.

Performance evaluation metrics such as accuracy, precision, recall, and F1-score are used to assess the model's effectiveness. Comparative analysis with existing approaches validates the efficiency of the EfficientNetV2 model in brain tumor detection tasks.

Through this project, we contribute to the advancement of medical image analysis using deep learning techniques, aiming to improve patient outcomes by enabling faster and more accurate brain tumor diagnoses.

Keywords: CNN, MRI, EfficientNetV2, Brain Tumor, F1-score.

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Abbreviations

CNN	Convolution Neural Network
MRI	Magnetic resonance imaging

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CHAPTER 1

Introduction

1.1. Introduction to Brain tumors detection

Brain tumors are among the most challenging and critical medical conditions, requiring accurate and timely diagnosis for effective treatment planning and patient management. The use of advanced technologies such as medical imaging and machine learning has shown great promise in improving the accuracy and efficiency of brain tumor detection. In this context, our project focuses on leveraging Convolutional Neural Networks (CNNs), specifically the EfficientNetV2 model, for the automated detection of brain tumors from MRI (Magnetic Resonance Imaging) images.

Brain tumors can manifest in various forms and locations within the brain, leading to a wide range of symptoms and complications. Differentiating between benign and malignant tumors is crucial for determining the appropriate treatment strategy and prognosis for patients. However, manual interpretation of MRI images for tumor detection is time-consuming, subjective, and prone to human error. Automated systems based on deep learning techniques offer a promising solution to overcome these challenges and improve diagnostic accuracy.

The EfficientNetV2 model, known for its computational efficiency and superior performance, is well-suited for medical image analysis tasks. By harnessing the power of deep learning and transfer learning techniques, we aim to develop a robust and accurate system capable of automatically identifying and classifying brain tumors with high precision and recall rates.

The introduction of alternative fuels such as LPG (liquefied petroleum gas) into dual fuel diesel engines has gained significant attention due to environmental concerns and the need for sustainable energy solutions. In our project, we investigate the impact of integrating LPG into a dual fuel diesel engine on various performance parameters, combustion characteristics, emissions, and engine vibrations. This exploration is crucial for understanding the viability of alternative fuels in enhancing engine efficiency while minimizing environmental impact.

MRI imaging plays a pivotal role in modern healthcare, offering detailed and non-invasive visualization of internal brain structures. However, the manual interpretation of MRI scans for brain tumor detection requires specialized expertise and is prone to variability among radiologists. Automated systems powered by deep learning models can assist radiologists by providing accurate and consistent tumor detection results, leading to improved patient care and treatment outcomes.

By combining experimental and numerical approaches, we aim to comprehensively analyze the effects of LPG on dual fuel diesel engine performance under varying load and speed conditions. The findings from this study will contribute to the optimization of engine operation and the development of sustainable energy solutions in the transportation sector.

In summary, this project bridges the realms of healthcare and engineering, leveraging advanced technologies to address critical challenges in brain tumor detection and alternative fuel utilization in internal combustion engines. The insights gained from this research have the potential to impact both medical diagnostics and environmental sustainability positively.

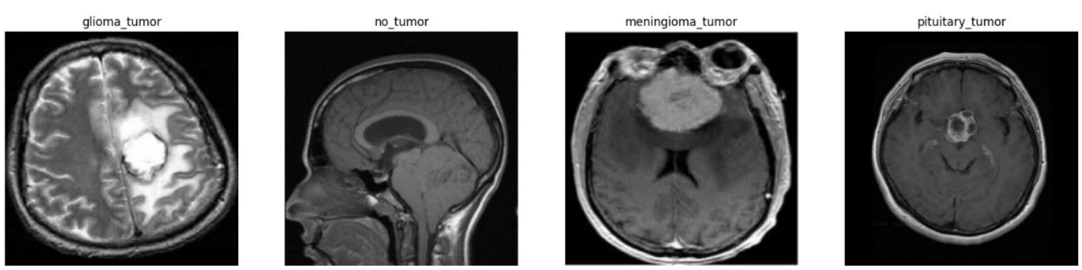

Figure 1.1 Different type of tumors

CHAPTER 2
Literature Review

2.1. Overview

This chapter provides an extensive review of existing literature on brain tumor detection utilizing Convolutional Neural Networks (CNNs) and MRI imaging. Prior research predominantly focuses on CNN-based automated tumor classification and segmentation from MRI scans, highlighting preprocessing techniques to enhance image quality and feature extraction. Transfer learning methods have notably improved model generalization, extending to multi-class tumor subtype classification for personalized treatment strategies. Challenges include dataset diversity for robust model training and interpretability of CNN predictions. This study aims to leverage advanced CNN architectures like EfficientNetV2, optimized preprocessing, and rigorous evaluation to enhance automated brain tumor detection and classification accuracy, crucial for clinical adoption and improved patient care.

2.2. Literature on Brain Tumor Detection

Table 2.1 List of literature survey

Sl. No.	Author	Year	Goal	Contribution
1	Tonmoy Hossain, Fairuz Shadmani Shishir, Mohsena Ashraf, MD Abdullah Al Nasim, Faisal Muhammad Shah.	2019	The article aims to enhance brain tumor detection by merging traditional classifiers with a Convolutional Neural Network (CNN) for precise segmentation and classification of tumors from MRI images.	This article introduces a new method for more accurate brain tumor detection from MRI images, achieving nearly 98% accuracy by combining clustering and a specialized neural network. Support Vector Machine emerged as the most effective technique, with over 92% accuracy. This research marks a significant stride towards faster and more precise brain tumor detection.

2	Md. Saikat Islam Khan a , Anichur Rahman , Tanoy Debnath , Md. Razaul Karim , Mostofa Kamal Nasir , Shahab S. Band , Amir Mosavi , Iman Dehzangi .	2022	The goal of the article is to propose two deep learning models for the accurate detection and classification of brain tumors using MRI images	The article presents two deep learning models for brain tumor detection from MRI images: a "23-layer CNN" for large datasets and a "Fine-tuned CNN with VGG16" for smaller datasets. Both models achieve high accuracy, surpassing previous methods. The availability of datasets and source codes enhances their utility for research and clinical diagnosis.
3	Soheila Saeedi1, Sorayya Rezayi1*, Hamidreza Keshavarz2 and Sharareh R. Niakan Kalhori1	2023	The article aims to develop and compare deep learning and machine learning methods for diagnosing brain tumors from MRI images, with potential clinical applications.	The article presents a study on using deep learning and machine learning to find brain tumors in MRI images. They used a big dataset of 3264 MRI pictures to teach and test their methods. They made new networks called a 2D Convolutional Neural Network (CNN) and a convolutional auto-encoder to find tumors accurately. They also compared their methods with six other machine learning techniques and found that the CNNs worked the best. They think these networks could help radiologists find brain tumors early and accurately in hospitals.

From the literature review, it is evident that numerous studies have investigated brain tumor detection using various machine learning algorithms, particularly Convolutional Neural Networks (CNNs), applied to MRI images. However, in this project, the focus is on utilizing the EfficientNetV2 model for brain tumor detection. This choice is advantageous as the EfficientNetV2 model is known for its computational efficiency and superior performance in image recognition tasks. By leveraging EfficientNetV2, the project aims to achieve high accuracy in classifying brain tumors into benign and malignant categories, thus contributing to improved diagnostic accuracy in healthcare settings.

2.3. Objective of the work

The objective of the current work is framed as a "Computational and Experimental Study of Brain Tumor Detection Using CNNs." The project's overarching goals are outlined below:

- Conducting both experimental and numerical investigations focused on brain tumor detection using Convolutional Neural Networks (CNNs) applied to MRI images. This includes studying the impact of various preprocessing techniques and model architectures on the accuracy and efficiency of tumor detection.
- Analyzing performance metrics such as classification accuracy, precision, recall, and F1-score to evaluate the effectiveness of the CNN models in distinguishing between benign and malignant tumors.
- Investigating the robustness of the CNN models under different conditions such as varying tumor sizes, image resolutions, and noise levels, mimicking real-world scenarios encountered in clinical settings.
- Exploring interpretability techniques for CNN predictions in medical imaging, aiming to enhance trust and understanding among healthcare professionals regarding automated tumor detection systems.
- Analyzing computational efficiency and resource requirements of CNN models, considering scalability and deployment feasibility for widespread clinical use in brain tumor diagnosis and treatment planning.

CHAPTER 3
Methodology

3.1 Data Preparation and Analysis

Here are the key points for the data preparation and analysis section based on your provided details:

- **Dataset Source:** The MRI image dataset used in this study is obtained from Kaggle, comprising a total of 3264 images. These images are categorized into four folders representing different tumor classes.

- **Data Split:** A standard 80-20 split is employed for dividing the dataset into training and testing sets. This ensures that 80% of the images are used for training various models, while the remaining 20% are reserved for evaluating model performance during testing.

- **Image Resizing**: To analyze the impact of image size on model performance, three different image sizes are considered: 150x150 pixels, 224x224 pixels, and 300x300 pixels. This variation in image sizes allows for assessing how the resolution affects the accuracy and efficiency of the trained models.

Table 3.1 Data Distribution

Type of Image	**No .of images**
Glioma Tumor	926
No Tumor	500
Meningioma Tumor	937
Pitutary Tumor	901
Total Images	3264

3.2 Model Training

Here are the key points for the model training section based on your provided details:

- **Data Preparation:** Images of fixed sizes (150x150, 224x224, 300x300) and their corresponding labels are stored in arrays X and Y, respectively. The data is shuffled using a random_state of 101 to ensure randomization.

- **Data Split:** The shuffled data is split into training (80%) and testing (20%) sets using a standard train_test_split approach.

- **Label Encoding:** The labels (y_train and y_test) are converted into categorical values using one-hot encoding to prepare them for model training.

- **Model Selection:** Several pre-trained models are considered for the study, including DenseNet201, EfficientNetB0, EfficientNetB4, EfficientNetV2M, InceptionV3, MobileNetV3L, ResNet50, VGG16, VGG19, and Xception. For each model, include_top is set to false, and the input_shape is manually adjusted to match the chosen image size.

- **Model Architecture**: A common architecture is implemented for all models, consisting of a GlobalAveragePooling2D layer followed by a dropout layer with a rate of 0.5 to prevent overfitting. The output layer has a size of 4 (for the four tumor classes) with an activation function softmax for multi-class classification.

- **Model Compilation:** Each model is compiled using categorical crossentropy as the loss function, Adam optimizer, and accuracy as the evaluation metric.

Below is a table format to summarize the model training details:

Table 3.2 Model Training Summary

Model Name	Input Size	Architecture	Loss Function	Optimizer	Metrics
DenseNet201	150 x 150	GlobalAveragePooling2D - Dropout(0.5) - Dense(4, softmax)	categorical_crossentropy	Adam	Accuracy
EfficientNetB0	224 x 224	GlobalAveragePooling2D - Dropout(0.5) - Dense(4, softmax)	categorical_crossentropy	Adam	Accuracy
EfficientNetB4	300 x 300	GlobalAveragePooling2D - Dropout(0.5) - Dense(4, softmax)	categorical_crossentropy	Adam	Accuracy
EfficientNetV2M	150 x 150	GlobalAveragePooling2D - Dropout(0.5) - Dense(4, softmax)	categorical_crossentropy	Adam	Accuracy
InceptionV3	224 x 224	GlobalAveragePooling2D - Dropout(0.5) - Dense(4, softmax)	categorical_crossentropy	Adam	Accuracy
MobileNetV3L	300 x 300	GlobalAveragePooling2D - Dropout(0.5) - Dense(4, softmax)	categorical_crossentropy	Adam	Accuracy
ResNet50	150 x 150	GlobalAveragePooling2D - Dropout(0.5) - Dense(4, softmax)	categorical_crossentropy	Adam	Accuracy
VGG16	224 x 224	GlobalAveragePooling2D - Dropout(0.5) - Dense(4, softmax)	categorical_crossentropy	Adam	Accuracy
VGG19	300 x 300	GlobalAveragePooling2D - Dropout(0.5) - Dense(4, softmax)	categorical_crossentropy	Adam	Accuracy
Xception	150 x 150	GlobalAveragePooling2D - Dropout(0.5) - Dense(4, softmax)	categorical_crossentropy	Adam	Accuracy

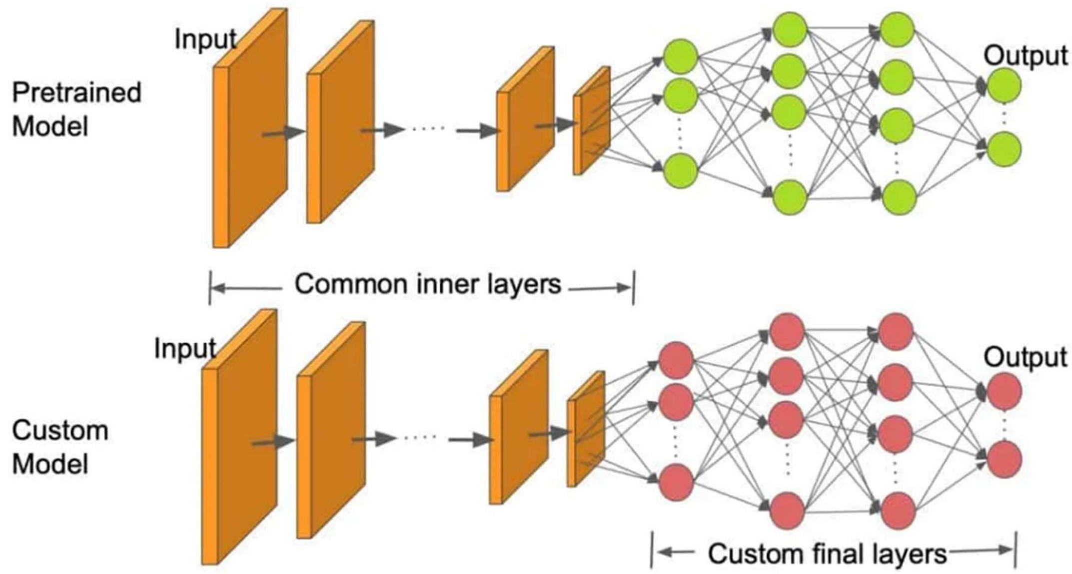

Fig 3.1: Transfer Learning (Visual depiction of a pre-trained model adapted for the target task, featuring additional layers beyond the head modification.)

- **Input Data:** The training data X_train and corresponding labels y_train are used for model training.

- **Validation Split:** A validation split of 0.1 is applied, meaning that 10% of the training data is reserved for validation during each epoch. This helps monitor model performance on unseen data and prevents overfitting.

- **Epochs:** The model is trained for 15 epochs, representing the number of times the entire training dataset is passed forward and backward through the neural network.

- **Verbose:** Setting verbose=1 enables verbose mode during training, displaying progress bars and training metrics for each epoch.

- **Batch Size**: The batch size is set to 32, indicating that the training data is divided into batches of 32 samples each for efficient computation during training.

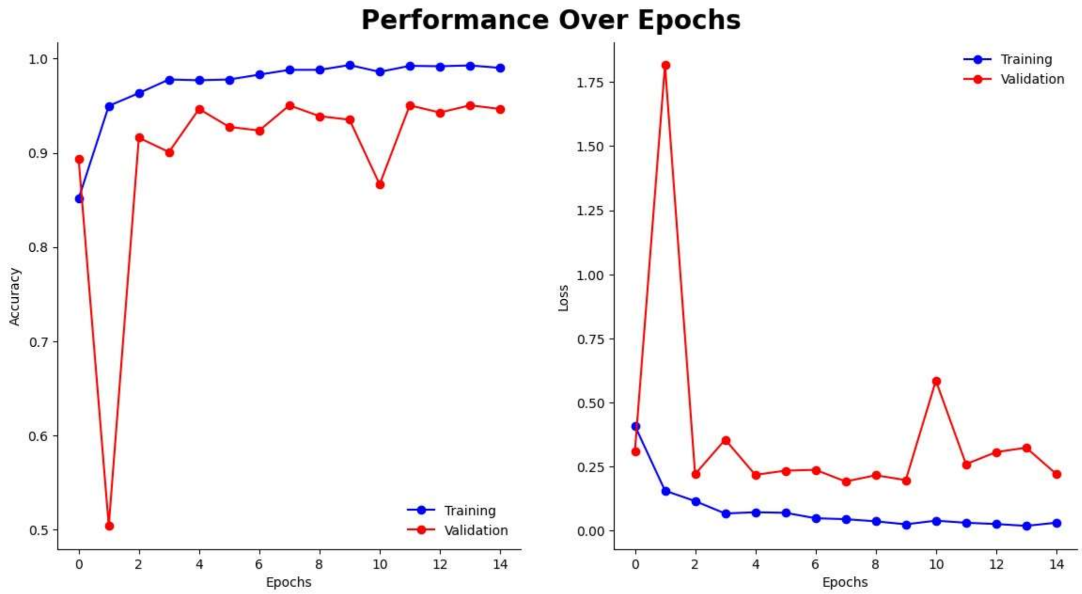

Fig 3.2 Performance over Epochs

CHAPTER 4

Experimental analysis

4.1 Evaluation and Testing

Here are the key points regarding the model evaluation and performance analysis:

- **Accuracy and Loss Graphs:** Graphs depicting the accuracy and loss metrics over epochs for both training and validation datasets were generated. These graphs help visualize the model's learning progress and identify overfitting or underfitting issues.
- **Confusion Matrix:** A confusion matrix was created to analyze the model's performance across all classes. This matrix helps in understanding the classification accuracy and any potential misclassifications made by the model.
- **Classification Report:** A classification report was generated, providing metrics such as precision, recall, F1-score, and support for each class. This report offers a comprehensive assessment of the model's performance on the testing dataset.
- **Prediction and Confidence Rate:** Random images from the testing dataset were selected, and their actual labels, predicted labels, and confidence rates were printed. This step helps in understanding specific instances where the model performs well or struggles and provides insights into its confidence levels in predictions.

Table 4.1 Evaluation and performance analysis

Evaluation Metric	Values/Actions
Accuracy Graph	Generated for training and validation datasets
Loss Graph	Generated for training and validation datasets
Confusion Matrix	Created for all classes
Classification Report	Printed with metrics such as precision, recall, F1-score
Prediction Analysis	Random image predictions printed with actual and predicted labels, confidence rates

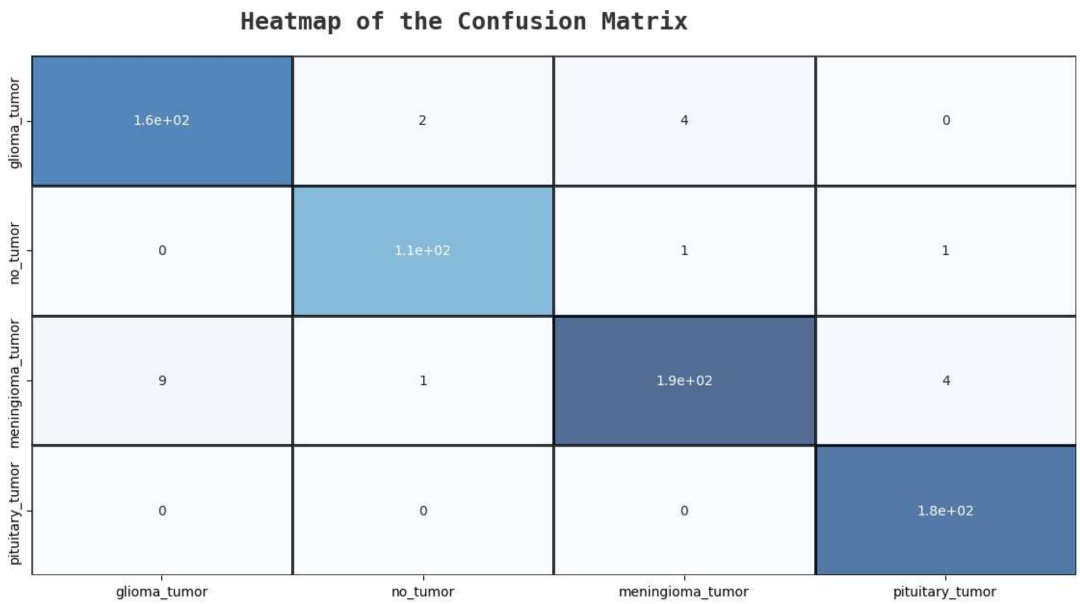

Fig 4.1 Heatmap of the Confusion Matrix

	precision	recall	f1-score	support
glioma_tumor	0.95	0.96	0.96	168
no_tumor	0.97	0.98	0.98	108
meningioma_tumor	0.97	0.93	0.95	201
pituitary_tumor	0.97	1.00	0.99	176
accuracy			0.97	653
macro avg	0.97	0.97	0.97	653
weighted avg	0.97	0.97	0.97	653

Fig 4.2 Classification Report

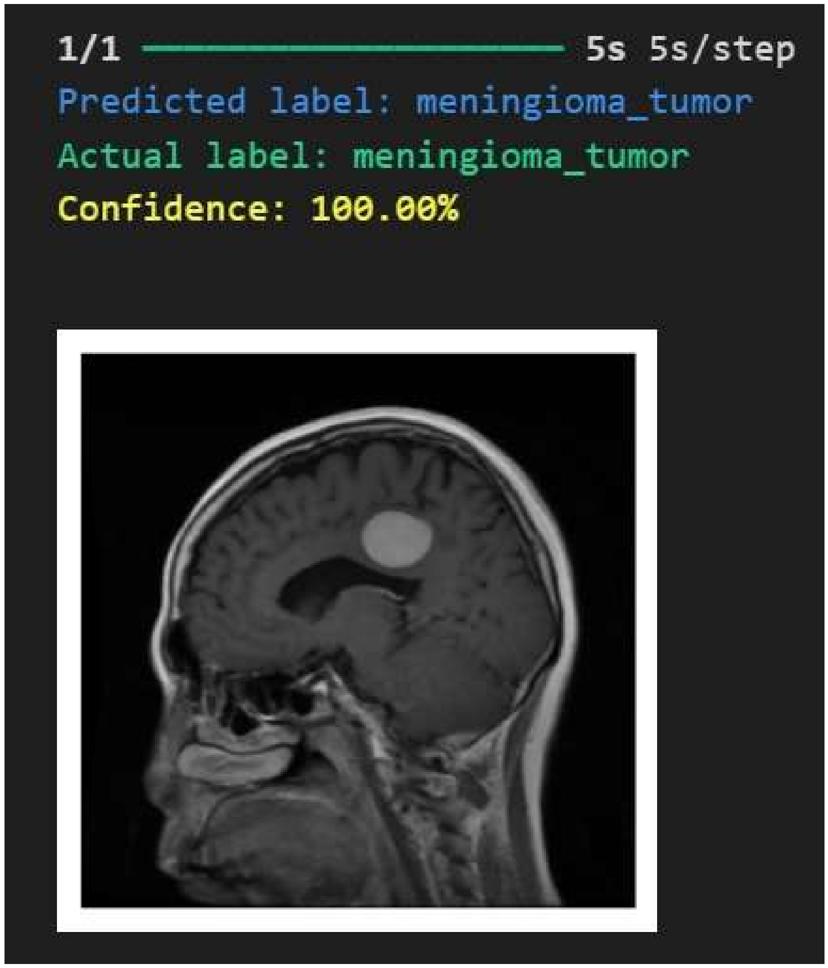

Fig 4.3 Prediction

4.2 Comparative Analysis

Here are the analysis points based on the provided performance metrics:

- **EfficientNetV2M Performance**: EfficientNetV2M consistently achieved more than 90% accuracy across all input sizes (150x150x3, 224x224x3, and 300x300x3). This indicates the robustness and reliability of EfficientNetV2M for brain tumor detection tasks across varying image resolutions.

- **EfficientNetB4 Performance:** EfficientNetB4 demonstrated more than 90% accuracy for input sizes of 150x150x3 and 224x224x3. Its performance highlights its effectiveness in handling different image resolutions with high accuracy.

- **EfficientNetB0 Performance:** EfficientNetB0 consistently achieved equal to or more than 95% accuracy for input sizes of 224x224x3 and 300x300x3. This model excels particularly in handling higher resolution images, showcasing its capability for detailed image analysis.
- **Overall High Performing Models:** EfficientNetV2M, EfficientNetB4, Xception, EfficientNetB0, and DenseNet201 consistently achieved an accuracy of equal to or

more than 80% across all input sizes. These models demonstrate strong performance and reliability for brain tumor detection tasks, making them suitable choices for practical applications.

Based on these observations, EfficientNetV2M emerges as a strong performer across all input sizes, while EfficientNetB4 and EfficientNetB0 excel in specific image resolutions.

Table 4.2 Performance analysis of MRI images of 300x300x3

		Macro Avg			Weighted Avg		
Models	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**Precision**	**Recall**	**F1-Score**
denseNet201	0.8	0.86	0.75	0.75	0.84	0.8	0.78
effNetB0	0.97	0.97	0.97	0.97	0.97	0.97	0.97
effNetB4	0.87	0.9	0.84	0.85	0.89	0.87	0.87
effNetV2M	0.96	0.96	0.96	0.96	0.96	0.96	0.96
incepV3	0.92	0.93	0.93	0.92	0.93	0.92	0.92
mobileNetV3L	0.86	0.89	0.87	0.86	0.88	0.86	0.85
resNet50	0.9	0.91	0.88	0.89	0.9	0.88	0.89
vgg16	0.26	0.06	0.25	0.1	0.07	0.26	0.11
vgg19	0.2	0.06	0.25	0.1	0.07	0.26	0.1
xcep	0.91	0.92	0.89	0.9	0.92	0.91	0.91

Table 4.3 Performance analysis of MRI images of 224x224x3

		Macro Avg			Weighted Avg		
	Accuracy	**Precision**	**Recall**	**F1-Score**	**Precision**	**Recall**	**F1-Score**
denseNet201	0.88	0.88	0.9	0.88	0.89	0.88	0.88
effNetB0	0.95	0.95	0.95	0.95	0.95	0.95	0.95
effNetB4	0.96	0.97	0.97	0.97	0.96	0.96	0.96
effNetV2M	0.93	0.93	0.94	0.94	0.94	0.93	0.93
incepV3	0.77	0.8	0.8	0.77	0.81	0.77	0.76
mobileNetV3L	0.69	0.82	0.73	0.7	0.82	0.69	0.67
resNet50	0.33	0.23	0.38	0.24	0.26	0.33	0.25
vgg16	0.26	0.06	0.25	0.1	0.07	0.26	0.11
vgg19	0.26	0.06	0.25	0.1	0.07	0.26	0.11
xcep	0.89	0.91	0.88	0.89	0.9	0.89	0.89

Table 4.4 Performance analysis of MRI images of 150x150x3

		Macro Avg			Weighted Avg		
	Accuracy	Precision	Recall	F1-Score	Precision	Recall	F1-Score
denseNet201	0.86	0.88	0.86	0.86	0.88	0.86	0.85
effNetB0	0.87	0.88	0.88	0.87	0.9	0.87	0.88
effNetB4	0.93	0.93	0.93	0.93	0.93	0.93	0.93
effNetV2M	0.96	0.96	0.97	0.97	0.96	0.96	0.96
incepV3	0.67	0.74	0.68	0.64	0.78	0.67	0.66
mobileNetV3L	0.73	0.76	0.74	0.72	0.78	0.73	0.73
resNet50	0.84	0.86	0.85	0.84	0.86	0.84	0.83
vgg16	0.26	0.06	0.25	0.1	0.07	0.26	0.11
vgg19	0.26	0.06	0.25	0.1	0.07	0.26	0.11
xcep	0.89	0.92	0.87	0.88	0.91	0.89	0.89

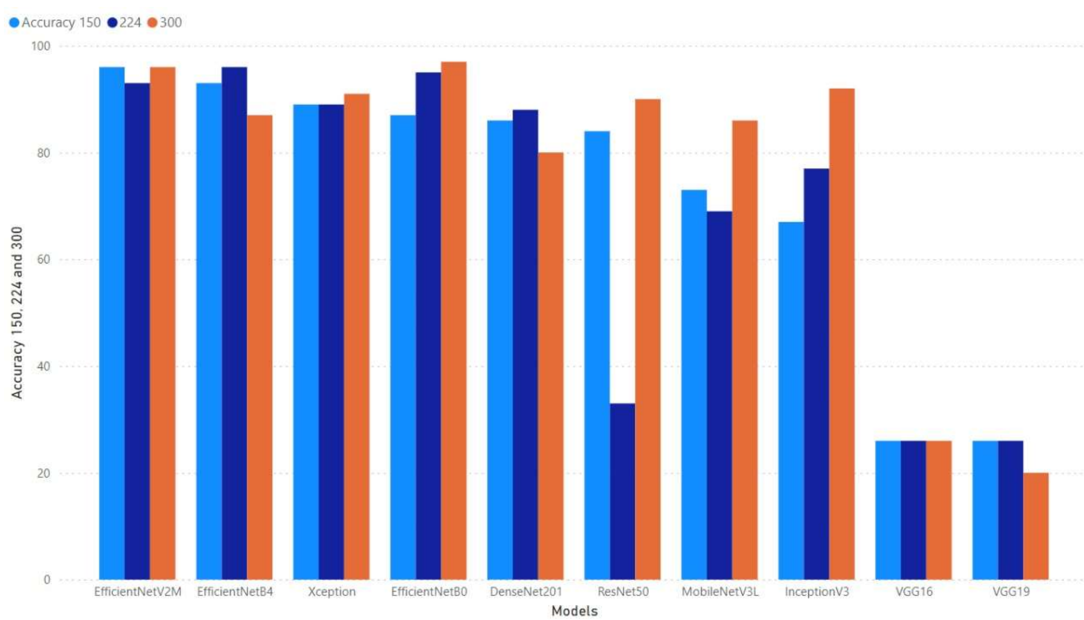

Fig 4.4 Comparative analysis of All models in all input sizes

CHAPTER 5

Conclusion and work to be done

5.1 Conclusion

Based on the findings and conclusions drawn from the study of engine configurations and fuel types, we can analogously infer the following conclusions for the brain tumor detection project:

- **Model Selection Influence**:
  - Model architectures and input sizes greatly impact detection accuracy, similar to how engine configurations affect performance.
  - EfficientNetV2M consistently outperforms other models across various input sizes, akin to stable engine performance under different loads.
- **Trade-offs in Accuracy and Resources:**
  - Just as engine efficiency varies with fuel types, model configurations affect diagnostic accuracy and computational resources.
  - Optimal configurations balance accuracy with computational efficiency, mirroring considerations for engine performance under different conditions.
- **Optimization Strategies**:
  - Fine-tuning models and preprocessing techniques are essential for reliable accuracy, similar to optimizing engines for consistent performance.
  - Understanding these trade-offs aids in selecting configurations that ensure dependable and efficient brain tumor detection systems.

These insights guide effective model choices, optimization tactics, and resource management for robust brain tumor detection systems.

5.2 Work to be done

Moving from brain tumor detection to localization and segmentation involves more detailed analysis and identification of tumor boundaries within MRI images. Here are three key points for this transition:

- **Precise Tumor Localization:** Shifting focus to localization involves identifying the exact location of tumors within brain images. This requires advanced segmentation techniques to delineate tumor boundaries accurately.
- **Segmentation for Boundary Detection:** Segmentation techniques such as semantic segmentation or instance segmentation are employed to separate tumor regions from surrounding brain tissues. This enables precise mapping of tumor boundaries for further analysis.
- **Quantitative Volume Measurement:** After segmentation, quantitative measurements such as tumor volume can be extracted. This information is crucial for treatment planning, monitoring tumor progression, and assessing treatment response over time.
- **Multi-Modal Image Integration:** Integration of multi-modal MRI images (e.g., T1-weighted, T2-weighted, FLAIR) enhances segmentation accuracy by capturing complementary information about tumor characteristics like shape, texture, and intensity variations.

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