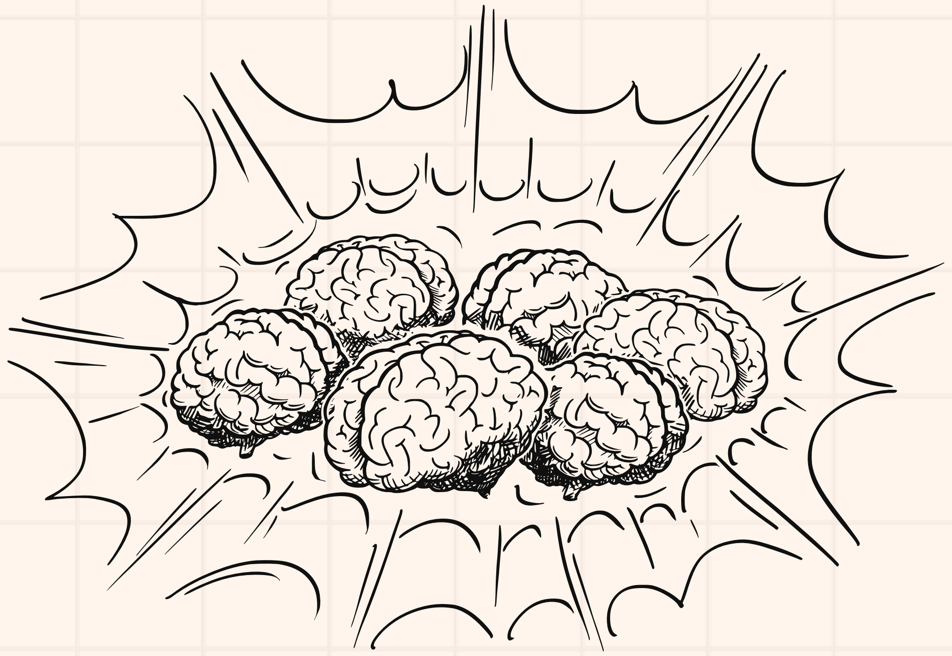
BRAIN TUMOR



Classification & Object Detection System

TEAM MEMBERS

Sarah Alaa
CNN Model From Scrotch

Menna Mahmoud
Applied RESNET Versions

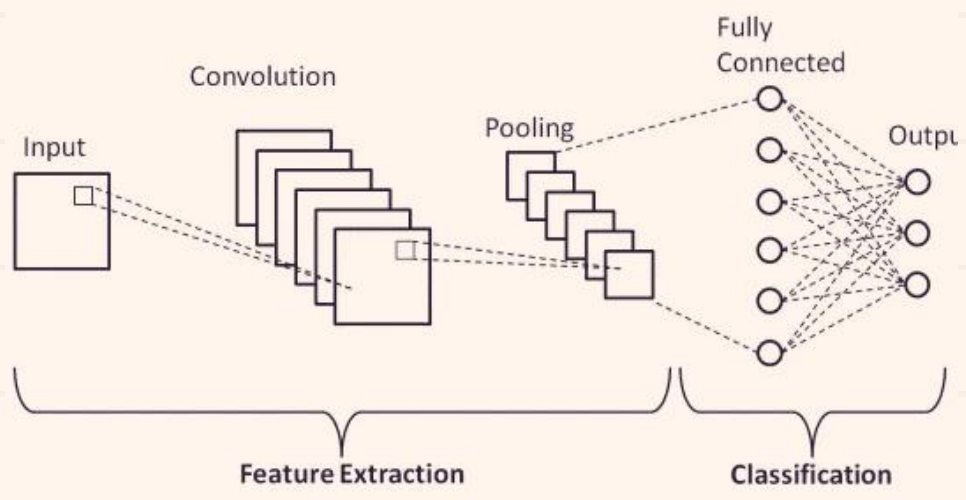
Abdullah Yasser
Applied Effiecent Versions

Nour Yahia
Applied Desnet Versions

Ahmed Abo ELnaga
Object Detection Model

Amr Ibrahim
Model Deployment

PROJECT COMPONENTS



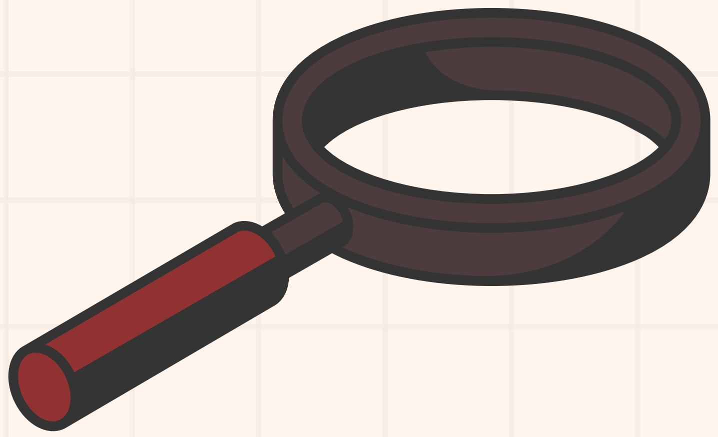


IMAGE CLASSIFICATION

OBJECT DETECTION

MODEL DEPLOYMENT

DATA SELECTION

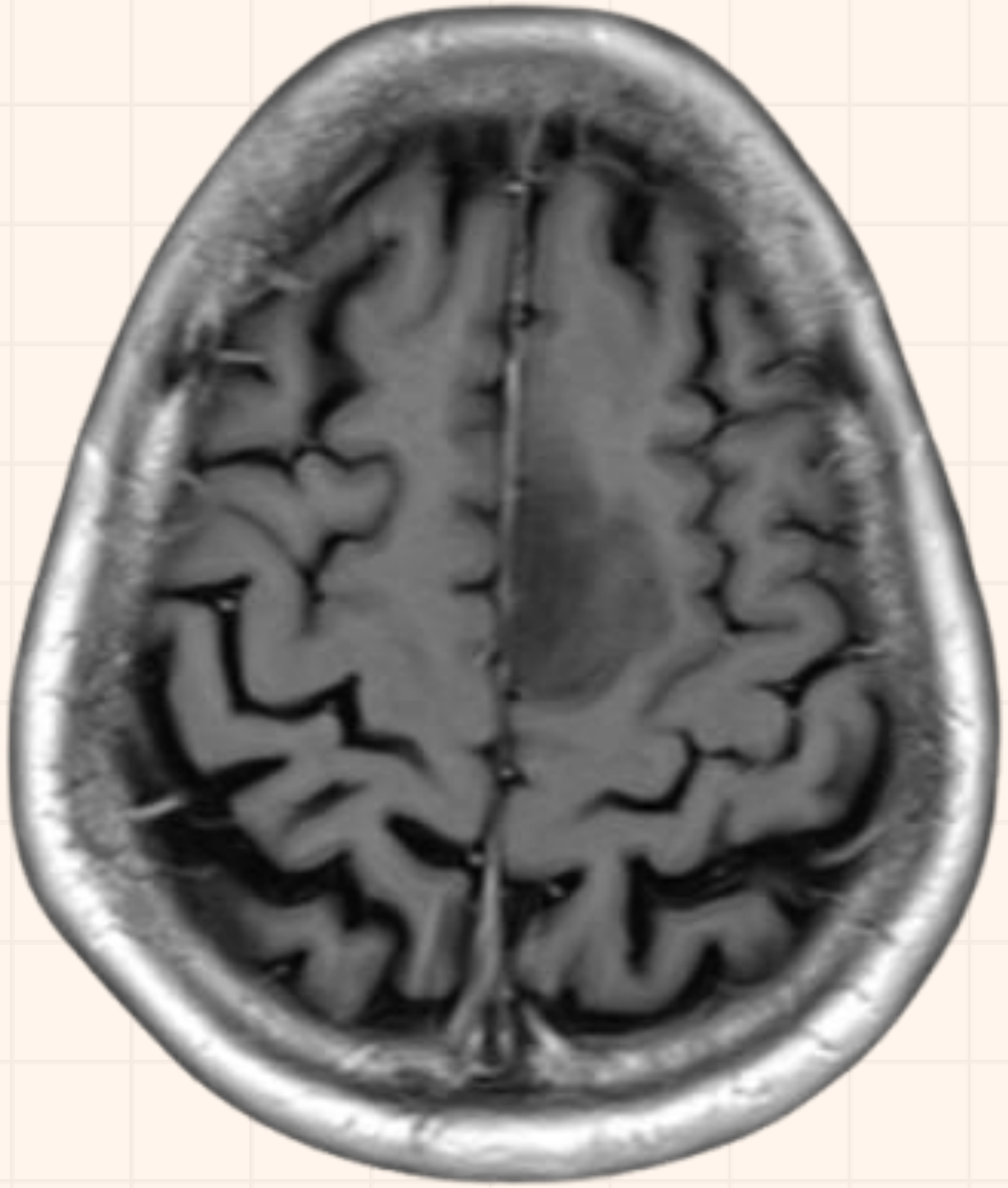
Brain Tumor MRI Images 44 Classes

collection of T1, contrast-enhanced T1, and T2 magnetic

Images without any type of marking or patient identification, interpreted by radiologists and provided for study purposes.

The images are separated by astrocytoma, carcinoma, ependymoma, ganglioglioma, germinoma, glioblastoma, granuloma, medulloblastoma, meningioma, neurocytoma, oligodendroglioma, papilloma, schwannoma and tuberculoma.

Artificial intelligence in neuro-oncology: advances and challenges in brain tumor diagnosis, prognosis, and precision treatment



CNN Model From Scratch

ResNet Pretrained Model

CLASSIFICATION

DenseNet Pretrained Model

CNN Model
FROM SCRATCH

- Built a deep CNN model from scratch with 4 convolutional blocks, dropout, and batch normalization to classify brain tumor MRI images.
- Used Adamax optimizer, categorical_crossentropy loss, and callbacks (EarlyStopping, ReduceLROnPlateau) for stable and efficient training.

Classification Report:

	precision	recall	f1-score	support
Astrocitoma	0.90	0.95	0.92	58
Carcinoma	0.96	0.96	0.96	25
Ependimoma	1.00	0.93	0.97	15
Ganglioglioma	1.00	0.83	0.91	6
Germinoma	1.00	1.00	1.00	10
Glioblastoma	1.00	1.00	1.00	21
Granuloma	1.00	0.88	0.93	8
Meduloblastoma	1.00	1.00	1.00	13
Meningioma	0.99	0.92	0.95	88
Neurocitoma	0.96	0.98	0.97	45
Oligodendroglioma	1.00	0.95	0.98	22
Papiloma	0.88	1.00	0.94	23
Schwannoma	0.96	1.00	0.98	47
Tuberculoma	1.00	0.93	0.97	15
_NORMAL	0.96	1.00	0.98	52
accuracy			0.96	448
macro avg	0.97	0.96	0.96	448
weighted avg	0.96	0.96	0.96	448

We tried using pretrained Models for better performane

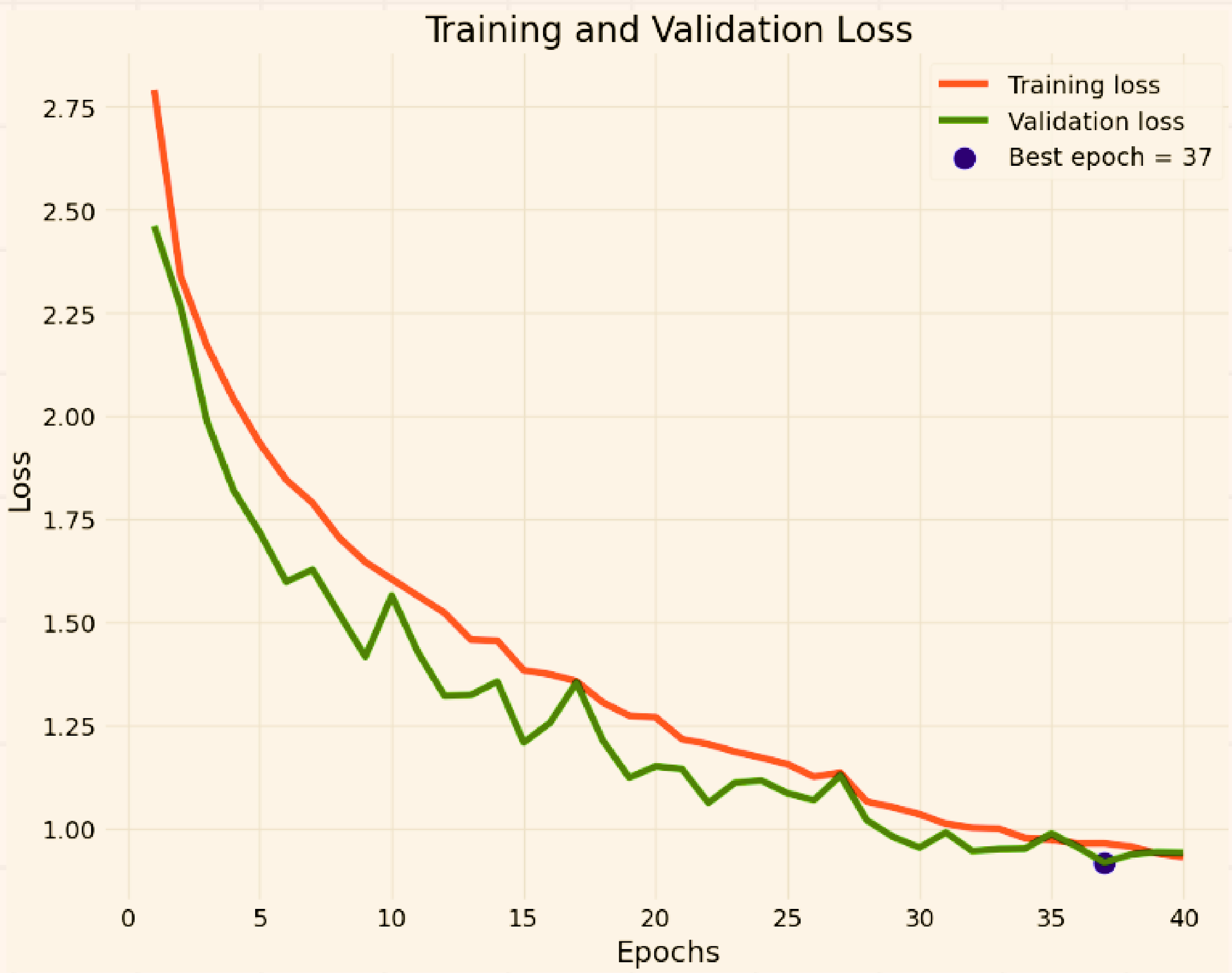
ResNet
PRETRAINED MODEL

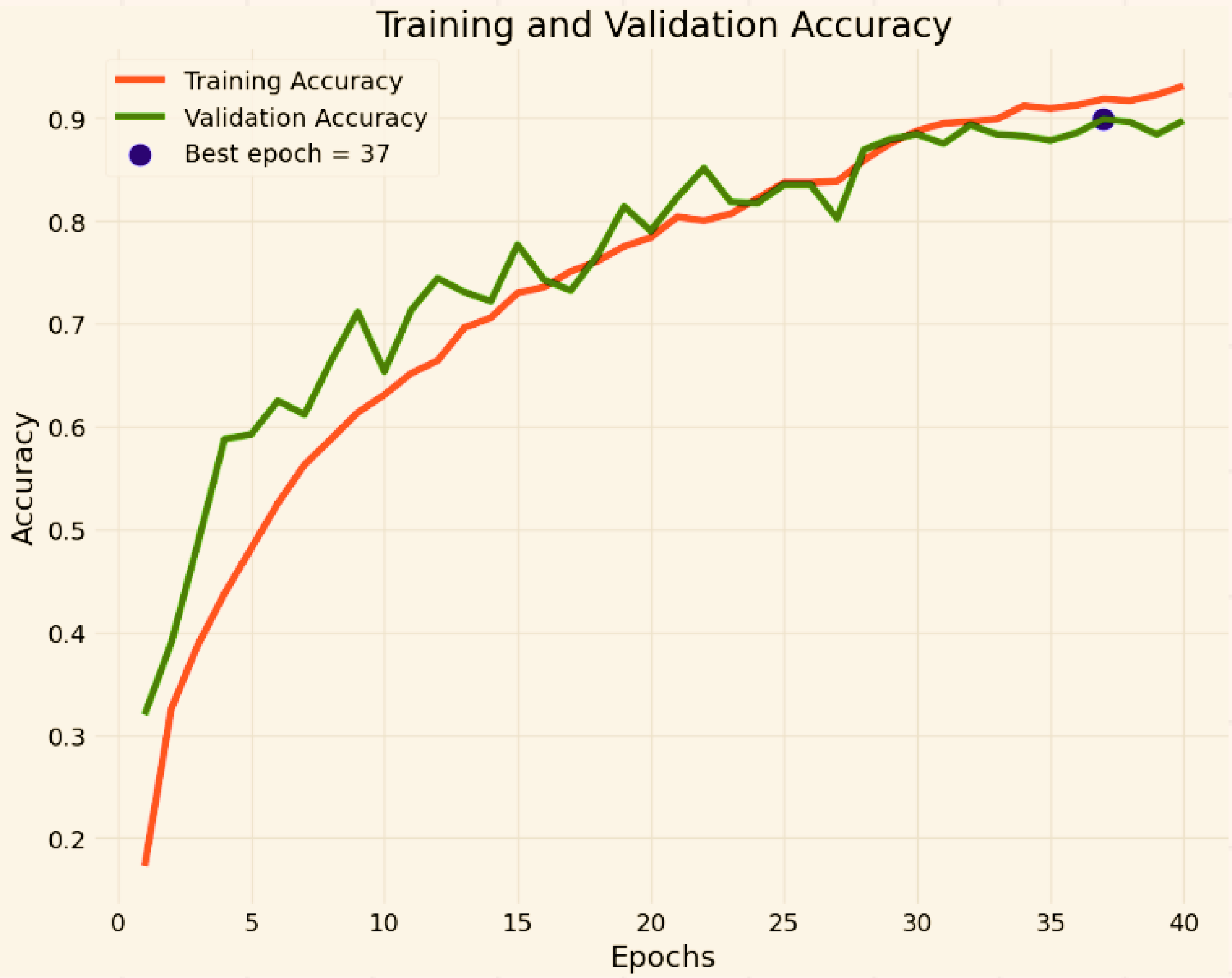
Explored various versions of the ResNet architecture to identify the most effective one for our classification task.

After testing and fine-tuning models like , ResNet50, and ResNet101... etc.

ResNet50V2 stood out by delivering the best accuracy and overall best performance of resnet versions

Still not the best Performance Metrics
So we tried Another pretrained Model





DenseNet

PRETRAINED MODEL

Next, we employed the DenseNet121 & DenseNet169 architecture, leveraging its pre-trained weights on ImageNet. We fine tuned the model to adapt it to our specific classification task.

DenseNet121's design, characterized by dense connections between layers, facilitated efficient feature propagation and reuse, leading to improved performance.

Throughout training, we monitored the model's performance using accuracy and loss metrics, ensuring optimal convergence and generalization

Still not the best Performance Metrics
So we tried Another pretrained Model

Evaluation: DenseNet-121

Accuracy: 69.07%

	precision	recall	f1-score	support
Astrocitoma T1	0.87	0.75	0.81	36
Astrocitoma T1C+	0.72	0.66	0.69	47
Astrocitoma T2	0.64	0.40	0.49	35
Carcinoma T1	1.00	0.86	0.92	14
Carcinoma T1C+	0.96	0.96	0.96	23
Carcinoma T2	1.00	0.67	0.80	15
Ependimoma T1	1.00	0.11	0.20	9
Ependimoma T1C+	0.80	0.40	0.53	10
Ependimoma T2	0.00	0.00	0.00	12
Ganglioglioma T1	1.00	0.50	0.67	4
Ganglioglioma T1C+	1.00	0.50	0.67	4
Ganglioglioma T2	1.00	0.40	0.57	5
Germinoma T1	0.50	0.17	0.25	6
Germinoma T1C+	0.75	0.38	0.50	8
Germinoma T2	0.00	0.00	0.00	7
Glioblastoma T1	1.00	0.55	0.71	11
Glioblastoma T1C+	0.94	0.79	0.86	19
Glioblastoma T2	0.67	0.36	0.47	11
Granuloma T1	0.00	0.00	0.00	6
Granuloma T1C+	0.44	0.57	0.50	7
Granuloma T2	0.00	0.00	0.00	4
accuracy			0.69	915
macro avg	0.71	0.54	0.58	915
weighted avg	0.72	0.69	0.67	915

Evaluation: DenseNet-169

Accuracy: 73.77%

	precision	recall	f1-score	support
Astrocitoma T1	0.74	0.72	0.73	36
Astrocitoma T1C+	0.78	0.62	0.69	47
Astrocitoma T2	0.56	0.57	0.56	35
Carcinoma T1	0.80	0.86	0.83	14
Carcinoma T1C+	0.96	0.96	0.96	23
Carcinoma T2	1.00	0.67	0.80	15
Ependimoma T1	0.56	0.56	0.56	9
Ependimoma T1C+	0.67	0.40	0.50	10
Ependimoma T2	0.36	0.42	0.38	12
Ganglioglioma T1	0.40	0.50	0.44	4
Ganglioglioma T1C+	1.00	0.75	0.86	4
Ganglioglioma T2	0.00	0.00	0.00	5
Germinoma T1	0.50	0.67	0.57	6
Germinoma T1C+	1.00	0.62	0.77	8
Germinoma T2	0.75	0.43	0.55	7
Glioblastoma T1	0.88	0.64	0.74	11
Glioblastoma T1C+	0.84	0.84	0.84	19
Glioblastoma T2	0.33	0.36	0.35	11
Granuloma T1	0.86	1.00	0.92	6
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
accuracy			0.74	915
macro avg	0.69	0.64	0.65	915
weighted avg	0.74	0.74	0.73	915

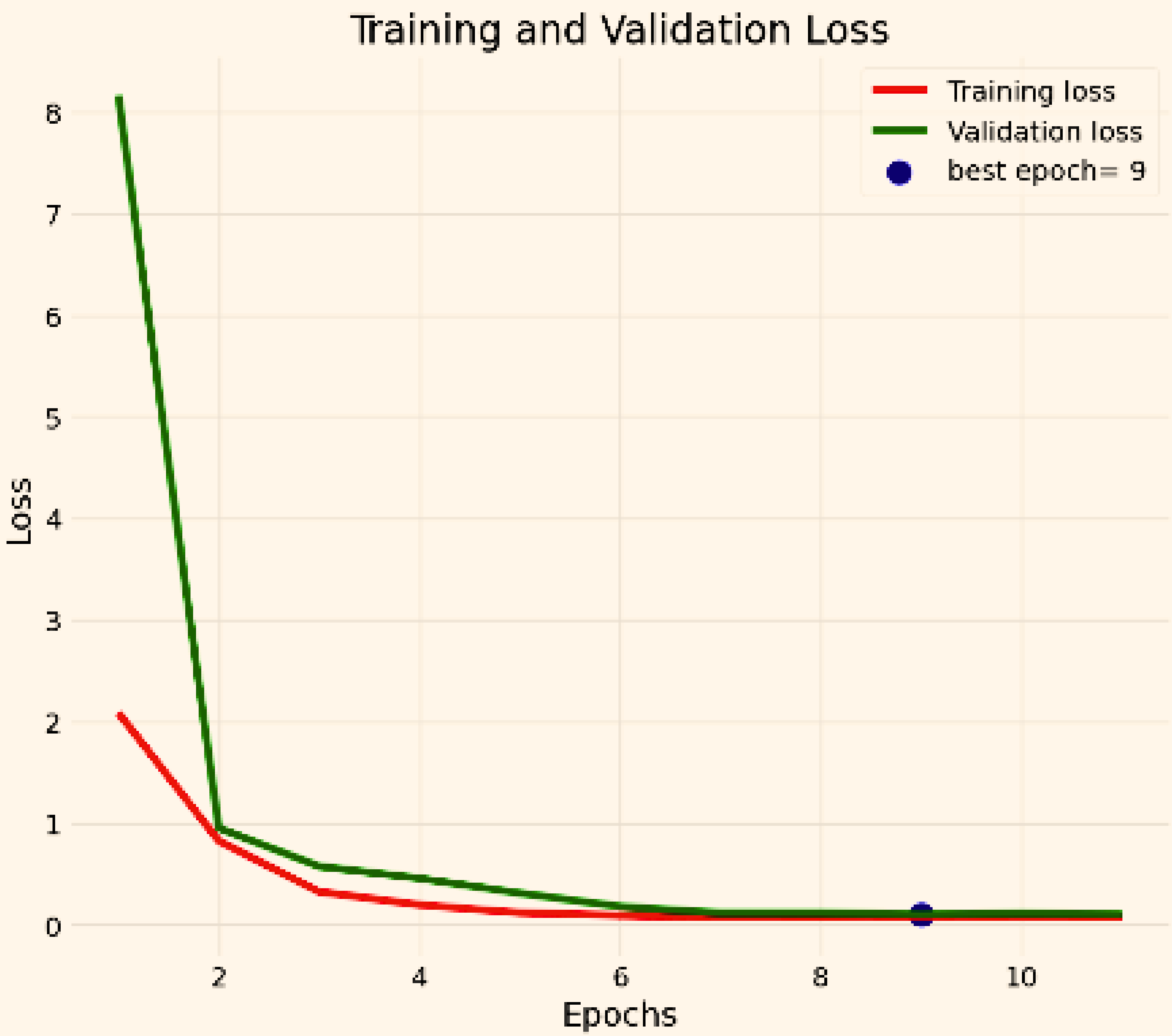
EffiecentNet
PRETRAINED MODEL

Applied the EfficientNet versions to leverage its optimized scaling capabilities for image classification.
After evaluating different variants, EfficientNetB5 was selected as the final model due to its excellent balance of accuracy and computational efficiency, achieving the best results among the tested versions.

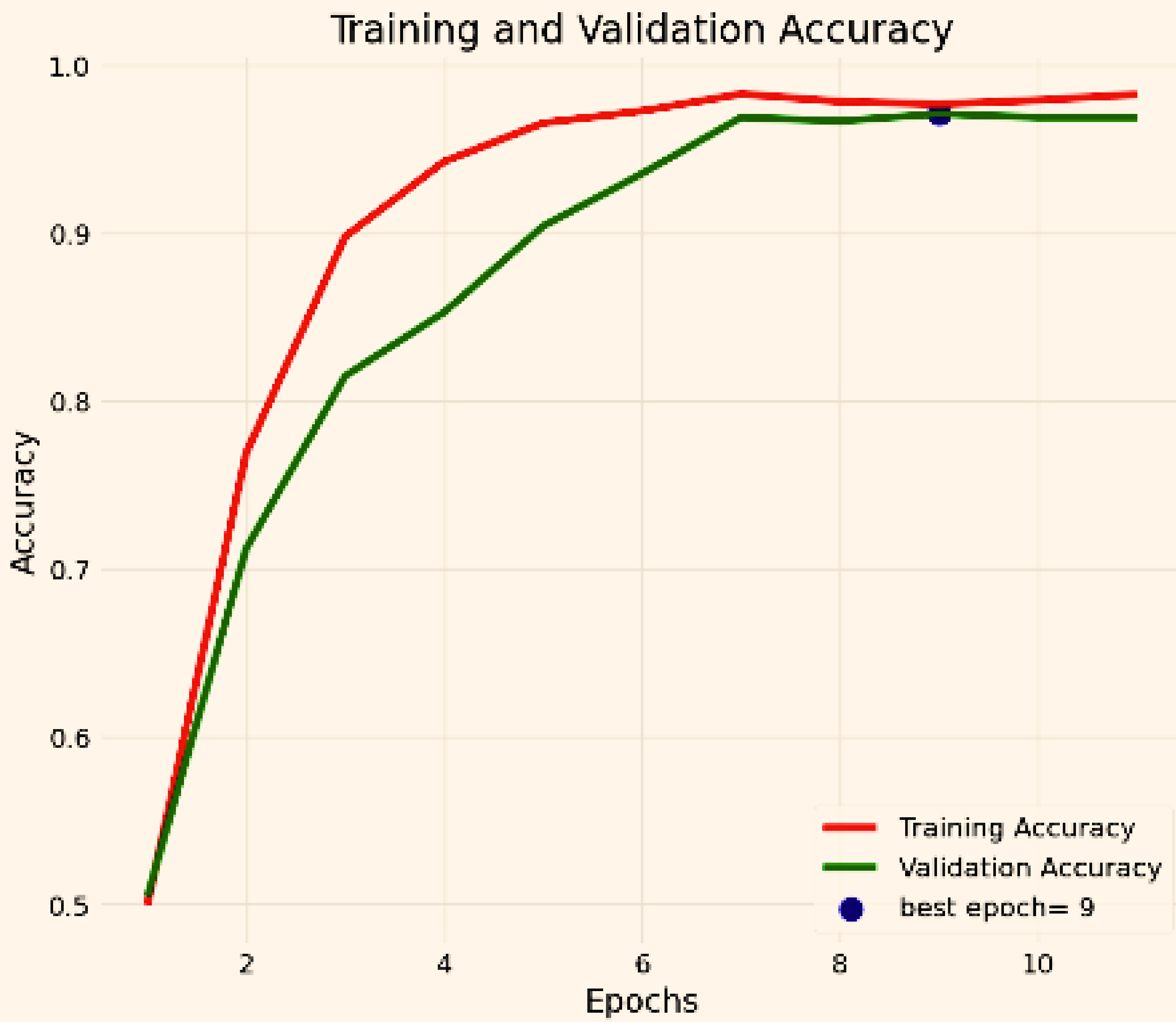
Best Performance Metrics Approved

Evaluating model: EfficientNetB5
Classification Report:

	precision	recall	f1-score	support
Astrocitoma	0.93	0.97	0.95	58
Carcinoma	1.00	1.00	1.00	25
Ependimoma	1.00	0.93	0.97	15
Ganglioglioma	1.00	0.83	0.91	6
Germinoma	1.00	1.00	1.00	10
Glioblastoma	1.00	1.00	1.00	20
Granuloma	1.00	1.00	1.00	8
Meduloblastoma	1.00	1.00	1.00	13
Meningioma	0.98	0.99	0.98	87
Neurocitoma	1.00	0.96	0.98	46
Oligodendroglioma	0.96	0.96	0.96	23
Papiloma	1.00	0.96	0.98	24
Schwannoma	0.98	1.00	0.99	46
Tuberculoma	0.93	0.93	0.93	14
_NORMAL	0.98	1.00	0.99	53
accuracy			0.98	448
macro avg	0.98	0.97	0.98	448
weighted avg	0.98	0.98	0.98	448



Training and Validation Loss
Training loss
Validation loss
best epoch= 9
Loss
Epochs
0
1
2
3
4
5
6
7
8
2
4
6
8
10

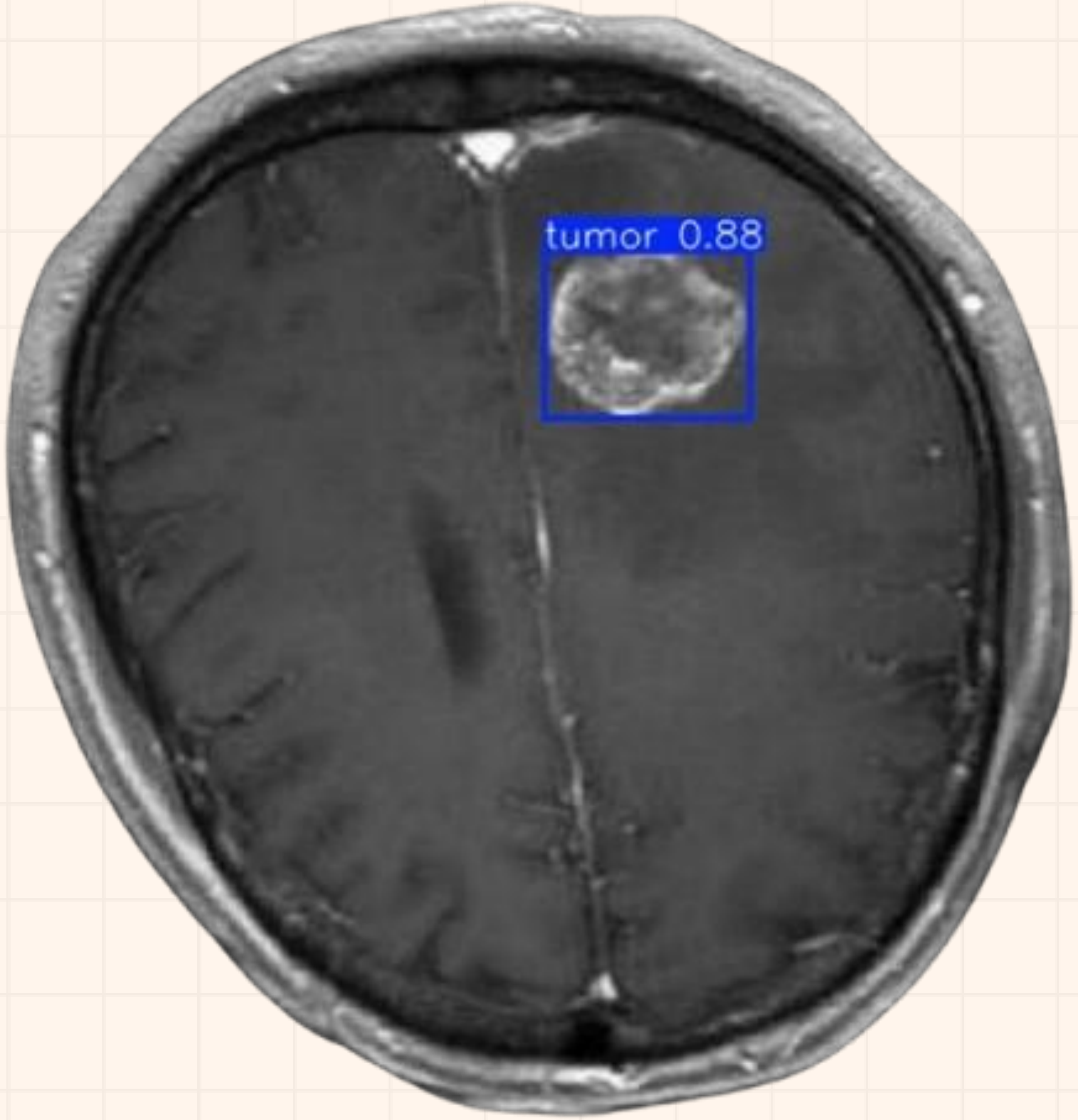


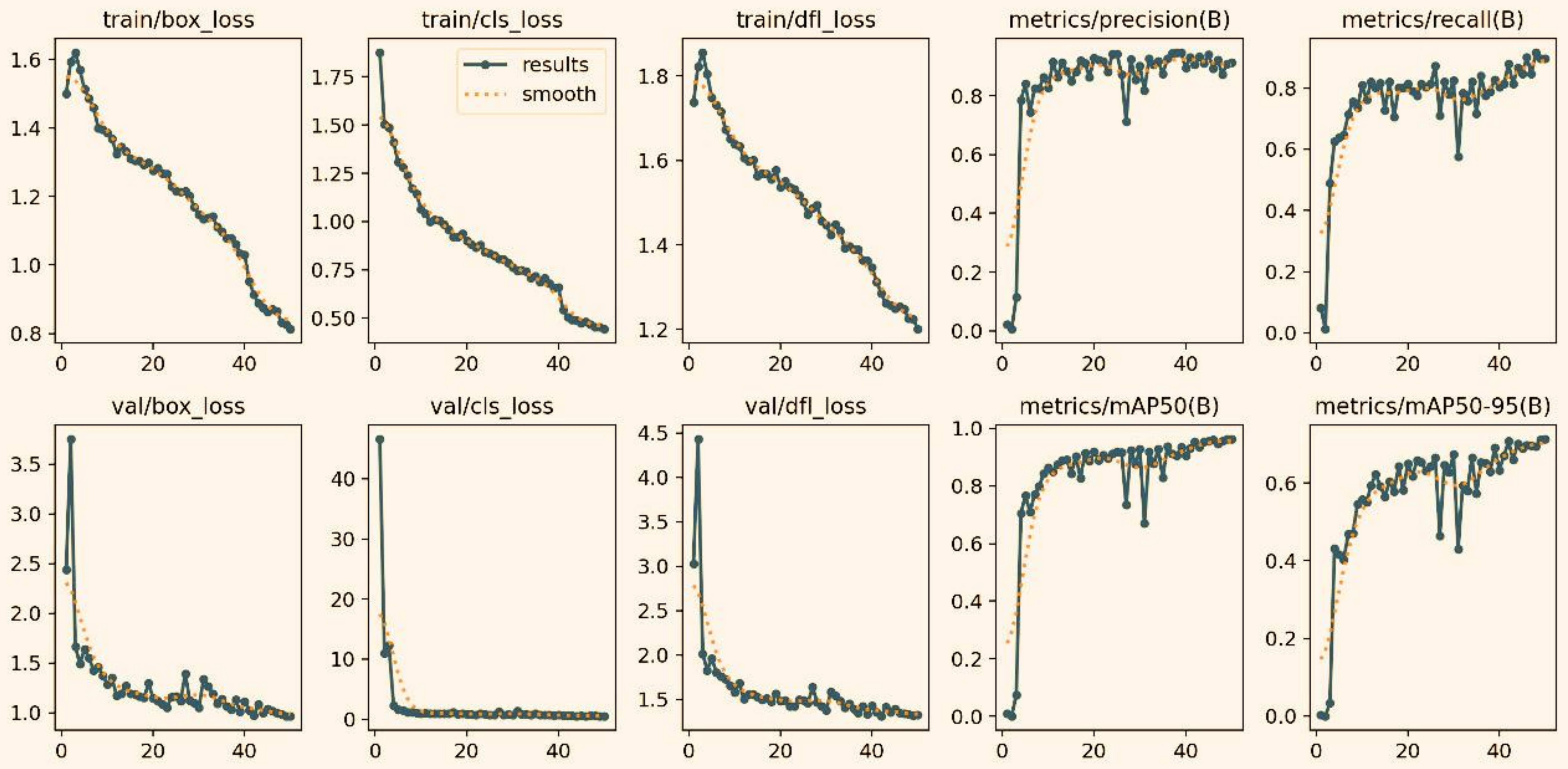
Training and Validation Accuracy
Accuracy
Epochs
1.0
0.9
0.8
0.7
0.6
0.5
2
4
6
8
10
Training Accuracy
Validation Accuracy
best epoch= 9

OBJECT DETECTION

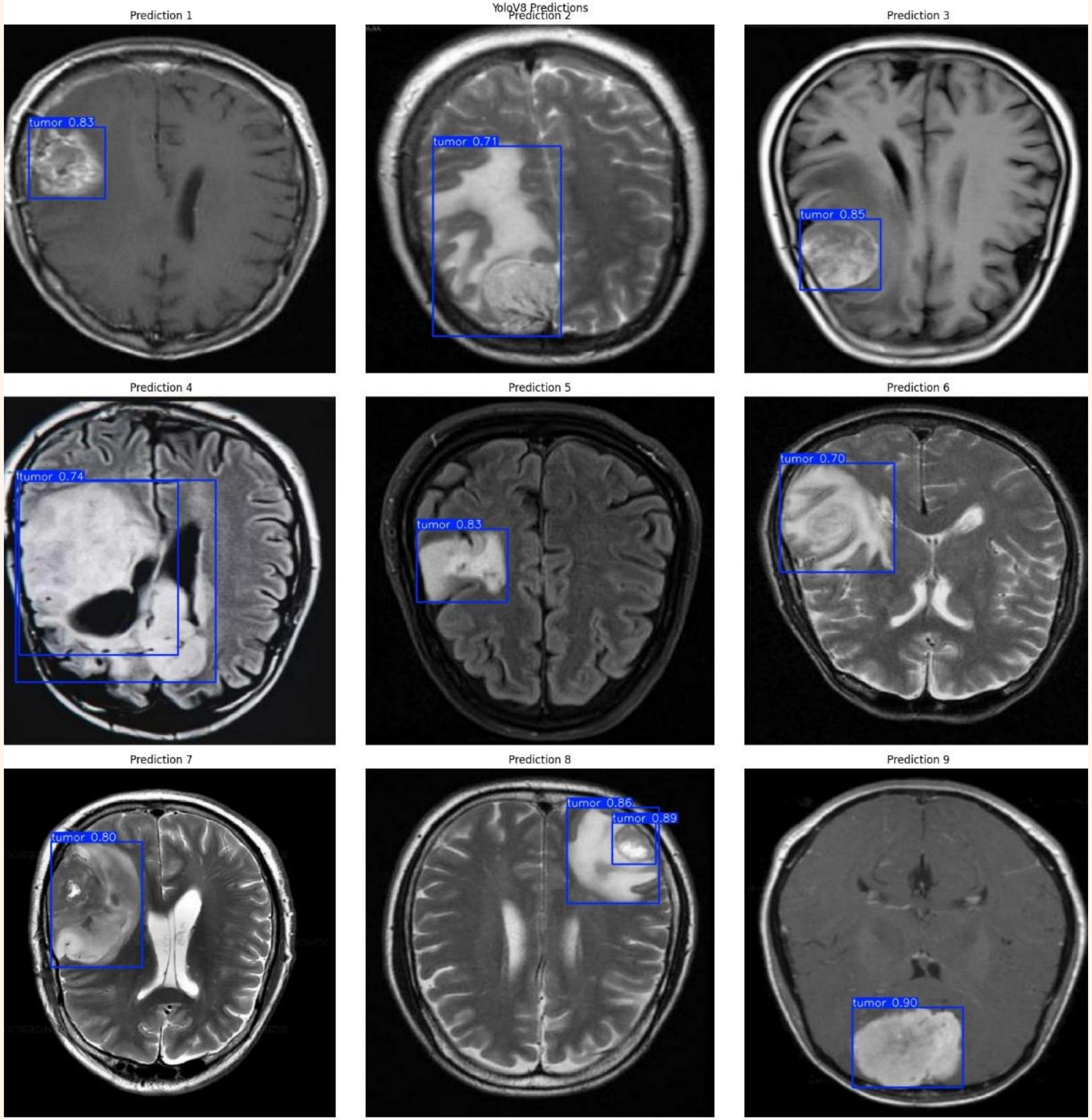
Developed a deep learning-based object detection model to automatically detect and classify brain tumors from medical images using the YOLOv8 architecture.

The goal is to assist radiologists and medical practitioners by providing fast and accurate detection to support early diagnosis and treatment planning





train/box_loss
train/cls_loss
results
smooth
train/dfl_loss
metrics/precision(B)
metrics/recall(B)
val/box_loss
val/cls_loss
val/dfl_loss
metrics/mAP50(B)
metrics/mAP50-95(B)


YoloV8 Predictions
Prediction 1
tumor 0.83
Prediction 2
tumor 0.71
Prediction 3
tumor 0.85
Prediction 4
tumor 0.74
Prediction 5
tumor 0.83
Prediction 6
tumor 0.70
Prediction 7
tumor 0.80
Prediction 8
tumor 0.89
Prediction 9
tumor 0.90

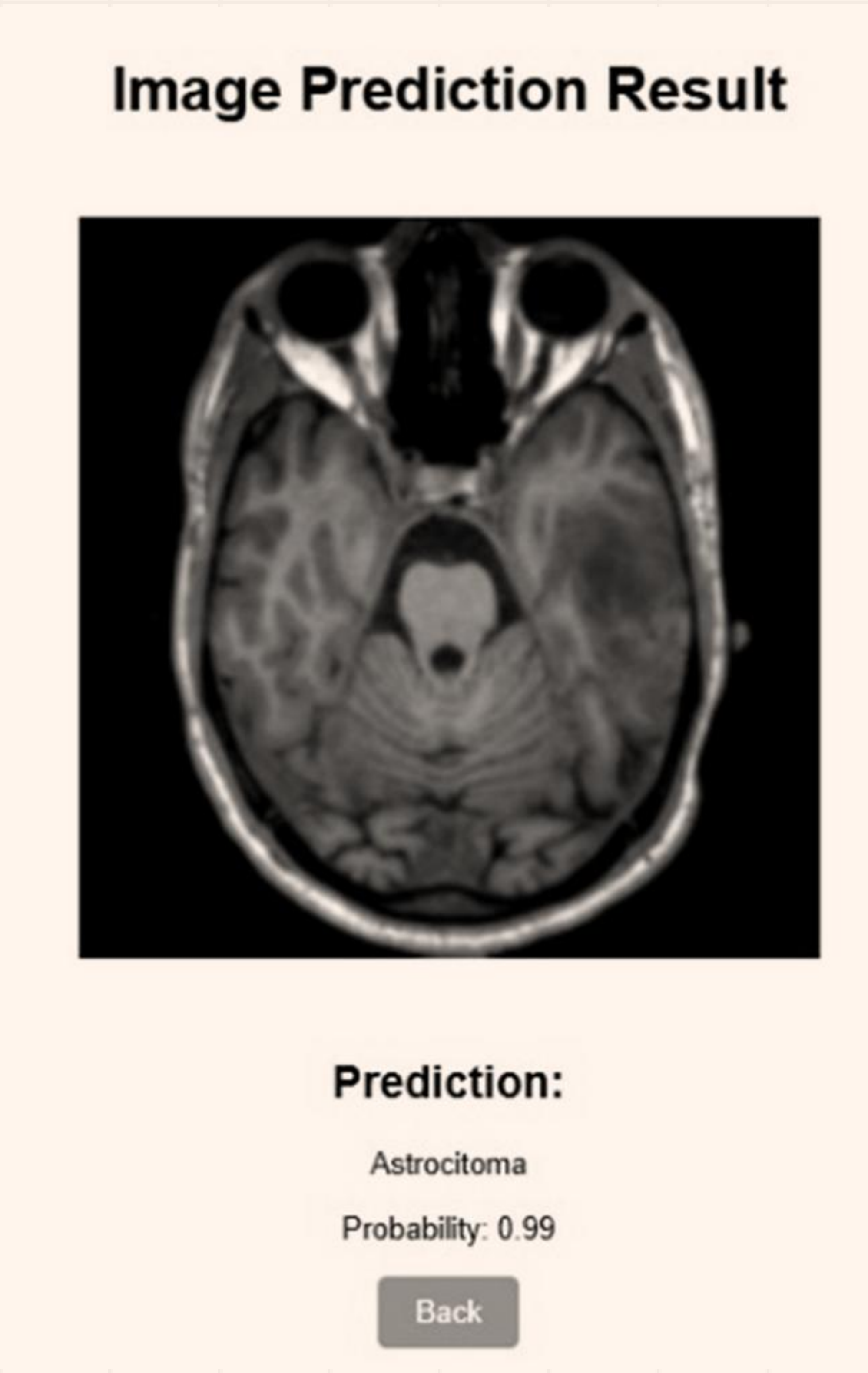
DEPLOYMENT

This Python script is a Flask web application that provides a user interface for classifying brain tumor images using a pre-trained deep learning model based on EfficientNetB5.

The app loads the model, processes uploaded images, performs predictions, and returns the tumor type along with the prediction probability.

Users can upload images via a web interface, where the backend resizes and preprocesses the images before running them through the model.

The prediction results are then displayed on a results page along with the uploaded image, which is encoded in base64 for embedding in the HTML.

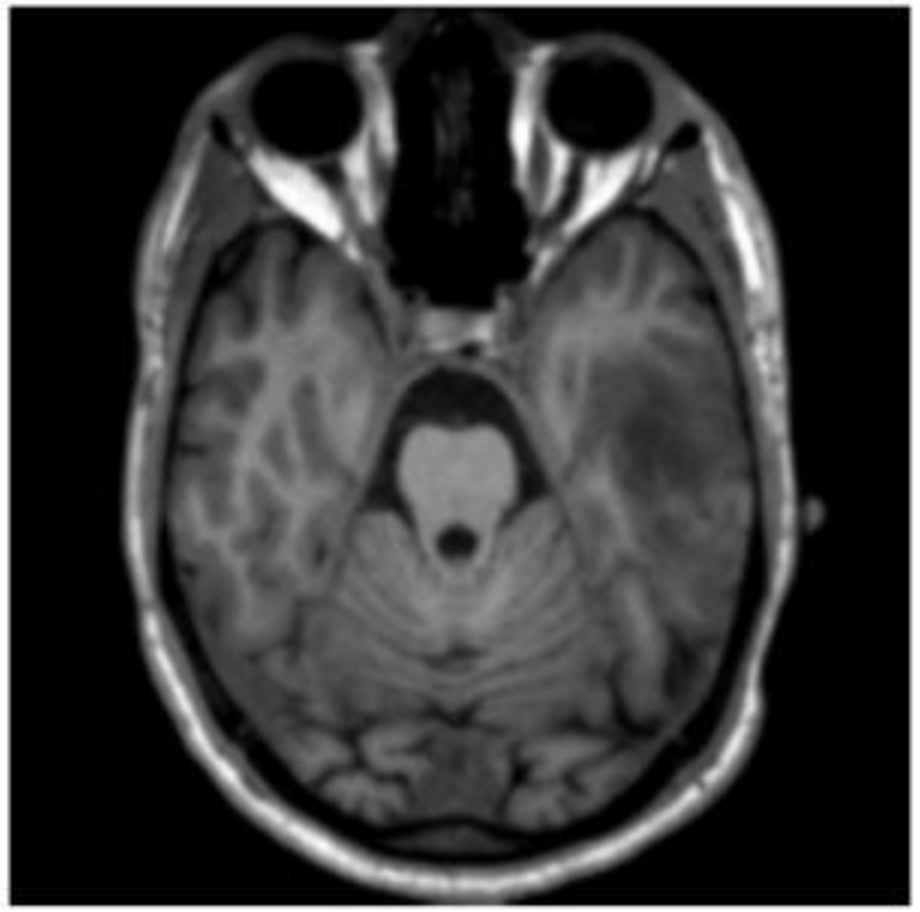


Brain tumor 15 class | Kaggle
Image Prediction Result

127.0.0.1:7860/classify

Gmail YouTube Maps Translate Microsoft Machine... (1) Amr Ibrahim | Li... All Bookmarks

Image Prediction Result



Prediction:

Astrocitoma

Probability: 0.99

Back

01:56 ص
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THANK YOU