Presentation on,

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EfficientNet-Based and YOLO-Driven Brain Tumor Detection and Segmentation

Authors:

Najla Musthafa[1], Mohammed Aflah[2], Minhaj Akavalappil[2], Mohammed Jasim A[2], Mohammed Aseel[2], Shanid Malayil[3], Mubeena A K[1].

[1]Assistant Professor, Dept. of CSE, MEA Engineering College, Kerala, India
[2]Dept. of CSE, MEA Engineering College, Kerala, India
[3]Associate Professor, Dept. of CSE, MEA Engineering College, Kerala, India

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PERINTHALMANNA
VENGOOR - PATTIKKAD PO, PERINTHALMANNA, MALAPPURAM DISTRICT, KERALA - PIN 679325

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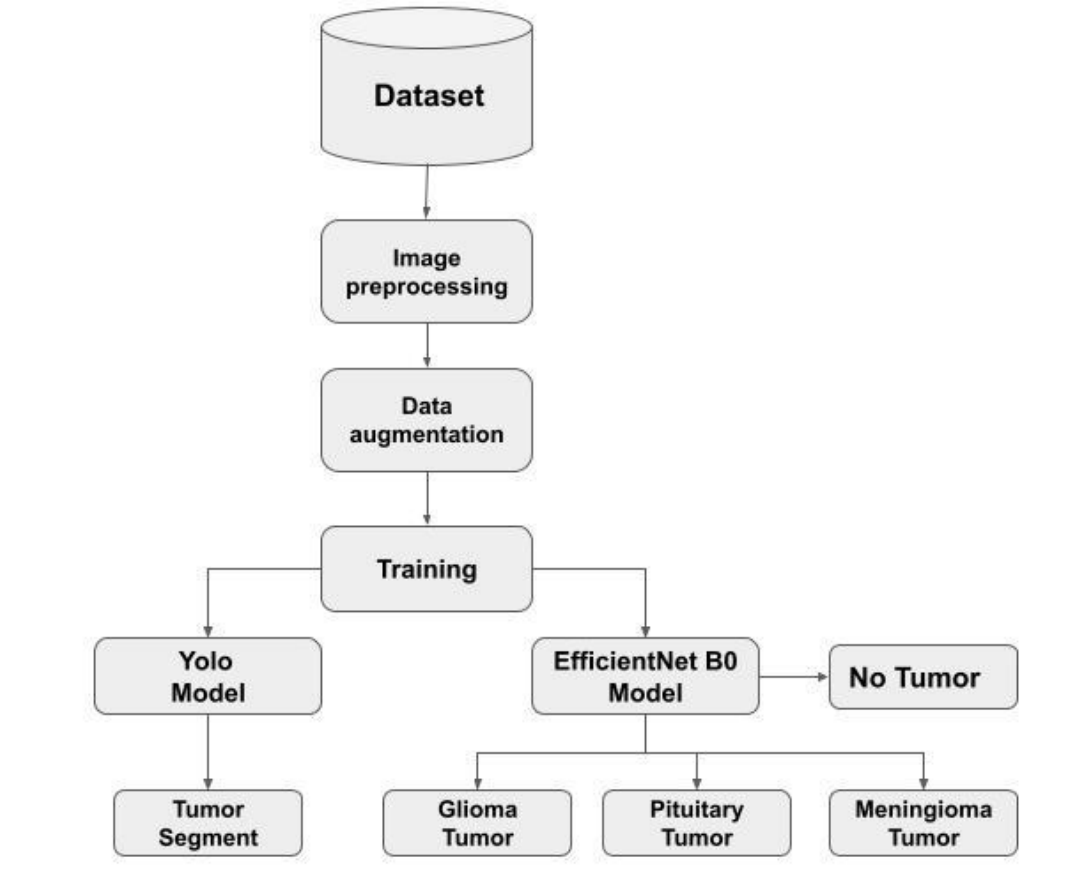
Introduction

- **Brain tumors** are life-threatening and require early, accurate diagnosis to improve survival rates.
- **Manual MRI diagnosis** is time-consuming, subjective, and prone to human error.
- **AI and Deep Learning** offer automation, speed, and increased diagnostic accuracy.
- **EfficientNet-B0** is used to classify tumors into four categories (glioma, meningioma, pituitary, no tumor).
- **YOLOv8** performs real-time segmentation to localize the tumor in MRI scans.
- This integrated system supports radiologists with **fast and reliable** second opinions.

Background Information

- **MRI** is the standard imaging tool for brain tumors due to its detailed visualization of soft tissues.
- **Traditional ML methods** (like SVMs, kNN) rely on handcrafted features and struggle with complex medical data.
- **CNNs** automatically extract deep features and improve image classification and segmentation performance.
- **Transfer Learning** enables pre-trained models to work effectively on small medical datasets.
- **EfficientNet** balances model size and accuracy through compound scaling.
- **YOLOv8** ensures fast, accurate segmentation—ideal for clinical use and real-time diagnosis.

Proposed System



Methodology

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1. Dataset Collection:

Collect **5000 MRI images** across 4 categories — glioma tumor, meningioma tumor, pituitary tumor, and no tumor.

2. Data Preprocessing:

- **Augmentation:** Apply rotation, flipping, zooming for data diversity.
- **Annotation:** Tumor regions manually marked for segmentation.

3. Model Selection:

- Use **EfficientNet-B0** (pretrained on ImageNet) for classification.
- Use **YOLOv8** for segmentation (to detect and outline tumor regions).

4. Training:

- **EfficientNet-B0:** Fine-tuned using Transfer Learning for 4-class classification.
- **YOLOv8:** Trained to detect and segment tumors using annotated images.

Methodology

5. Loss Functions:

- **Classification Loss:** Categorical Cross-Entropy:

  $$L = -\sum(y\_true * \log(y\_pred))$$

- **Segmentation Loss:** Intersection over Union (IoU):

  $$IoU = |A \cap B| / |A \cup B|$$

6. Evaluation:

- **Classification Metrics:** Accuracy, Sensitivity, Specificity, F1-score.
- **Segmentation Metric:** IoU (measures overlap between predicted and actual tumor area).

7. Deployment:

- Plan to develop a simple application for radiologists to upload MRI scans and get instant tumor detection and classification results.

Methodology - Classification

- Images resized to **150×150** for EfficientNet input.
- Transfer learning applied using weights from ImageNet.
- Final layer: **Softmax** for 4-class probability distribution.

$$\hat{y}_i = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

  - Each class probability = (exponentiated value) / (sum of all exponentiated values).
  - z_i = raw score for class i.
  - **Example:** If scores for 4 classes are: [2, 1.5, 0.5, -0.5]

$$\hat{y}_{glioma} = \frac{e^2}{e^2 + e^{1.5} + e^{0.5} + e^{-0.5}}$$

This gives probabilities like [0.7, 0.2, 0.08, 0.02].

- **Loss Function:** Categorical Cross-Entropy

$$L = -\sum(y\_true * \log(y\_pred))$$

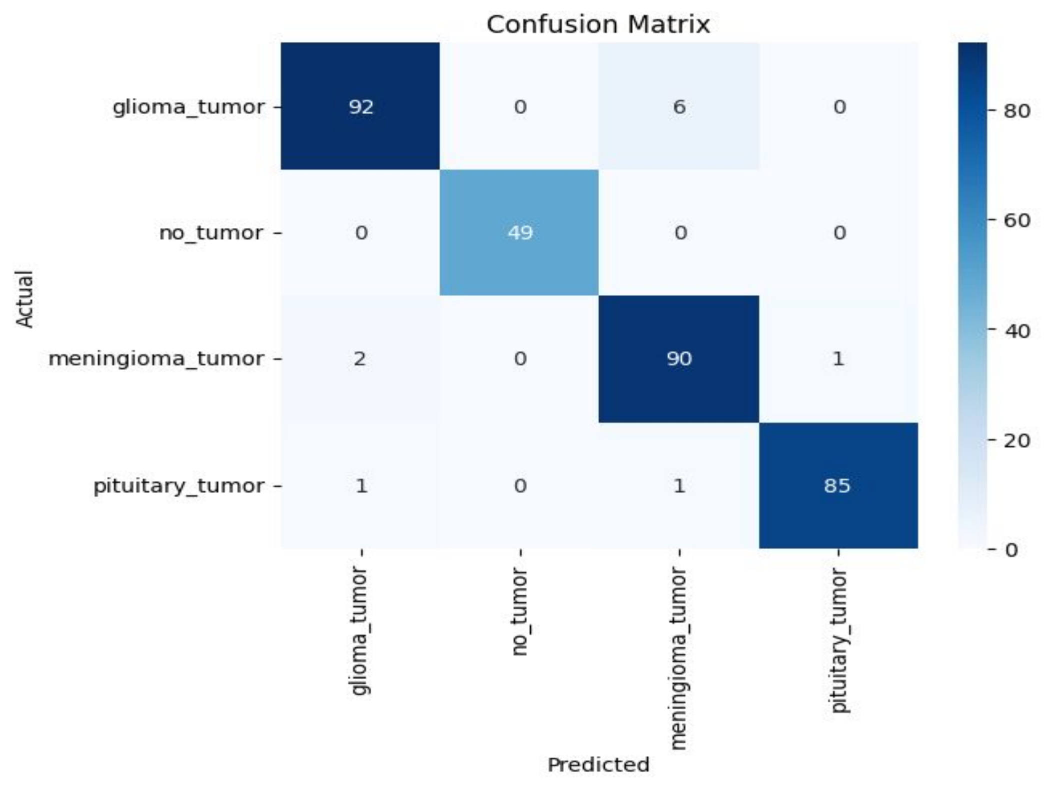
Methodology - Segmentation

- Images resized to **416×416** for YOLOv8.
- Annotated tumor regions (bounding boxes and masks) fed into model.
- Segmentation performance measured using: **IoU (Intersection over Union):**

$$\mathbf{IoU = |A \cap B| / |A \cup B|}$$

- A: The predicted tumor region.
- B: The actual tumor region (from the dataset).
- YOLOv8 provides **real-time segmentation** outputs.

Confusion Matrix



Result

Accurate Tumor Classification

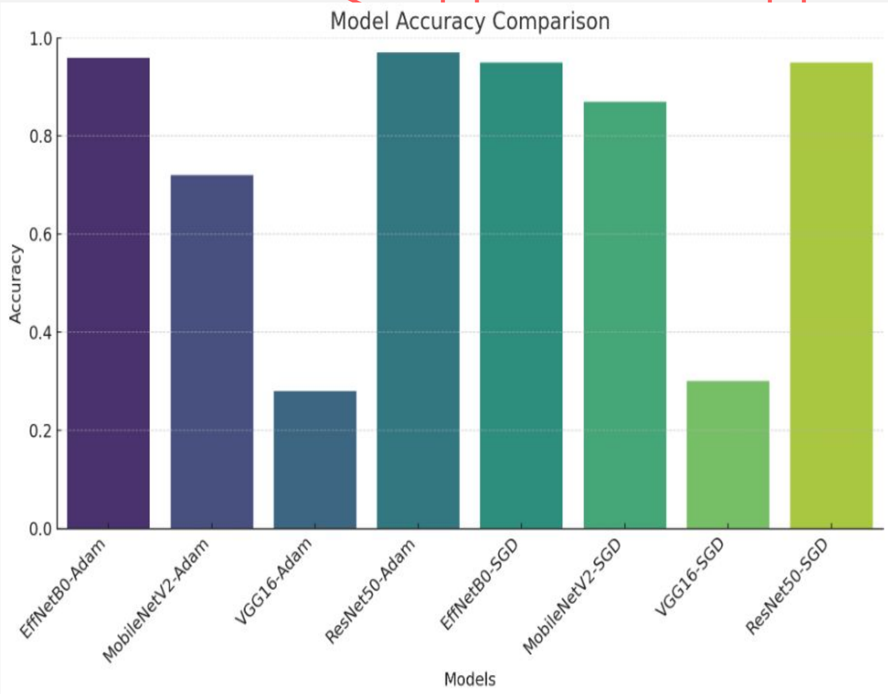
- **EfficientNet-B0** achieves **final training accuracy of approximately 99.7%**.
- Validation accuracy reaches **98.3%**, indicating **excellent generalization** to unseen data.
- High **F1-score of 96%** across all classes confirms **balanced performance**.

Efficient Segmentation

- **YOLOv8 segmentation model** achieves a **mean Average Precision (mAP) of 81.2%**.
- Tumor regions (glioma, meningioma, pituitary) are accurately highlighted in MRI scans.
- Real-time segmentation ensures **faster processing**.

Result

- **Best Model: EfficientNetB0 with Adam.**
- **Why EfficientNetB0?**
    - **Higher accuracy** than MobileNetV2, VGG16, and ResNet50.
    - **More efficient** with fewer parameters than ResNet50 and VGG16.
    - **Better feature extraction** with compound scaling.
- **Key Takeaway: EfficientNetB0-Adam is the best choice** for brain tumor detection, ensuring high accuracy with efficiency.



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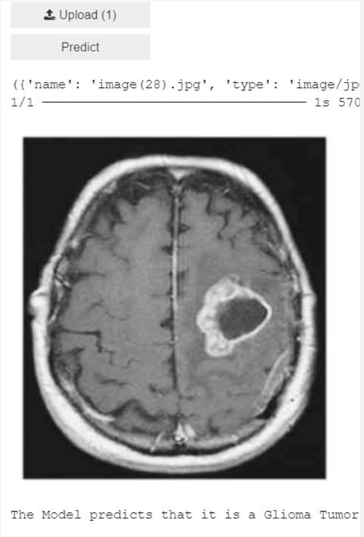
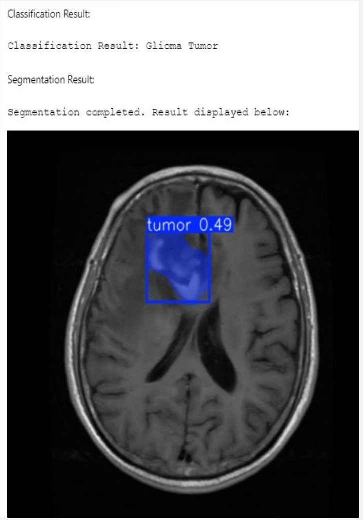
Result

No Tumor

Classification



Segmentation



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Discussion And Future Scope

- **Diagnosis & Surgery**
  Automates tumor detection and aids in surgical planning with precise segmentation.
- **Remote Access**
  Enables diagnosis via cloud platforms and telemedicine in underserved areas.
- **Mobile Health**
  Integrates into smartphone apps for quick, accessible tumor screening.
- **Emergency Use**
  Real-time analysis supports fast decisions in critical care settings.
- **Monitoring & Research**
  Tracks treatment progress and supports medical AI research.
- **Explainability & Expansion**
  Adds interpretability for clinical trust and combines data from CT, PET, and genetics for better accuracy.

Conclusion

- The proposed system successfully combines **EfficientNet-B0 for classification** and **YOLOv8 for segmentation** of brain tumors.
- It achieves **high classification accuracy (99.7%)** and **strong segmentation performance (81.2% mAP)**.
- **Transfer Learning** significantly reduces training time and enhances performance on small datasets.
- The framework delivers **real-time results**, aiding radiologists in faster and more accurate diagnoses.
- The system supports **automated medical diagnostics**, reducing radiologist workload and minimizing human error.
- This research highlights the potential of **AI-driven healthcare solutions** to improve early detection and patient outcomes.

THANK YOU.....