AI-Driven Innovations in Brain Cancer Research

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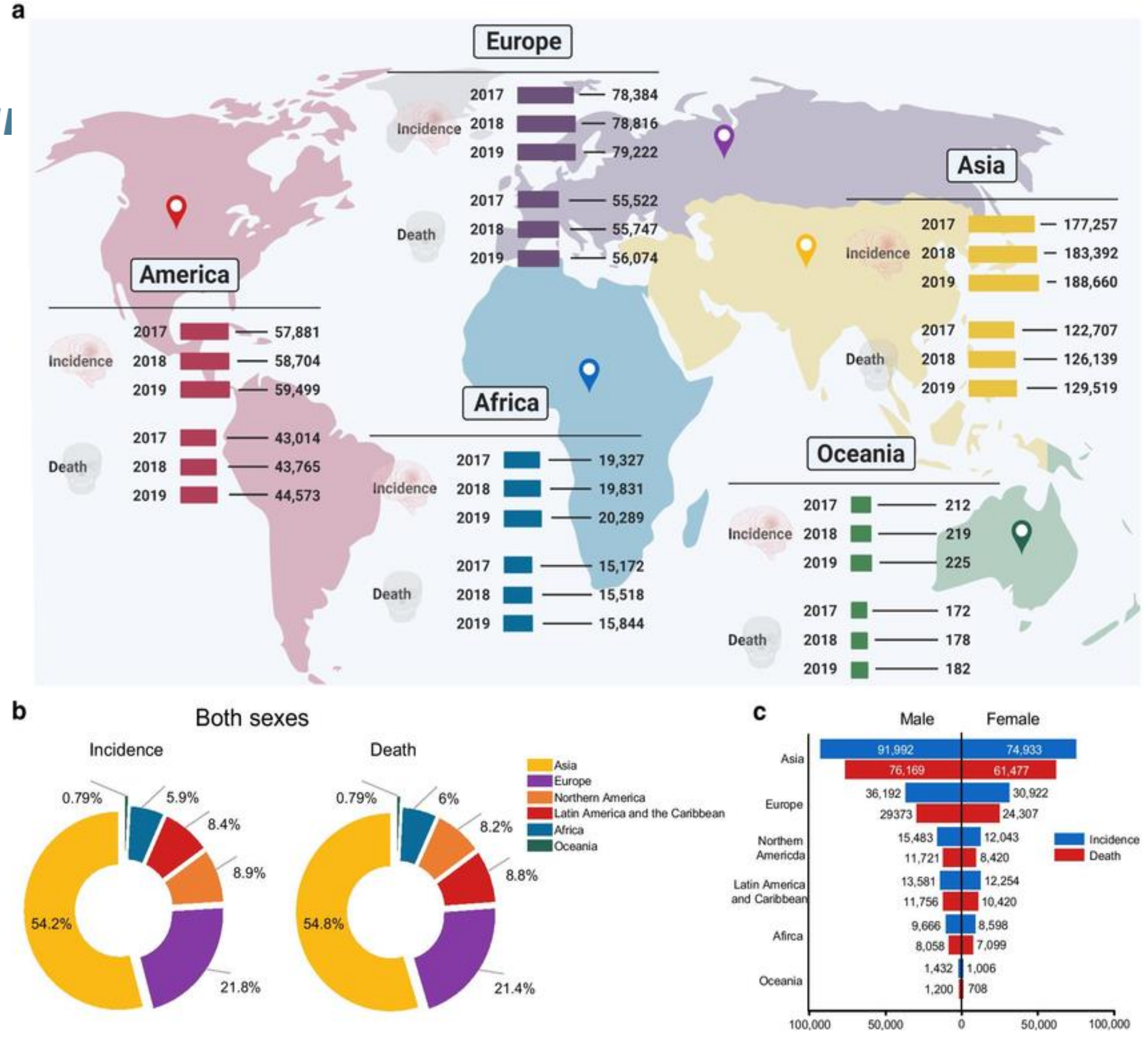
Net4Brain
Let's beat brain cancer together

DONUT

Motivation

- A tumor is an **abnormal growth** of tissues in the brain
- The incidence rate of brain tumor is **increasing** worldwide
- Brain tumor **types**: glioma meningioma, pituitary, etc.
- Trends:
    - Rising **incidence**
    - High **mortality** and **disability**
    - Clinical **complexity**



AI Applications in Brain Cancer

Tissue & Tumor Classification

- Healthy vs malignant tumor tissues,
- Low-grade vs high-grade gliomas.

Tumour Segmentation

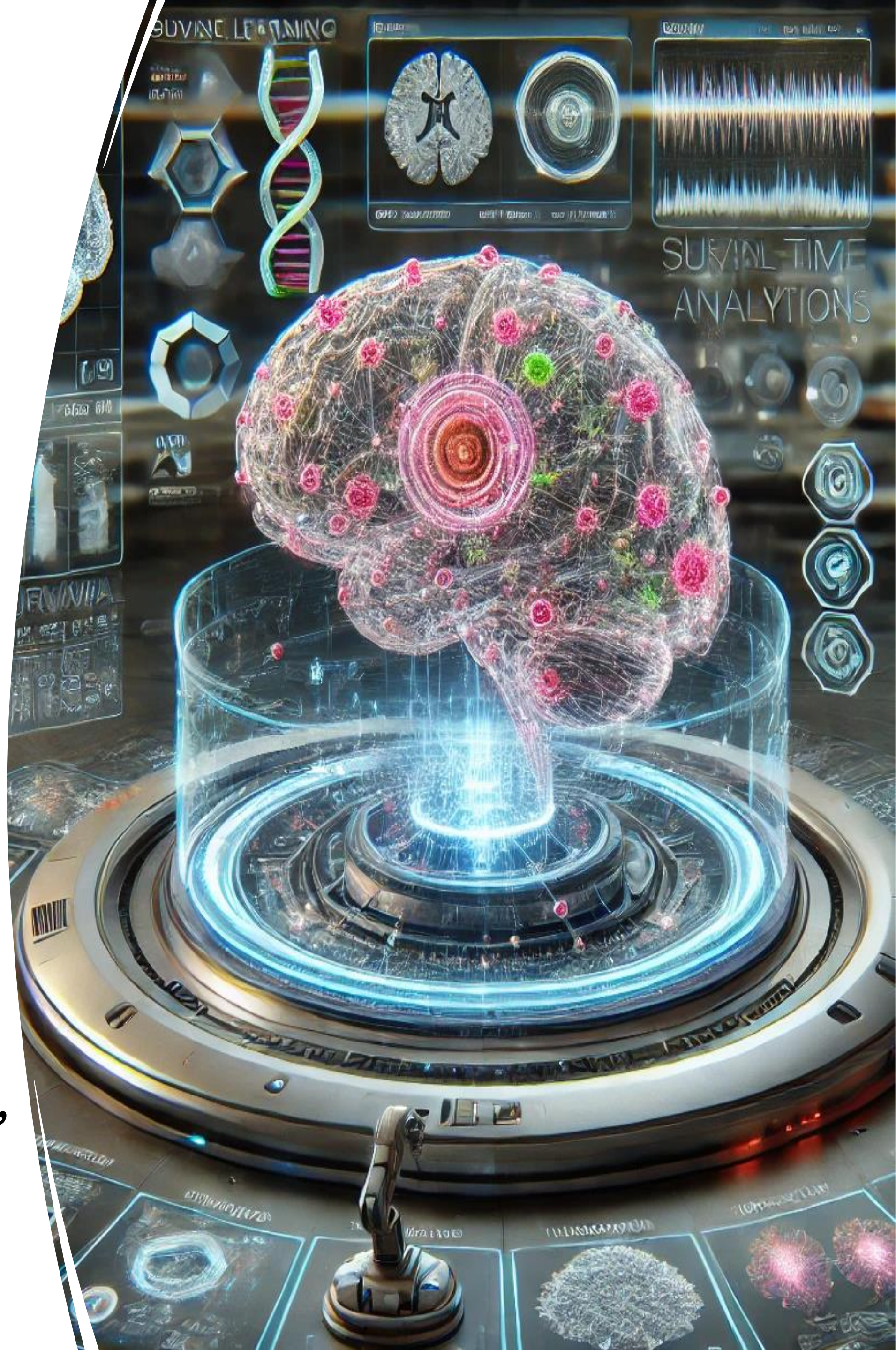
- Identify tumor boundaries from MRI scans.

Explainable AI (XAI)

- Visualize features and regions influencing AI decisions.

Survival Time Prediction

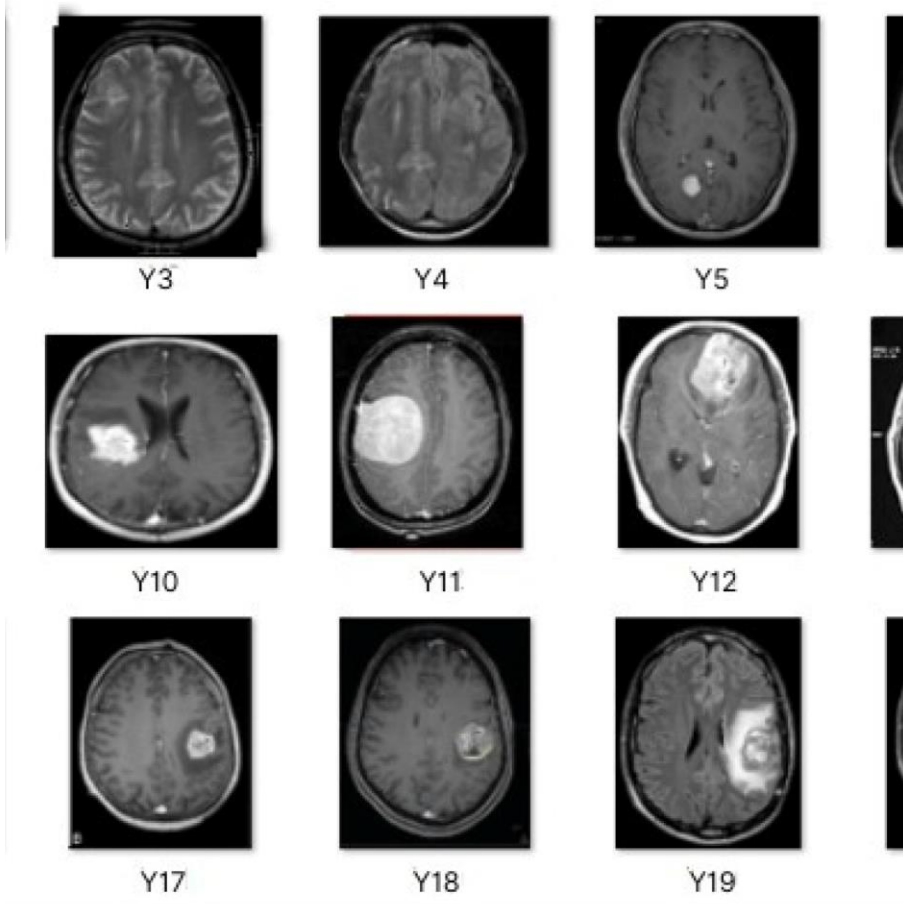
- Predict patient survival time based on tumor volume, age, tumor type, etc.
- Provide data for personalized treatment plans.



Inputs & Outputs for AI Models in Tumor Classification

Inputs:

- **Medical Imaging Data**: MRI scans (T1, T2, FLAIR) offer detailed insights into brain's structure and potential abnormalities.
- **Clinical Data**: Patient demographics (age, gender), medical history, and tumor-related characteristics (size, location).
- **Histopathological Data**: biopsy data or molecular profiles.

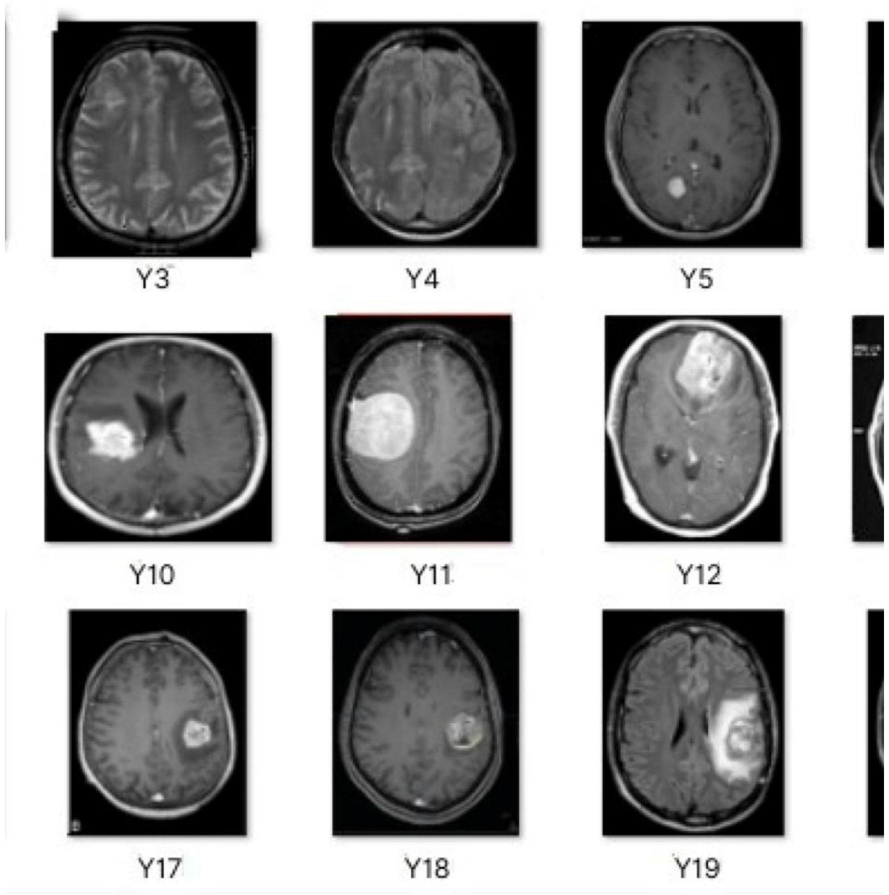


Normal Brain MRI (Y3 to Y5) Benign tumor MRI (Y10 to Y112) Malignant tumor MRI (Y17 to Y19)

Inputs & Outputs for AI Models in Tumor Classification

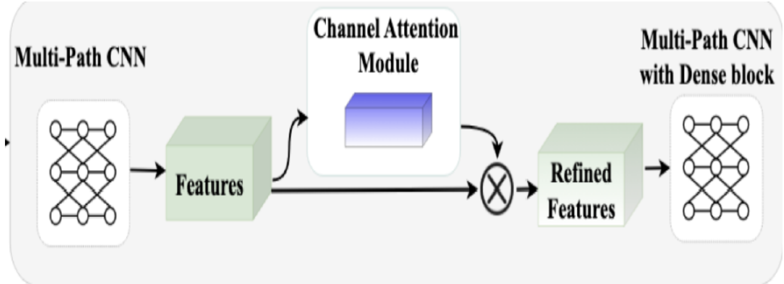
Outputs:

- **Tumor Type**:
  - **Binary** classification (e.g., glioma vs. non-glioma),
  - M**ulti-class** (low-grade vs. high-grade glioma), or
  - Differentiate between **specific subtypes** of tumors (e.g., astrocytoma, oligodendroglioma).
- **Tumor Grade**:
  - Classification into **grades** (I-IV) based on aggressiveness of tumor.
- **Probability Scores**:
  - **Confidence score** that indicates likelihood of tumor belonging to a certain class.



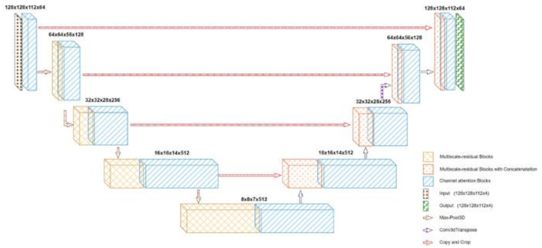
Normal Brain MRI (Y3 to Y5) Benign tumor MRI (Y10 to Y112) Malignant tumor MRI (Y17 to Y19)

Recent Evolution of Deep Learning Models for Brain Tumor Recognition



Hybrid Models Introduced
CNN + attention blocks, self-supervised pretraining strategies emerge.

3D ViTs & Ensemble Architectures
Models like ViT3D, ResViT, UNetFormer dominate benchmarks.



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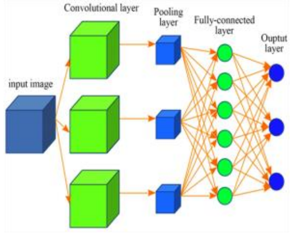
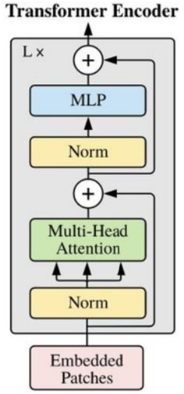
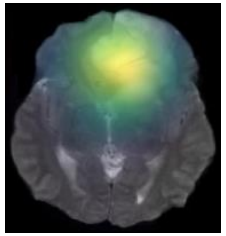


Rise of CNNs
Strong results in classification & segmentation with VGG, ResNet, U-Net.

Vision Transformers Appear
Initial studies with ViT, Swin-T, and transformer-based 2D models.





Multimodal Fusion & Explainability
Integration of MRI + PET/clinical metadata with explainable AI.

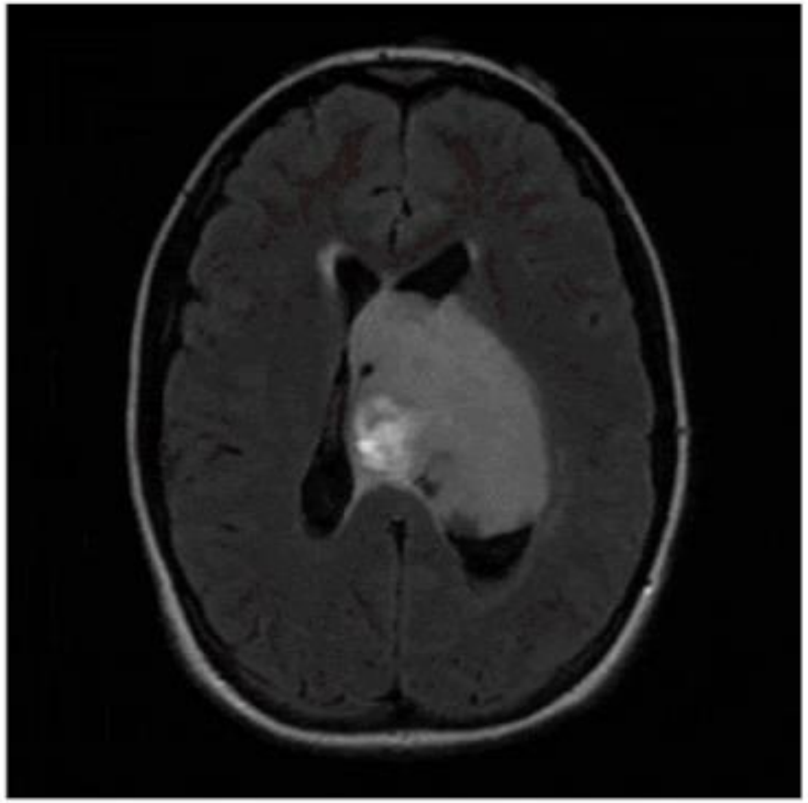
Brain MRI Feature Extraction using Deep Convolutional Neural Network (CNN)

Hierarchical Feature Learning:

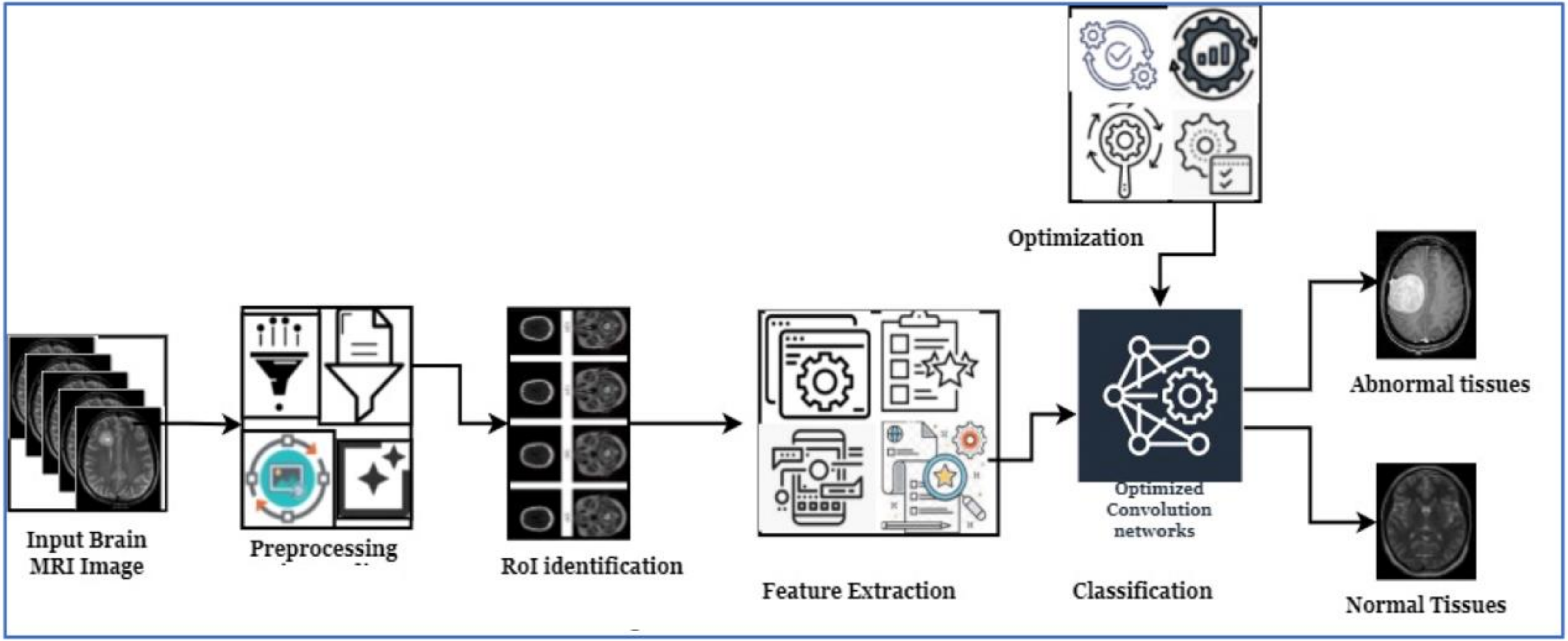
- Learn **low-level** (edges, textures, contrasts),
- **mid-level** (shapes, structures), and
- **high-leve**l (tumor regions, anatomical features) representations from MRI scans.

Extract Spatial and Structural Features:

- **Fine-grained texture features** that differentiate between healthy and abnormal brain tissues.



Typical Workflow of Brain Tumor Classification



Kurdi, S.Z.; Ali, M.H.; Jaber, M.M.; Saba, T.; Rehman, A.; **Damaševičius, R**. **Brain Tumor Classification Using Meta-Heuristic Optimized Convolutional Neural Networks.** *J. Pers. Med. 2023,* 13, 181. https://doi.org/10.3390/jpm13020181

Brain Tumor Localization by Image Segmentation

Partitioning a brain image into multiple regions to isolate and identify specific Areas of Interest (AoI)

- Better understanding of brain structures
- Accurate diagnosis & treatment planning
- Monitoring disease progression

Tumor heterogeneity:

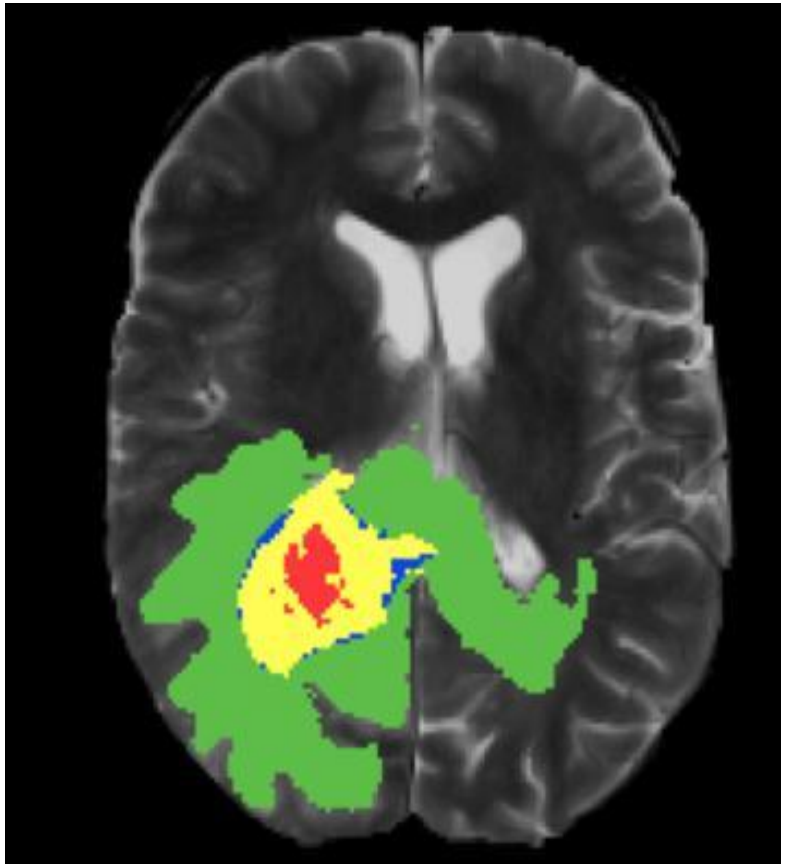
- Brain tumors vary greatly in shape, size, and appearance
- Variability makes segmentation challenging

Manual segmentation challenges:

- Labor-intensive and time-consuming, inconsistent results

AI solutions:

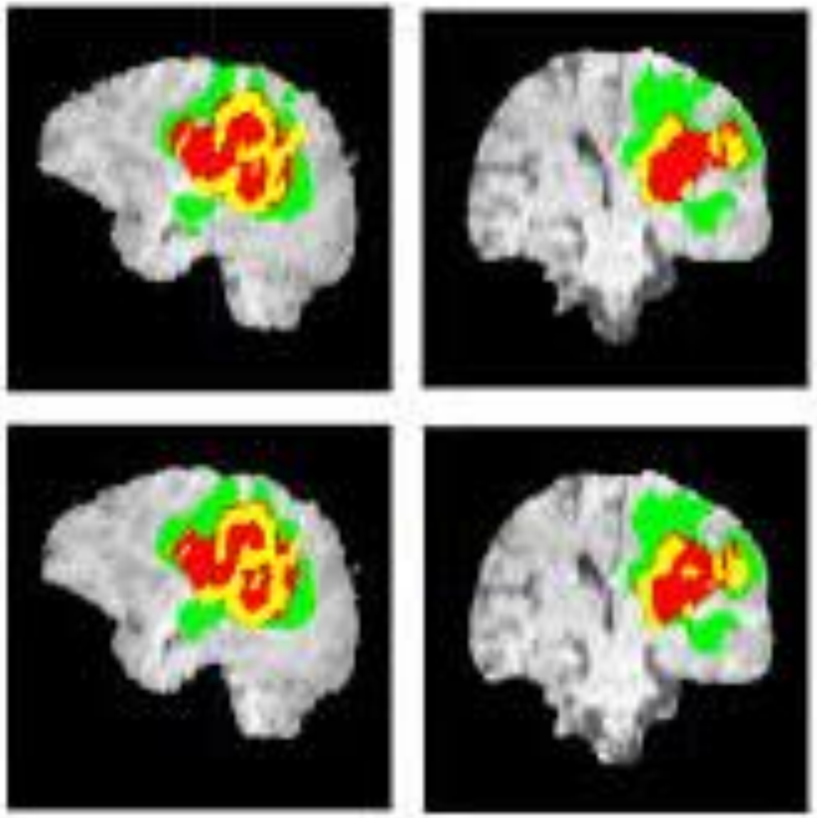
- Automate tumor segmentation
- Identifying tumor boundaries



Inputs & Outputs for AI Models in Brain Tumor Segmentation

Inputs for AI Models in Brain Tumor Segmentation

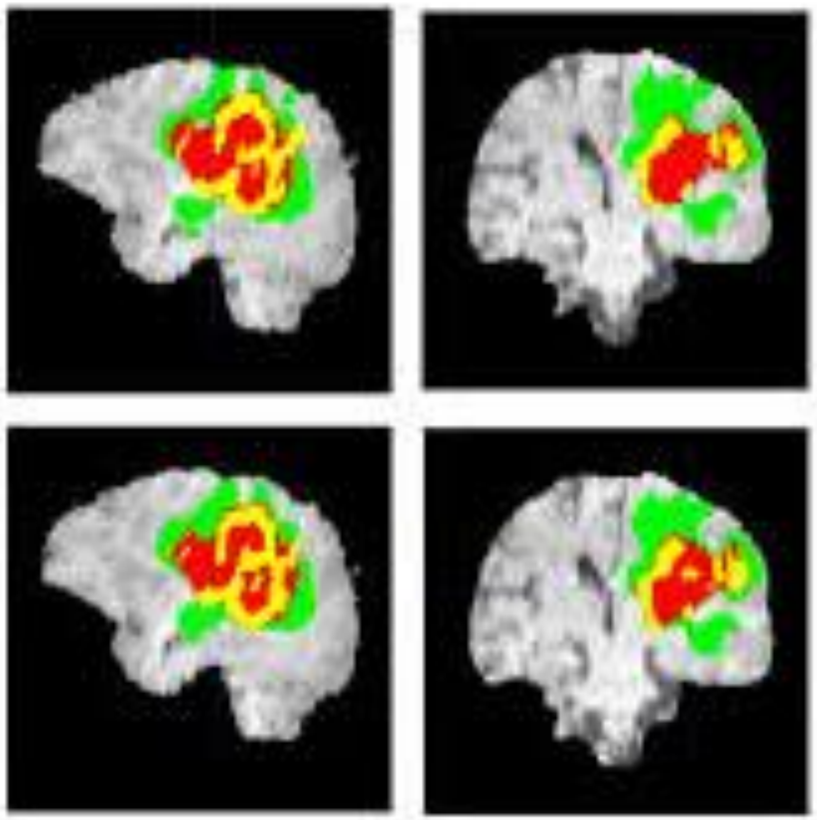
- **Medical Imaging Data**: MRI scans are the most common type of input data used for brain tumor segmentation.
- **Preprocessing Information**: enhance contrast, remove noise, and standardize the imaging format, which ensures that the AI model can effectively interpret the images.
- **Clinical Information (Optional)**: patient's age, medical history, or previous treatment outcomes.



Inputs & Outputs for AI Models in Brain Tumor Segmentation

Outputs of AI Models in Brain Tumor Segmentation

- **Segmented Tumor Regions**: A colored segmentation **map** that separates tumor from surrounding healthy tissue.
- **Quantitative Metrics**: tumor's size, shape, and volume, vital for diagnosis, disease monitoring and treatment planning.

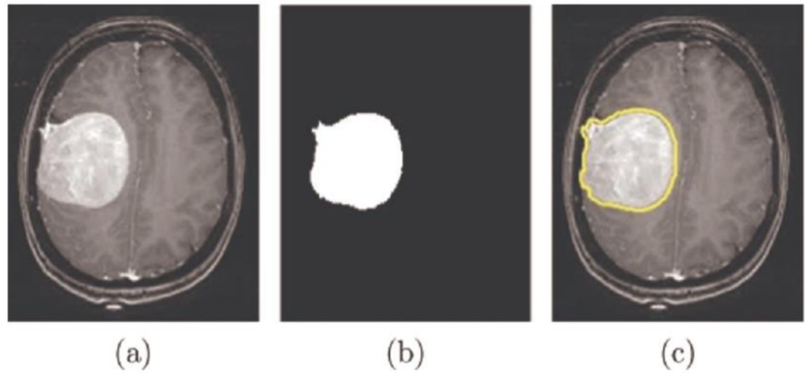


Example: Brain Tumor Localization using Fuzzy Edge Detection

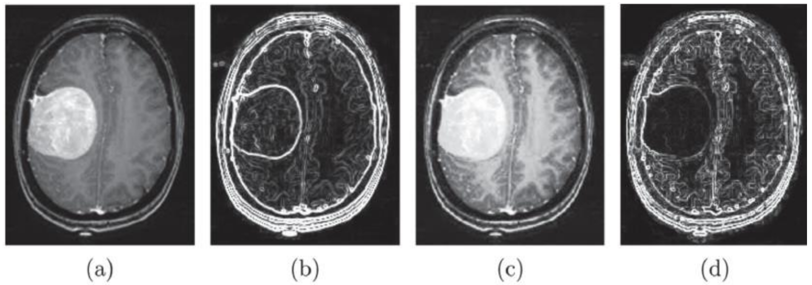
Objective: Identify and extract tumor regions from brain MRI scans.

Fuzzy Edge Detection Method

- **Fuzzy Logic**: handle **uncertainty** and **imprecision** in identifying boundaries between tumor and healthy tissues.
- **Edge Detection**: Locates tumor **edges** in MRI scans.



brain image. (a) Source image, (b) Tumor segmented image, and (c) Tumor extraction.



Edge detection results. (a) Source brain MRI, (b) Gradient of (a) using fuzzy edge detection, (c) Contrast enhancement using NMHE [30], and (d) Gradient of (c) using fuzzy edge detection.

Maqsood, S., Damasevicius, R., Shah, F.M. (2021). **An Efficient Approach for the Detection of Brain Tumor Using Fuzzy Logic and U-NET CNN Classification.** *ICCSA 2021*. https://doi.org/10.1007/978-3-030-86976-2_8

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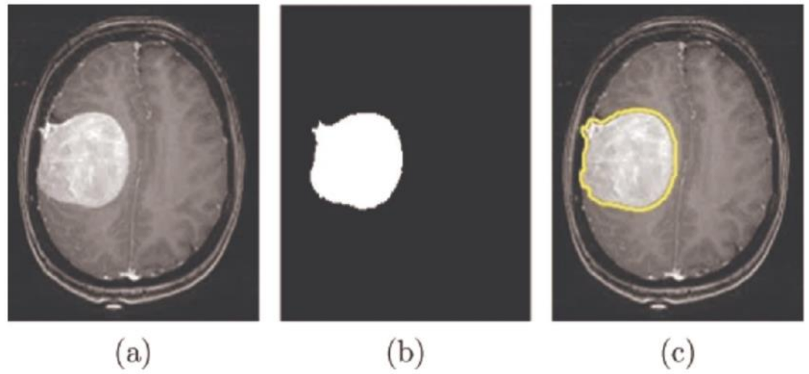

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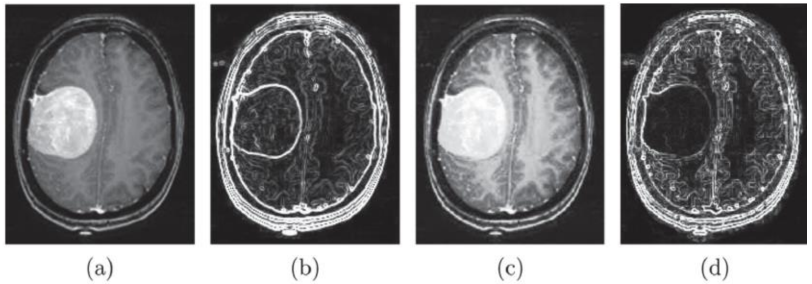
Steps in Fuzzy Edge Detection for Tumor Segmentation

- **Contrast enhancement** to improve image clarity.
- **Fuzzy Rules** to detect edges in image.
- **3x3 Convolution Mask** to extract neighborhood of pixels.
- **Fuzzy Inference** converts pixels into fuzzy domain to detect edges.
- **Fuzzy Edge Patterns** identify edge shapes in tumor region.



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Integration of Classification and Segmentation Tasks for Multimodal Analysis Using AI Models

Multimodal analysis

- Various types of input data (MRI modalities - T1-weighted, T2-weighted, and FLAIR) to improve both segmentation and classification accuracy.
- **Segmentation** identifies and extracts the tumor region from the MRI scan.
- **Classification** determines type and grade of the tumor based on extracted features from segmented regions.

Inputs for Multimodal Analysis

- **Multiple MRI Modalities** (T1, T2, FLAIR) provide detailed structural views of brain and tumor.
- **Clinical Data**: Patient demographics, medical history, and genetic information (optional) can be incorporated to refine AI predictions.

Integration of Classification and Segmentation Tasks for Multimodal Analysis Using AI Models

Deep Learning Models

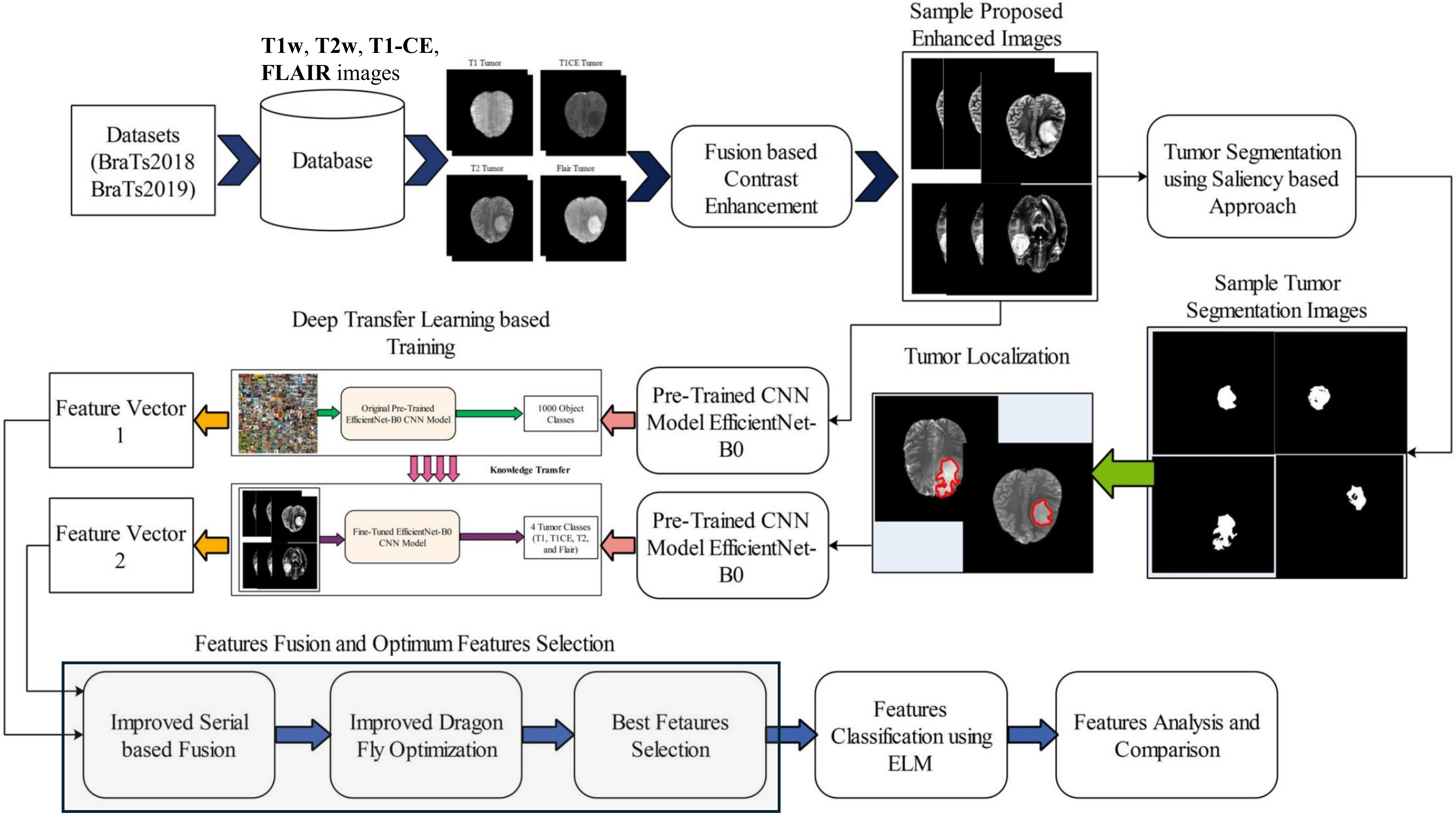
- **CNNs**: for both segmentation (to identify tumor boundaries) and classification (to categorize tumor types and grades).
- **Transfer Learning**: Pre-trained models are fine-tuned on medical datasets, reducing training time and improving accuracy.
- **Fusion Techniques**: Fuse features from different modalities for a more robust and comprehensive analysis.

Integration of Classification and Segmentation Tasks for Multimodal Analysis Using AI Models

Outputs:

- **Tumor Segmentation Maps**: The AI model generates precise segmentation maps that highlight the tumor's location and extent within the brain.
- **Tumor Classification**: Outputs include tumor type (e.g., glioma vs. meningioma) and tumor grade (I-IV), which are crucial for determining treatment approaches.
- **Quantitative Metrics**: Models output metrics like tumor size and volume, which are essential for tracking progression.

Multimodal MRI Image Analysis and Feature Fusion Workflow



Khan, M. A., Khan, A., Alhaisoni, M., Alqahtani, A., Alsubai, S., Alharbi, M., Malik, N. A., & **Damaševičius, R.** (2022). **Multimodal brain tumor detection and classification using deep saliency map and improved dragonfly optimization algorithm.** *International Journal of Imaging Systems and Technology* (Vol. 33, Issue 2, pp. 572–587).

Brain Image Segmentation Results

Original Images (*First* Column):

- Raw brain MRI scans.
- Limited contrast and noisy, blurry tumor boundaries.

Enhanced Images (*Second* Column):

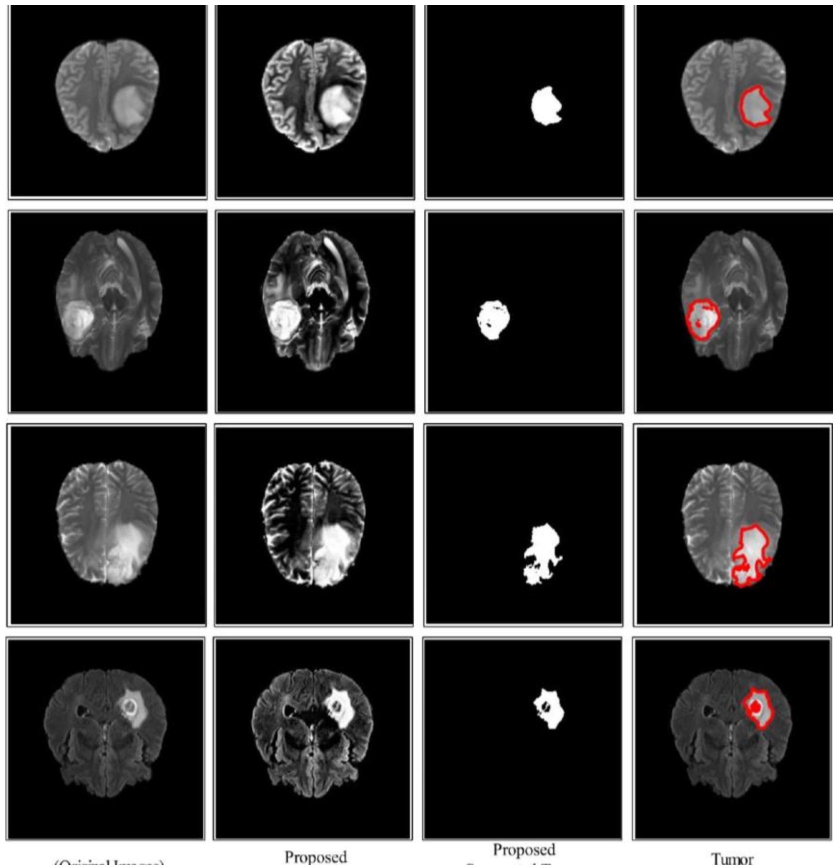
- Contrast-enhanced images for improved visibility of tumor
- Key features of the tumor become more distinguishable.

Segmented Tumor Region (*Third* Column):

- AI model isolates and segments the tumor region.
- Provides visualization of tumor size and shape for diagnosis.

Tumor Localization (*Fourth* Column):

- Final result with tumor boundaries outlined in red.
- Accurately pinpoints tumor's position within the brain.



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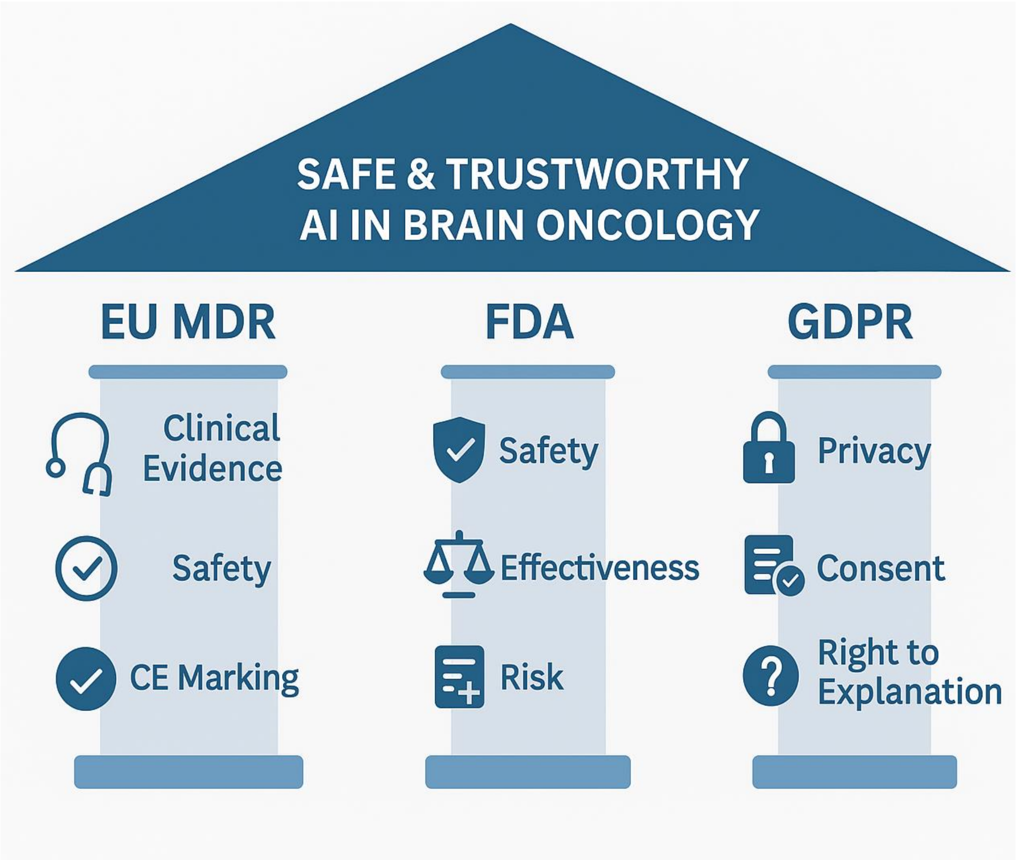
Regulations for Deploying AI in Brain Oncology

EU MDR (European Union Medical Device Regulation)

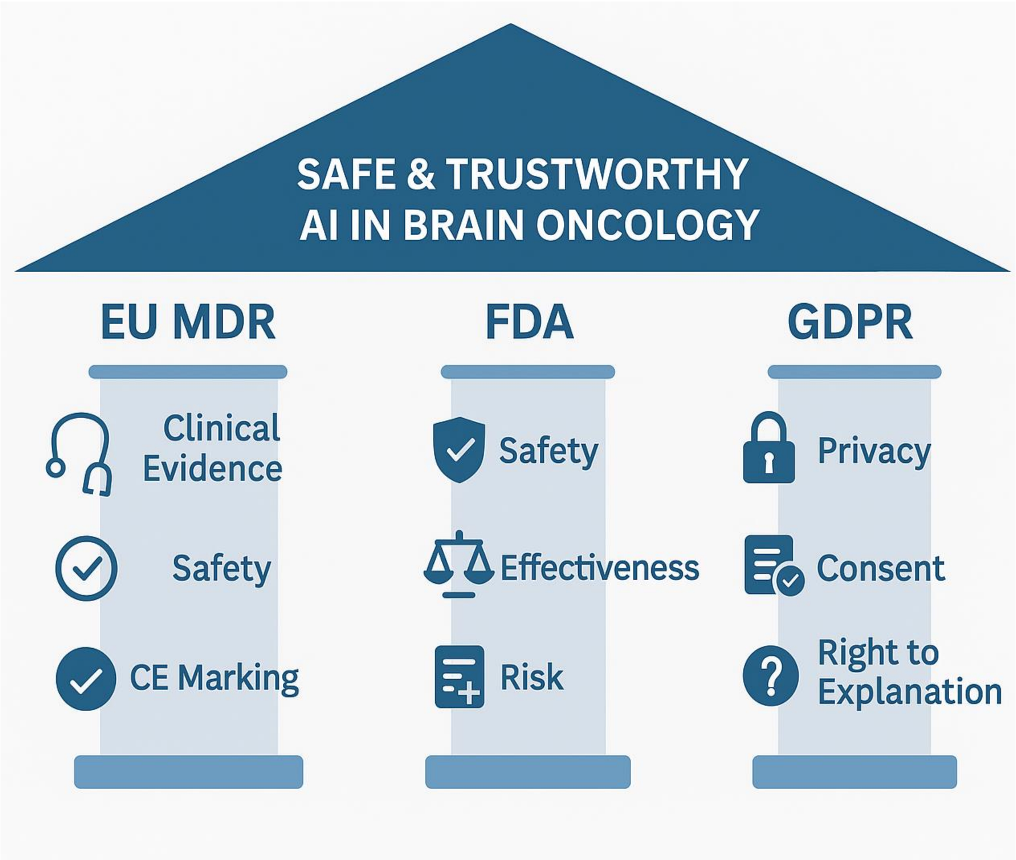
- Governs medical devices and diagnostic systems in the EU, including **AI-based software** for medical purposes.
- Requires **clinical evidence**, **safety validation**, and often **explainability** of algorithms before approval.
- AI diagnostic tools classified as **medical devices** and must undergo conformity assessment and CE marking.



Regulations for Deploying AI in Brain Oncology

FDA (U.S. Food and Drug Administration)

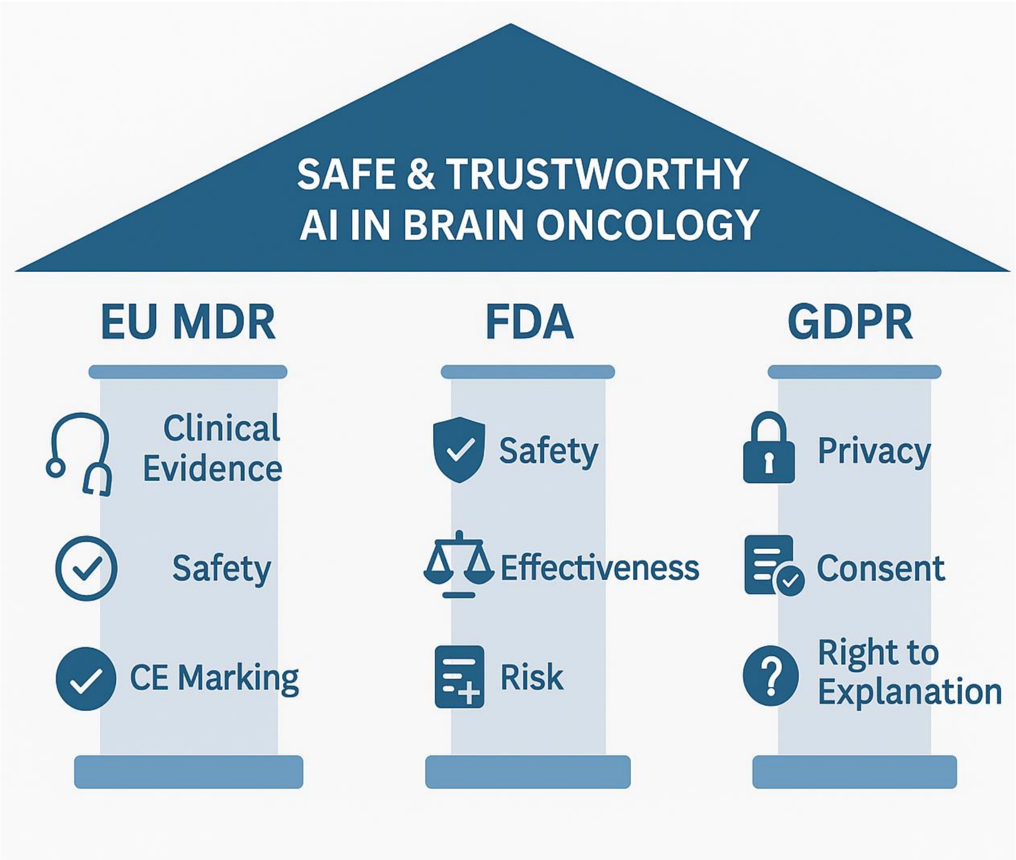
- Evaluates **safety, effectiveness, generalizability, and risk management** of algorithms.
- **Software as a Medical Device (SaMD)**, covering adaptive AI/ML models that continuously learn after deployment.



Regulations for Deploying AI in Brain Oncology

GDPR (General Data Protection Regulation)

- Includes the **“right to explanation”**: patients can demand to know how algorithmic decisions about their health were made.
- Requires **data anonymization, and consent management** in AI-driven medical research.



Black-box Nature of AI Models and Need for XAI (eXplainable AI)

Black-box AI models lack transparency and interpretability in their decision-making processes.

- Understand how AI models arrive at predictions.
- Lack of transparency limits adoption in clinical settings.

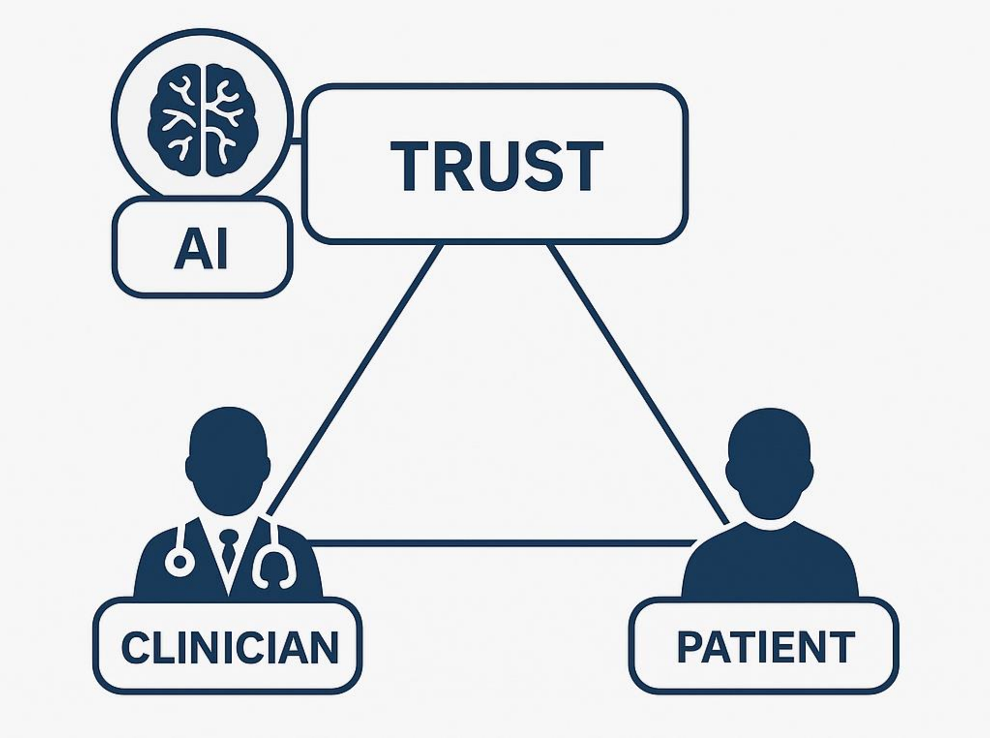
Challenges of Black-box AI in Healthcare

- **Trust**: Cannot rely on AI models if cannot understand or validate results.
- **Accountability**: Difficult to assign responsibility in cases of errors or adverse outcomes.
- **Regulatory Barriers**: Proving safety of AI models for regulatory approval.

Kazimir Malevich, **Black Square**, 1915

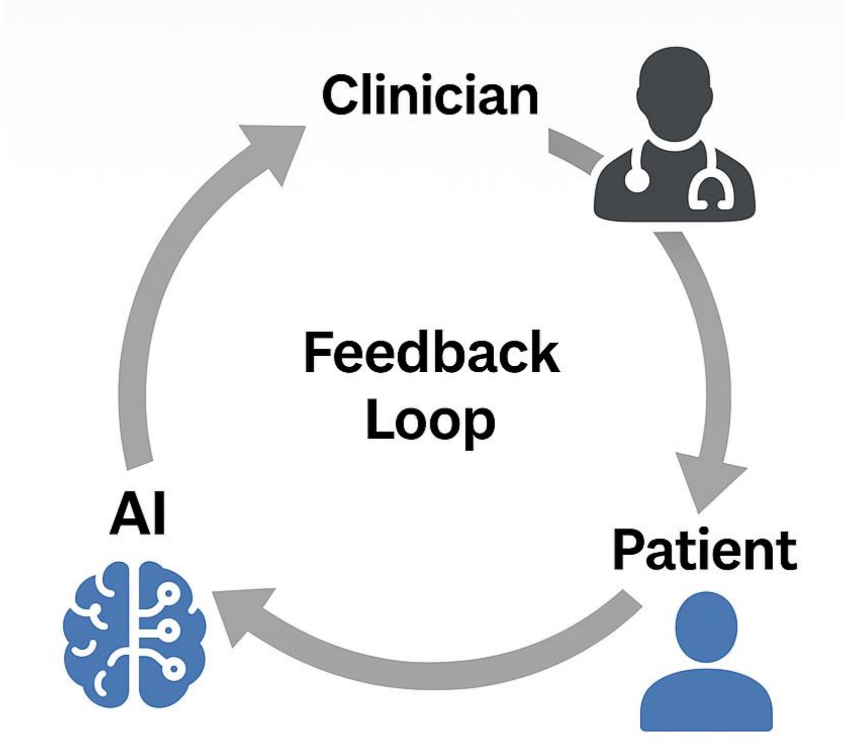
Why AI Explainability Matters?

- Transparent **reasoning** to integrate AI outputs into diagnostic workflows.
- Reduce **risk of misdiagnosis** and ensures **accountability** in life-critical decisions for patient safety.
- **Explain** predictions across MRI image modalities.
- **Regulatory compliance** to satisfy EU MDR & GDPR requirements such as for informed consent.



Human-in-the-Loop in Brain Tumor Recognition

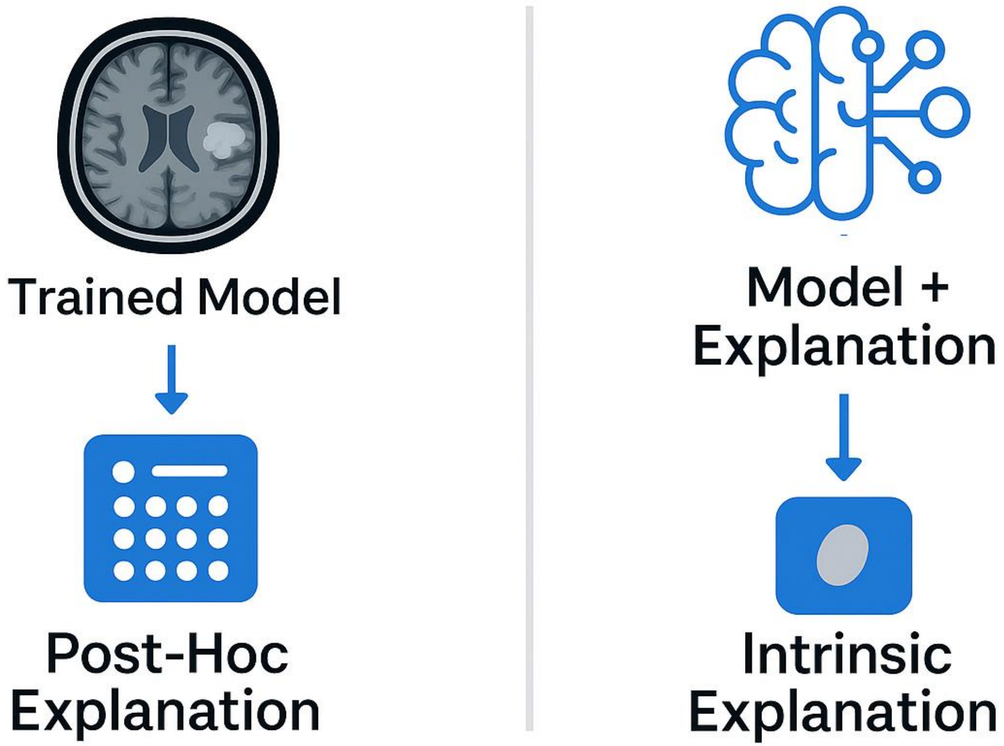
- **Collaborative decision-making:** AI suggests, clinicians validate, adjust, or override outputs.
- **Human oversight** reduces risks of false positives/negatives in diagnosis and segmentation.
- Expert corrections to retrain and fine-tune AI models in **continuous feedback loop**.
- Human experts identify spurious correlations or clinically implausible features flagged by AI.
- Meets **regulatory requirements** by ensuring AI is a support tool, not an autonomous diagnostic authority.



Two Ways to Explain: Post-Hoc vs Intrinsic

Post-Hoc Explainability

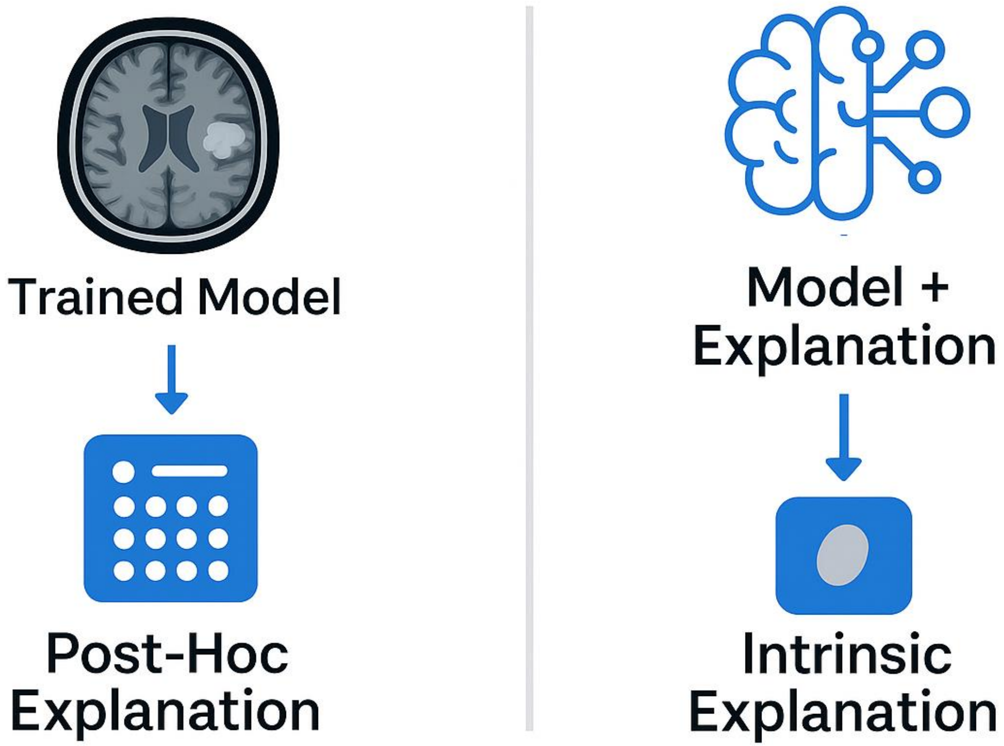
- Explanation generated **after prediction**
- Works with any pre-trained CNN
- <u>**Strength**</u>: **flexible, model-agnostic**
- <u>**Limitation**</u>: separate from training, explanations are an **add-on**



Two Ways to Explain: Post-Hoc vs Intrinsic

Intrinsic Explainability

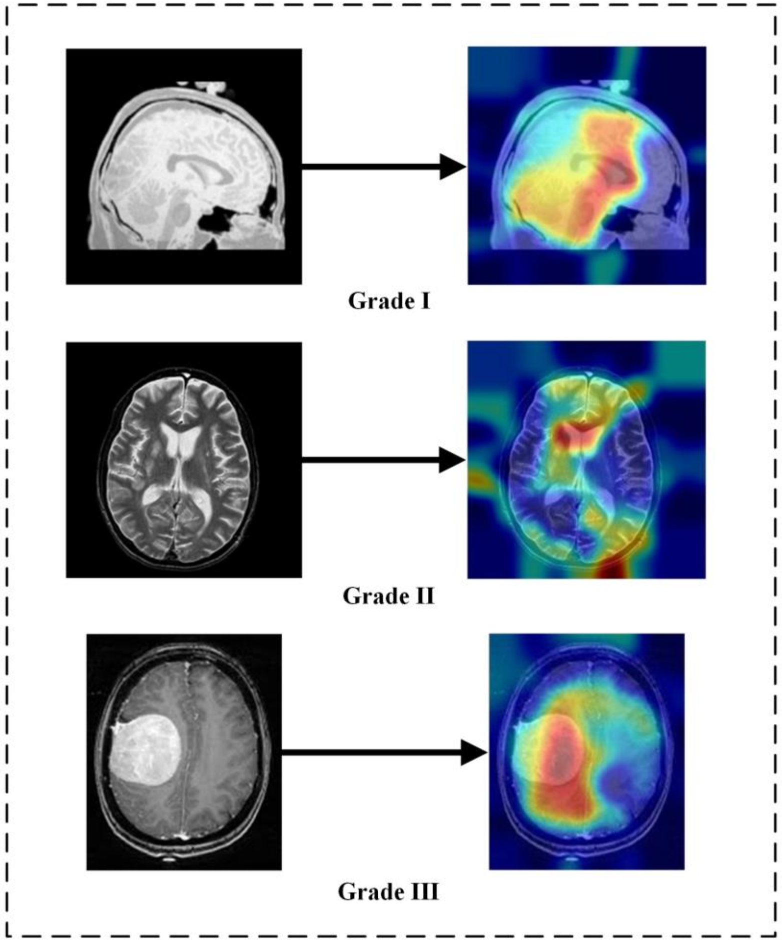
- Explanation built **into the model architecture**
- **Strength**: explanations are **integrated & faithful**
- **Limitation**: requires **custom CNN design**



Post-hoc Explanability using Grad-CAM

Grad-CAM (Gradient-weighted Class Activation Mapping)

- Highlight **<u>important</u>** regions in an image contributing to a model's prediction.
- Computes **gradients** of the class prediction (e.g., tumor) concerning feature maps in the final convolutional layers of the CNN.
- Produces a **heatmap** that overlays on the brain MRI to indicate areas with highest influence on the decision.
- **Highlights** most significant regions in the scan, helping to localize the tumor.



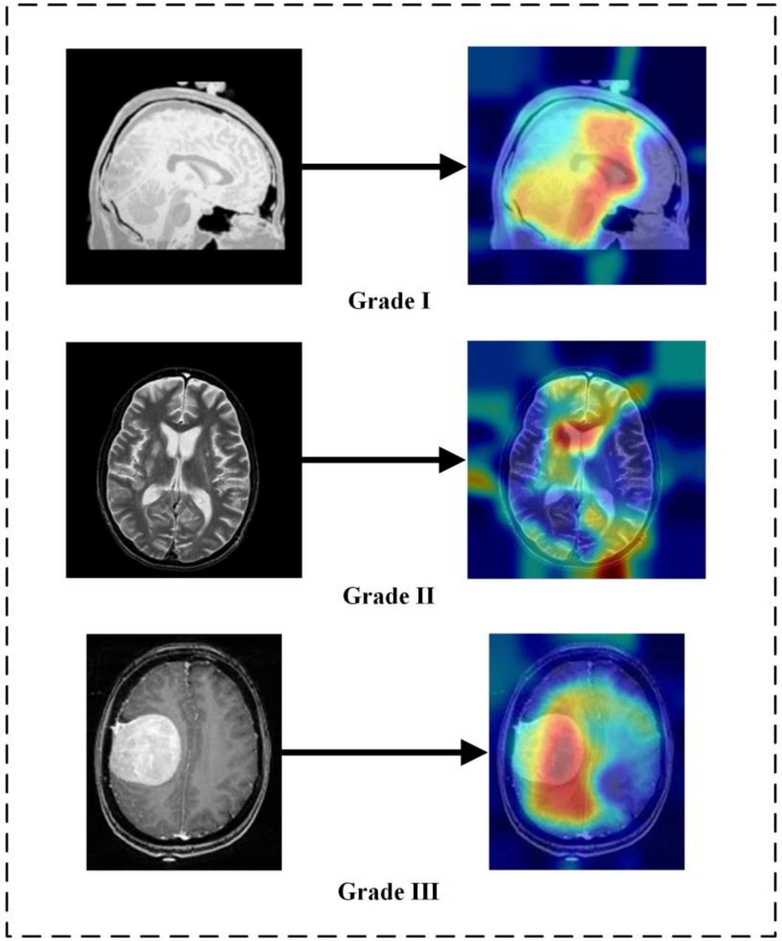
Localization of Tumor using Grad-CAM

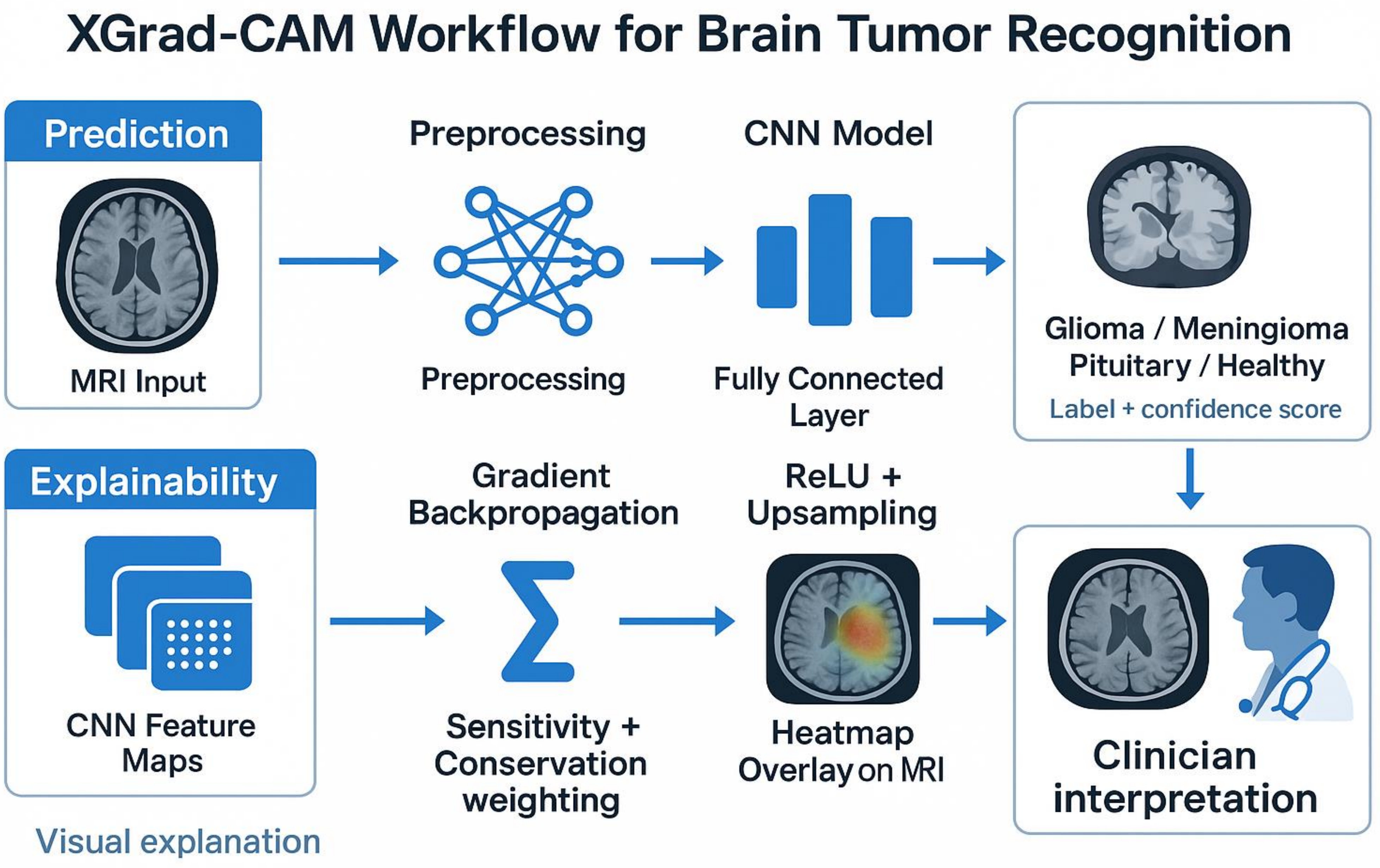
Application of Grad-CAM in Brain Cancer

- Shows **specific** tumor regions within brain MRI scans that AI model has flagged as abnormal tissue.
- Enhances traditional classification methods by adding **localization**.

Benefits of Grad-CAM

- Provides **insight** into how the AI model "sees" the tumor, increasing transparency and trust in AI-based diagnostic tools.
- Helps clinicians **understand** the AI model's decision-making process by showing which parts of the MRI led to a tumor classification decision.





Sara Tehsin, Inzamam Mashood Nasir, **Robertas Damasevicius.** Interpreting CNN for Brain Tumor Classification Using XGrad-Cam. *ARTIIS Workshops* (1) 2024: 282-296

Sensitivity vs Conservation in Explainability

Sensitivity

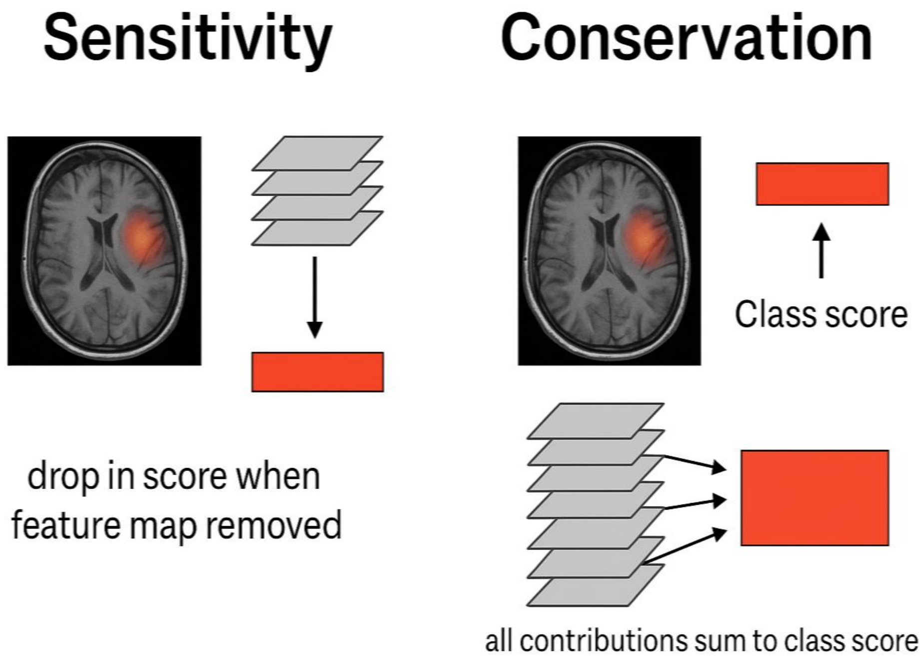
- *If I remove a feature, how much does prediction confidence for the class drop?*
- Measures the **true influence** of each feature map.

Conservation

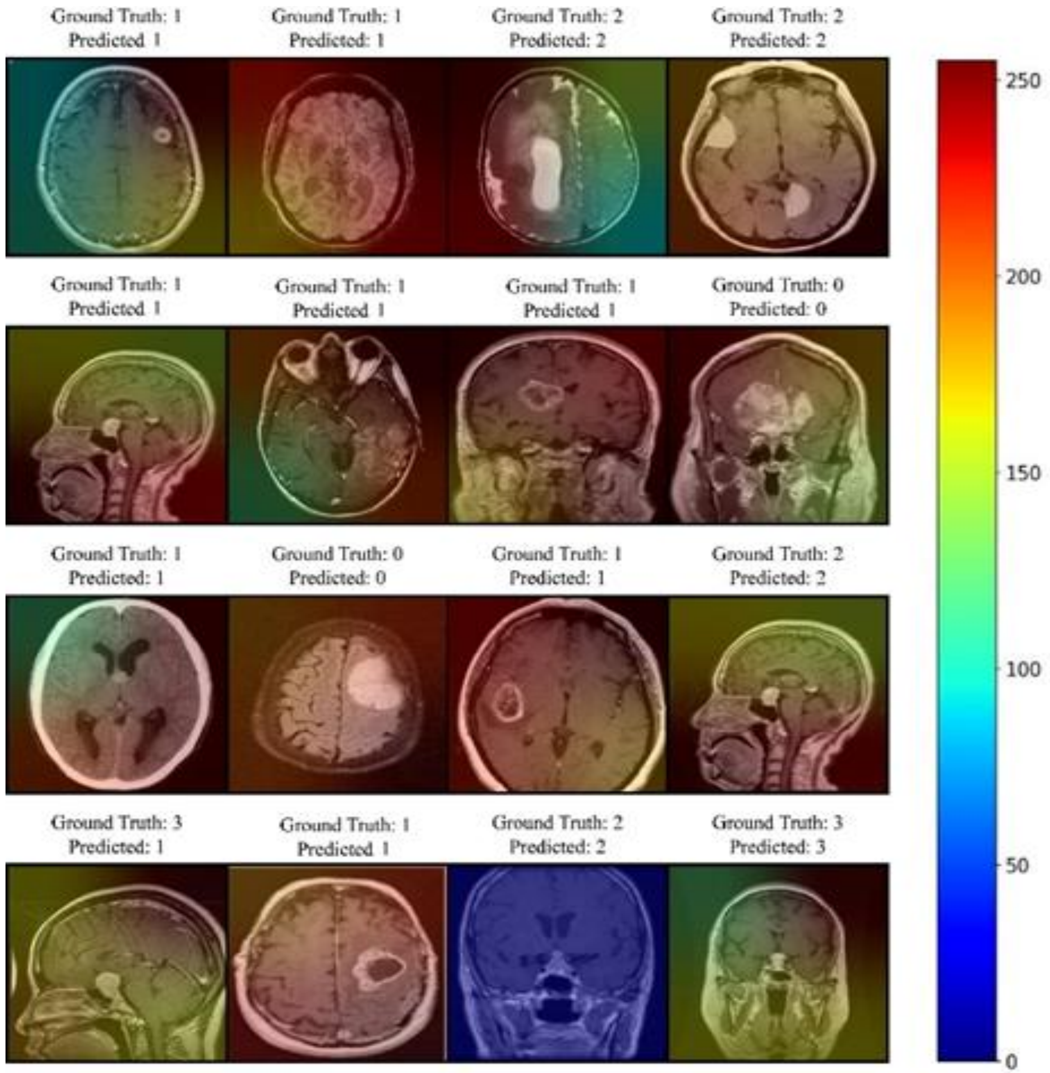
- Enforce that **sum of feature contributions equals class score**
- Prevent explanations from drifting away from decisions of CNN.

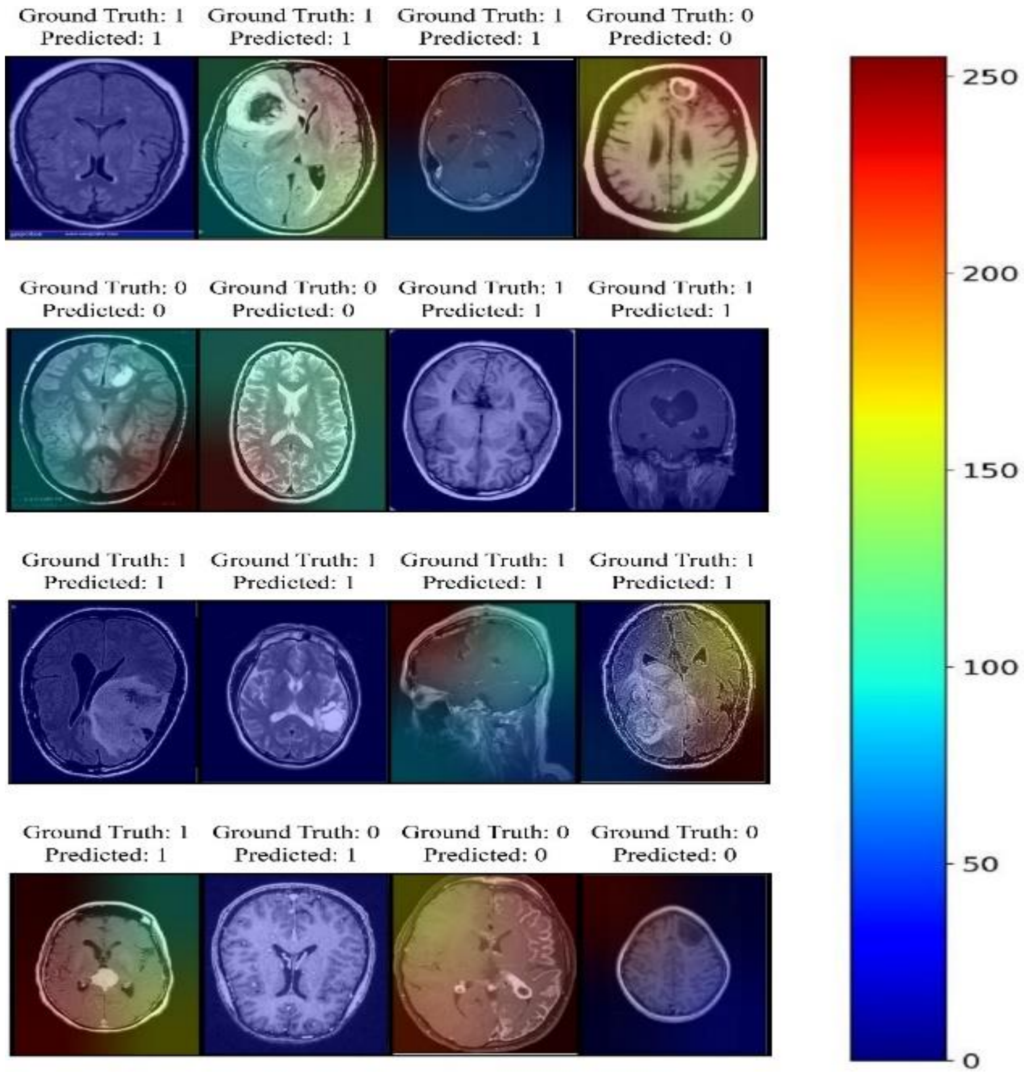
In XGrad-CAM:

- **Sensitivity** ensures *relevance*: only feature maps that truly affect the prediction are emphasized.
- **Conservation** ensures *faithfulness*: explanation accounts for optimal prediction score



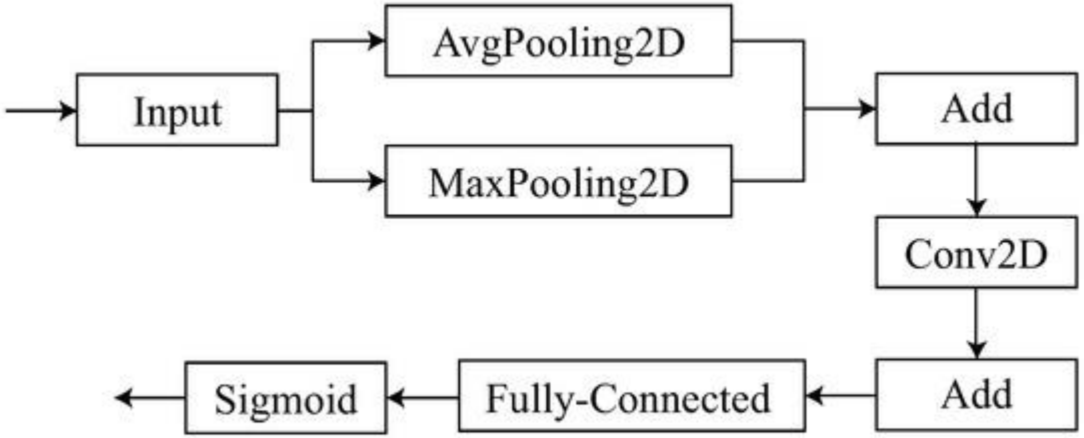
X-Grad Cam Visualization Results

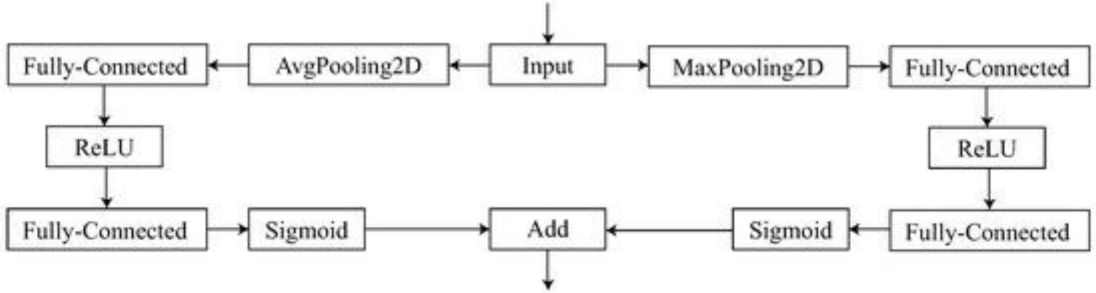




<u>Intrinsic Explainability</u> Using DaSAM (Disease and Spatial Attention Module)

- **DASAM**: A custom CNN architecture enhanced with **two attention modules**:
  - **Disease Attention Module (DAM):** Filters out irrelevant areas, focusing only on tumor-related regions.
  - **Spatial Attention Module (SAM):** Learns which spatial features across channels are most discriminative for tumor types.
- Attention maps are generated **during feature learning**, not after prediction.
- Produces interpretable feature maps showing *where the network is focusing*



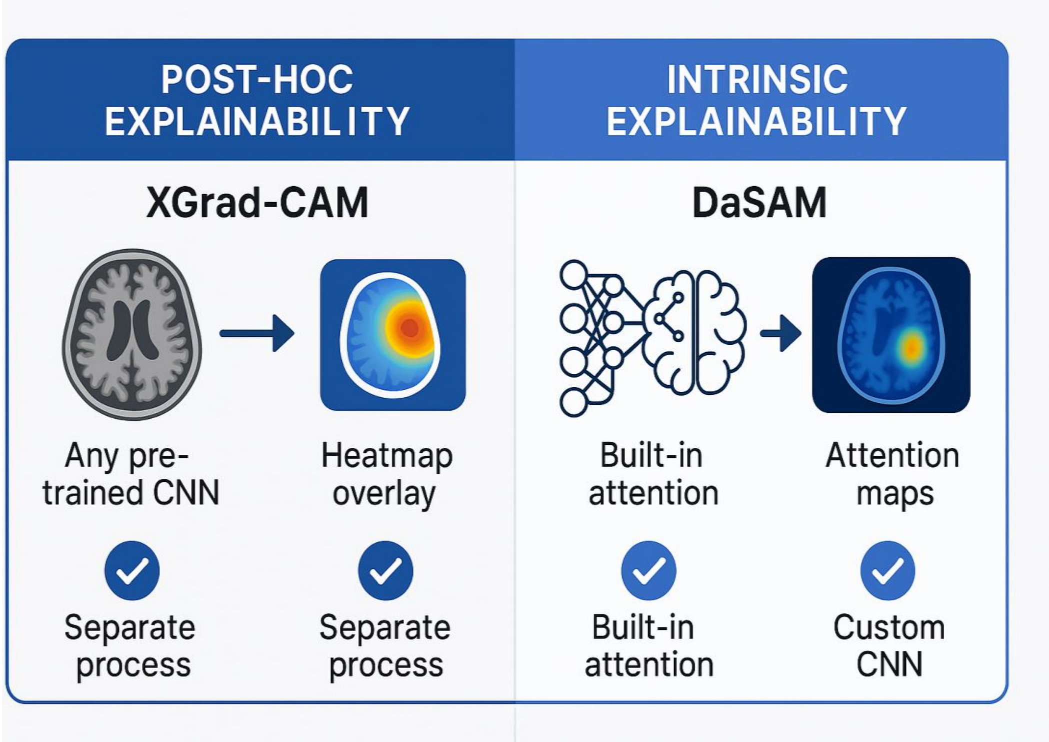


Tehsin, S., Nasir, I. M., **<u>Damaševičius, R.,</u>** & Maskeliūnas, R. (2024). **DaSAM: Disease and Spatial Attention Module-Based Explainable Model for Brain Tumor Detection.** *Big Data and Cognitive Computing,* 8(9), 97. https://doi.org/10.3390/bdcc8090097

Intrinsic Explainability Using DaSAM (Disease and Spatial Attention Module)

- **XGrad-CAM**: **Post-hoc explanation** method.
  - Works after prediction, backpropagating gradients to create a heatmap of influential regions.
  - **Strength**: faithful attribution using sensitivity + conservation.
  - **Limitation**: explanation is separate from model.

- **DaSAM**: **Intrinsic explainability** approach.
  - Builds interpretability *into the model itself*.
  - **Strength**: explanations are part of the feature extraction process, not an afterthought.
  - **Limitation**: requires custom CNN design



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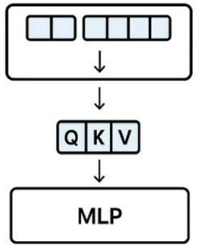
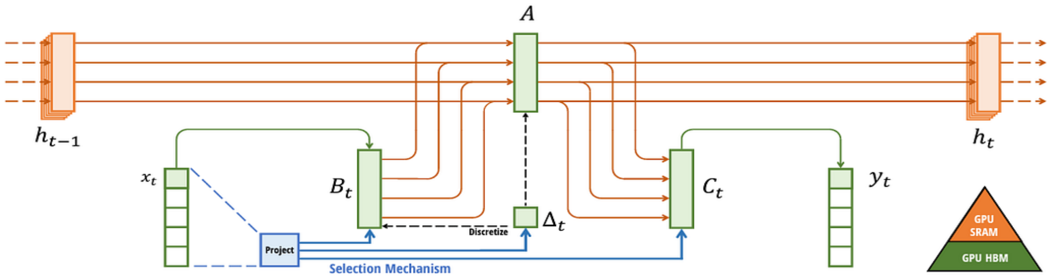
State-Of-The-Art Deep Learning Models for Brain Tumors

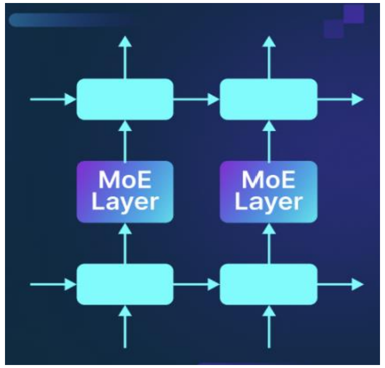
- **Vision Transformers (ViTs)** – capture **global context** across image



- **Mamba (State-Space Models) –long-range dependency modeling** with **linear efficiency**

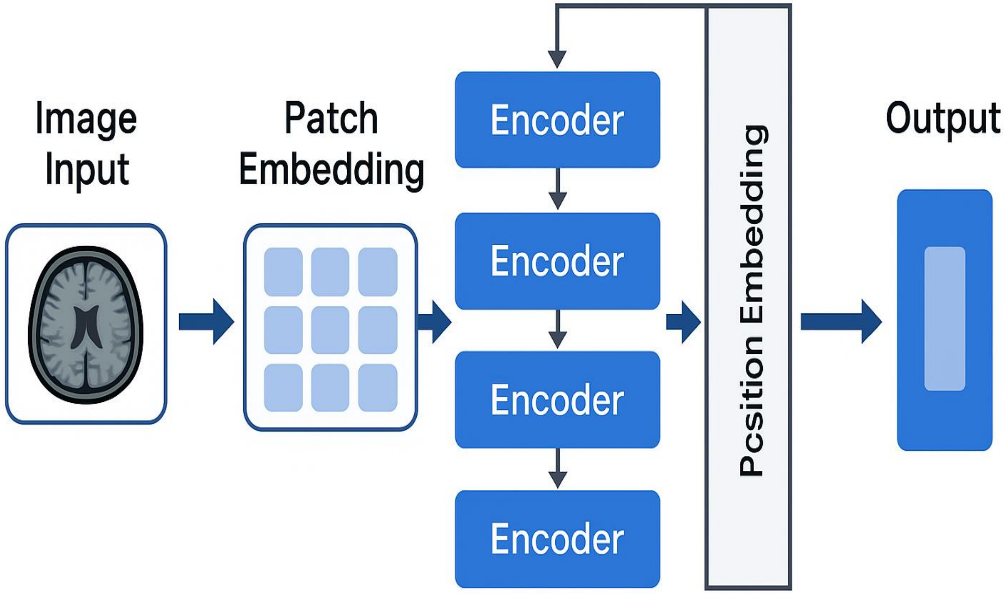


- **Mixture of Experts (MoE)** – route data to **specialized subnetworks**

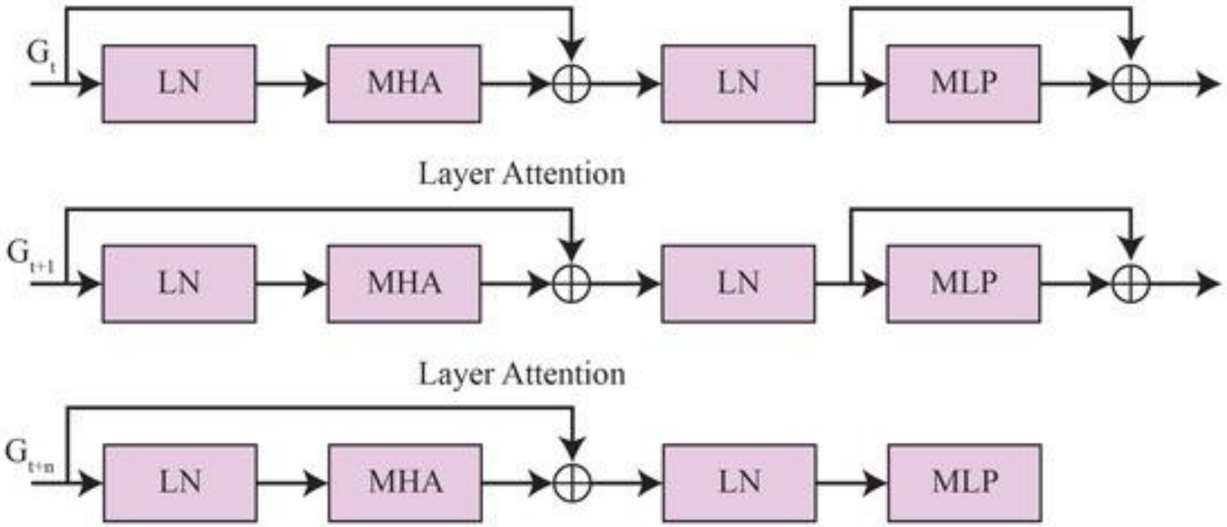


Explainable Transformers for Brain Tumor Detection

- Capture **long-range dependencies** through self-attention.
- **Patch Embedding**: each image is divided into fixed-size patches and projected into a feature vector
- **Positional Encoding**: restores spatial information *where* each patch belongs in image.
- Each encoder layer has **multi-head self-attention.**
- Self-attention lets each patch attend to all others, capturing **long-range dependencies**
- Multi-head design learns different types of relationships
- Attention maps from self-attention can be visualized as **explainability heatmaps** overlaid on the MRI.
- Better understanding of both **global tumor context** and **local fine-grained structures**



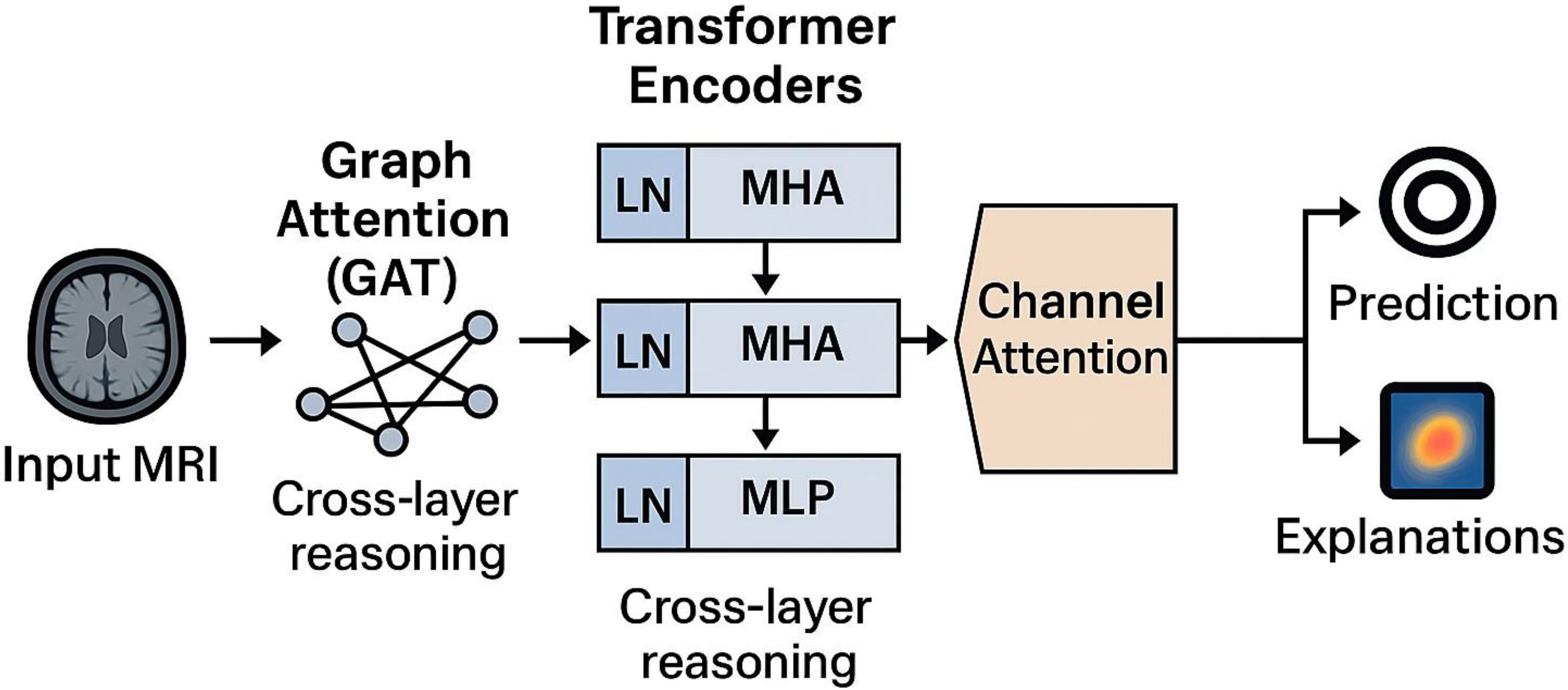
The GATransformer



- Integrates **Graph Attention Networks (GAT)** with Transformers.
- GAT identifies **relationships between neural network channels**, i.e., which features matter most.
- The Transformer then computes **inter-channel correlations across layers**, enabling cross-layer reasoning.
- A **channel attention module** highlights critical channels and prunes redundant ones.
- Unlike black-box CNNs, pruning process produces **explainable importance scores**.

Tehsin, S., Nasir, I. M., & **Damaševičius, R**. (2025). **GATransformer: A Graph Attention Network-Based Transformer Model to Generate Explainable Attentions for Brain Tumor Detection.** *Algorithms*, 18(2), 89. https://doi.org/10.3390/a18020089

Explainability Workflow with GATransformer



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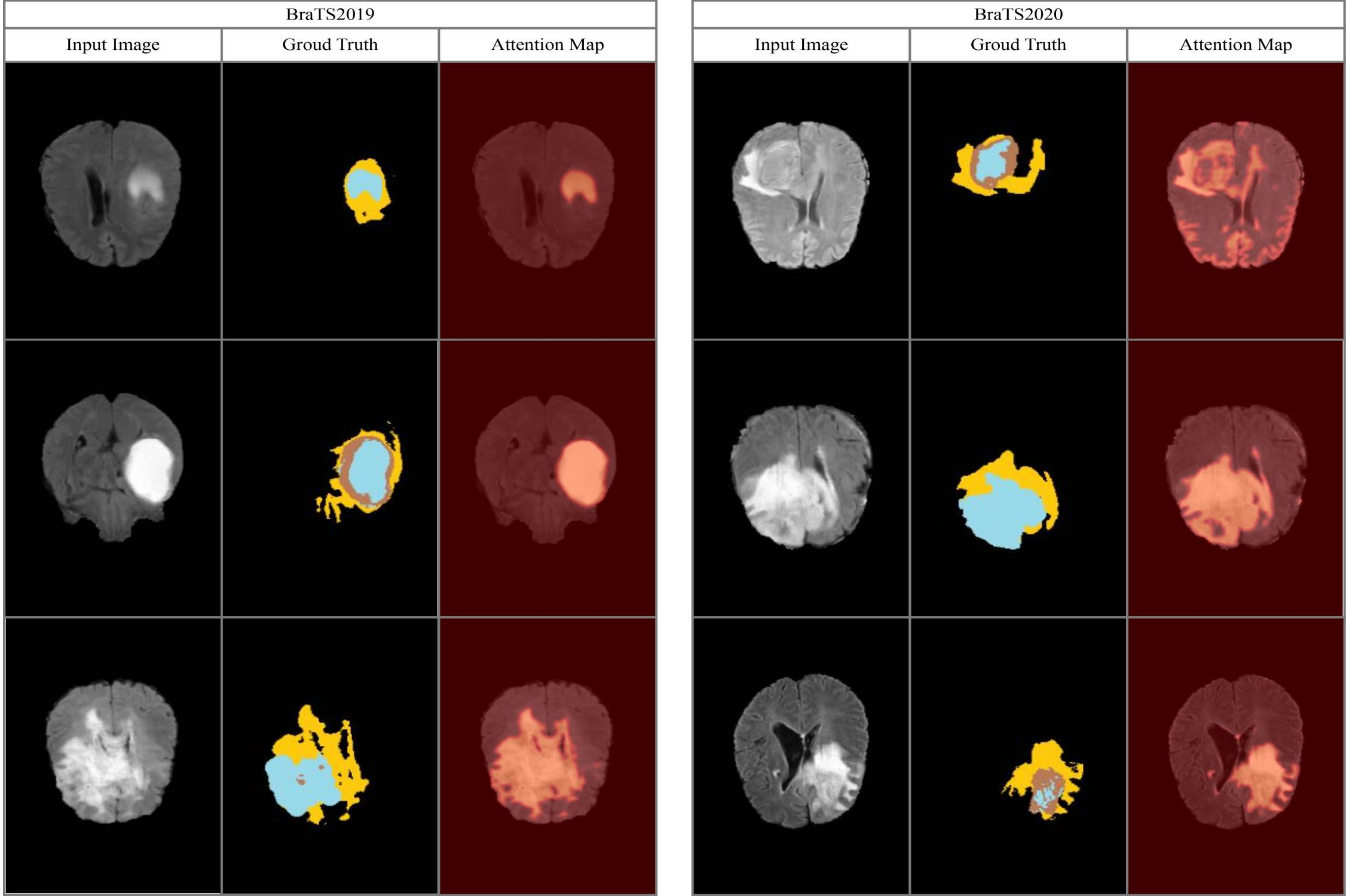
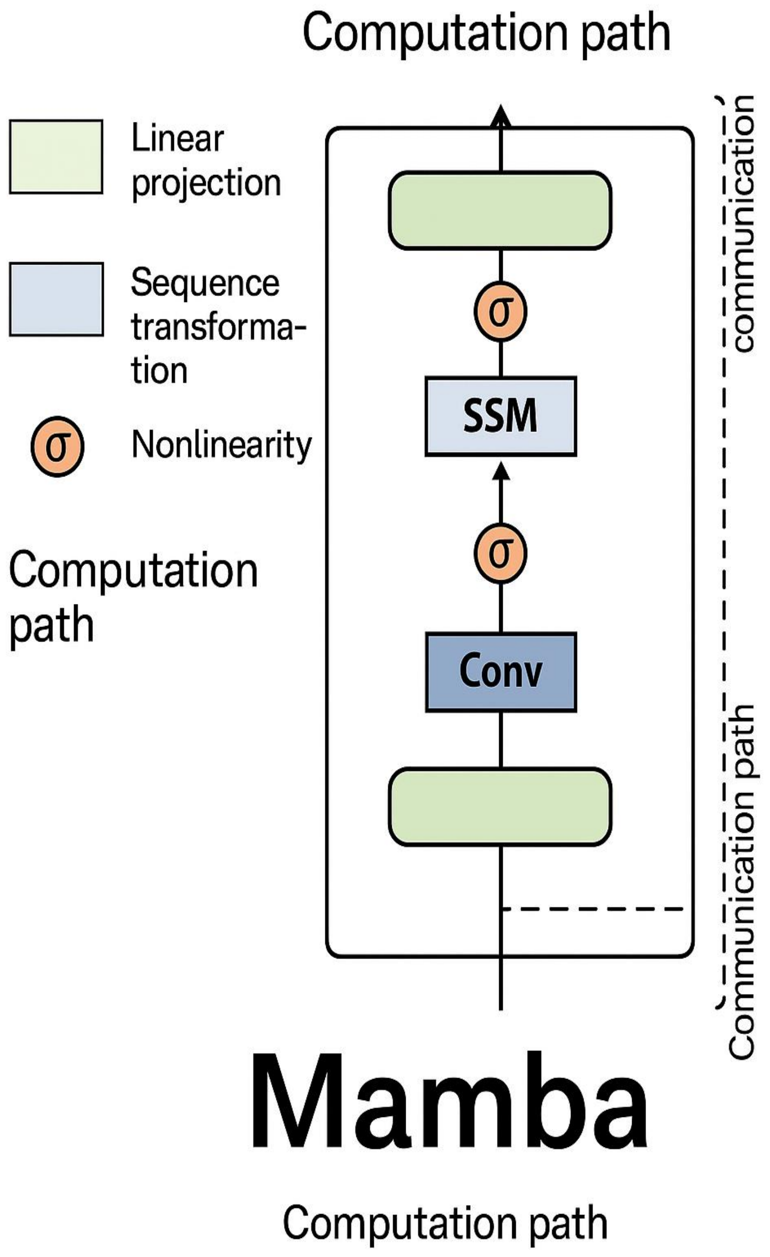

BraTS2019
Input Image
Groud Truth
Attention Map
BraTS2020
Input Image
Groud Truth
Attention Map

Mamba – State Space Model (SSM) for Long-Range Dependencies

- **Why it matters:**
  - Transformers are computationally expensive $O(n^2)$, especially for 3D MRI volumes.
  - Mamba has **linear-time architecture** that can model **long-range dependencies**.
- **How it applies to brain tumor recognition:**
  - More efficient processing of 3D MRI Images
  - **Real-time inference** in settings with limited compute.
- **Explainability:** visualization of **temporal dynamics and selective attention**, how model prioritizes tumor versus healthy tissue across multiple MRI sequences.



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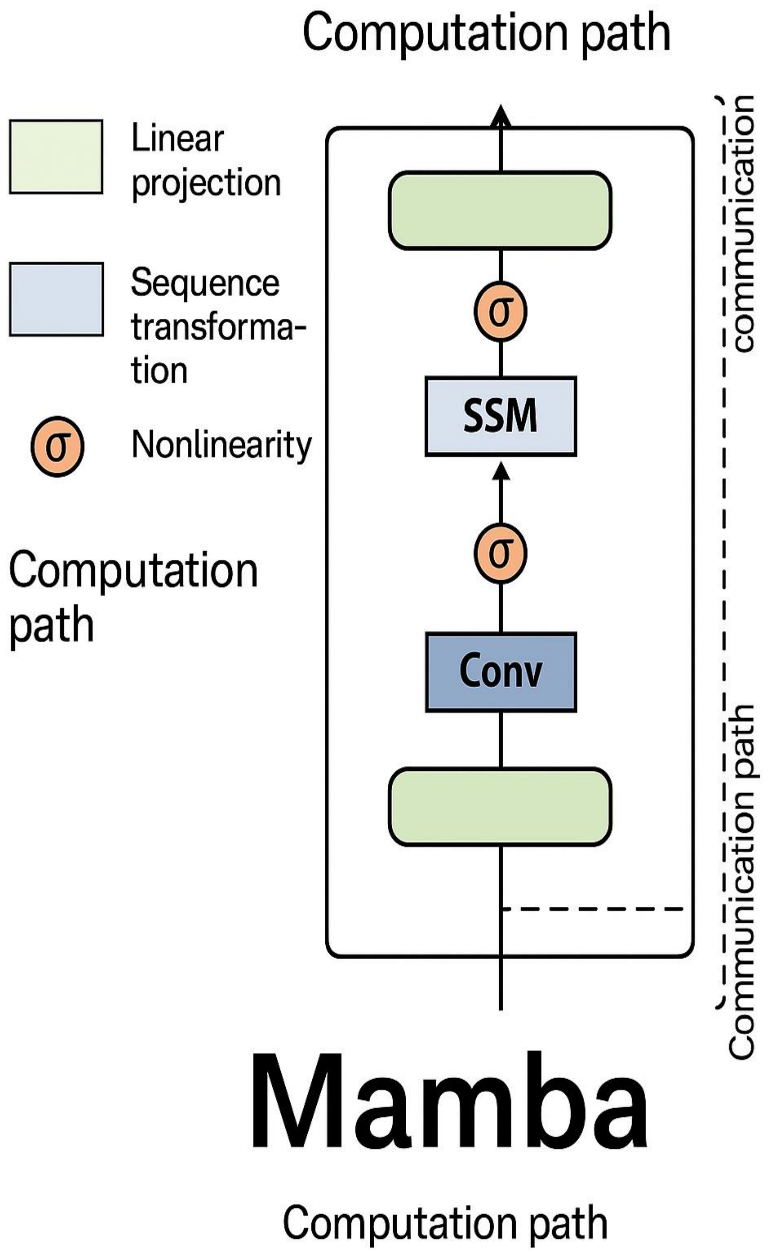
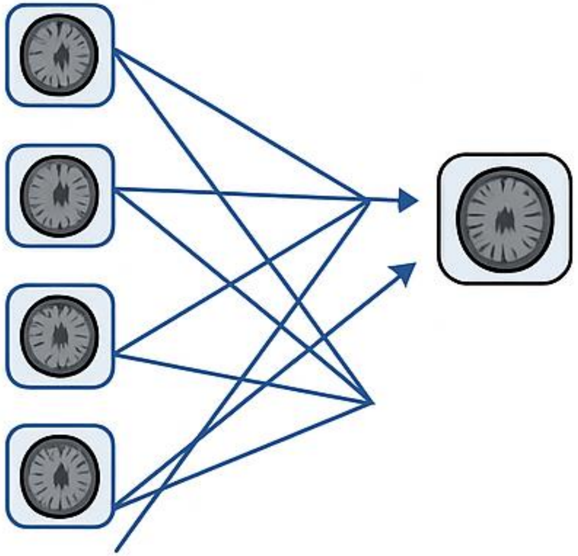


Mamba vs Transformer: Modeling Long-Range Dependencies

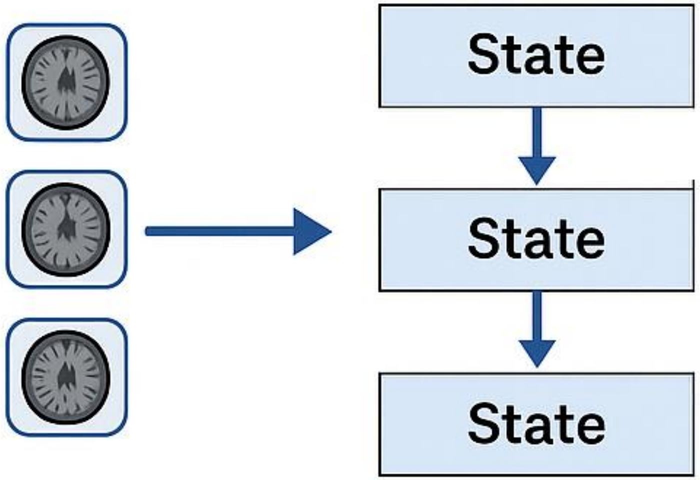
Transformer (Self-Attention)



Quadratic cost ($O(n^2)$)

- Captures global dependencies
- Computationally expensive, memory heavy

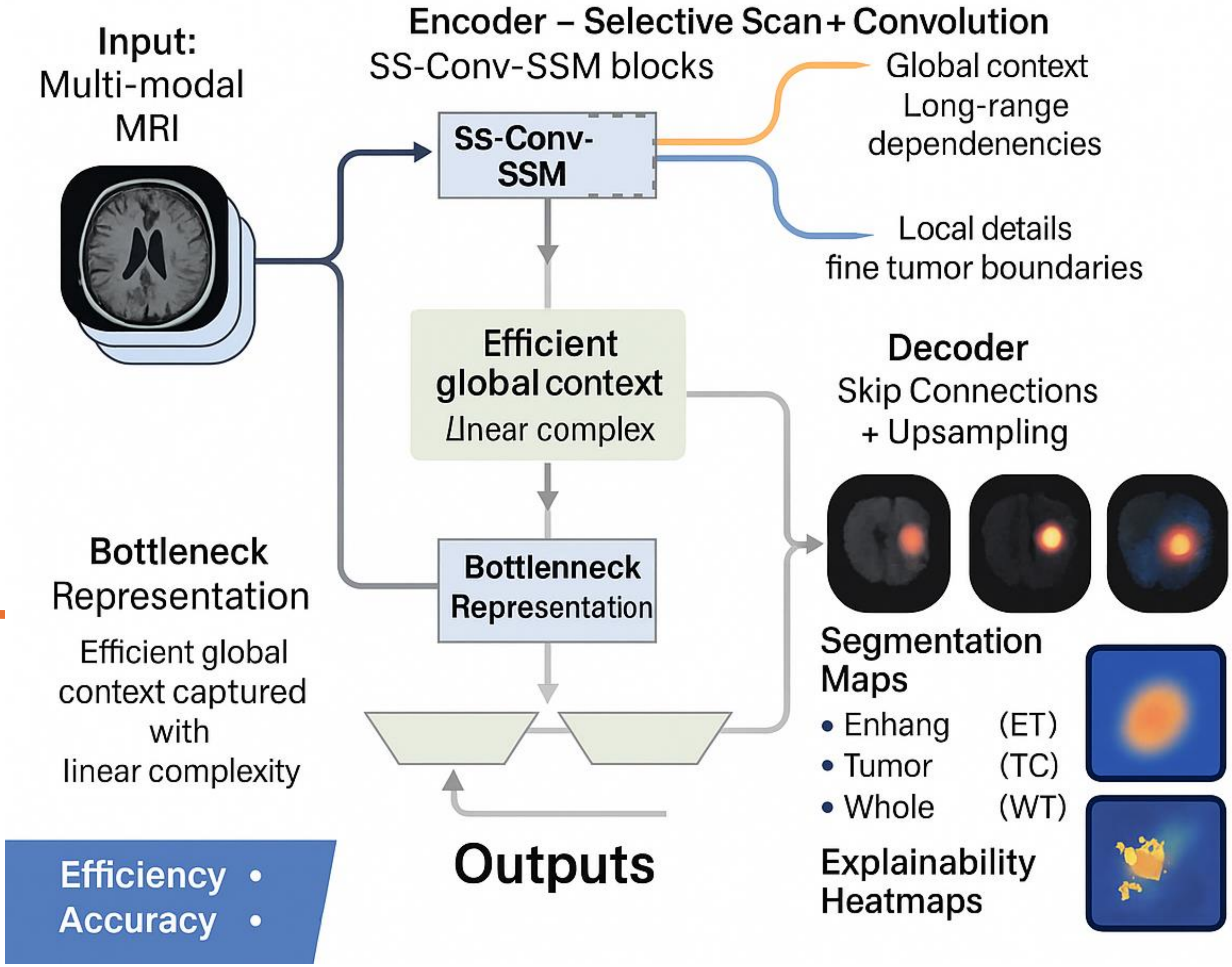
Mamba (State Space Model)



Linear cost ($O(n)$)

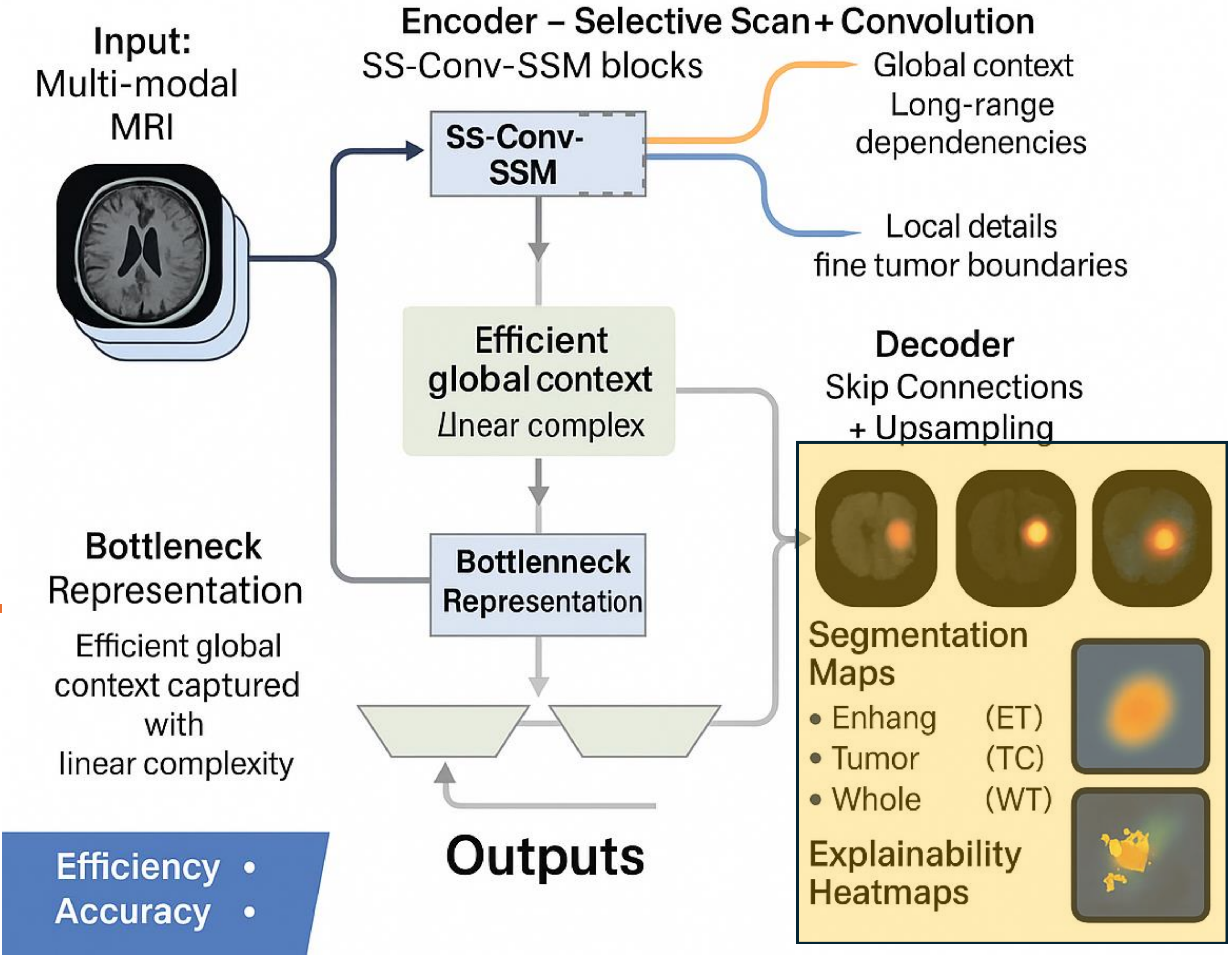
- Efficient, scalable
- Long-range context preserved
- Selective propagation → **interpretable** feature trace

NeuroMamba: Efficient State-Space Model for Explainable Brain Tumor Segmentation



NeuroMamba: Efficient State-Space Model forExplainable Brain Tumor Segmentation. Submitted to *IEEE International Conference on Computational Intelligence, Security, and Artificial Intelligence (IEEE-IntelliSecAI 2025)*

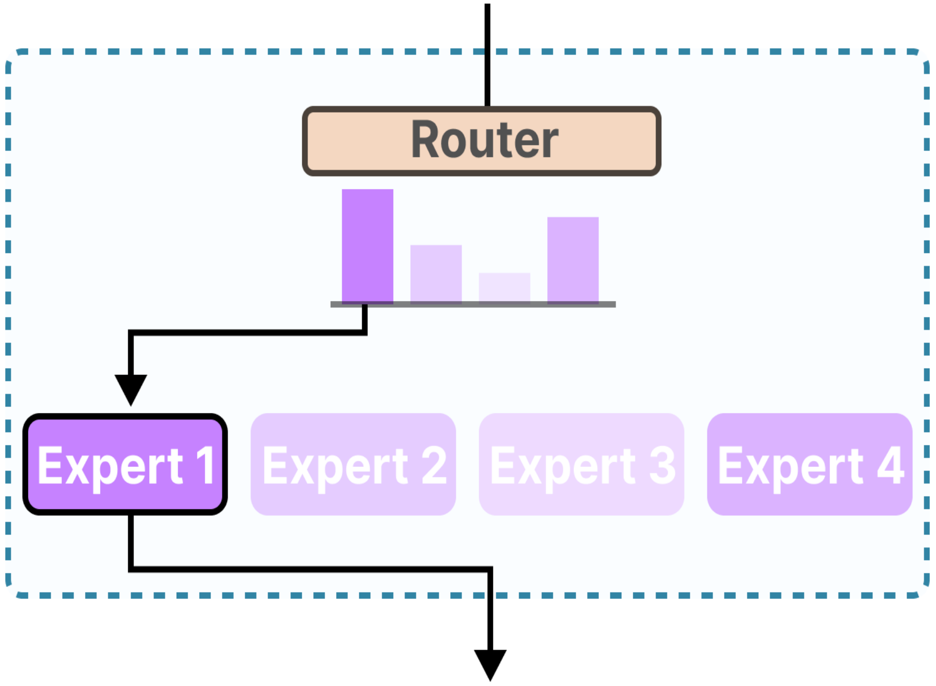
NeuroMamba: Efficient State-Space Model for Explainable Brain Tumor Segmentation



NeuroMamba: Efficient State-Space Model forExplainable Brain Tumor Segmentation. Submitted to *IEEE International Conference on Computational Intelligence, Security, and Artificial Intelligence (IEEE-IntelliSecAI 2025)*

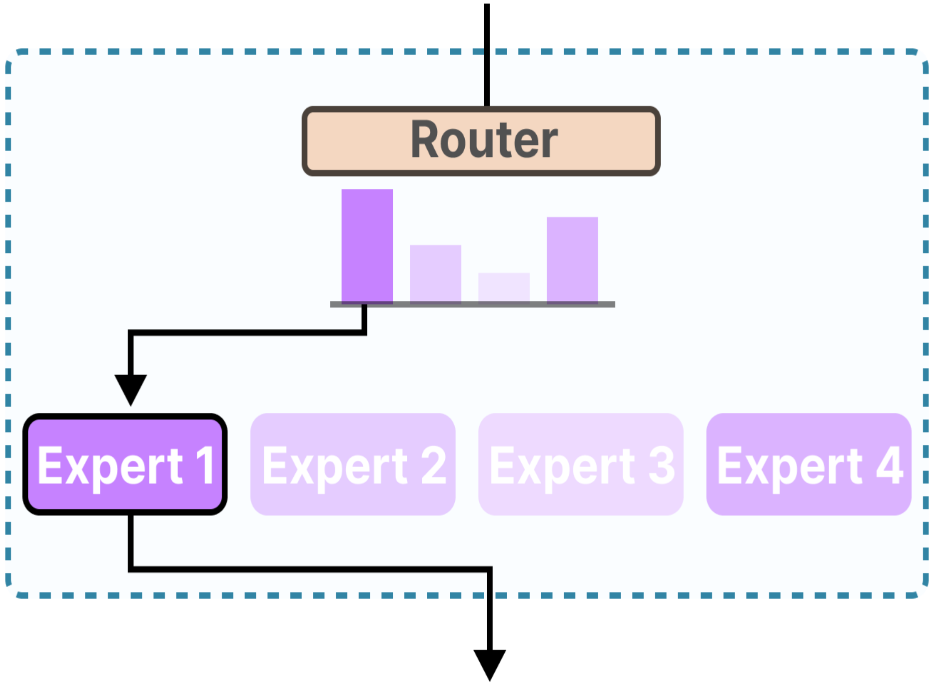
Mixture of Experts (MoE) – Specialization at Scale

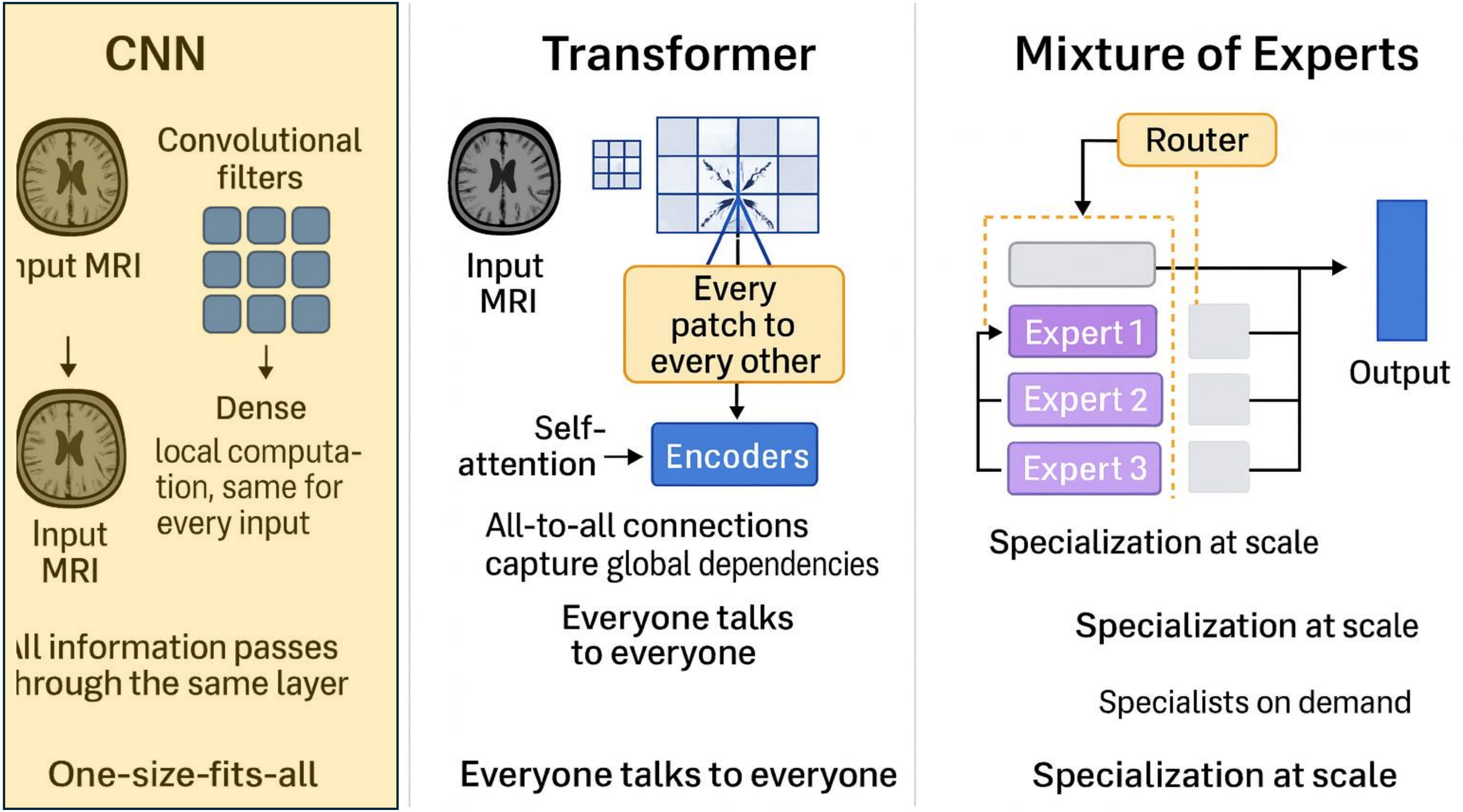
- Multiple "**expert**" subnetworks are trained, and a **gating mechanism** dynamically selects which experts to activate.
- **Why it matters:**
  - **Specialization**: one expert might be specialized for gliomas, another for meningiomas, another for rare subtypes.
  - Only a subset of experts is activated per sample, making the system more **scalable and computationally efficient**.



Mixture of Experts (MoE) – Specialization at Scale

- **How it applies to brain tumor recognition:**
  - Reflect real-world **radiology workflows**: a **glioma expert** for infiltrative tumors, a **pituitary expert** for sellar lesions, etc.
  - **Incremental updates:** new experts can be added for new tumor types **without retraining** whole system.
- **Explainability:**
  - Support **transparency**: gating mechanism reveals **which expert was responsible** for the decision.




CNN
Convolutional filters
put MRI
Dense
local computa-tion, same for every input
Input MRI
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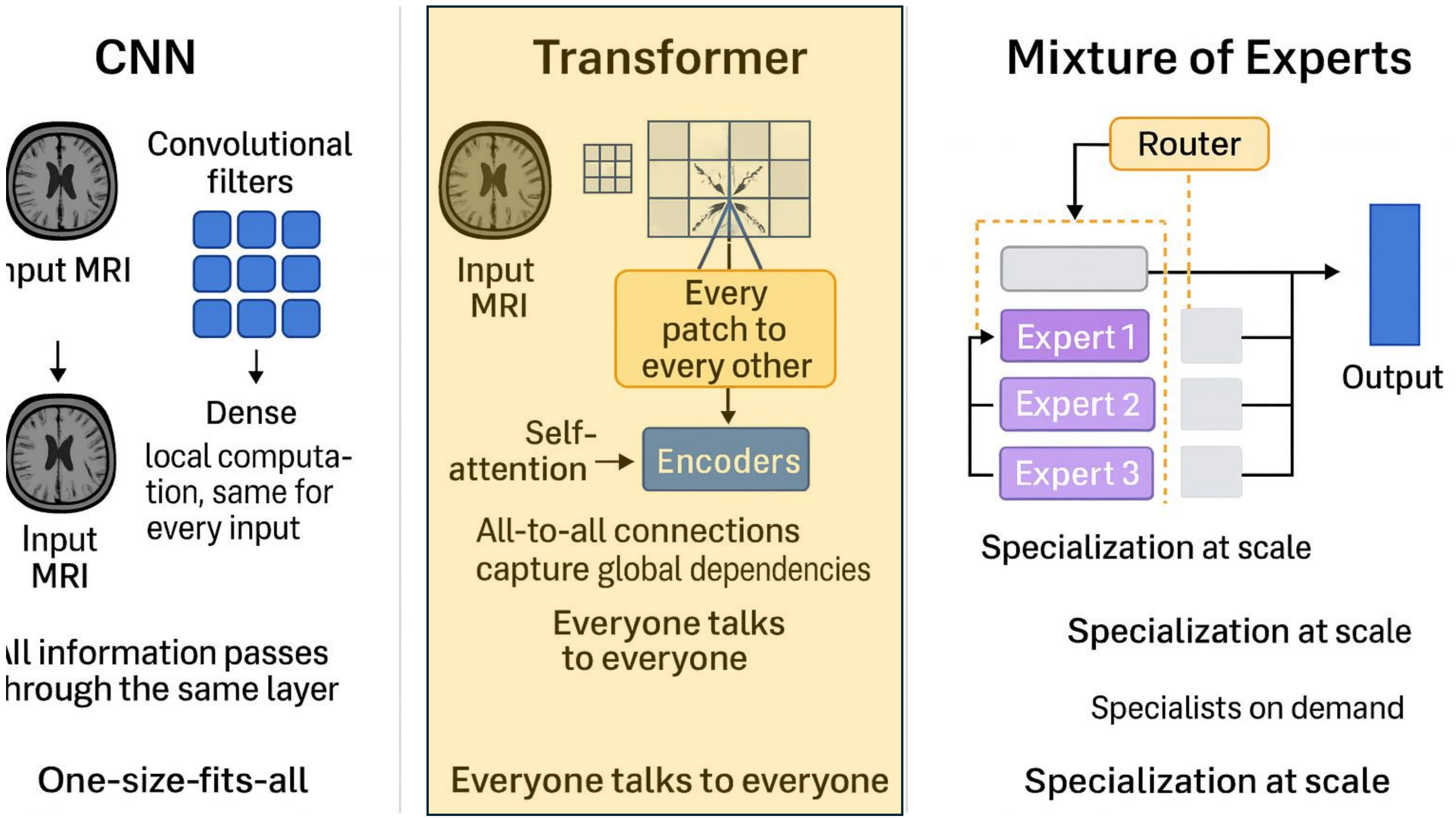
One-size-fits-all
Transformer
Input MRI
Every patch to every other
Self-attention
Encoders
All-to-all connections capture global dependencies
Everyone talks to everyone
Everyone talks to everyone
Mixture of Experts
Router
Expert 1
Expert 2
Expert 3
Output
Specialization at scale
Specialization at scale
Specialists on demand
Specialization at scale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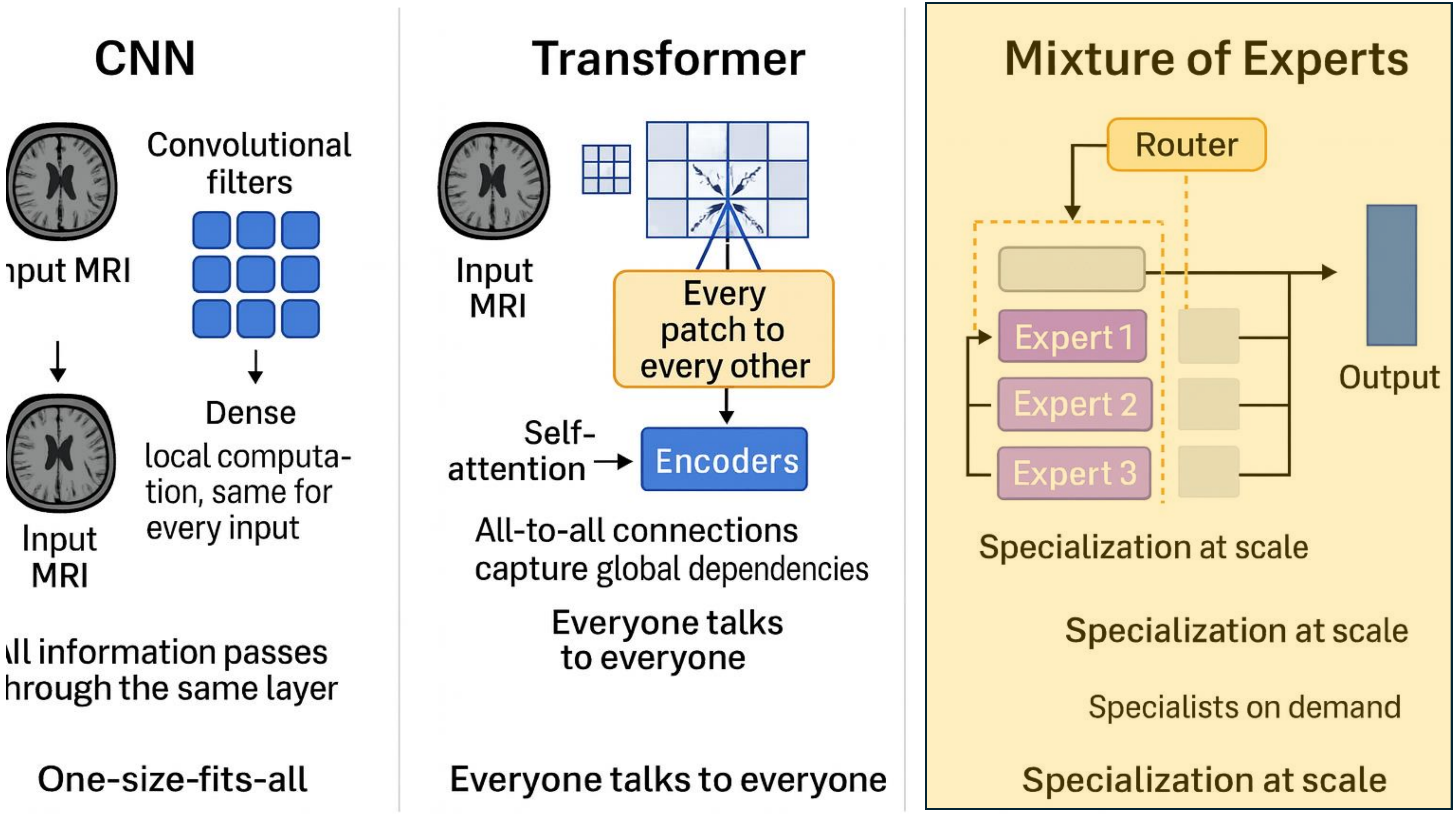
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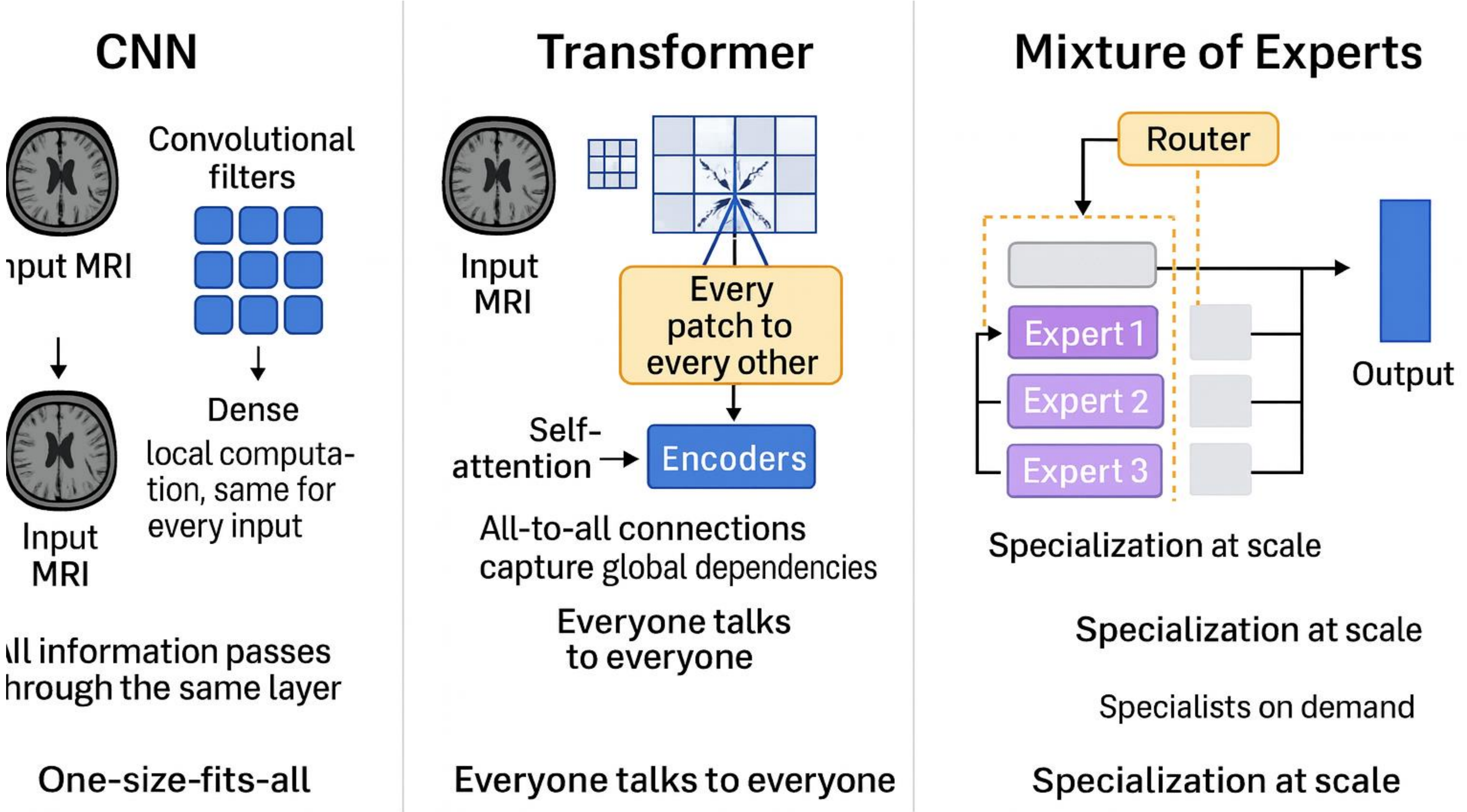
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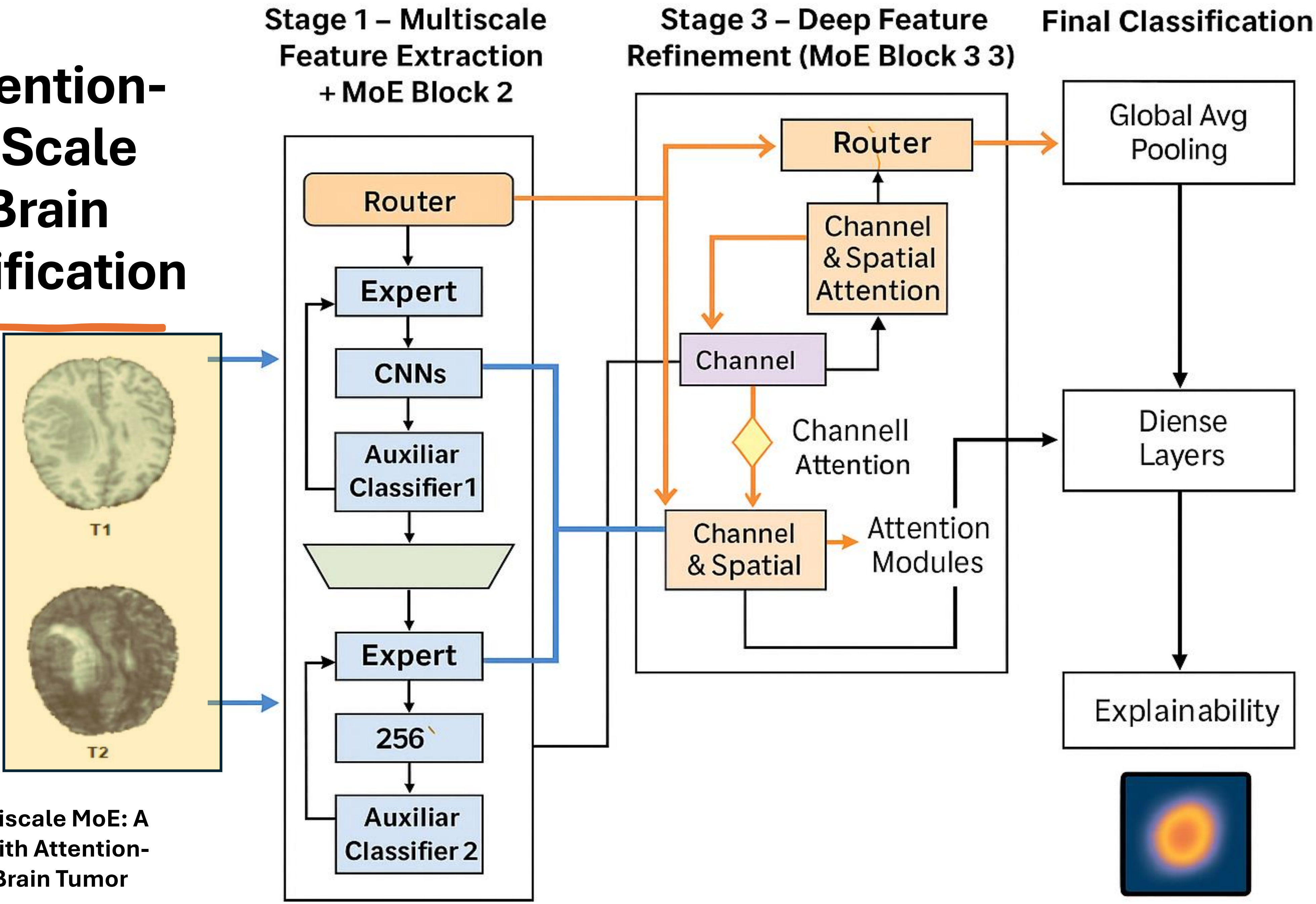
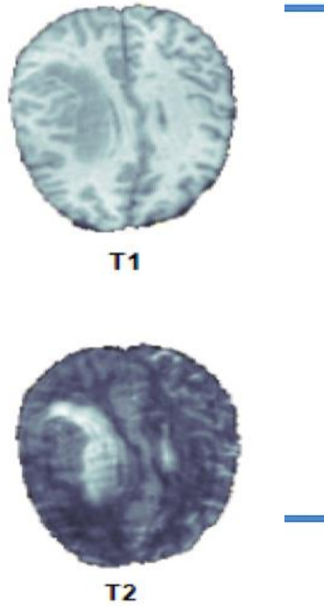
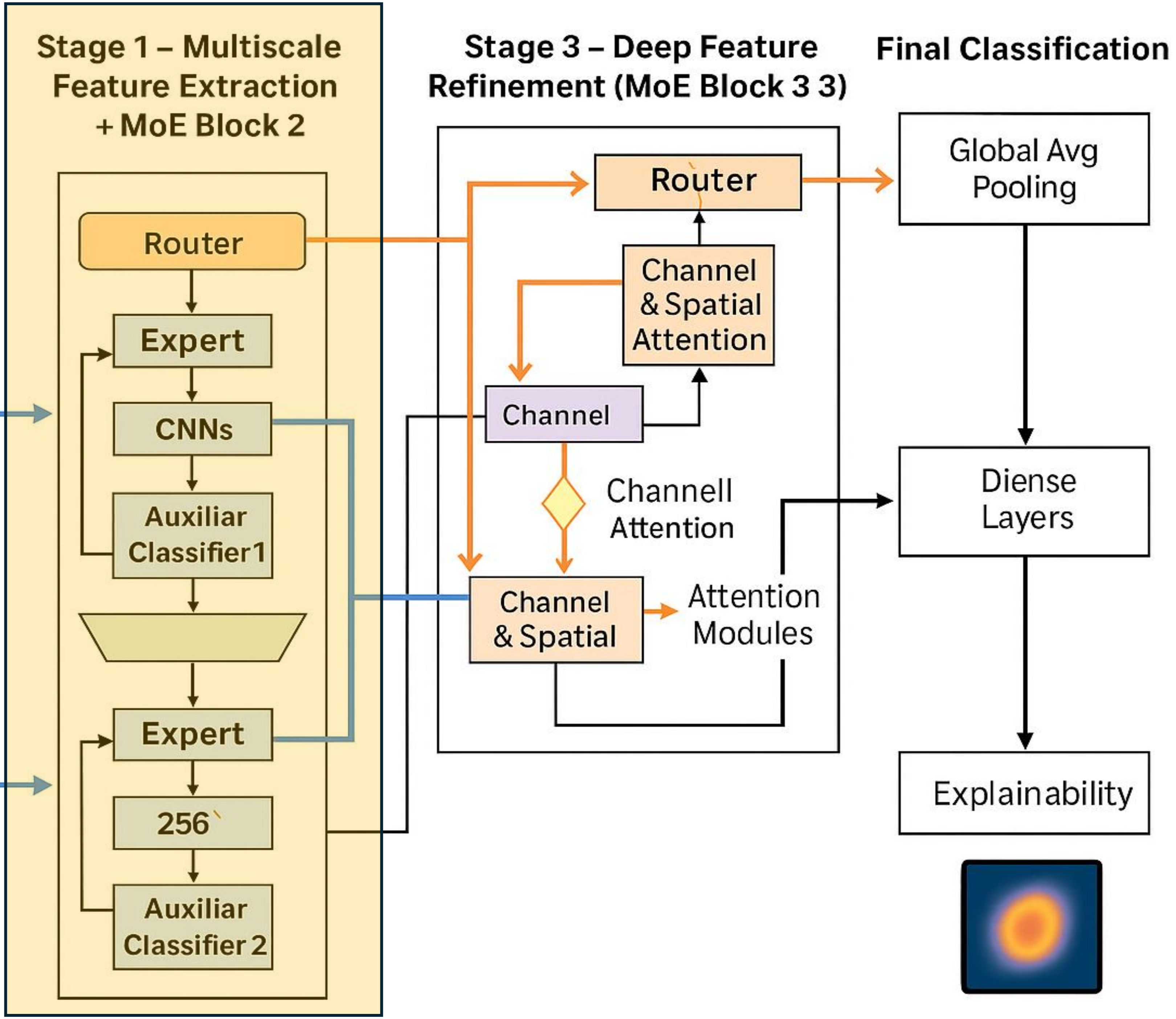
MoE with Attention-Driven Multi-Scale Learning for Brain Tumor Classification



A. Hamza, R. Damaševičius. **Multiscale MoE: A Mixture of Experts Framework with Attention-Driven Multi-Scale Learning for Brain Tumor Classification.** *FedCSIS 2025.*

MoE with Attention-Driven Multi-Scale Learning for Brain Tumor Classification





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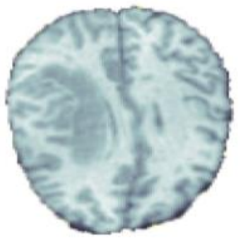
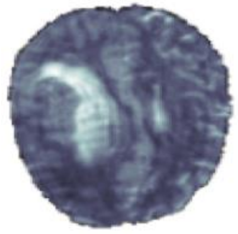
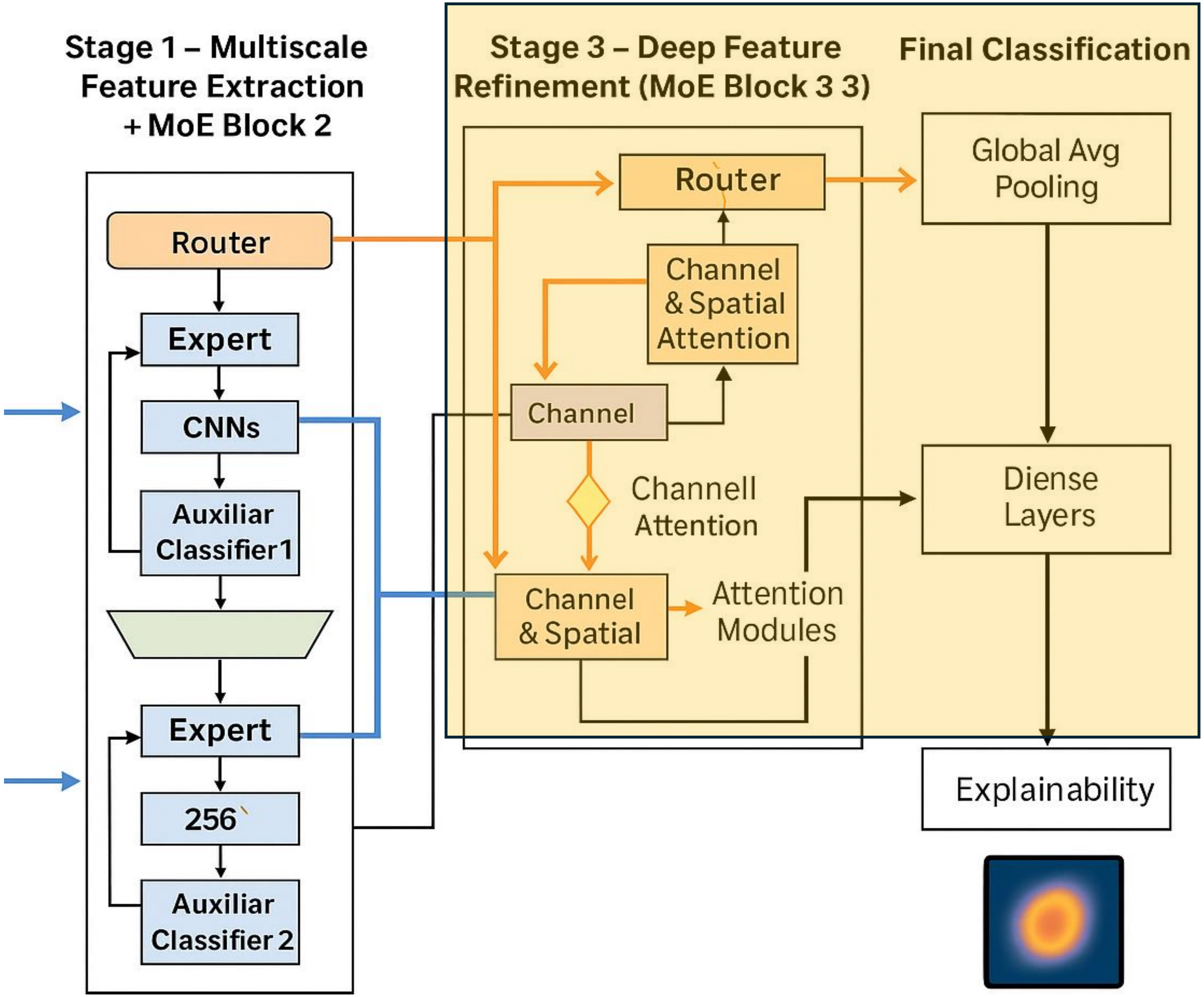


T1



T2



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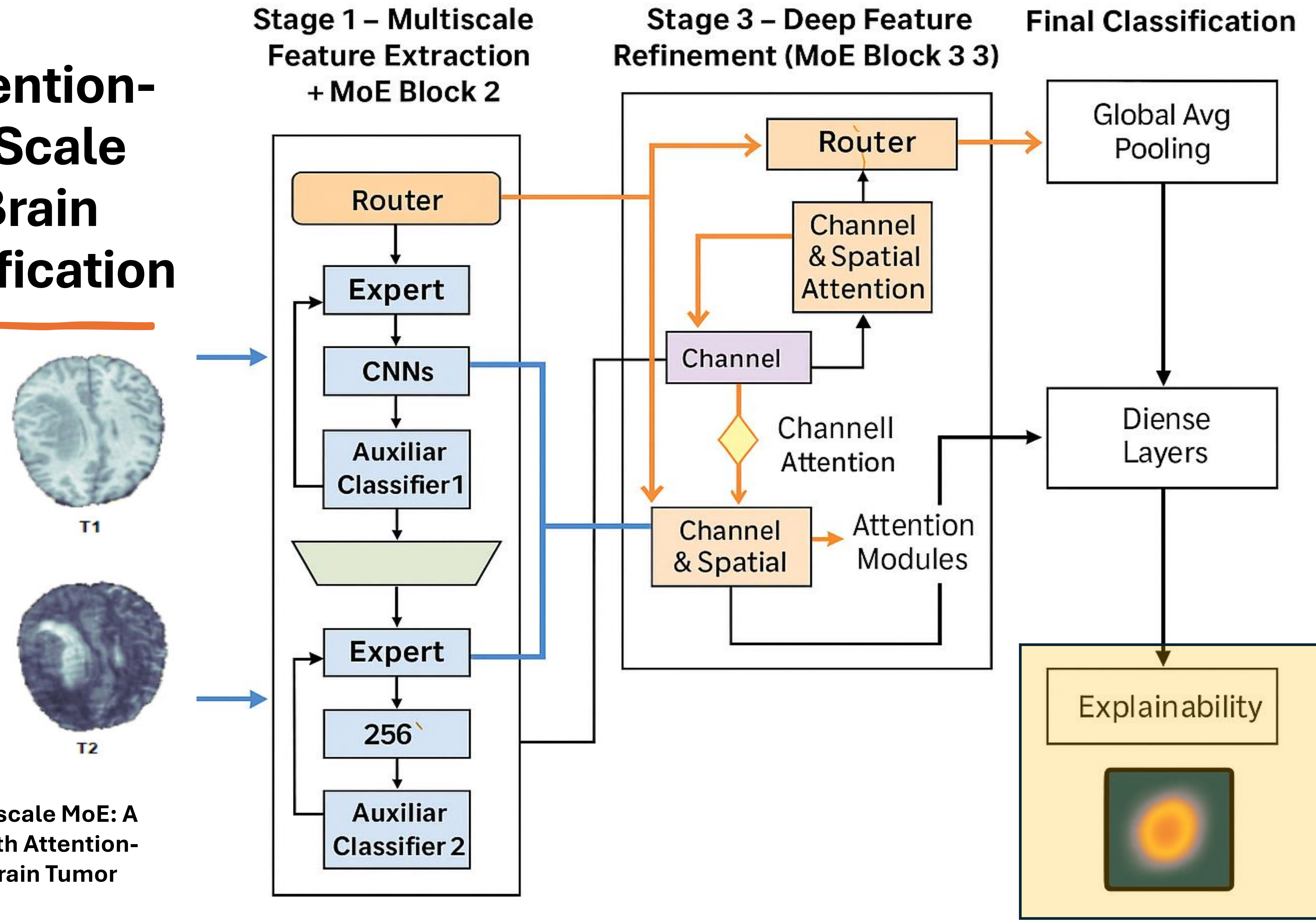

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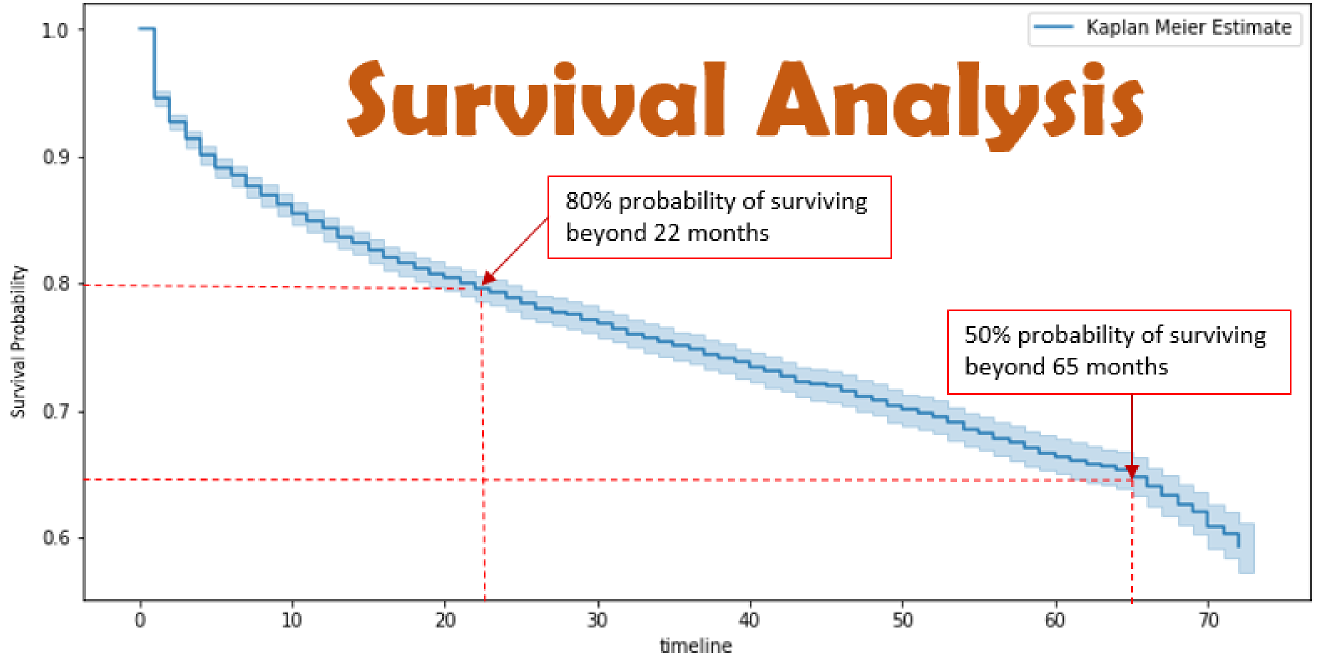
Survival Time Prediction



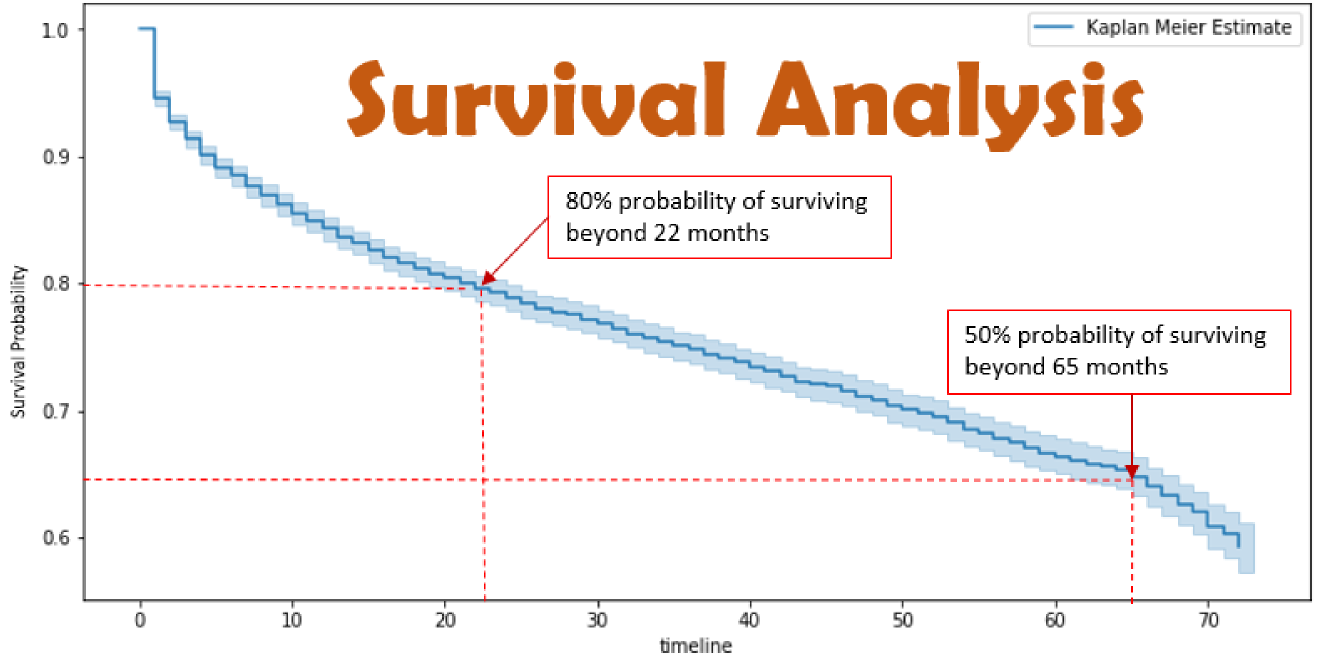
Survival Time Prediction:

- Estimate **remaining lifespan** of a patient

Key Parameters in Prediction:

- **Tumor Size**: 2D size or 3D tumor volume
- **Patient Age, Gender, etc.**
- **Tumor Grade** (low-grade vs. high-grade glioma)
- **Treatment status (Gross Total Resection, GTR**)

Survival Time Prediction



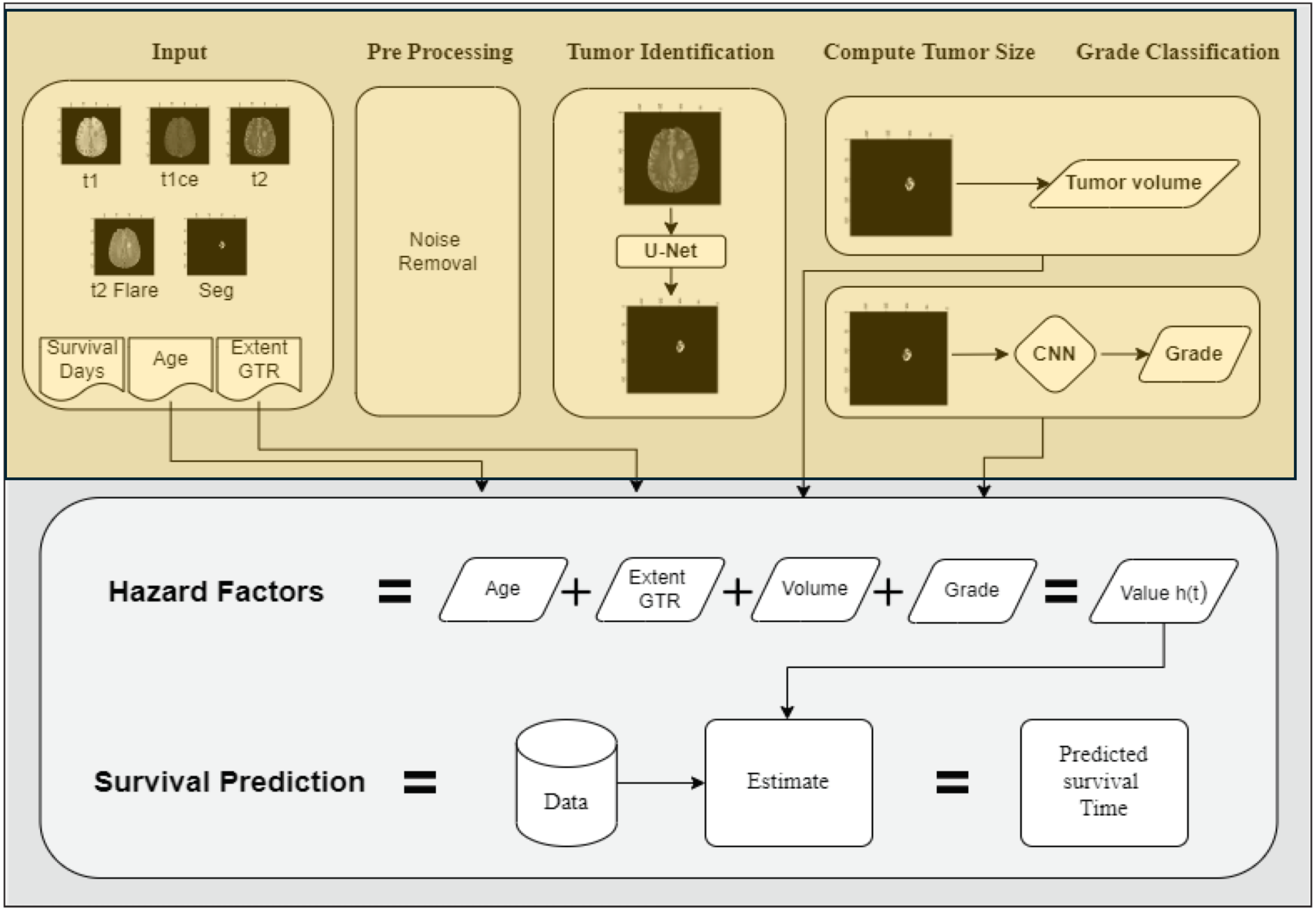
AI Models Role:

- parameters **integrated** into machine learning models, such as *Cox Proportional Hazard* (CoxPH) model, to predict survival time

Importance:

- **Optimizes Treatment:** Tailors treatment strategies to patient’s prognosis.
- **Improves Patient Care:** Provides a personalized outlook on survival.
- **Supports Decision-Making:** Assists clinicians in creating effective treatment plans.

AI Workflow for Survival Time Prediction



Hussain, S.; Haider, S.; Maqsood, S.; **Damaševičius, R**.; Maskeliūnas, R.; Khan, M. **ETISTP: An Enhanced Model for Brain Tumor Identification and Survival Time Prediction**. *Diagnostics* 2023, 13, 1456. https://doi.org/10.3390/diagnostics13081456

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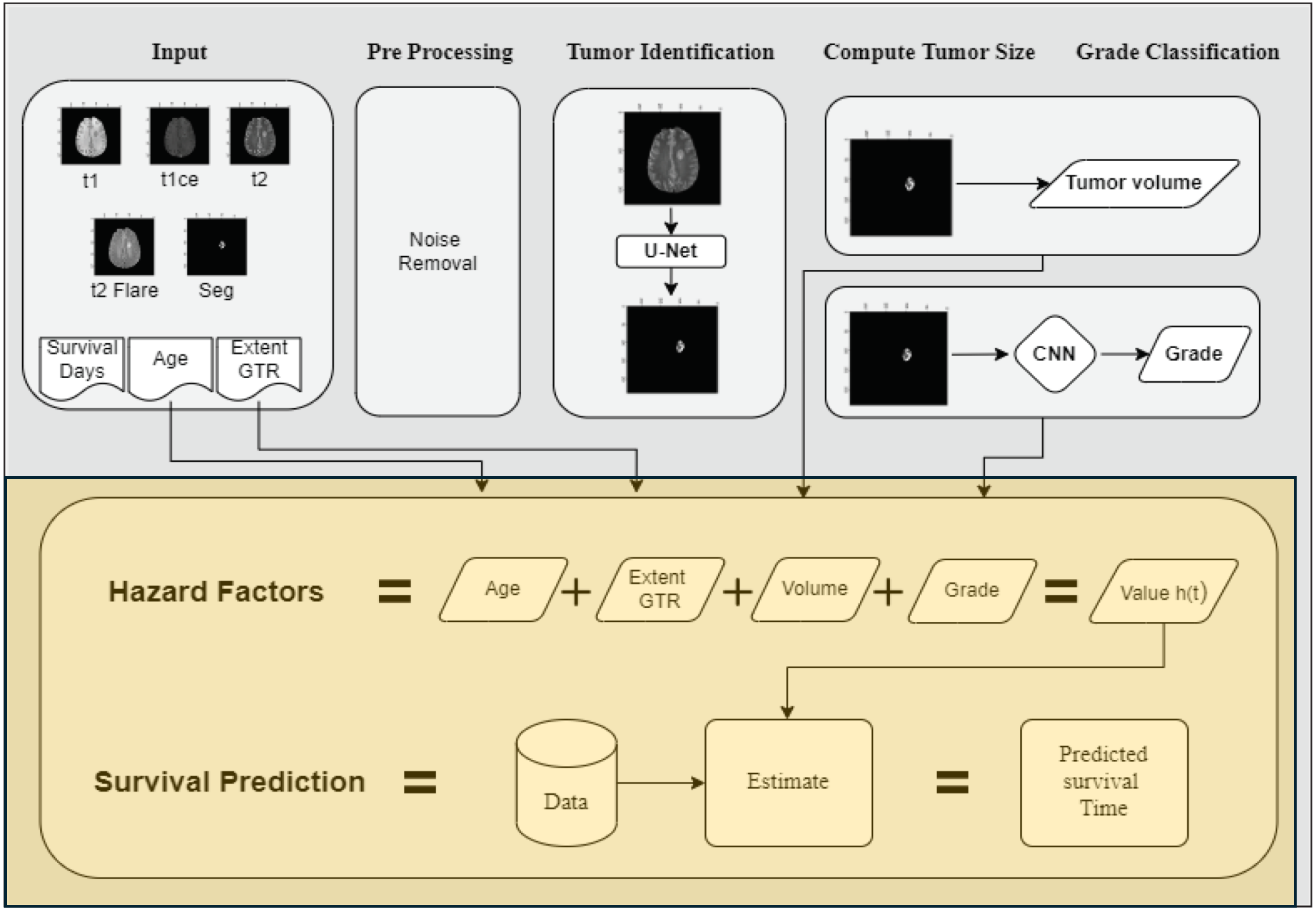

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Future Directions in AI for Brain Cancer Research

- **Multimodal Fusion:** Integrating MRI, PET, histopathology, genomics, and clinical metadata into **unified AI frameworks.**
- **Longitudinal & Predictive Modeling:** Tracking **tumor evolution** to forecast progression and treatment response.
- **Digital Twin Frameworks:** Creating patient-specific **virtual twin models** to personalize treatment planning.

Concluding Insights

- **AI has matured** from CNN-based local feature extractors to Transformers, MoE, and Mamba models enabling global **reasoning** and **specialization**.
- **Explainability is non-negotiable**: heatmaps, attention maps, and expert routing provide transparency & trust.
- **Efficiency matters**: linear-complexity models make large-scale 3D MRI analysis feasible.
- **Multiscale and multimodal fusion** ensures tumor features are captured across size, resolution, and modality.
- **Clinical alignment**: AI to mirror radiologist workflows and provide decision support in cooperation with humans (**Human-In-The-Loop**)

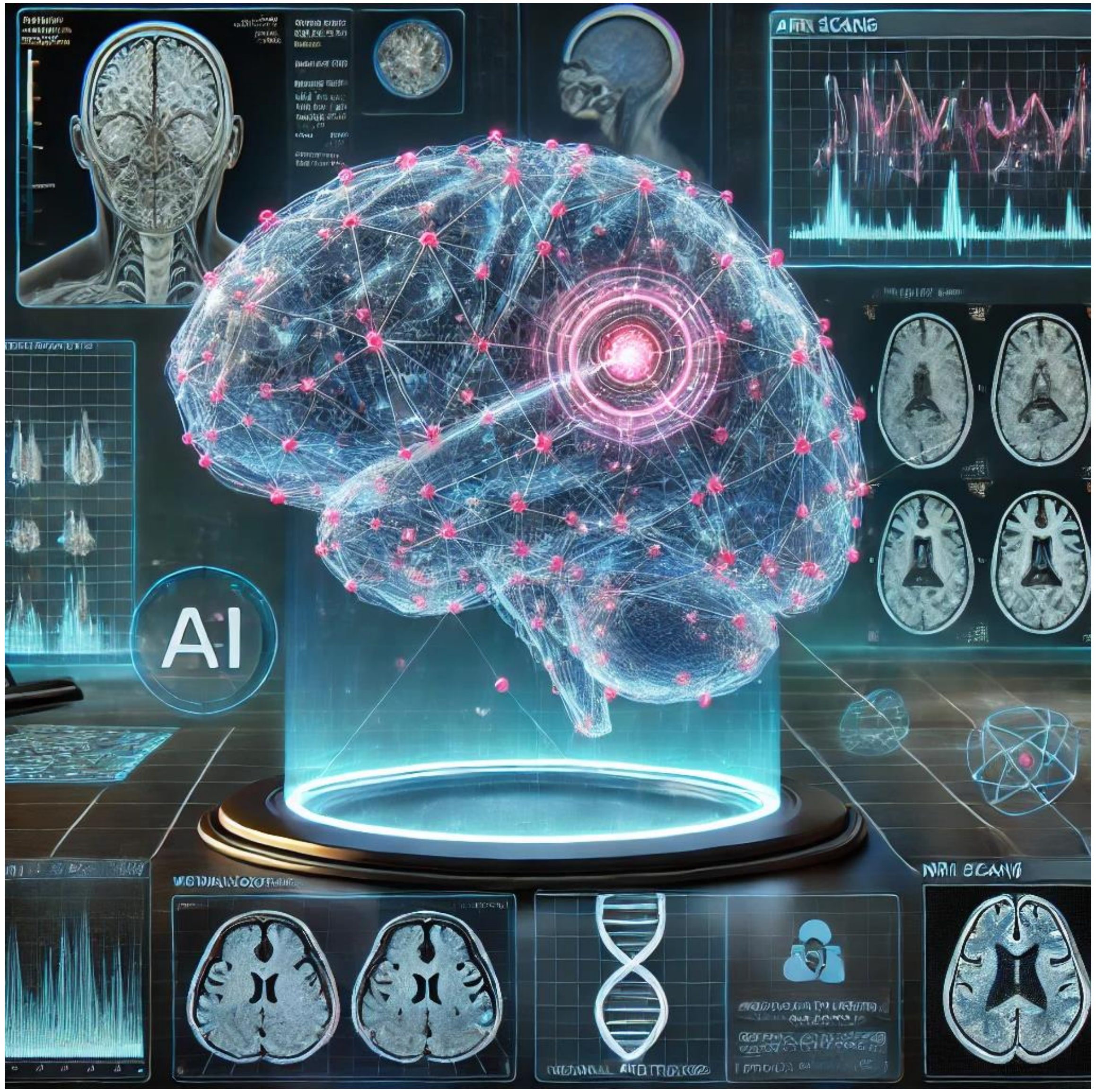
Thank You!

PhD Students (former and current):

- Dr. Sarmad Maqsood
- Dr. Olusola Abayomi-Alli
- Sara Tehsin
- N. Inzamam Mashood
- Ameer Hamza
- Irfan Abbas

Collaborators:

- Prof. Rytis Maskeliūnas
- Prof. Seifedine Kadry
- Prof. Tanzila Saba
- Dr. M. Attique Khan
- Dr. Mazin Abed Mohammed
- Dr. V. Rajinikanth



The future of brain tumor diagnosis isn't just about smarter models - it's about models we can trust