College Dublin
Computing · IT · Business

Brain Tumor Classification using Deep Learning: Custom CNN vs. ResNet50

Author: Rayen Bentemessek
Supervisor: Dr. Muhammad Iqbal

ABSTRACT

The project presents deep learning solutions to classify brain tumors through MRI images. Two Convolutional Neural Network (CNN) models were developed, a custom CNN designed from scratch and a pretrained ResNet50 that was transfer learned and fine-tuned.

Both models were implemented following CRISP-DM methodology from data understanding to deployment, and they were evaluated using different metrics such as accuracy, precision, recall and F1-score.

Key Highlights:

- The custom CNN model achieved higher accuracy but failed to locate tumors.
- ResNet50 provided a good performance while balancing explainability through Grad-CAM.
- Model was deployed through Gradio to demonstrate a real-world use of the solution.

RESEARCH QUESTIONS

The four questions below represent the core focus of the entire study:

1. Is it possible to develop an accurate CNN-based model for classifying brain tumors from MRI scans ?
2. What preprocessing techniques can optimize the model's performance ?
3. How does the custom CNN architecture compare to a pretrained ResNet-50 model in terms of accuracy, interpretability, and generalization?
4. What are the practical considerations for deploying the selected model in real-world medical imaging scenarios?

BUSINESS UNDERSTANDING

Implementing a robust deep learning model that classifies brain tumors would provide a significant assistance to healthcare professionals leading to reduced diagnosis times and more efficient treatment.

To approach the challenge, Cross-Industry Standard Process for Data Mining (CRISP-DM) framework was adopted to guide the project across the six phases as shown in the Figure 1 below.

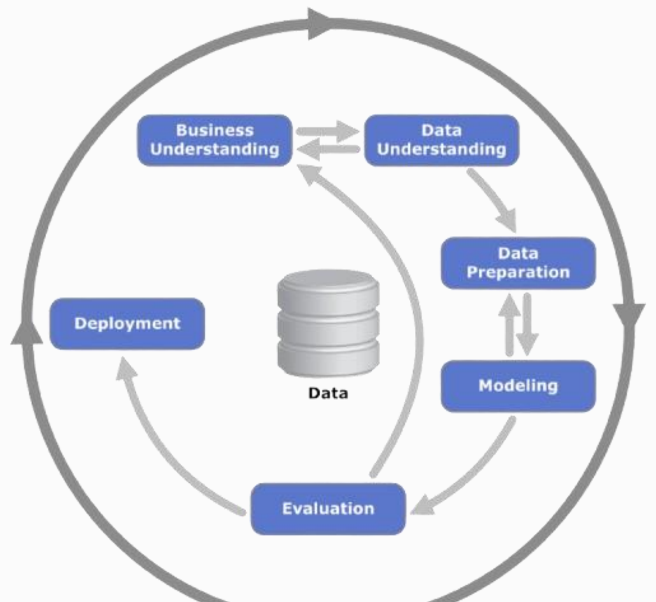

Figure 1: CRISP-DM Framework

DATA UNDERSTANDING

The original dataset consisted of 7023 brain MRI images, divided into four diagnoses: glioma, meningioma, pituitary tumor, and no tumor.

Key Highlights:

- Images had different dimensions and mode (RGB and Grayscale).
- Images included a variety of orientations (axial, coronal and sagittal).

Figure 2 shows representative samples of each diagnosis.

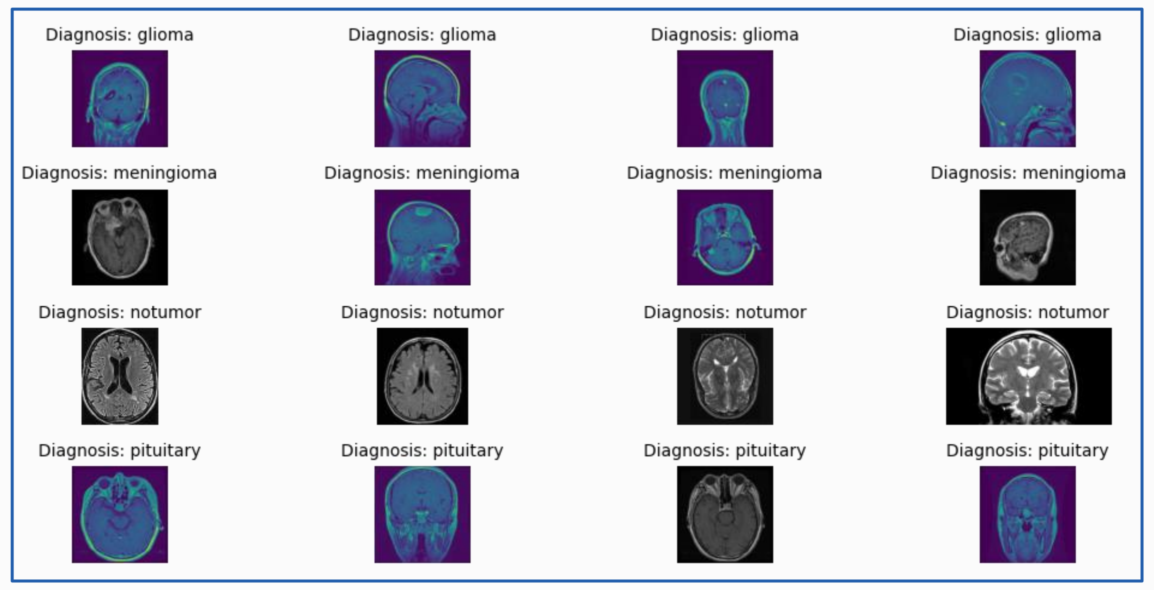

Figure 2: Image samples

DATA PREPARATION

The dataset was preprocessed and augmented:

- Removed duplicates resulted in a final set of 6726 images and split into 80% and 20% testing with balanced classes as shown in Figure 3.
- Images were resized to 224x224, converted to RGB, normalized to [0,1] pixel range.
- Data augmentation techniques (rotation, zoom, flipping etc.) were applied to reduce overfitting by increasing the data variety helping the model generalize better to unseen images (Mikołajczyk and Grochowski, 2018) as shown in Figure 4.

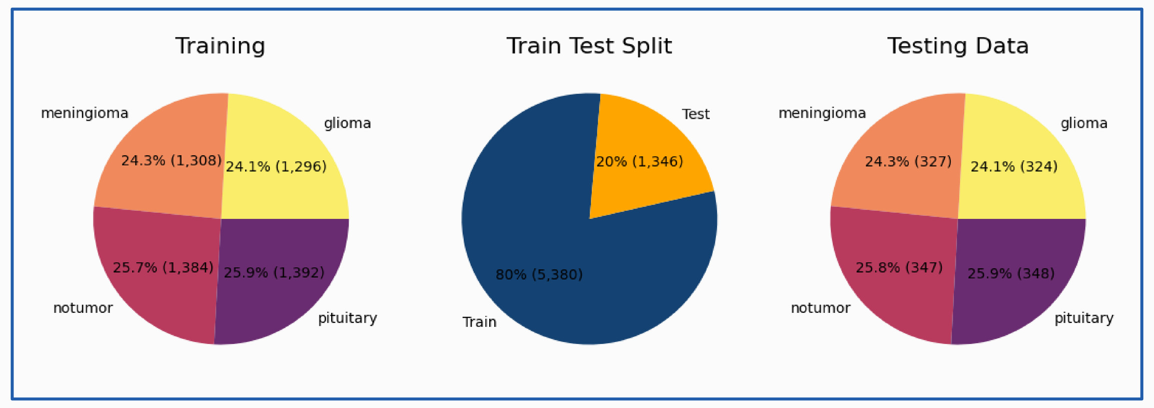

Figure 3: Cleaned Dataset distribution across training, testing, and class labels.

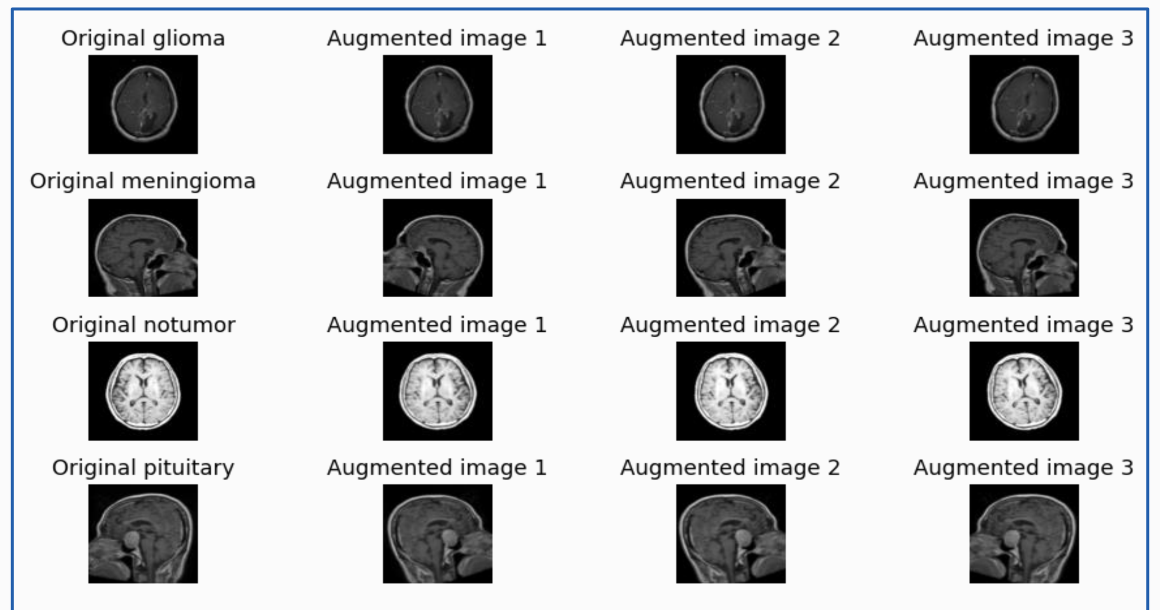

Figure 4: Data Augmentation Results

MODELLING

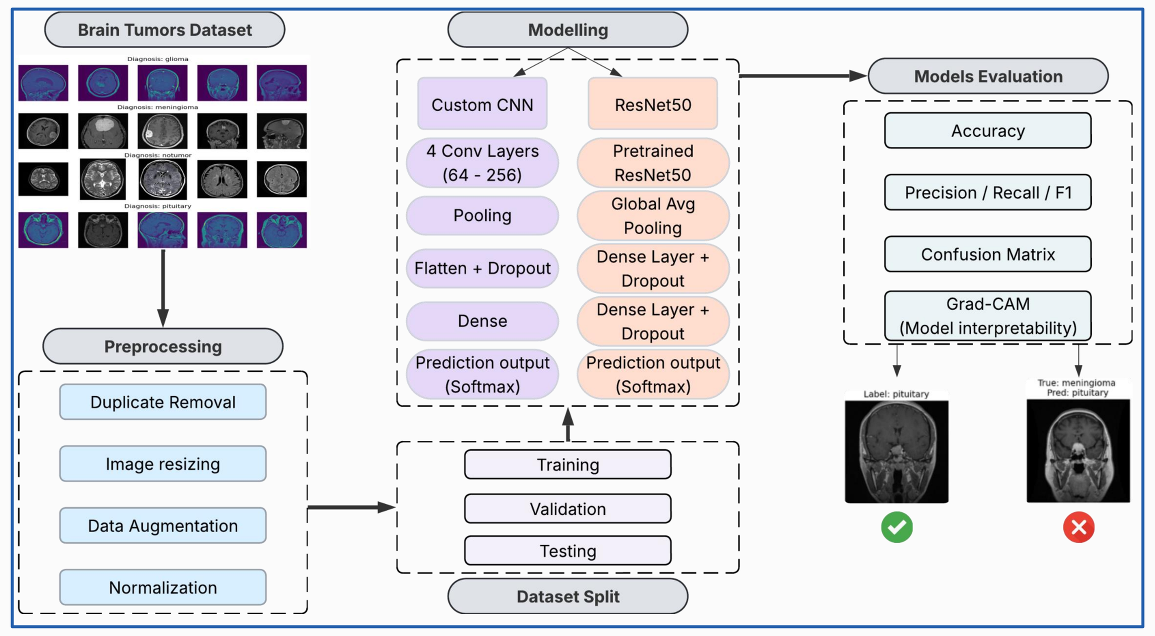

Figure 5: Pipeline overview

Two convolutional neural networks were developed:

Custom CNN:

- Four Convolutional layers (64-256 filters) with ReLu activation for nonlinearity, max pooling and dropout.
- Trained for 100 epochs using Adam optimizer and sparse categorical cross-entropy loss.
- Hyperparameters were tuned using Hyperband, allowing a smart and efficient resources allocation for promising sets.

ResNet50:

- A deep CNN with 50 layers that uses residual (skip) connections which helps the model learn and remain stable as it gets deeper (He et al., 2015).
- Two dense layers with dropout were added on top of the base model.
- Model was trained with a frozen base for feature extraction, then full model was unfrozen and fine-tuned on the dataset.

EVALUATION

Model	Train Accuracy	Test Accuracy	Trainable Parameters	Training Time
Custom CNN	100 %	99.03 %	2.8 Million	14 Minutes
ResNet50	98.79 %	98.44 %	24 Million	40 Minutes

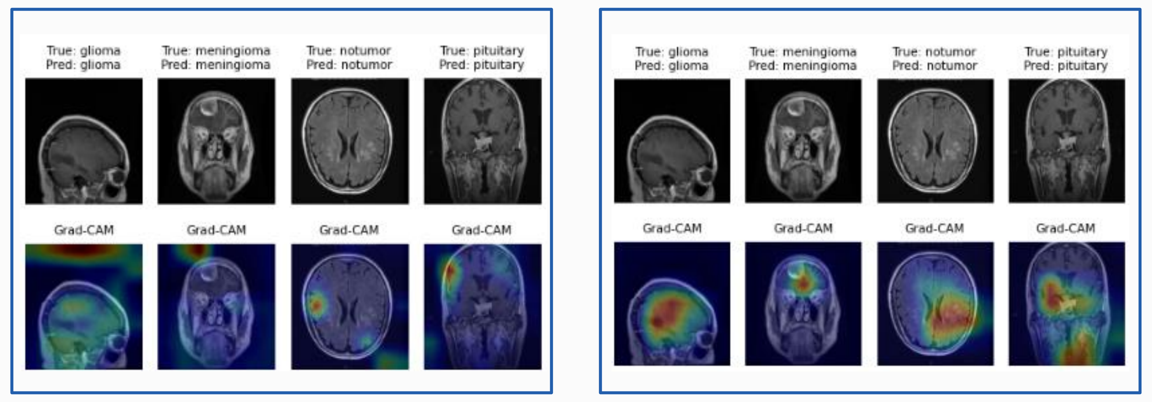

Figure 6: Predicted labels and Grad-CAM heatmaps for the same images.
Left: Custom CNN. Right: ResNet50

Despite achieving a better test result, the custom CNN architecture has showed clear signs of shortcut learning, as shown in the Grad-CAM heatmaps on the left in Figure 6, which highlights important regions for the model's prediction (Selvaraju et al., 2020). This indicates that the model was classifying tumors based on features that are outside the brain region, which is a common sign of shortcut learning (Geirhos et al., 2020).

In contrast, **ResNet50** not only maintained a high test accuracy (98.44%) but also showed a superior consistency and focus on the tumor region, making it more reliable and trustworthy for deployment.

DEPLOYMENT

The final model (ResNet50) was deployed using Gradio, allowing users to upload MRI scans and receive instant tumor classification with a confidence score and a Grad-CAM heatmap that highlights the region of interest used for the prediction.

This demonstrates how deep learning can be efficient in medical imaging offering an accessible way to assist clinical decision-making.

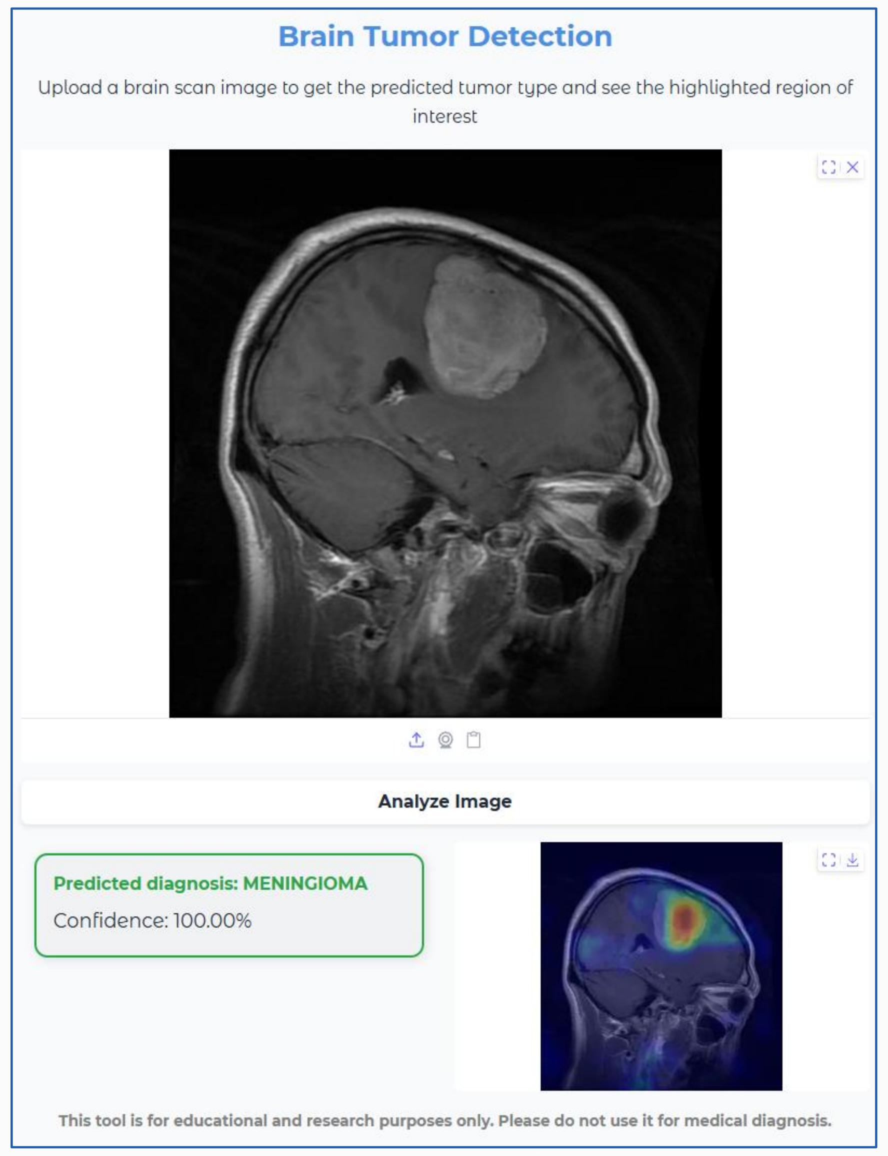

Figure 6: Deployed Model interface

CONCLUSIONS

A summarised answer to the research questions are presented below:

1. Yes, both models have achieved high test accuracies on the four tumors, showing that CNN can classify brain tumors accurately.
2. Removing duplicate images, resizing images to a uniform size and same color format, normalizing pixel values to standardize the input data, in addition to data augmentation are considered necessary to optimize the model's performance.
3. Custom CNN trained faster due to its architecture, slightly higher accuracy but showed weak explainability in tumor localization compared to ResNet50.
4. Deploying the model should not only be limited to standard performance metrics, as explainability matters especially in medical imaging applications.

REFERENCES

Mikołajczyk, A. and Grochowski, M. (2018). Data augmentation for improving deep learning in image classification problem. [online] IEEE Xplore. doi:https://doi.org/10.1109/IIPHDW.2018.8388338.

He, K., Zhang, X., Ren, S. and Sun, J. (2015). Deep Residual Learning for Image Recognition. [online] Available at: https://arxiv.org/pdf/1512.03385.

Geirhos, R., Jacobsen, J.-H., Michaelis, C., Zemel, R., Brendel, W., Bethge, M. and Wichmann, F. (n.d.). Shortcut Learning in Deep Neural Networks. [online] doi:https://doi.org/10.1038/s42256-020-00257-z).

Selvaraju, R.R., Cogswell, M., Das, A., Vedantam, R., Parikh, D. and Batra, D. (2020). Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization. International Journal of Computer Vision, 128(2), pp.336–359.doi:https://doi.org/10.1007/s11263-019-01228-7.

www.PosterPresentations.com