Progress Report

on

Brain Tumor Classification Using Deep Learning

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INDEX

List of Figures

List of Tables

DECLARATION

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We, Aditi Sah (2021UIT3077), Pranav Singh Kanwar (2021UIT3135), and Rahul Batra (2021UIT3140) of the B. Tech., Department of Information Technology, hereby attest that the Project I report, "**Brain Tumour Classification Using Deep Learning**," that we have submitted to the Department of Information Technology at Netaji Subhas University of Technology, is authentic and authenticated. Prior to now, no degree has been granted based on this work.

Place: Delhi
Date: December 8th 2024

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Certificate

This certifies that the Project(I)-Report titled "Brain Tumour Classification Using Deep Learning," which Aditi Sah (2021UIT3077), Pranav Singh Kanwar (2021UIT3135), and Rahul Batra (2021UIT3140) are submitting to the Department of Information Technology at Netaji Subhas University of Technology, Delhi, in partial fulfilment of the requirements for the award of the Bachelor of Technology degree, is a record of the work completed by the students under my supervision and direction. The paper contains unique content that has not been plagiarised without due citation.

Prior to now, no degree has been granted based on this work.

Place: Delhi
Date: December 8th 2024

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(Supervisor)

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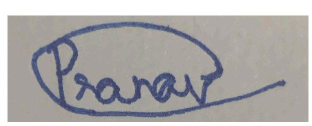
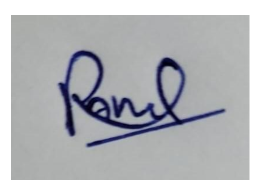
We express our sincere thanks and gratitude to all individuals whose valuable contributions played a crucial role in the successful fulfillment of our project "Brain Tumor Classification Using Deep Learning". A special acknowledgement is reserved for our esteemed Project Supervisor, Dr. Nisha Kandhoul. Her invaluable guidance, thought-provoking suggestions, and unwavering encouragement played a pivotal role in shaping and refining this report. Dr. Nisha's expertise and support were instrumental in navigating the complexities of the project, and her dedication to our academic and professional development is truly commendable. We are sincerely thankful for her mentorship and the positive impact she has had on the culmination of this endeavor.

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ABSTRACT

An estimated 18,600 people will die from malignant brain tumours (brain cancer) in 2021, while over 84,000 people are anticipated to acquire a primary brain tumour diagnosis. Brain tumours are an aggressive disease. Magnetic Resonance Imaging (MRI) is the best method for finding brain tumours. More than any other form of cancer, brain tumours have the potential to significantly and permanently affect a patient's physical, mental, and emotional well-being. Therefore, increasing life expectancy and well-being requires prompt diagnosis and the creation of the finest treatment strategies. When it comes to picture classification and segmentation tasks, neural networks have proven to be highly accurate.

In order to identify and categorise brain tumours, this project compares several deep learning models, such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Transfer Learning (TL). 3,260 T1-weighted contrast-enhanced photos that have been enhanced and cleaned make up the dataset. Binary classification was the main emphasis of early studies; later, multi-class classification of benign, malignant, and pituitary tumours was included.

CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

1.1 INTRODUCTION

There are more than 200 varieties of tumours that can harm people, and they are categorised as either benign or malignant. The American Cancer Society states that because of the formation of aberrant tissue, brain tumours impair brain function. Over the previous 30 years, the number of deaths from brain tumours has increased by 300%, according to the National Brain Tumour Foundation. Non-surgical techniques like MRI are essential for diagnosis because brain tumour biopsies necessitate surgery, whereas early identification is vital for life.

Medical imaging analysis has greatly improved thanks to developments in machine learning, especially deep learning. Autoencoders offer unsupervised learning for feature extraction, while Convolutional Neural Networks (CNNs) are very good at processing images. These methods have shown excellent tumour detection accuracy. But there are drawbacks to earlier research on brain tumour identification, namely the exclusion of healthy participants or the absence of comparisons with conventional techniques.

Machine learning can assist radiologists by improving diagnostic accuracy and reducing human error in brain tumor detection. These computational methods enhance the ability to classify tumors more effectively than manual processes.

Key contributions:

- **Large Dataset:** A substantial dataset of 3,264 MRI images was utilized for training and testing, ensuring diverse representation of various brain conditions. This extensive dataset enhances the model's ability to generalize across different tumor types and healthy tissues, providing a solid foundation for effective training.

- **Optimized Architecture**: A modified architecture was developed, combining ResNet (Residual Neural Network) with autoencoder networks. This hybrid approach was fine-tuned to optimize accuracy, leveraging autoencoders for feature extraction and dimensionality reduction while maintaining ResNet's capacity to capture complex patterns in MRI images.

- **Tumor Classification:** Models were implemented to classify three distinct types of brain tumors—gliomas, meningiomas, and pituitary tumors—alongside healthy subjects. This classification utilized ResNet, autoencoder, and six different machine learning techniques, demonstrating the models' effectiveness in differentiating between tumor types and enhancing diagnostic accuracy.

- **Performance Analysis:** A rigorous performance evaluation was conducted using one-way ANOVA, revealing significant differences (p-value < 0.001) among the eight models assessed. This analysis focused on key metrics such as precision, recall, and F-measure, providing a comprehensive understanding of each model's strengths and weaknesses, and guiding future model selection and refinement.

1.2 MOTIVATION

Early identification is crucial for successful treatment and better patient outcomes since brain tumours represent a serious health concern. Even with improvements in medical imaging technologies, it can still be difficult to correctly identify and categorise brain tumours, especially in environments with limited resources. This research uses deep learning models to help medical professionals and institutions diagnose brain tumours more accurately and efficiently, addressing the demand for a dependable and easily available solution.

Improving Brain Tumor Detection: The project aims to develop an AI-driven system for accurate brain tumor classification, supporting timely and informed treatment decisions.

- **Data-Driven Model Development**: By utilizing and enhancing publicly available MRI datasets, the project showcases the potential of deep learning in medical diagnostics, encouraging collaboration with medical professionals for further data collection and model refinement.

- **Empowering Patients and Doctors:** The system can be accessed by doctors and patients of any age group, enabling better communication between healthcare providers and those seeking treatment, fostering an informed and patient-centric approach to brain tumor diagnosis.

1.3 LITERATURE SURVEY

Research on deep learning architectures in medical imaging has attracted a lot of interest, with scientists investigating different convolutional neural network (CNN) models for their potential to efficiently analyse and categorise medical pictures. Because of their strong performance and residual learning framework, ResNet-based architectures have become the front-runners among them.

Overview of CNNs in Medical Imaging

Convolutional Neural Networks (CNNs) have revolutionized image processing, particularly in medical imaging, where tasks like tumor classification, segmentation, and detection require precise and reliable methods. CNNs extract hierarchical features from images, enabling them to identify subtle patterns critical for medical diagnosis. Popular architectures such as AlexNet, VGG, and Inception have paved the way for deeper and more sophisticated networks like ResNet. [3] [4]

ResNet Architecture

By solving the vanishing gradient problem, ResNet (Residual Network) established the idea of residual learning, which made it possible to train extremely deep networks. By avoiding one or more layers using skip connections, this architecture guarantees gradient flow and enhances performance on challenging jobs. Variants with varying depth and complexity within the ResNet family include ResNet18, ResNet34, ResNet50, and ResNet101.

ResNet50: A 50-layer network known for its balance of depth and computational efficiency. It has been applied in various medical domains for tasks like brain tumor classification and organ segmentation. [1]

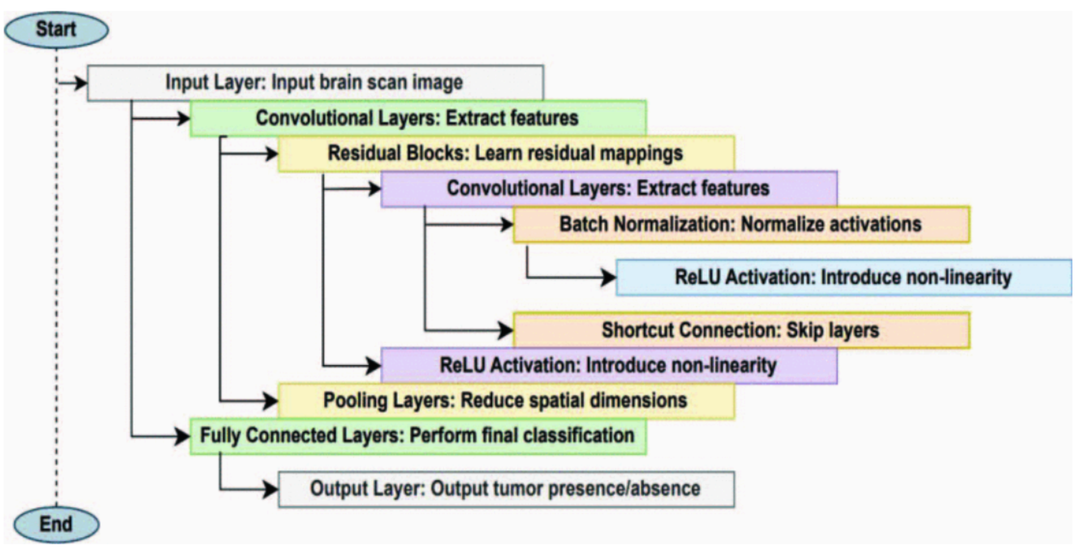

Figure 1.1: RESNET50 ARCHITECTURE

ResNet101: A deeper variant with 101 layers, designed to capture finer details and enhance performance on tasks requiring high-resolution feature extraction. [2]

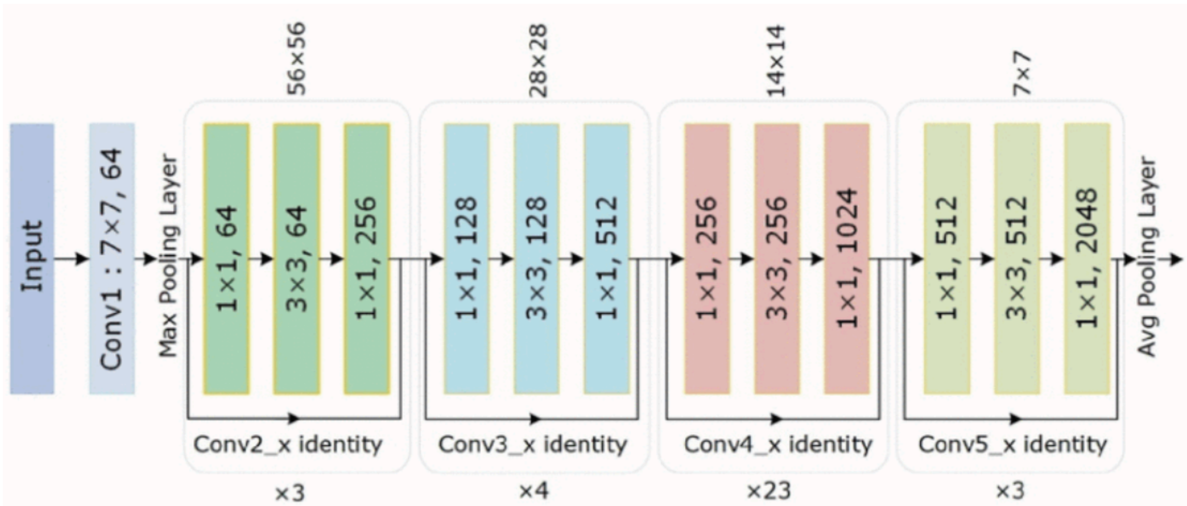

Figure 1.2: RESNET101 ARCHITECTURE

Applications in Brain Tumor Classification

ResNet-based models have been used in numerous research to classify brain tumours using MRI datasets:

Transfer Learning: To take use of their feature extraction capabilities, ResNet models pretrained on ImageNet have been refined on medical datasets. Research indicates that transfer learning lessens the requirement for sizable labelled datasets, which are frequently in short supply in the field of medical imaging.

Comparative Studies: Studies that contrast ResNet models with other CNNs, like as VGG and AlexNet, demonstrate how well they perform, especially when it comes to tasks that call for deeper feature learning.

Evaluation Metrics in Medical Imaging

The following evaluation metrics parameters are essential for evaluating CNN performance on medical imaging tasks:

- **Accuracy:** Indicates how accurate a prediction is overall.
- **Precision and Recall**: Measure the model's precision and recall to see how well it reduces false positives and false negatives.
- **F1 Score**: Through the provision of a harmonic mean of precision and recall, the F1 Score guarantees a fair evaluation.

- **AUC (ROC):** Assesses how well the model can differentiate between classes at all threshold values.

These metrics have been widely adopted in studies involving ResNet models, providing a standardized approach to performance comparison.

Insights from Prior Research
Prior research has explored various aspects of ResNet50 and ResNet101, including:

- Feature Extraction Capabilities: ResNet50 demonstrates robust feature extraction, enabling high accuracy on medium-sized datasets, while ResNet101 offers enhanced performance on tasks requiring fine-grained details.

- Computational Efficiency: ResNet50, with fewer layers, is computationally less expensive, making it suitable for real-time applications. Conversely, ResNet101 requires higher computational resources but achieves greater accuracy on complex datasets.

CHAPTER 2
PROBLEM STATEMENT AND OBJECTIVE

2.1 PROBLEM STATEMENT

Medical imaging and diagnosis still face major challenges in identifying and classifying brain tumours. Accurately identifying the many types of brain tumours, such as gliomas, meningiomas, and pituitary gland tumours, is essential for timely and effective treatment. However, achieving high tumour classification accuracy is challenging due to the complexity of MRI images and the limitations of existing deep learning techniques.

This project evaluates the efficacy of two advanced deep learning architectures based on convolutional neural networks (CNNs), ResNet-50 and ResNet-101, for the classification of brain tumours. Pituitary tumours, gliomas, meningiomas, and healthy brains are the four categories into which the 3,264 MRI images are separated.

The study's main objective is to assess ResNet-50 and ResNet-101's generalisation capacity, accuracy, and execution time. The study aims to determine the best model for clinical applications by examining how deeper network designs affect feature extraction and classification performance. To get the best results, important training parameters including learning rate, batch size, and optimisation techniques are adjusted.

The ultimate goal is to offer a strong and effective deep learning solution for classifying brain tumours that will help medical professionals, including radiologists, make accurate diagnosis, enhance patient outcomes, and advance medical imaging technologies.

2.2 OBJECTIVE

- The principal objective is to develop a sophisticated system specifically designed for brain tumour detection and classification using T1-weighted MRI images, with a focus on brain tumour type identification.

- The objective is to harness existing knowledge, publicly accessible datasets, and cutting-edge methodologies to construct models that exhibit superior detection and classification capabilities and performance metrics.

- A central emphasis is placed on mitigating the disruptive impacts stemming from variations encountered during MRI image acquisition, preprocessing protocols, and scanning procedures, particularly concerning detection and classification models.

- Advanced data augmentation techniques and domain adaptation strategies are employed to harmonize and standardize brain tumor MRI image datasets, facilitating greater consistency and precision in subsequent analytical processes.

- The primary motivation for this endeavour is the need to improve the classification process for brain tumour pathology by using cutting-edge computational techniques to increase the precision and dependability of brain tumour diagnosis and therapy.

These advancements aim to enable more effective medical interventions, leading to improved patient outcomes.

CHAPTER 3
METHODOLOGY

3.1 EXPLORATORY DATA ANALYSIS

The EDA phase provided insights into the dataset's structure, distribution, and characteristics through the following steps:

3.1.1 Sample Image Visualization

Representative images from each class (Glioma, Meningioma, Normal, Pituitary) were visualized to assess quality and variation.
Five grayscale images per class were displayed to understand anatomical structures.

3.1.2 Dataset Distribution

The number of images per class was counted and visualized using a bar chart, revealing slight class imbalance.
This analysis guided the need for data augmentation in underrepresented classes.

3.1.3 Data Organization

Images were split into training and validation subsets (80-20 ratio) and organized into class-specific directories.
Structured access was ensured for efficient preprocessing and model training.

3.2 DATA PREPROCESSING

In order to guarantee consistency, better the quality of the input data, and improve the performance of the deep learning models, the MRI images utilised for brain tumour classification were preprocessed. The input photos underwent normalisation, augmentation, and scaling as part of the preparation pipeline. Because it prepares the raw data for ResNet-50 and ResNet-101 model training and evaluation, this phase is crucial.

3.2.1 Image Resizing

MRI images in the dataset came in varying resolutions. To standardize the input size for the deep learning models, all images were resized to 224 x 224 pixels. This resolution was chosen as it aligns with the input size requirement for ResNet architectures pre-trained on ImageNet. Standardizing the size ensures consistency during training and reduces computational overhead.

3.2.2 Data Augmentation

To improve the models' ability to generalise to new data, data augmentation techniques were used to artificially expand the training dataset's size and add variability. TensorFlow/Keras' ImageDataGenerator class was used to implement the following augmentation techniques:

- Rotation: Up to 20 degrees of random rotation was applied to the images.
- Width and Height Shifts: Horizontal and vertical translations were applied with a range of 20% of the image size.
- Shear Transformation: To somewhat distort the photos, a 20% shear range was used.
- Zoom: Random zooming within a range of 20% was performed.
- Horizontal Flip: Images were flipped horizontally to simulate mirrored versions.
- Fill Mode: Missing pixels introduced by transformations were filled using nearest neighbor interpolation.

The augmentation pipeline enhances the diversity of training data and helps mitigate overfitting by introducing realistic transformations while preserving the essential features of MRI images.

3.2.3 Normalization

The images were normalized using the preprocess_input function from the ResNet module in TensorFlow. This function scales the pixel values to match the input distribution expected by the pre-trained ResNet models, which include:

- Centering the data around zero.
- Scaling pixel values to the range [-1, 1].
- Normalization ensures that the input images are compatible with the weights of the pre-trained ResNet models, leading to more stable and faster training.

3.2.4 Dataset Splitting

The dataset was split into two subsets:

- Training Set: Containing 2,475 images across 4 classes.
- Validation Set: Containing 621 images across 4 classes.

Both subsets were processed using the augmentation pipeline for the training set and a simple normalization pipeline for the validation set. This split was designed to ensure a 80-20 ratio between training and validation data.

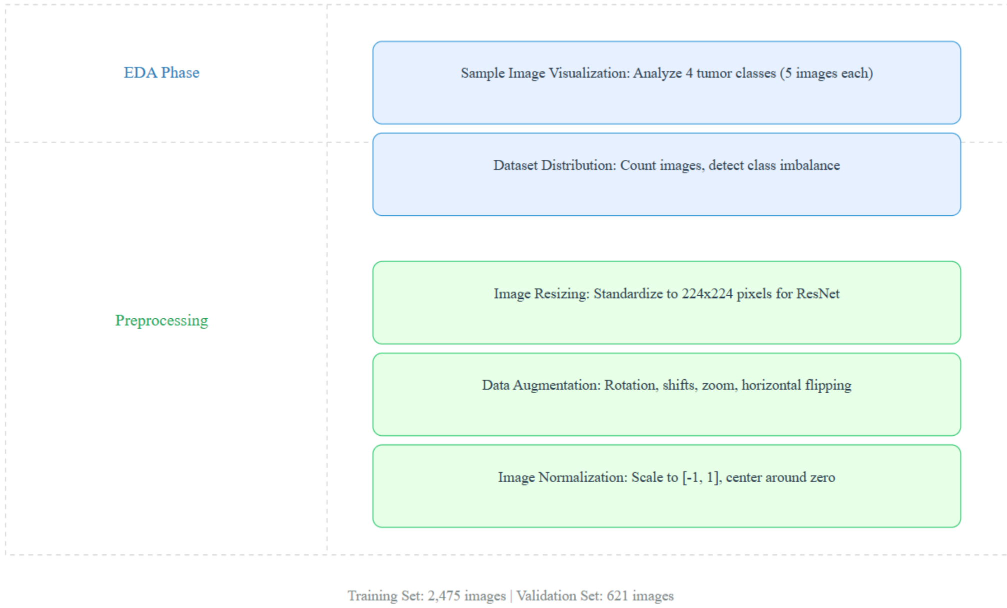

Figure 3.1: DATA PREPARATION WORKFLOW

CHAPTER 4
WORK DONE & IMPLEMENTATION

4.1 BRAIN TUMOR CLASSIFICATION WORKFLOW

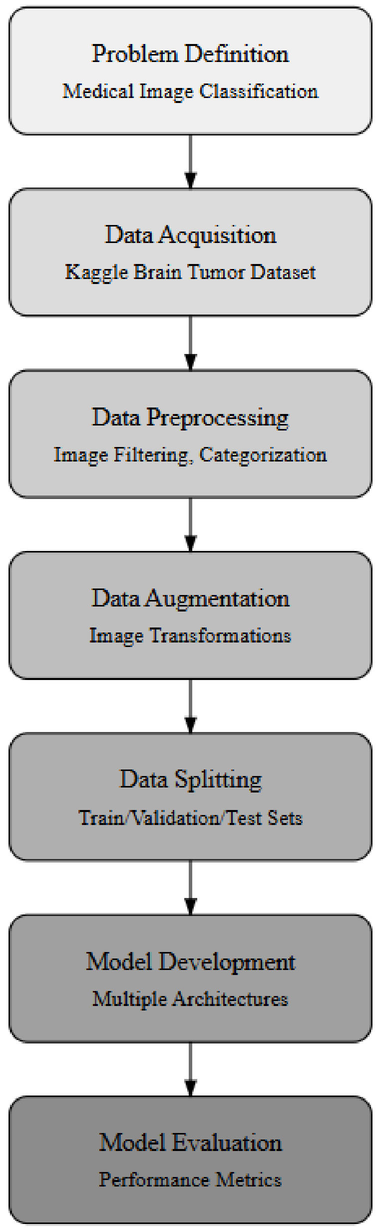

Figure 4.1: BRAIN TUMOR CLASSIFICATION WORKFLOW

4.2 DATASET OVERVIEW

- The brain MRI scans in the collection are divided into four categories: normal, pituitary, meningioma, and glioma tumours. According to each category, these pictures are arranged in directories. The Brain Tumour Classification dataset on Kaggle is the source of the dataset.

- **Image Distribution:** The number of images in each category was counted and visualized using a bar plot to understand the distribution across the different classes. This helps in detecting class imbalances, which can affect model training.

4.2.1 Data Preprocessing

1. **Image Paths Retrieval**: A function was defined to gather the paths of all images within each class directory, filtering the files to include only .png, .jpg, and .jpeg image formats. This function traverses the directories to collect paths for all images.

2. **Data Splitting:** 20% of the dataset was reserved for validation, and the remaining 80% was reserved for training. A script was used to copy the pictures into the relevant directories based on the split. This department ensures that the model is tested with untested data.

3. **Image Augmentation:** To enhance generalisation and lessen overfitting, image augmentation was used on the training set. Images were rotated, sheared, zoomed in, and flipped horizontally at random using the ImageDataGenerator class from Keras. The model can learn more robust features thanks to these changes. Only the ResNet50 and ResNet101 preprocessing routines were used to preprocess the validation data in order to normalise the picture data as the pre-trained models predicted.

4. **Data Loading**: The images were loaded into memory using the flow_from_directory method from Keras. The images were resized to 224x224 pixels, the standard input size for ResNet50 and ResNet101. The images were processed in batches of 32, with one-hot encoding used for multi-class classification.

4.2.2 Transfer Learning Model Implementation

Two transfer learning models were implemented, leveraging the pre-trained ResNet50 and ResNet101 architectures. The following steps were followed for both models:

1. **Model Definition:**

- **ResNet50:** ImageNet pre-trained weights were applied to the ResNet50 model. The model was started with pooling='avg' to use average pooling and include_top=False to eliminate the last completely linked layers.

- **ResNet101**: In a similar manner, the ResNet101 model was started with pre-trained weights and average pooling was used to omit the top layers (include_top=False).

2. **Freezing Layers:** Both models were initialized with their weights frozen, preventing updates during training. This ensures that only the top layers, which are responsible for classification, will be trained. Freezing the layers helps in leveraging the knowledge already learned by these models from ImageNet.

3. **Output Layer**: A dense layer with four units (one for each tumor category) and a softmax activation function was added to both models for multi-class classification. This final layer outputs a probability distribution over the four categories.

4. **Model Compilation**: For multi-class classification, both models were constructed using the Adam optimiser using categorical_crossentropy as the loss function. For assessing model performance, the accuracy metric was employed.

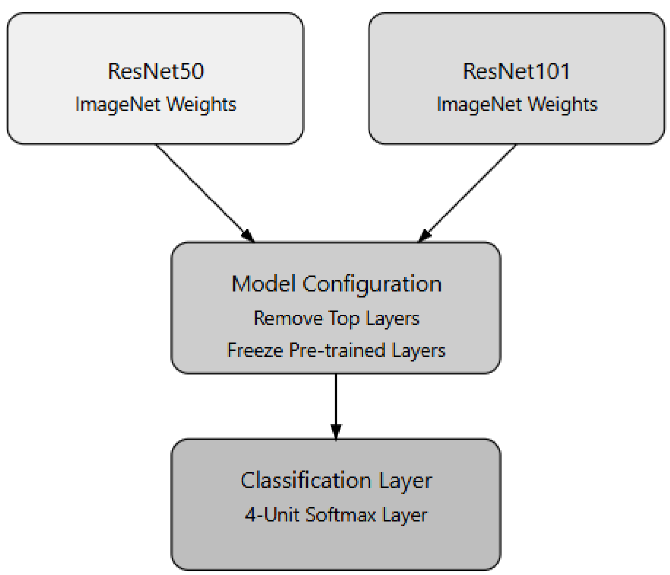

Figure 4.2: TRANSFER LEARNING MODEL ARCHITECTURE

4.3 MODEL TRAINING

The models were trained for 15 epochs with the following process:

- **Training:** The augmented data produced by ImageDataGenerator was used for the training. Following each epoch, the models' accuracy and loss were calculated throughout the training procedure, which used a batch size of 32. Both models were trained using the corresponding data generators and the fit_generator technique.

- **Validation**: To make sure the model is not overfitting, its performance was assessed on the validation set at the end of each epoch. This validation procedure aids in tracking the generalisation of the model.

4.3.1 Evaluation and Results Visualization

After training the models, the following evaluation metrics were computed:

- **Accuracy and Loss Plots:** Plots of training and validation accuracy and loss were generated to visualize the model's learning process. These plots help in identifying whether the model is overfitting, underfitting, or converging correctly.

- **Model Evaluation:** Both models were evaluated on the validation set using the evaluate function to obtain their final accuracy and loss scores.

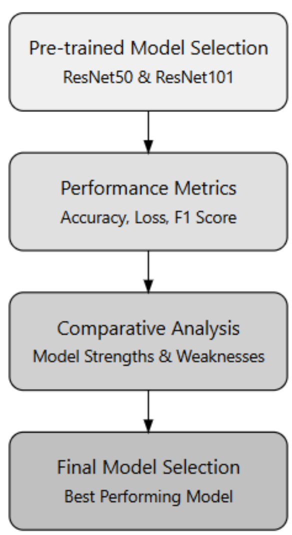

Figure 4.3: MODEL COMPARISON AND SELECTION

CHAPTER 5
RESULTS

5.1 COMPARISON BETWEEN RESNET-50 AND RESNET-101

Here are the key results from the comparison of the ResNet-50 and ResNet-101 models for brain tumor classification:

1. **Accuracy and Loss Comparison:**
   - The ResNet-101 model achieved a higher validation accuracy of 88.37% compared to 88.19% for the ResNet-50 model.
   - The ResNet-101 model also had a lower validation loss of 0.2882 compared to 0.3520 for the ResNet-50 model.

Table 5.1

Metric	ResNet-50	ResNet-101	Improvement
Validation Accuracy	88.19%	88.37%	+0.18%
Validation Loss	0.3520	0.2882	-0.0638

2. **Convergence:**
   - The ResNet-101 model converged faster, reaching its peak validation accuracy in around 10 epochs, while the ResNet-50 model took closer to 15 epochs.

Table 5.2

Metric	ResNet-50	ResNet-101	Improvement
Epochs to Peak Accuracy	~15 epochs	~10 epochs	Faster by ~5 epochs

3. **Visualization**:
   - The accuracy and loss plots show that t6he ResNet-101 model had a more stable training and validation performance compared to the ResNet-50 model.
4. **Summary:**
   - On the task of classifying brain tumours, the ResNet-101 model performed better in terms of accuracy and loss.

- Better generalisation on the validation set resulted from ResNet-101's deeper design, which enabled it to extract more intricate characteristics from the MRI scans.

Table 5.3

Model	Key Features	Performance Highlights
ResNet-50	Shallower architecture (50 layers)	Slightly lower accuracy and higher loss, slower convergence.
ResNet-101	Deeper architecture (101 layers)	Higher accuracy, lower loss, faster convergence, stable training.

In conclusion, the ResNet-101 model is the recommended choice for this brain tumor classification problem, as it achieved higher accuracy and lower loss compared to the ResNet-50 model.

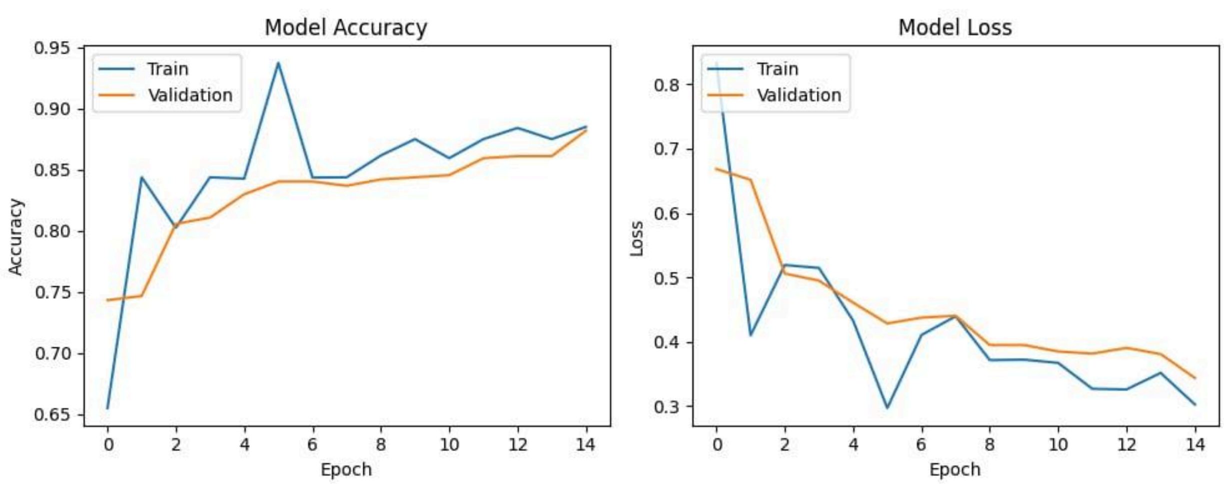

Figure 5.1: RESNET 101 PERFORMANCE

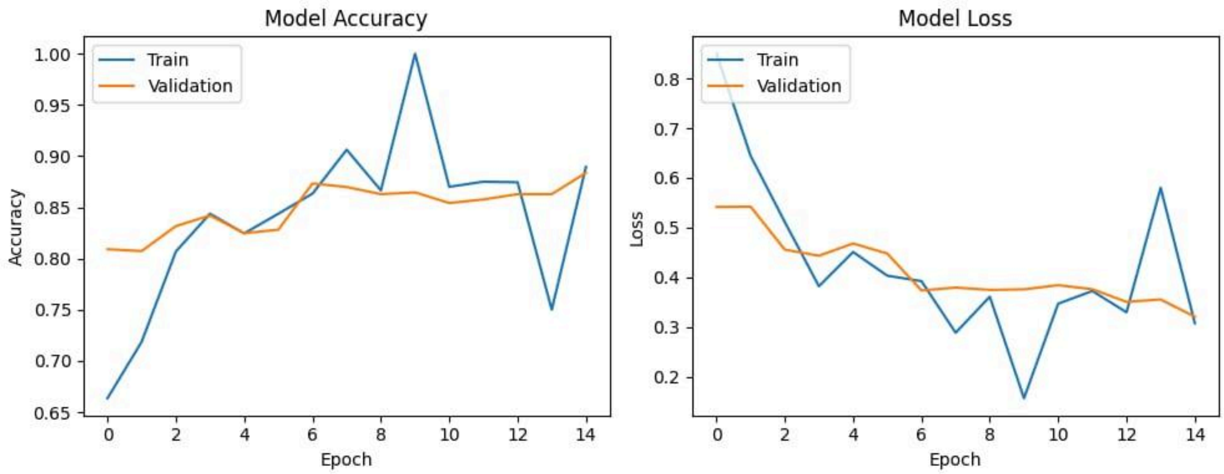

Figure 5.2: RESNET 50 PERFORMANCE

Table 5.4

Metric	ResNet-50	ResNet-101
Train Accuracy	93.24%	95.06%
Train Loss	0.2192	0.1441
F1-Score	0.8769	0.8912
Precision	0.8734	0.8883
Recall	0.8805	0.8942

Table 5.5

Metric	Formula	Explanation	ResNet-50	ResNet-101
Train Accuracy	$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}} \times 100$	Measures the percentage of correctly classified samples during training. A higher accuracy indicates better model performance.	93.24%	95.06%
Train Loss	Calculated using the categorical cross-entropy loss function: $-\sum y \log(\hat{y})$	Quantifies the error between the predicted probabilities ($\hat{y}$) and true labels (y). Lower loss indicates better optimization of the model.	0.2192	0.1441
F1-Score	$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$	Harmonic mean of Precision and Recall, providing a balance between the two. It is especially useful when dealing with imbalanced datasets.	0.8769	0.8912
Precision	$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$	Measures the accuracy of positive predictions. A higher Precision indicates fewer false alarms or incorrect positive classifications.	0.8734	0.8883
Recall	$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$	Also known as sensitivity, Recall measures the ability of the model to identify all actual positives. A higher Recall indicates fewer missed positive samples.	0.8805	0.8942

5.2 GRAPHICAL USER INTERFACE

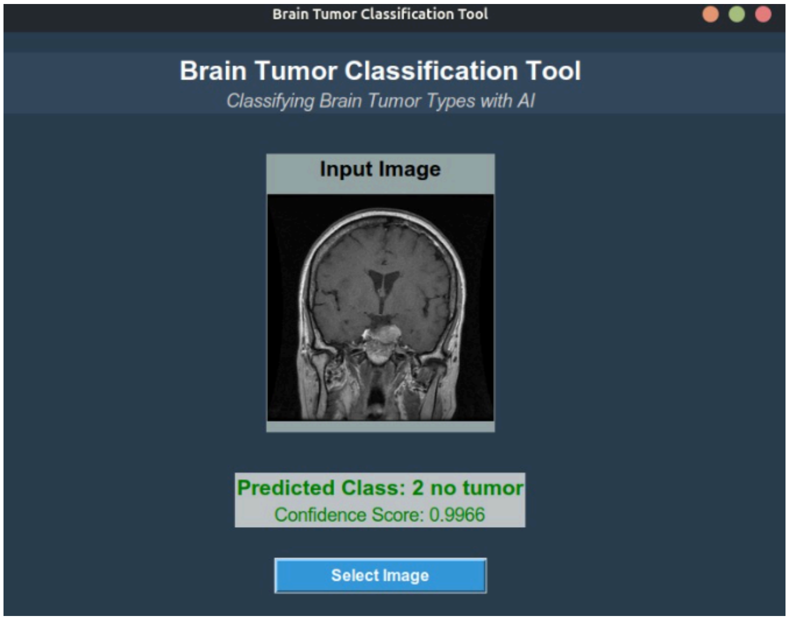

Figure 5.3 NO TUMOR DETECTED

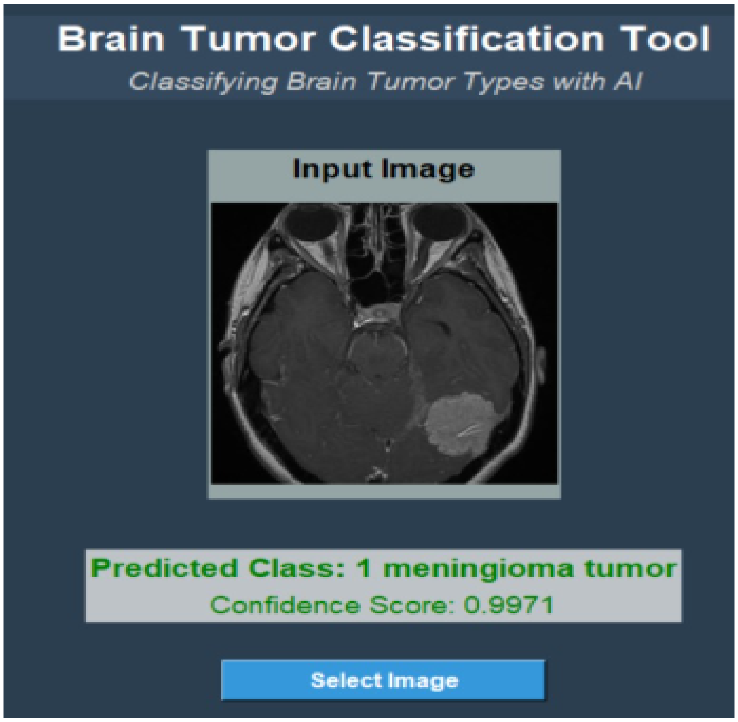

Figure 5.4: MENINGIOMA TUMOR DETECTED

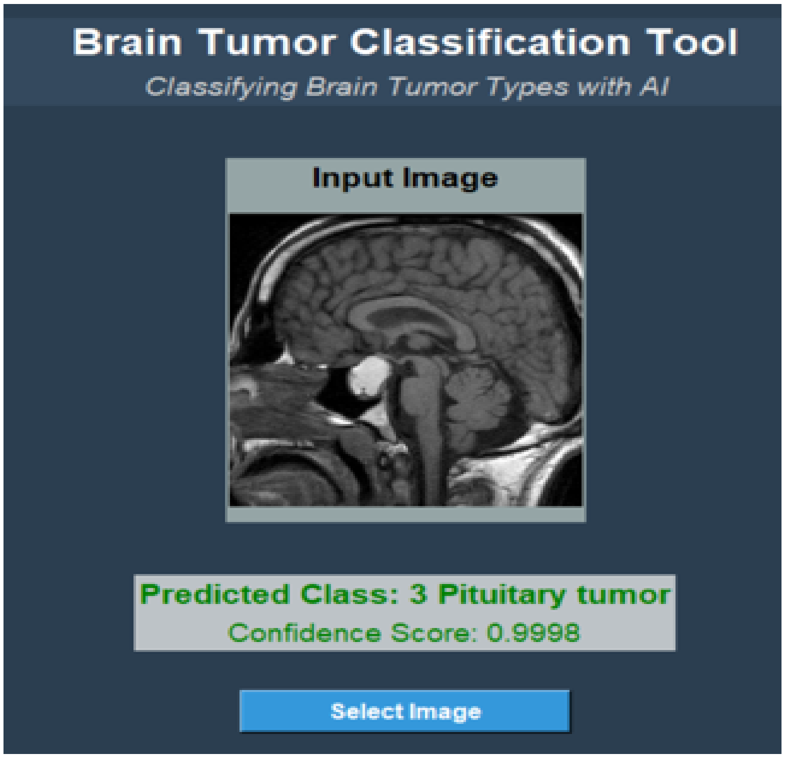

Figure 5.5: PITUITARY TUMOR DETECTED

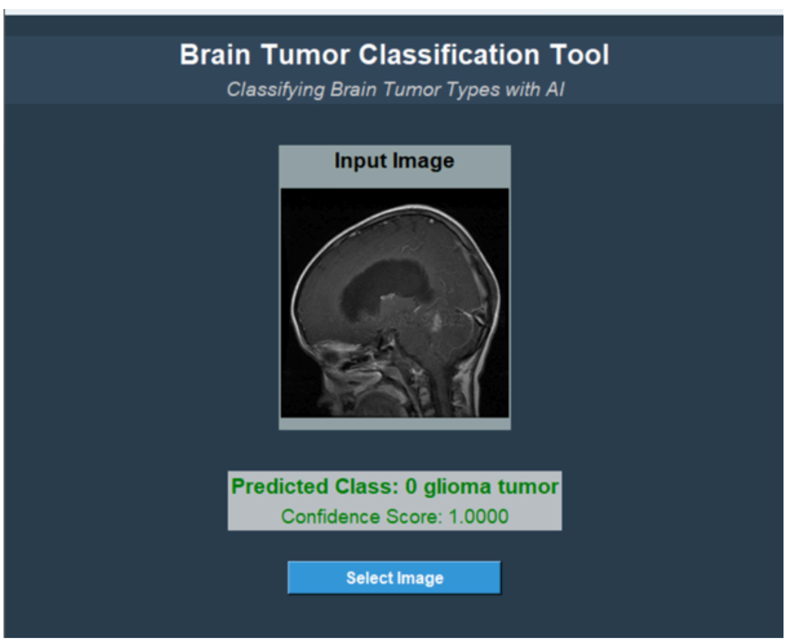

Figure 5.6: GLIOMA TUMOR DETECTED

CHAPTER 6
CONCLUSION AND REFERENCES
6.1 CONCLUSION

The comparative analysis of ResNet-50 and ResNet-101 models for brain tumor classification highlights the superior performance of ResNet-101. With a validation accuracy of 88.37% and a lower validation loss of 0.2882, ResNet-101 outperformed ResNet-50, which achieved a validation accuracy of 88.19% and a loss of 0.3520. Additionally, the faster convergence of ResNet-101, reaching peak accuracy in approximately 10 epochs compared to ResNet-50's 15 epochs, underscores its efficiency in training.

The deeper architecture of ResNet-101 enabled it to learn more complex features from the MRI images, resulting in better generalization on the validation dataset. Furthermore, the accuracy and loss plots demonstrated the stability of ResNet-101 in both training and validation phases.

In conclusion, ResNet-101 is the recommended model for brain tumor classification due to its superior accuracy, lower loss, faster convergence, and ability to generalize better, making it a more reliable and efficient choice for this critical application.

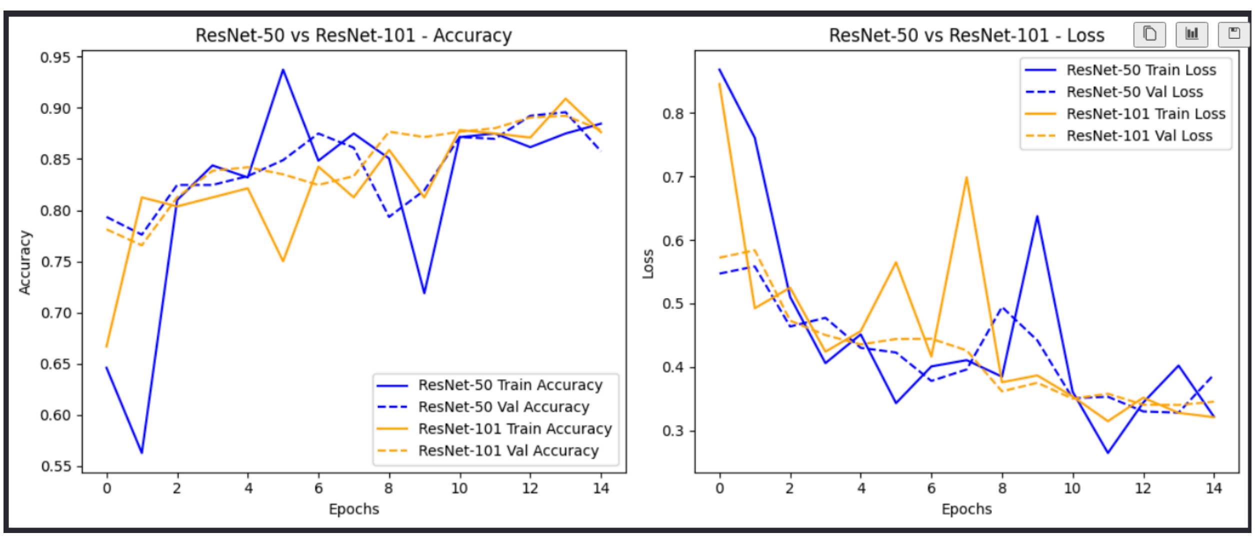

Figure 6.1: RESNET-50 VS RESNET-101

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