Brain Tumor Diagnosis Assistant

Group 8

Tarik Bilgin Demirci – Technical Lead (Student 1)
Umut Turklay – Figures, Tables & Presentation (Student 2)
Berk Kahraman – Report & Storytelling (Student 3)

Problem Statement

- Brain tumors are life-threatening conditions requiring accurate and timely diagnosis
- Manual MRI analysis is time-consuming and prone to inter-observer variability
- Need for automated, reliable, and interpretable diagnostic systems
- Challenge: Achieve high accuracy while maintaining clinical trust and explainability
- Goal: Develop a hybrid AI system combining deep learning with clinical knowledge

Research Questions

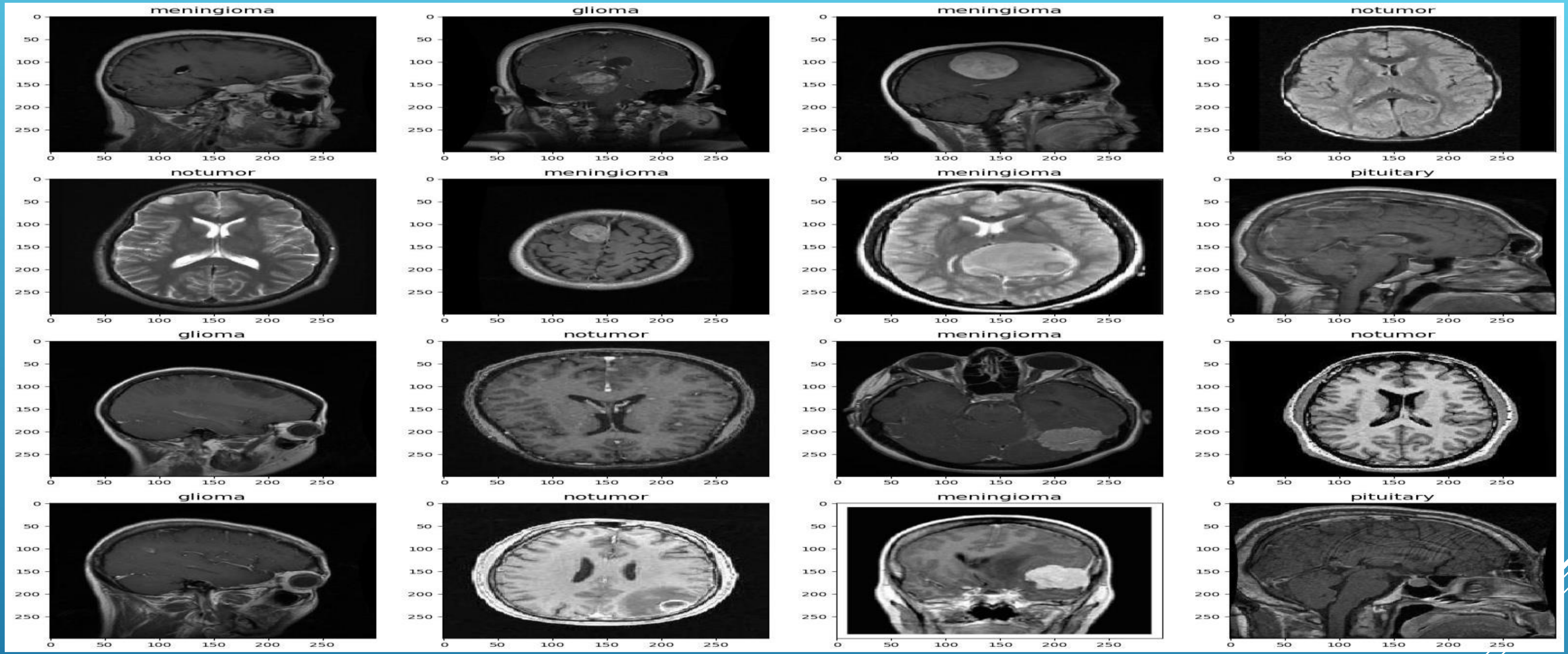
- RQ1: How effectively can CNNs classify brain tumor types from MRI scans?
- RQ2: Can meta-learning with shape descriptors improve classification accuracy?
- RQ3: How can rule-based clinical knowledge enhance diagnostic reliability?
- RQ4: What is the impact of explainability techniques (Grad-CAM) on interpretability?
- RQ5: How do different architectures (ResNet, EfficientNet, DenseNet) compare?

Literature Review / Related Work

Author	Year	Method	Dataset	Accuracy	Limitation
Deepak & Ameer	2019	GoogleNet + SVM	CE-MRI (3064)	98.0%	No explainability
Afshar et al.	2019	CapsNet	CE-MRI (3064)	90.9%	Limited tumor types
Badza & Barjaktarovic	2020	CNN (Custom)	Figshare (3064)	96.6%	No clinical integration
Swati et al.	2019	VGG-19 Transfer	CE-MRI (3064)	94.8%	Single architecture
Our Work	2025	Xception+Meta+Rules	Kaggle (7023)	99.5%	Hybrid approach

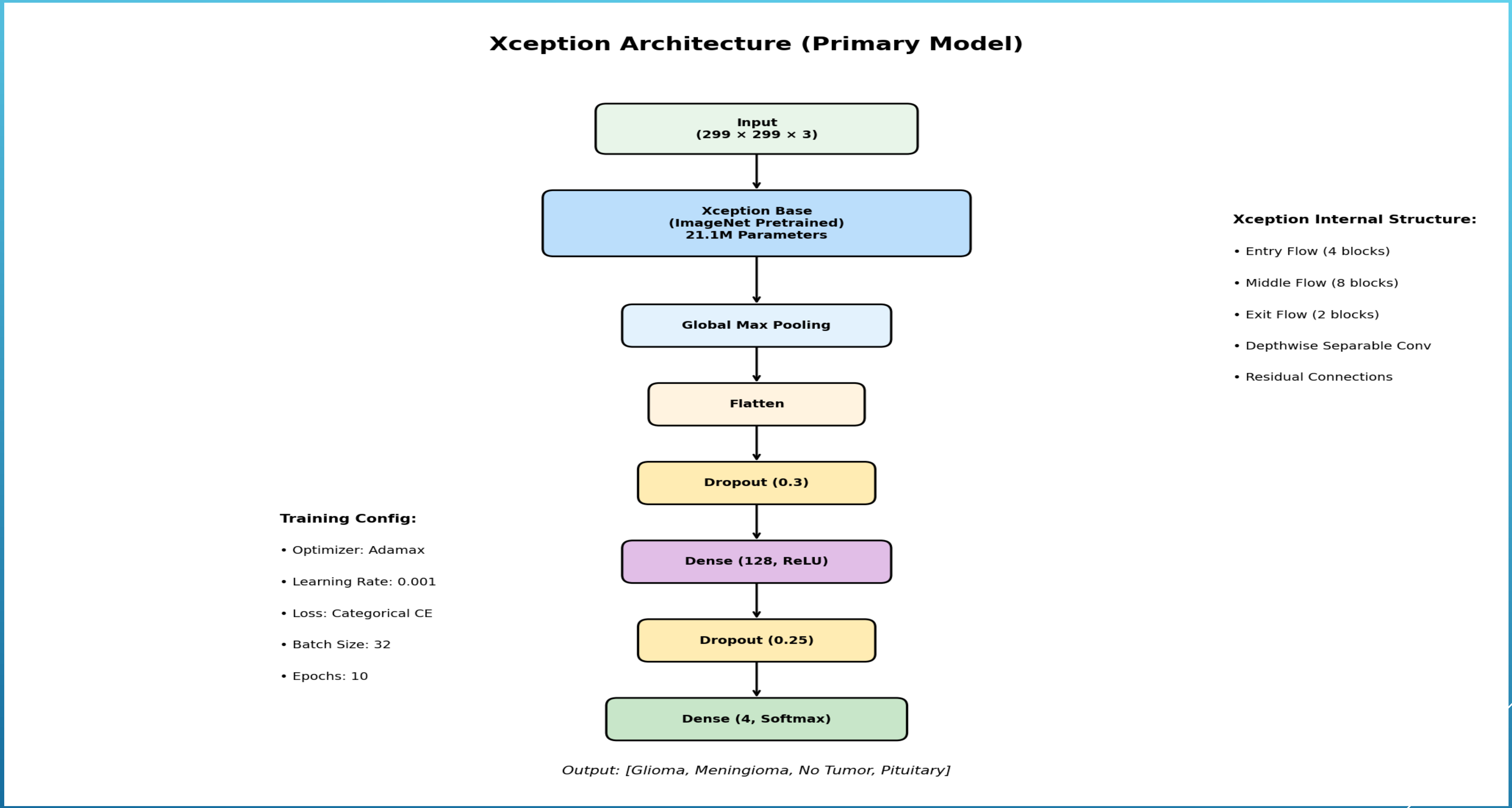
Our work differs by combining CNN with meta-learning and rule-based clinical integration for improved reliability.

Dataset



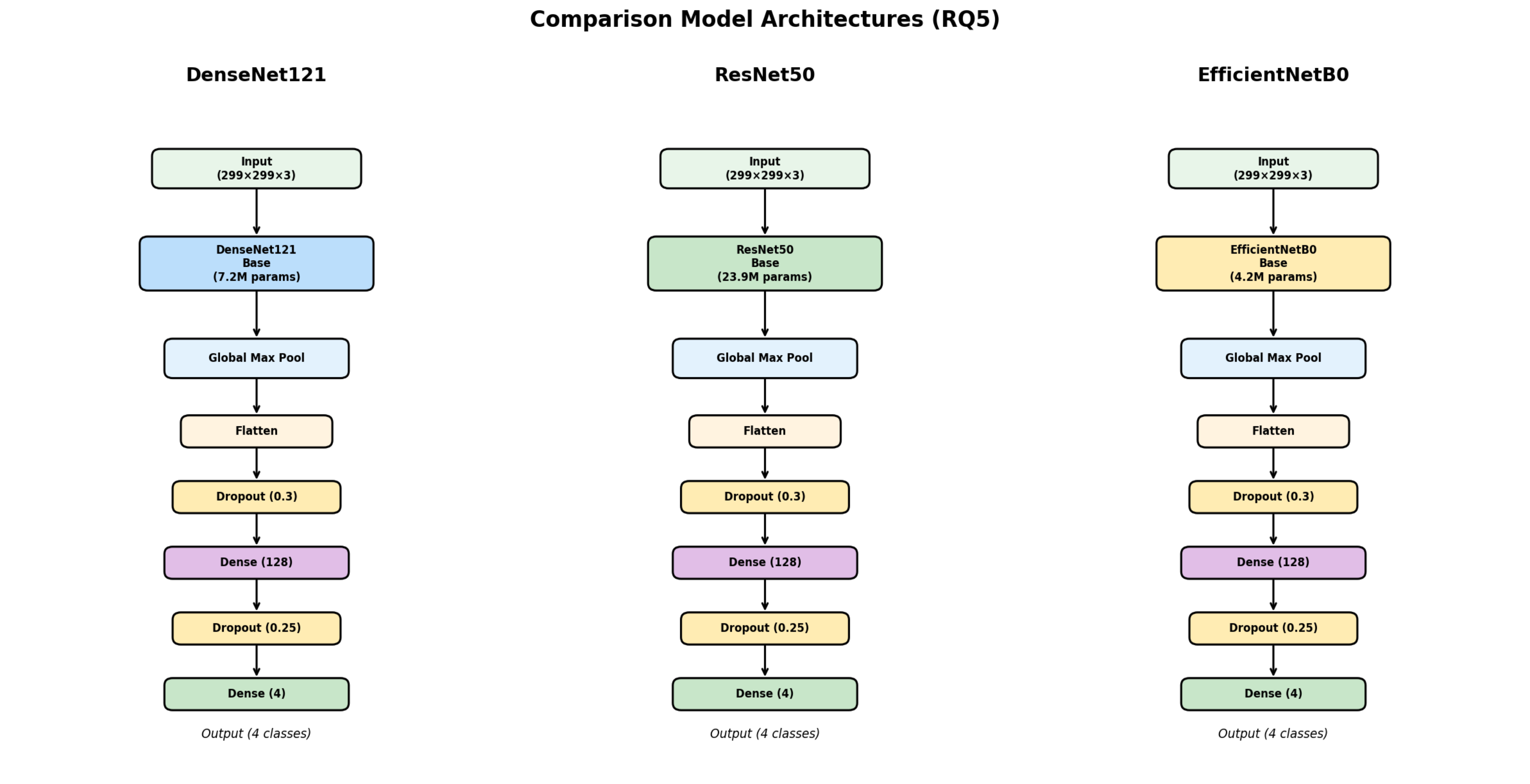
- Source: Kaggle Brain Tumor MRI Dataset
- 4 Classes: Glioma (1321), Meningioma (1339), Pituitary (1457), No Tumor (1595)
- Total: 5,712 training | 655 validation | 656 test images
- Image size: 299×299 pixels (RGB)

Network Architecture: Xception (Primary Model)



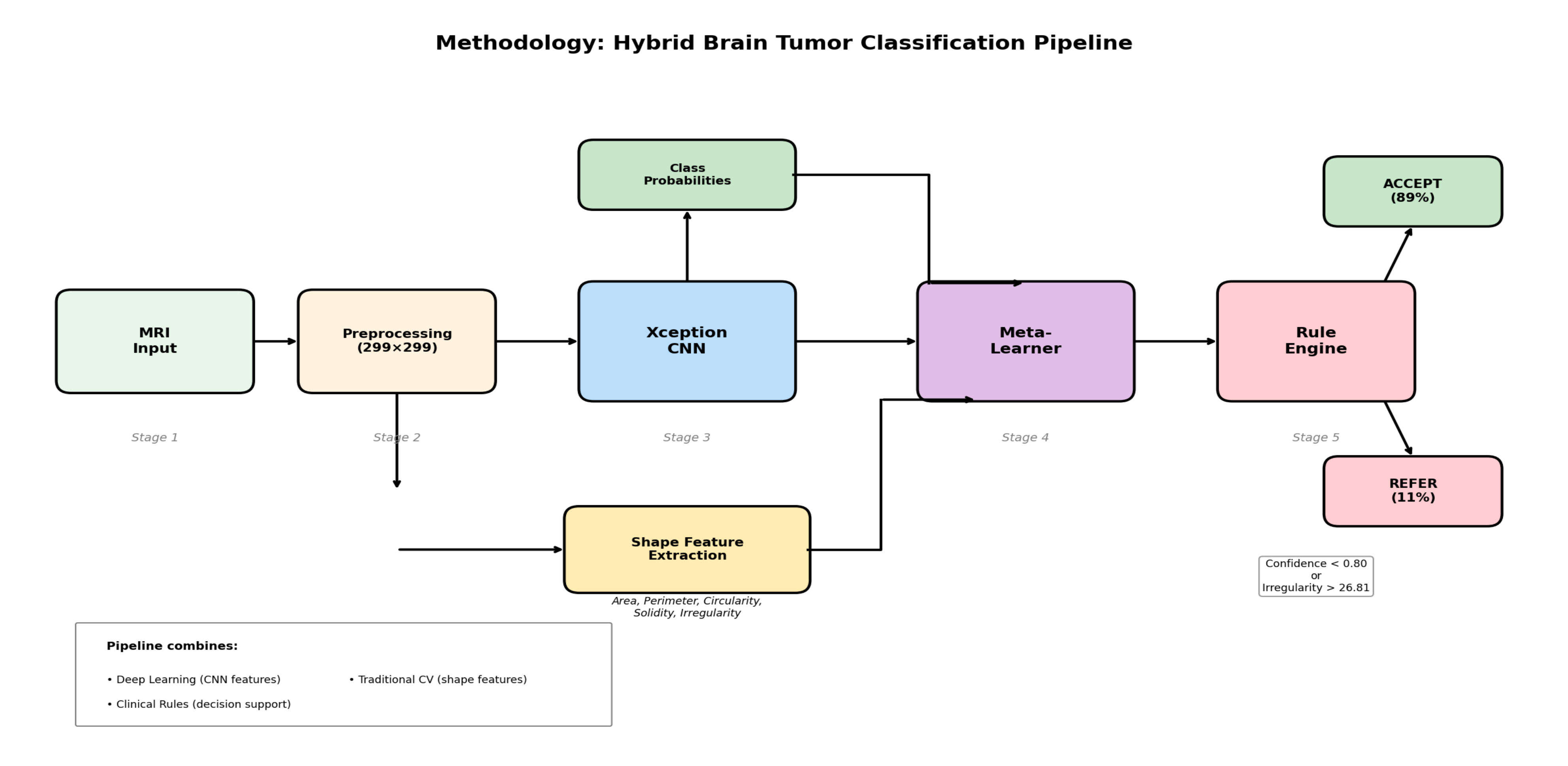
- Base: Xception (ImageNet pretrained) with depthwise separable convolutions
- Custom head: Flatten → Dropout(0.3) → Dense(128) → Dropout(0.25) → Dense(4)
- Total: 21.1M parameters | Optimizer: Adamax (lr=0.001)

Network Architecture: Comparison Models (RQ5)



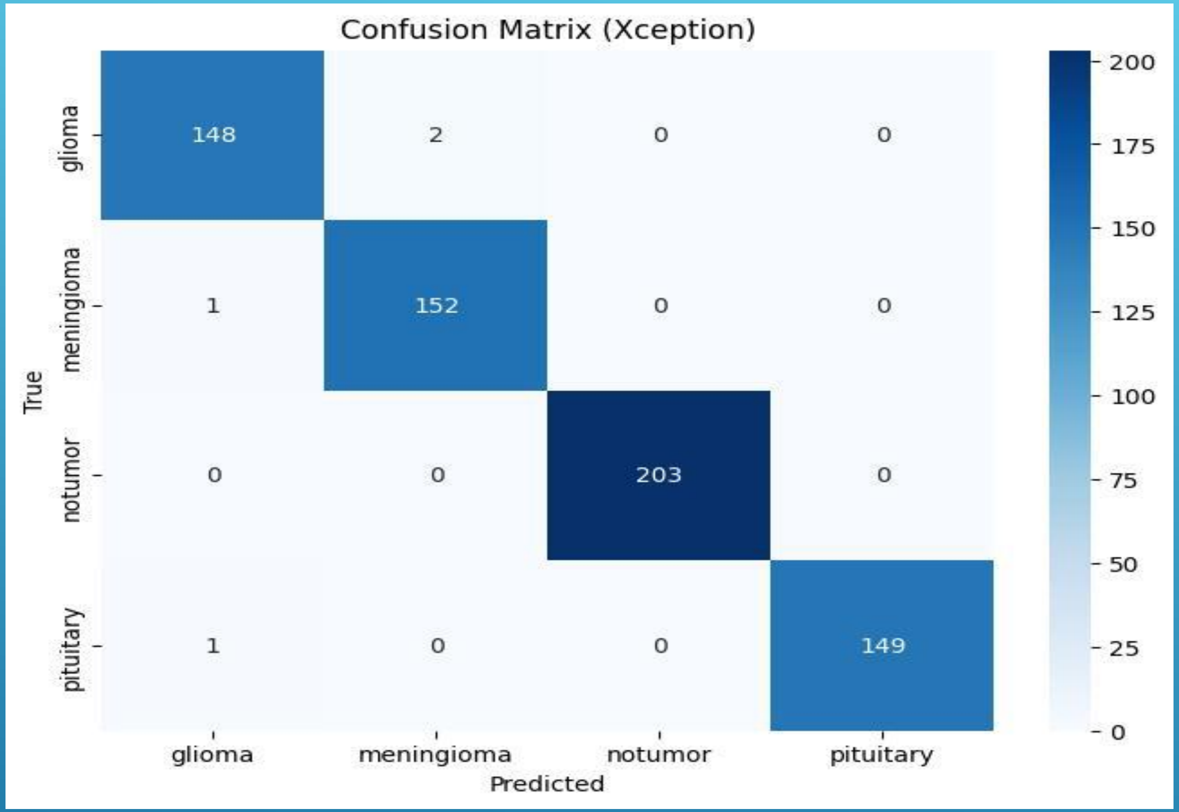
- DenseNet121: 7.2M params | ResNet50: 23.9M params | EfficientNetB0: 4.2M params
- Same head architecture applied to all models for fair comparison
- All models pretrained on ImageNet, fine-tuned on brain tumor dataset

Methodology



- Hybrid pipeline combining deep learning, traditional CV, and clinical rules
- CNN extracts features → Meta-learner fuses with shape descriptors → Rule engine for clinical decision support
- Result: 99.54% accuracy with 89% automatic acceptance rate

Results: RQ1 - CNN Classification Effectiveness

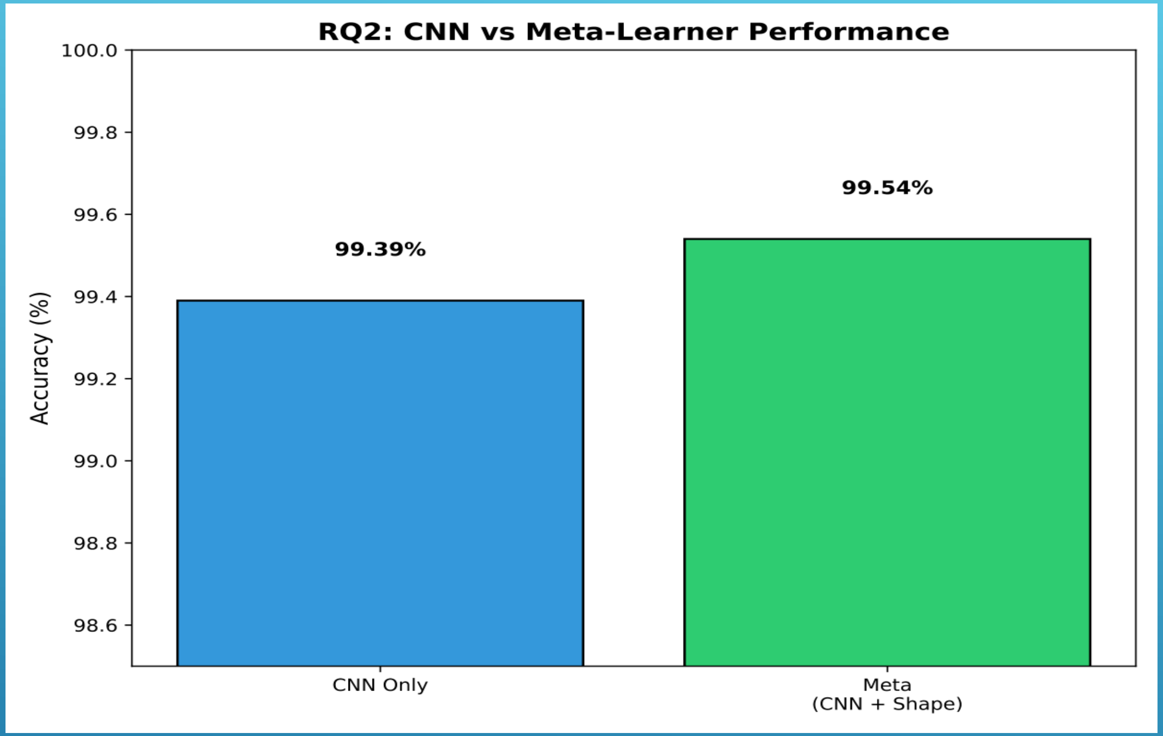


Class	Precision	Recall	F1	Support
Glioma	0.99	0.99	0.99	150
Meningioma	0.99	0.99	0.99	153
No Tumor	1.00	1.00	1.00	203
Pituitary	1.00	0.99	1.00	150
Overall	0.99	0.99	0.99	656

Key Observations:

- Xception achieves 99.39% test accuracy on 4-class brain tumor classification
- Perfect recall (100%) on No Tumor class - critical for avoiding false negatives
- Balanced performance across all tumor types with F1 ≥ 0.99

Results: RQ2 - Meta-Learning with Shape Features

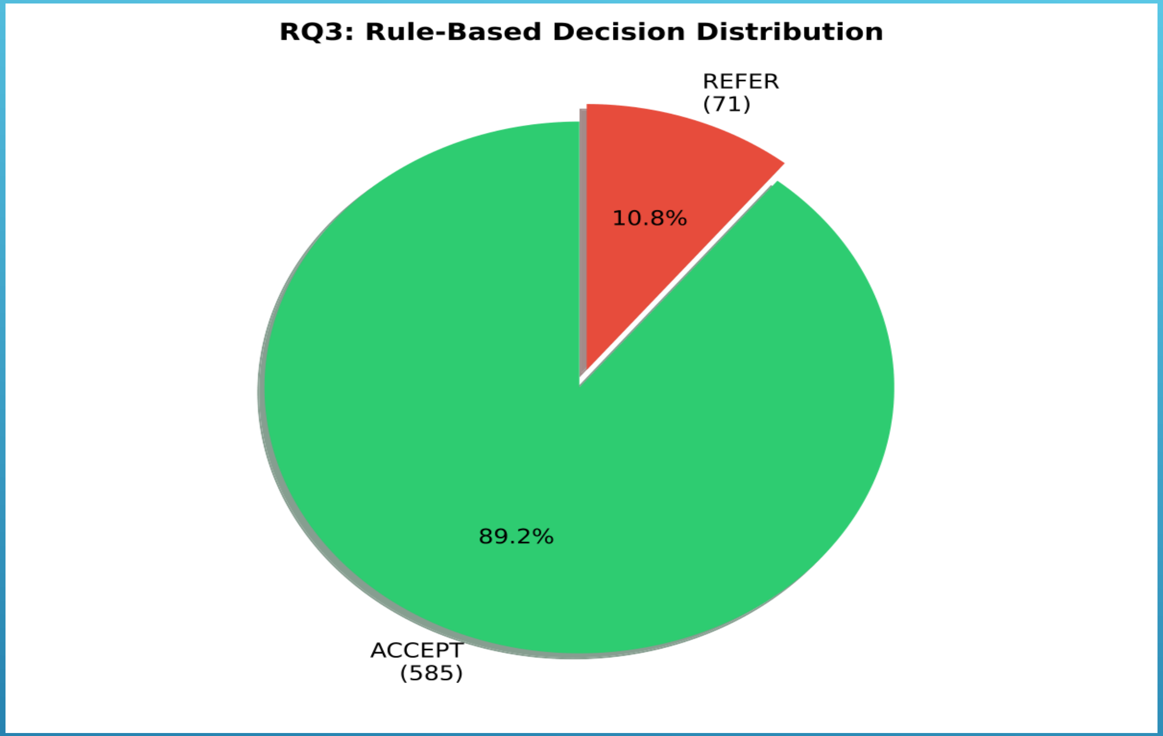


Model	Accuracy	Improvement
CNN Only (Xception)	99.39%	Baseline
Meta-Learner (CNN + Shape)	99.54%	+0.15%

Key Observations:

- Shape features (area, perimeter, circularity, solidity, irregularity) provide complementary information
- Meta-learner (Logistic Regression) successfully combines CNN softmax outputs with shape descriptors
- Modest but consistent improvement demonstrates value of hybrid approach

Results: RQ3 - Rule-Based Clinical Integration

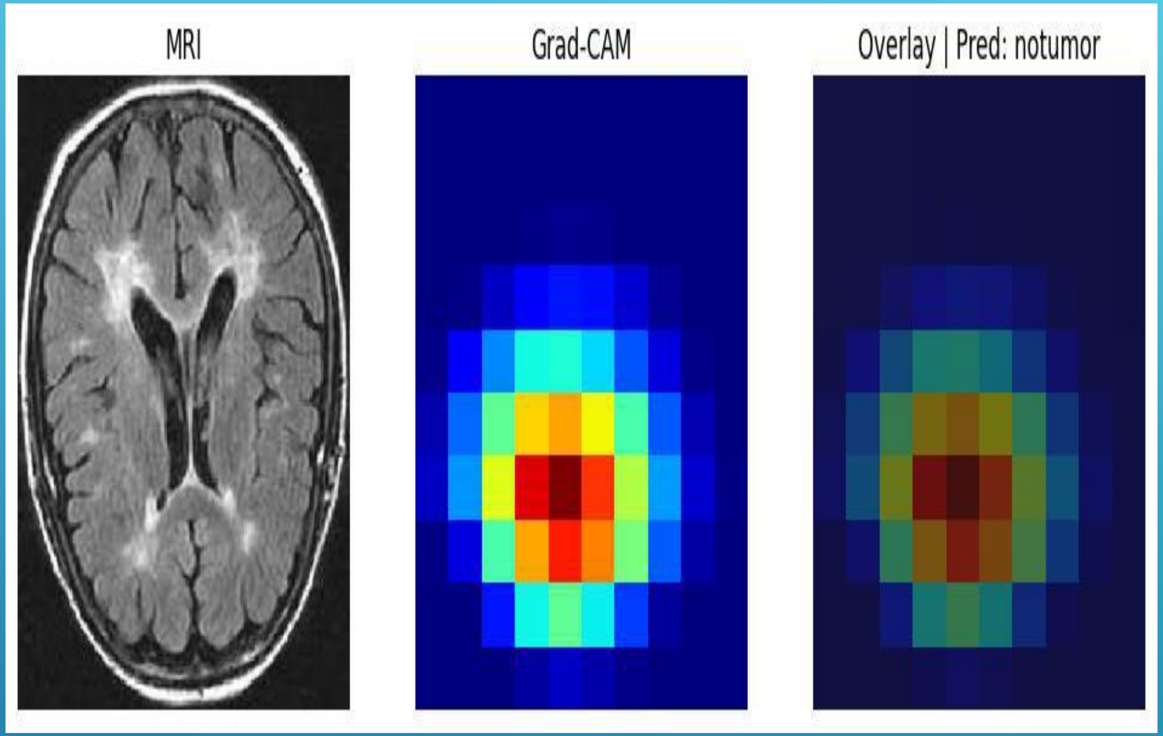


Metric	Value
Confidence Threshold	0.80
Irregularity Threshold	26.81 (90th percentile)
ACCEPT Rate	89.18% (585 cases)
REFER Rate	10.82% (71 cases)
Accuracy on ACCEPT	99.66%

Key Observations:

- Rule engine flags uncertain cases based on confidence and tumor irregularity
- 89% of cases can be automatically accepted with higher accuracy (99.66%)
- Remaining 11% referred to specialists - practical clinical workflow

Results: RQ4 - Explainability with Grad-CAM

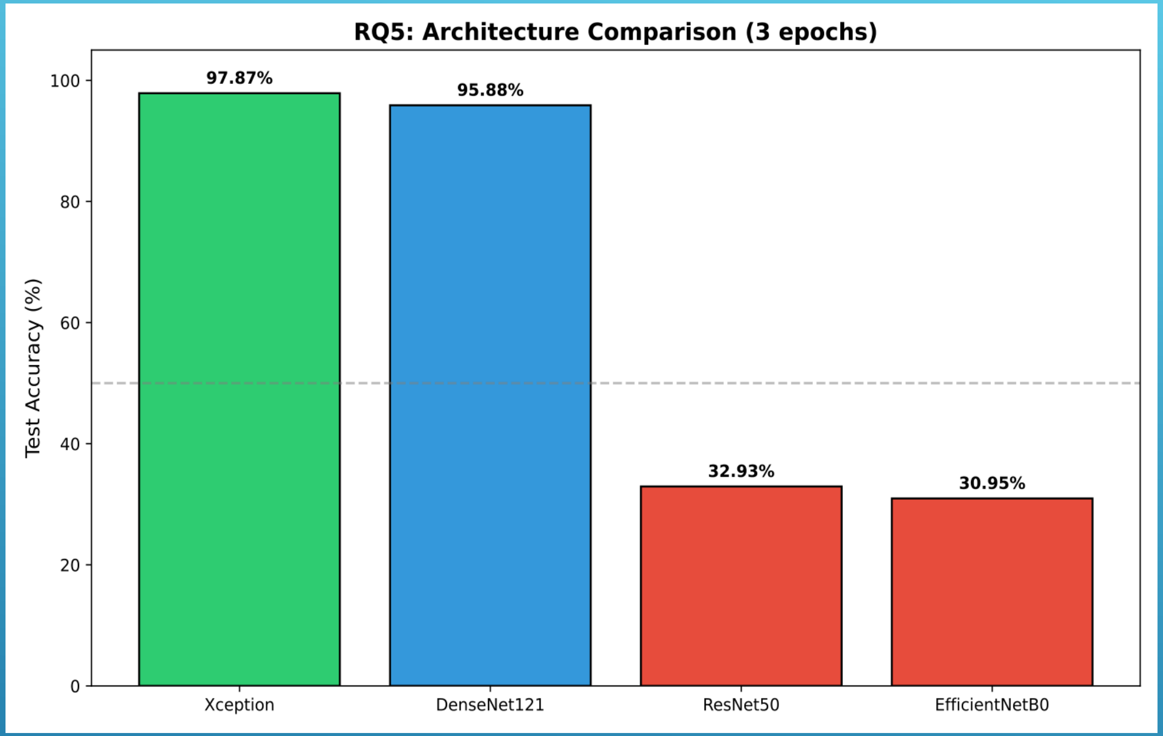


Aspect	Description
Method	Gradient-weighted Class Activation Mapping
Target Layer	block14_sepconv2_act (Xception)
Output	Heatmap highlighting influential regions
Purpose	Enable clinician trust and understanding

Key Observations:

- Grad-CAM successfully highlights tumor regions that influence predictions
- Provides visual explanation for each classification decision
- Critical for clinical adoption and regulatory compliance (explainable AI)

Results: RQ5 - Architecture Comparison



Architecture	Accuracy	Params	Time (s)
Xception	97.87%	21.1M	1,390
DenseNet121	95.88%	7.2M	2,431
ResNet50	32.93%	23.9M	2,416
EfficientNetB0	30.95%	4.2M	1,999

Key Observations:

- Xception significantly outperforms all other architectures for this task
- DenseNet121 shows reasonable performance but lower than Xception
- ResNet50 and EfficientNetB0 fail to generalize - likely need different fine-tuning strategies

Conclusion

- Key Findings:
-     - Xception CNN achieves 99.39% accuracy on brain tumor classification
-     - Meta-learning with shape features improves accuracy to 99.54%
-     - Rule-based engine enables 99.66% accuracy on 89% auto-accepted cases
-     - Grad-CAM provides interpretable visualizations for clinical trust
-
- Limitations:
-     - Single dataset - needs multi-center validation
-     - Limited to 4 tumor types