The Mission: Lightweight Brain Tumor Detection for Clinical Use

Early brain tumor detection is life-saving. Magnetic Resonance Imaging (MRI) is one of the most efficient methods for tumor detection, and deep learning can automate this vital task.

The Project Mandate

- **The Task:** Build a lightweight deep learning system that detects and classifies brain tumors from MRI scans using compact CNN architectures. The model should efficiently identify tumor presence and type on limited hardware.
- **Expected Outcome**: A trained classifier that labels MRI images as no tumor or specific tumor types, with suitable evaluation metrics.

A Tale of Two Philosophies: The Custom Build vs. The Pre-Trained Giant

To fully justify the task's emphasis on a "lightweight system," a comparative study was designed. This pits a custom-built, efficient model against a powerful, pre-trained industry standard.

The Challenger

Custom CNN

A lean CNN network built from the ground up. Each layer is added intentionally to balance classification accuracy with computational efficiency, making it suitable for clinical use where resources can be constrained.

The Champion

ResNet50

A state-of-the-art, pre-trained model based on a skip connection architecture. Known for its high performance on large datasets, it represents the power of transfer learning but comes with significant computational overhead.

The Lightweight Advantage: Why Efficiency Matters

Feature	Lightweight CNN	ResNet50 / VGG
Parameters	0.1M – 4M	25M - 138M
Training Speed	Very Fast	Slow
GPU Memory	Low	High
Overfitting Risk	Low	High on small data
Interpretability	Easy	Hard
Deployment	Excellent	Poor
Real-Time Use	Yes	Mostly No

On specialized tasks with limited data, an intelligently designed lightweight CNN can mitigate overfitting and offer a clear path towards practical clinical integration.

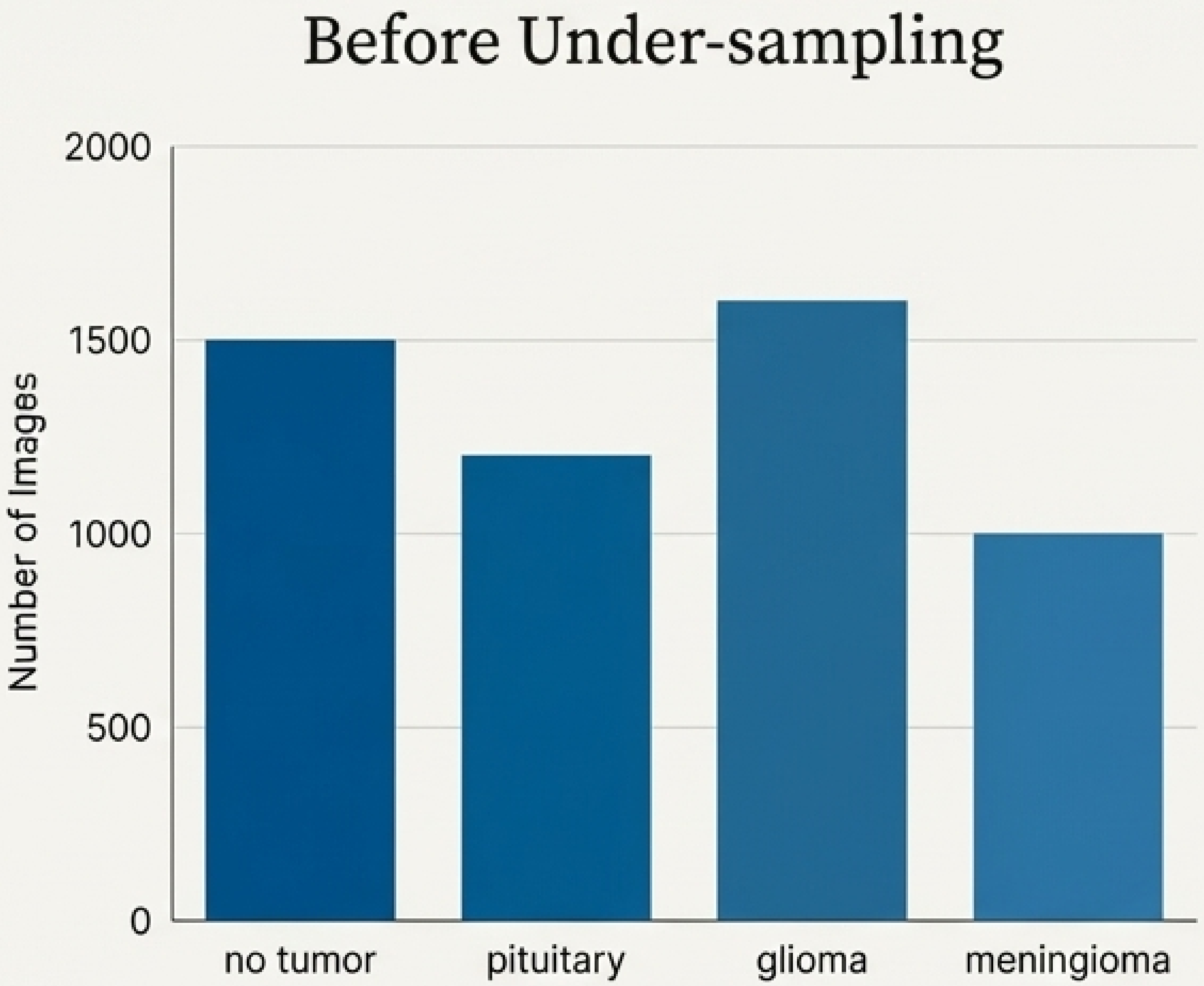
Preparing the Ground: Rigorous Data Analysis and Cleansing

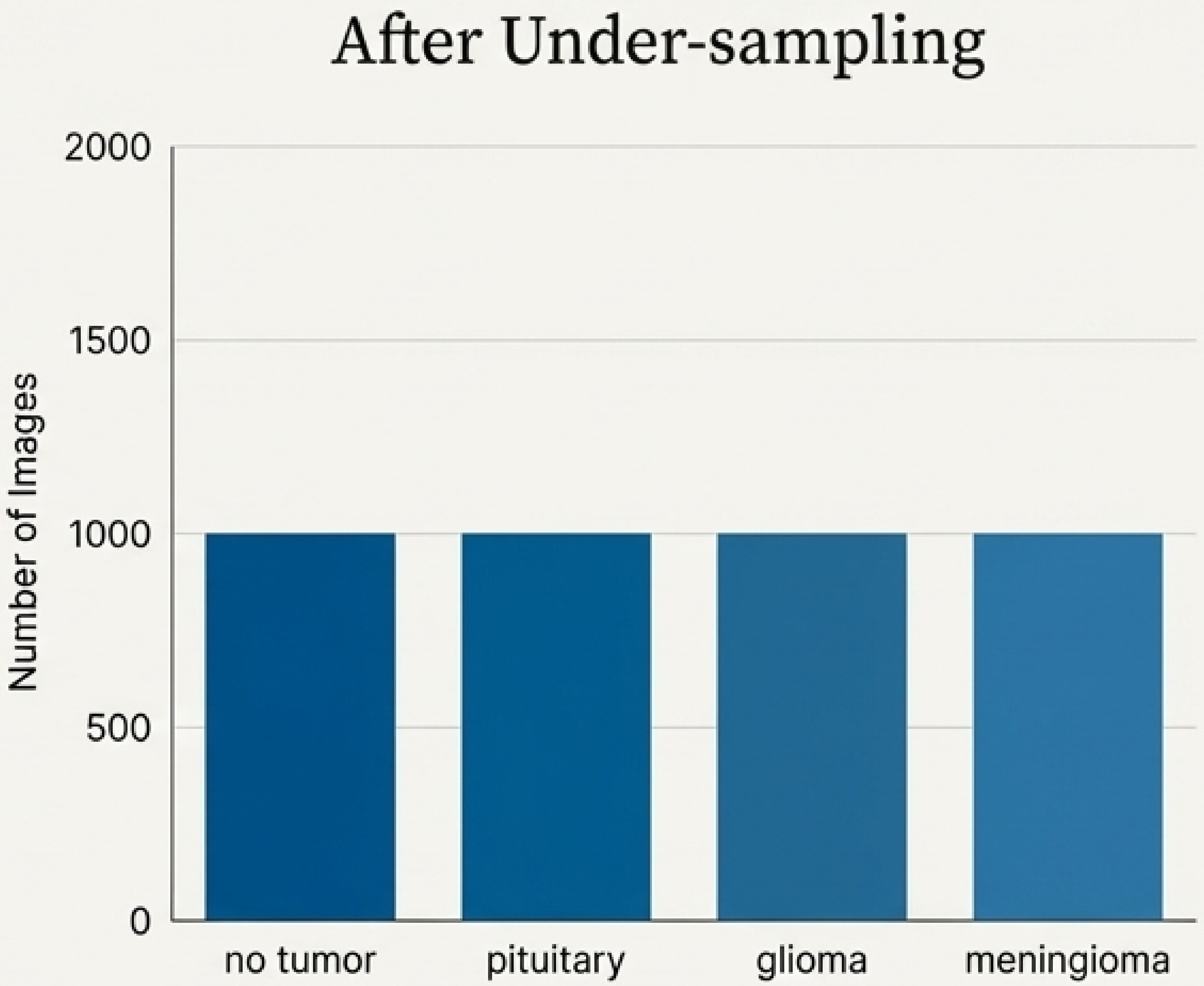
The model is only as good as its data. A thorough Exploratory Data Analysis (EDA) was performed on the Kaggle Brain Tumor MRI Dataset to ensure a clean, balanced foundation for training.

1. **Data Structuring:** Scanned Train and Test folders into a Pandas DataFrame for systematic analysis.
2. **Integrity Check:** Verified all images for corruption and removed problematic files.
3. **Duplicate Removal:** Hashed all images to identify and remove any duplicates lurking in the dataset.
4. **Balancing the Data:** Performed under-sampling on the training data to ensure equal representation of MRI images for each class category.

The result of this process is a new, curated folder named `train_balanced_dataset`, which was used for training both models to ensure a fair comparison.

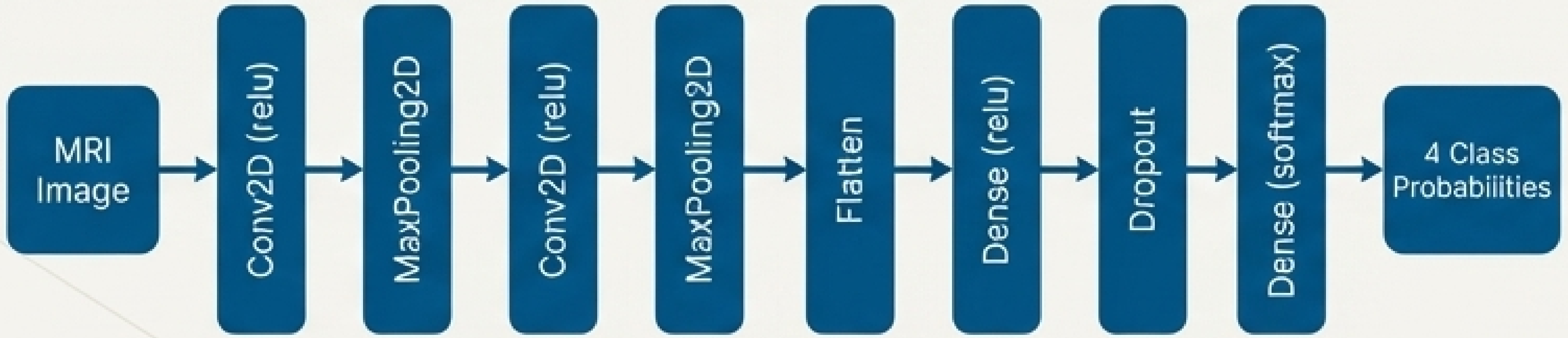
Visualizing the Impact of Data Balancing





Under-sampling created a balanced training set, preventing the models from developing a bias towards the majority class and ensuring a more robust evaluation.

The Challenger's Blueprint: A Custom CNN Built from Scratch



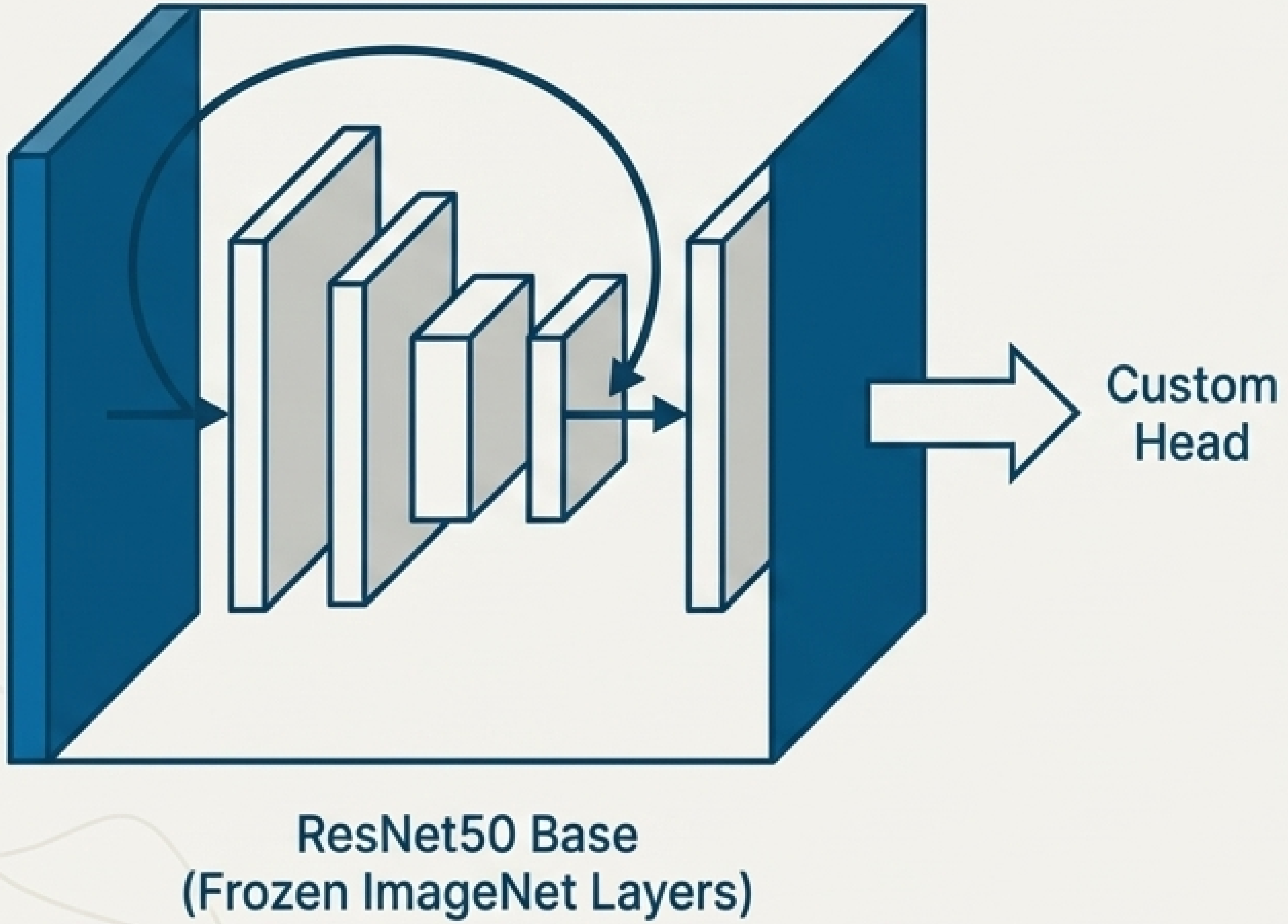
Key Layers & Philosophy

- `Conv2D` (activation='relu')
- `MaxPooling2D`
- `Conv2D` (activation='relu')
- `MaxPooling2D`
- `Flatten`
- `Dense` (activation='relu')
- `Dropout`
- `Dense` (output layer with activation='softmax')

The architecture progressively learns features, from simple edges in early layers to complex tumor shapes in deeper layers. A Dropout layer is included to combat overfitting. The entire model is designed for efficiency without sacrificing feature-learning capability.

The Champion's Power: Transfer Learning with ResNet50

ResNet50 is a 50-layer deep Residual Network pre-trained on the ImageNet dataset. We leverage transfer learning by loading the pre-trained model and adding custom final layers for our specific brain tumor classification task.



Base Model

ResNet50 with pre-trained ImageNet weights (input layers frozen).

Custom Head

- GlobalAveragePooling2D
- Dense (with activation='relu')
- Dropout
- Dense (output layer with activation='softmax')

Strategy

This approach aims to harness the powerful, generalized features learned from millions of images and fine-tune them for the specialized medical imaging domain.

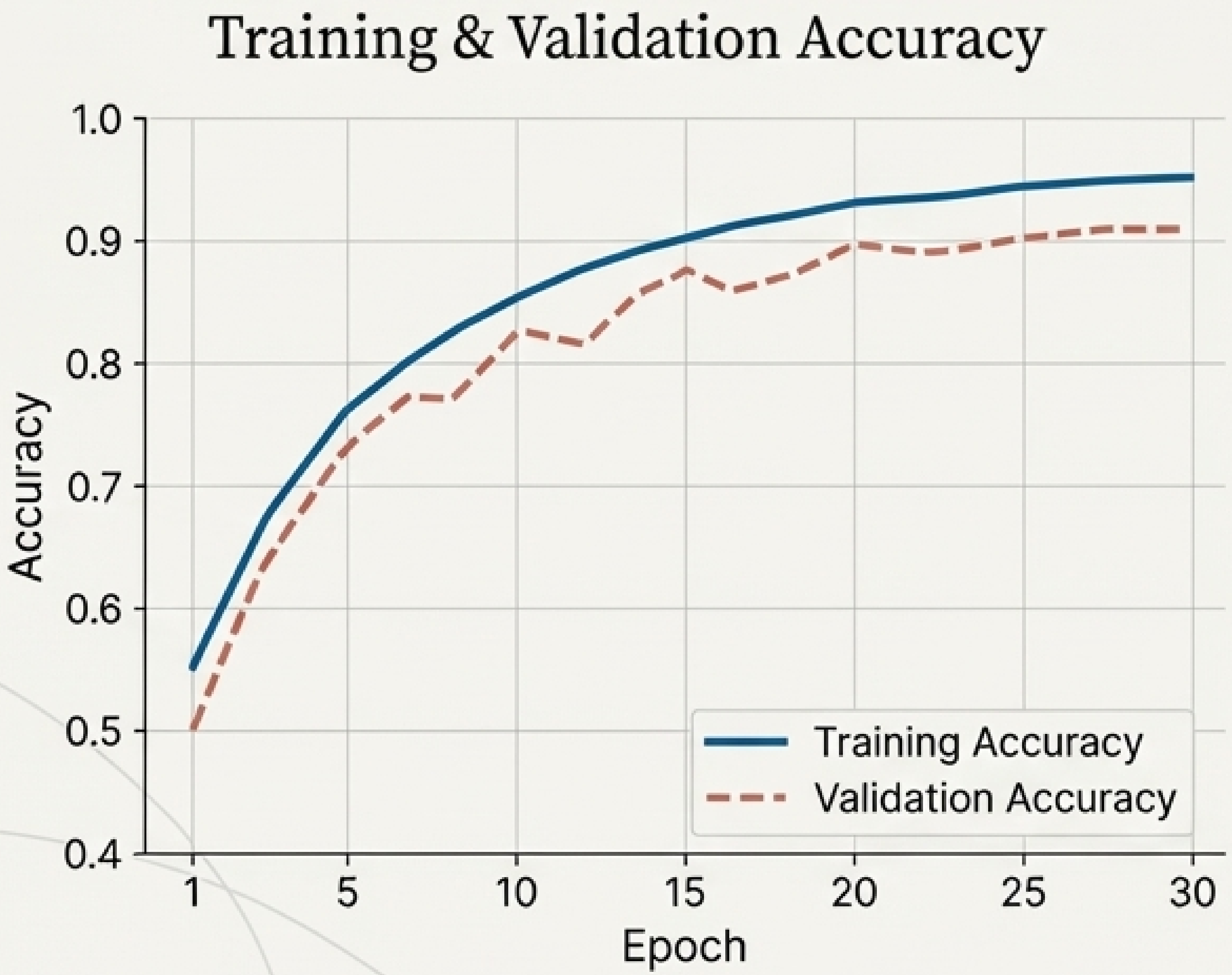
The Tale of the Tape: A Head-to-Head Parameter Comparison

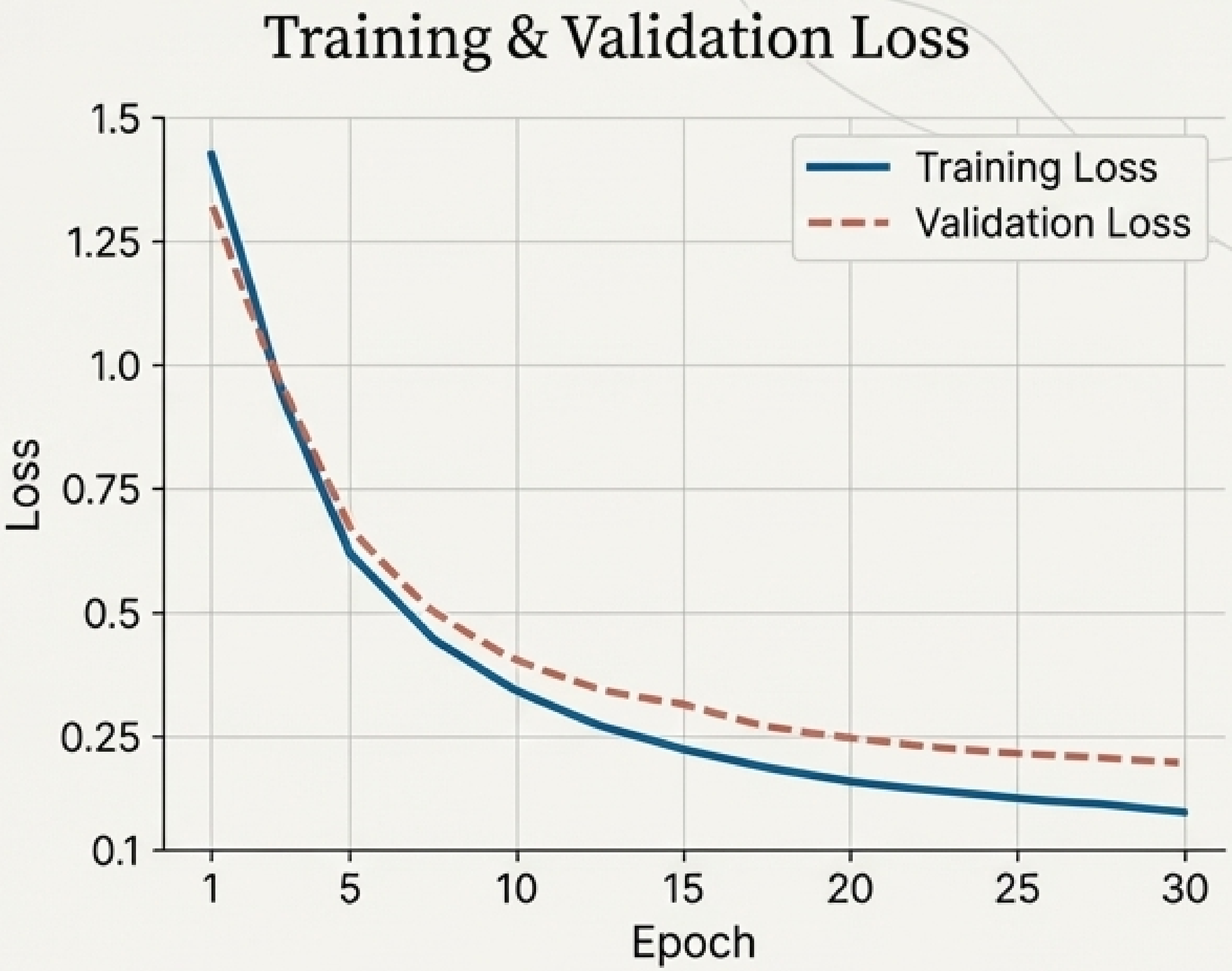
HEADER Custom CNN	
Total params:	198,308
Trainable params:	198,308
Non-trainable params:	0

25.6 Million
total parameters
vs.
198 Thousand

HEADER ResNet50	
Total params:	25,662,852
Trainable params:	2,123,012
Non-trainable params:	23,539,840

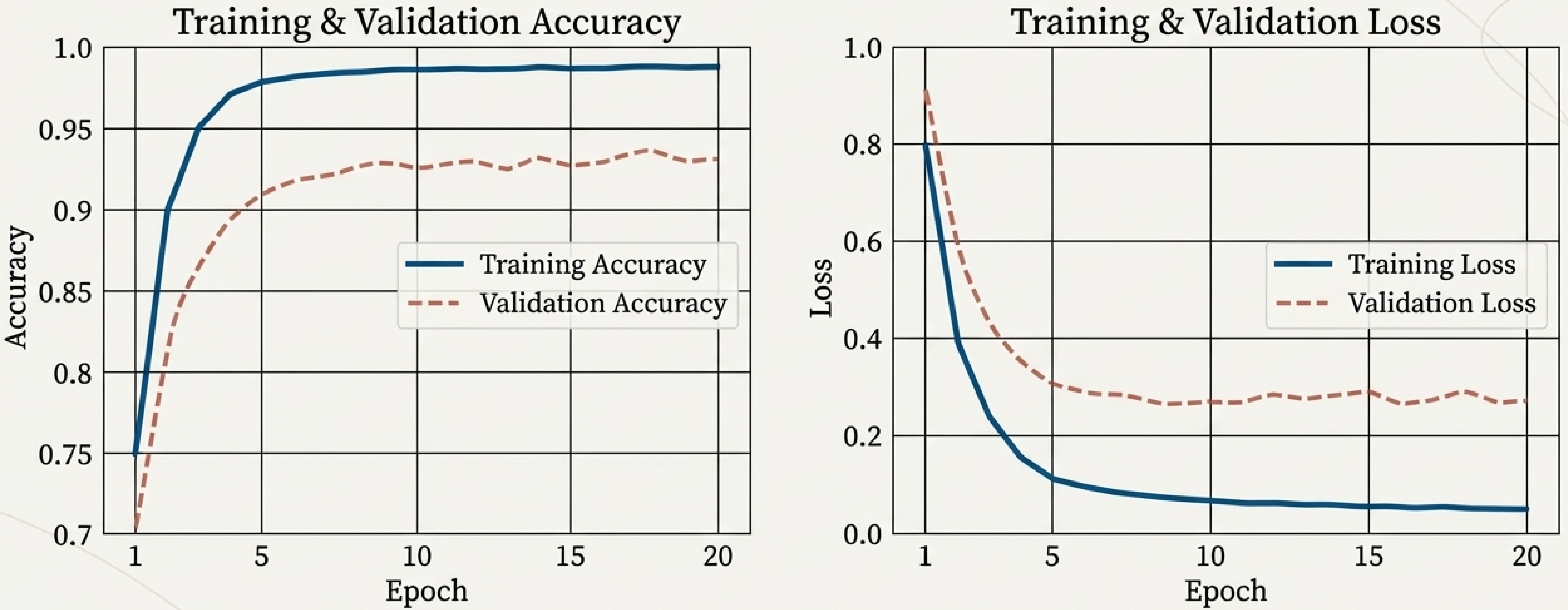
The Training Gauntlet: Custom CNN Learning Curves





The custom model shows a stable learning progression, with validation accuracy closely tracking training accuracy, indicating effective regularization and a low risk of overfitting on the balanced dataset.

The Training Gauntlet: ResNet50 Learning Curves



The pre-trained ResNet50 converges quickly to a high accuracy, demonstrating the power of transfer learning. Careful monitoring is required to manage the higher potential for overfitting due to its complexity.

The Final Scorecard: Performance Metrics

Model	Accuracy	Precision	Recall
Custom CNN	0.91	0.92	0.91
ResNet50	**0.93**	**0.94**	**0.94**

ResNet50 achieves the highest performance across all metrics, reaching 93% accuracy. The custom CNN performs commendably, achieving 91% accuracy, demonstrating strong performance for a lightweight model built from scratch.

A Deeper Look: Analyzing Classification Behavior

Custom CNN

True Label \ Predicted Label	glioma	meningioma	no tumor	pituitary
glioma	290	10	5	0
meningioma	8	250	3	2
no tumor	4	2	200	0
pituitary	0	0	0	190

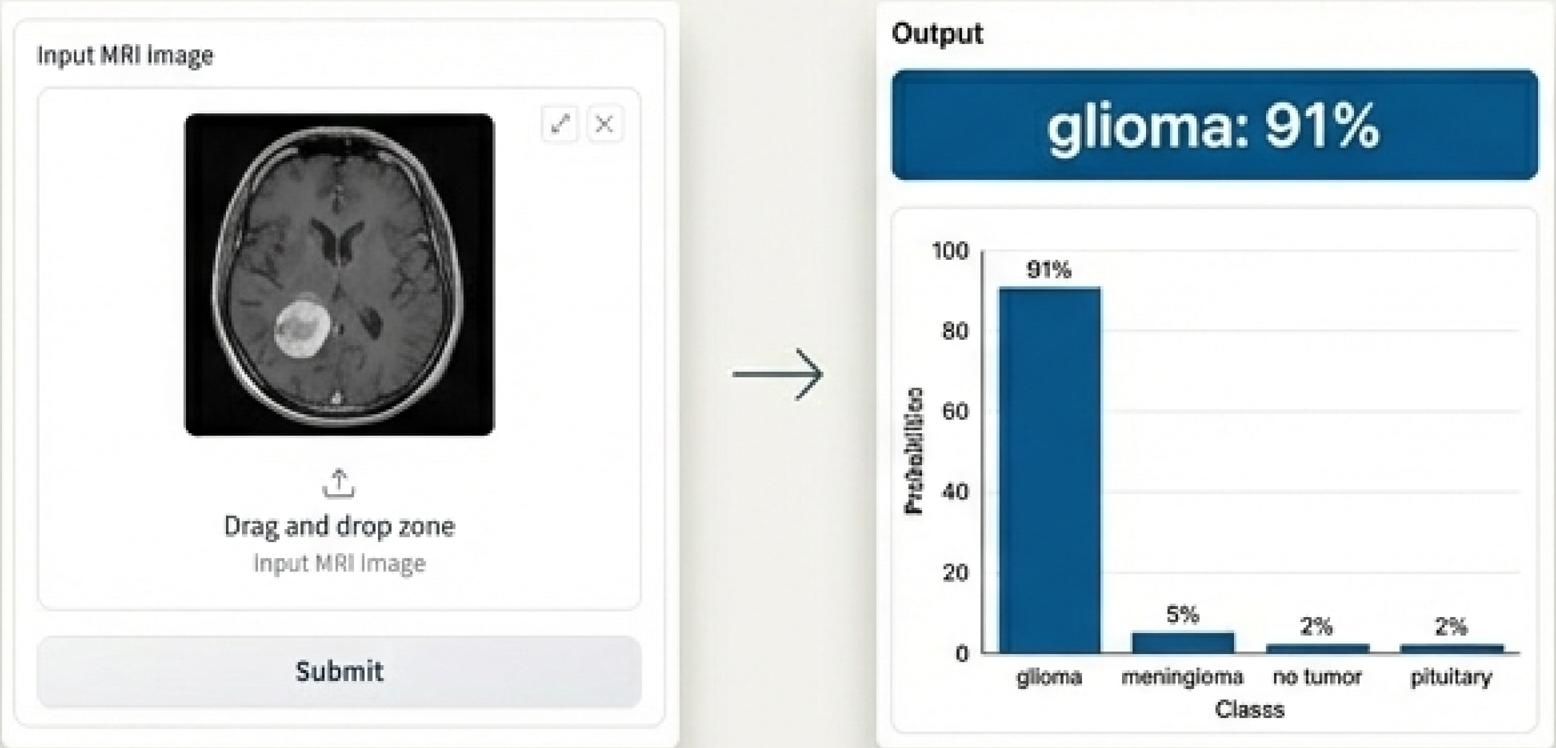
ResNet50

True Label \ Predicted Label	glioma	meningioma	no tumor	pituitary
glioma	298	2	0	0
meningioma	0	258	1	1
no tumor	0	0	205	0
pituitary	0	0	0	195

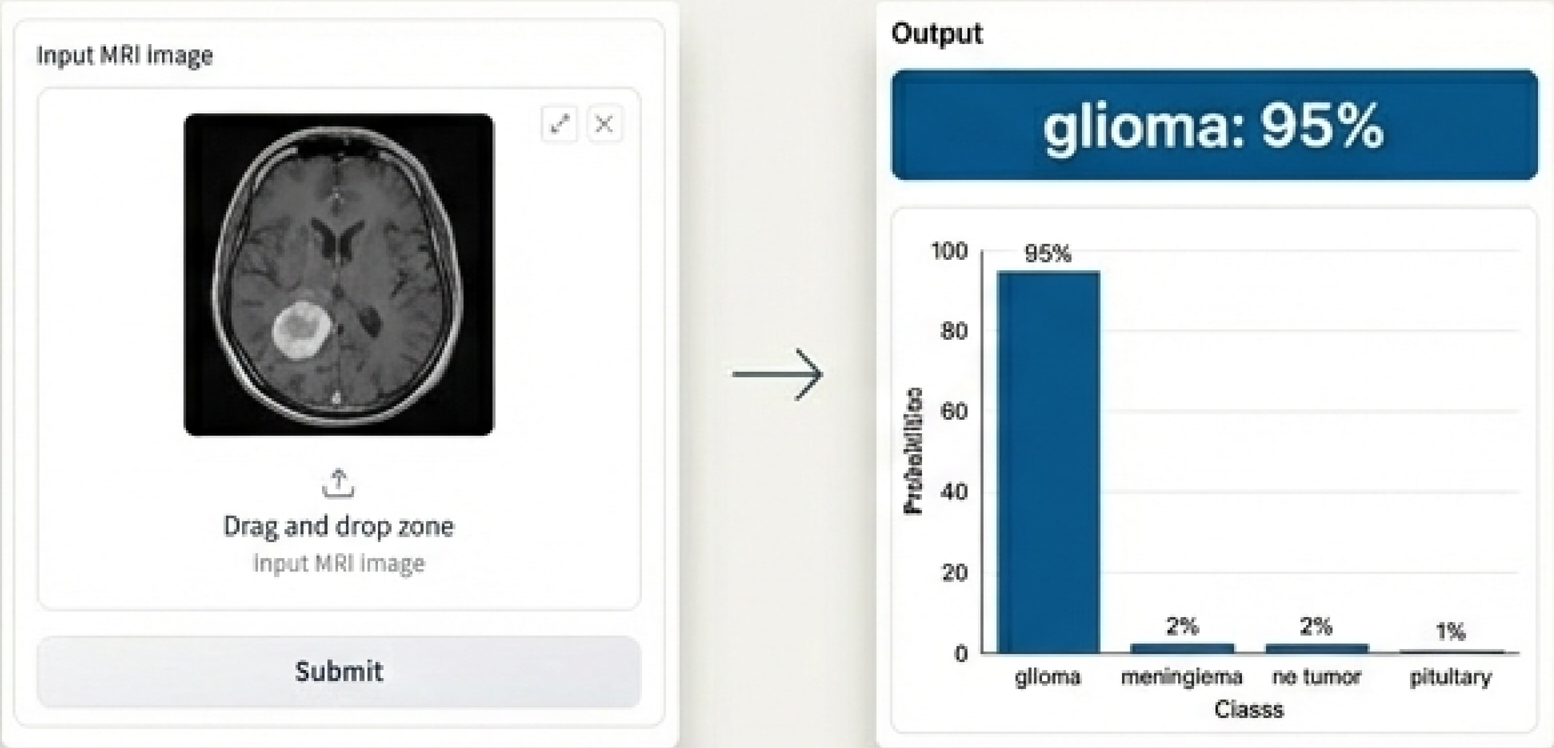
Both models show strong diagonal performance, indicating correct classifications. The matrices allow for a detailed analysis of misclassification patterns between specific tumor types.

From Theory to Practice: Live Prediction Demo

Custom CNN Prediction



ResNet50 Prediction



Both models were deployed in a Gradio web interface, successfully classifying user-submitted MRI images and displaying class probabilities in real-time.

The Verdict: Revisiting the Mission

Recall the Mandate

Build a lightweight deep learning system... The model should efficiently identify tumor presence and type on limited hardware.

The Final Analysis

- **ResNet50** generalized best, achieving the highest raw accuracy at 93%. It stands as a testament to the power of transfer learning.
- **The Custom CNN** performed adequately, achieving a strong 91% accuracy. More importantly, it successfully fulfilled the core mandate of being a lightweight, efficient, and deployable system.

The choice between models is not about a single metric, but about fitness for purpose. For applications requiring high deployability and efficiency on constrained hardware, the custom CNN presents a highly viable and successful solution.

The Path to Clinical Integration

An efficient brain tumor diagnosis system is necessary for the early treatment of the patient. The custom lightweight model provides a clear and practical path toward this goal.

Fast Training & Inference:
Reduces iteration time and enables real-time use.

Low Computational Cost:
Allows deployment on standard clinical clinical hardware without specialized GPUs.

Excellent Deployability:
Small model size and fewer dependencies simplify integration into existing medical software pipelines.

This project demonstrates that by prioritizing design efficiency, we can build powerful diagnostic tools that are not only accurate but also accessible and practical for real-world clinical environments.