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MRI Brain Tumor Classification

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Problem Statement

- ➢ Brain Tumor can led to life-threatening such as cognitive decline or the ability to function.
- ➢ Distinguishing brain tumors is difficult due to their variable appearance, similarity to healthy tissue, and MRI image quality.
- ➢ Early and accurate diagnosis is critical for effective treatment, but differentiating between no-tumor and tumor based on MRI scans can be challenging.
- ➢ Therefore, it is of utmost importance to properly diagnose and treat these patients before it’s too late.

Project Overview

- I developed a classification system using MRI brain scans to distinguish between tumor and no-tumor cases. By applying machine learning and deep learning models, the project aimed to improve accuracy in early detection and support clinical decision-making.

DataSet

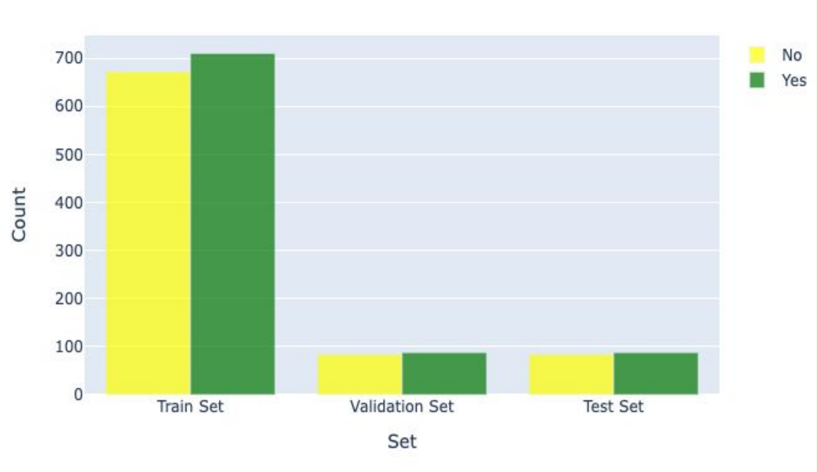
- The MRI dataset was acquired from kaggle
- Dataset size: 253 images (155 tumor, 98 no tumor).
- Image shape: 224 × 224 × 3.
- Labels: Binary classification (0 = No Tumor, 1 = Tumor).

EDA

- ➢ Labeled:
  - ❖ 0 = No Tumor, 1 = Tumor
- ➢ Random MRI samples displayed
- ➢ Normalization improves consistency

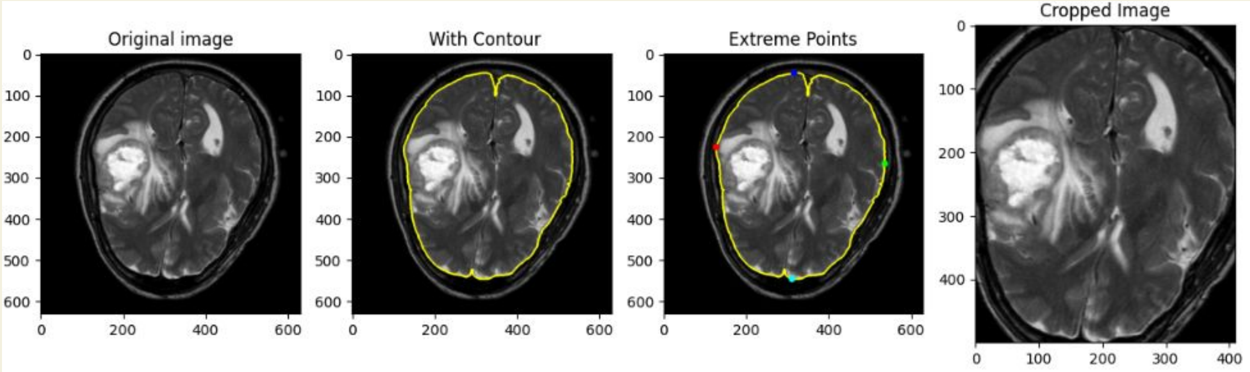
Augmentation Dataset

- ➢ Dataset expanded to 1,732 images.
- ➢ Balanced distribution: 894 tumor and 838 no tumor.
- ➢ Data Splitting:
  - ❖ **Training set:** 80% (1,385 images).
  - ❖ **Validation set:** 10% (172 images).
  - ❖ **Testing set:** 10% (172 images).



Pre-Processing

- simplified the MRI images by converting them to grayscale, then applied Gaussian blur to reduce noise.
- used thresholding to separate potential tumor regions from the background, followed by contour detection to outline those regions.
- Finally, cropped around the detected tumor area to provide a clear, focused input for our classification models.



Classification

- ➢ Convolutional Neural Network (CNN):
  - ❖ CNN is a deep learning model designed visual images by learning patterns.
  - ❖ The CNN automatically learns features like edges, textures, and tumor shapes directly from MRI scans, making it much more effective than manually extracting features. (Allowing the model distinguish between tumor and non-tumor images, even when tumors vary in size, shape, or intensity).

- ➢ Visual Geometry Group (VGG16):
  - ❖ VGG16 is a deep CNN that learns image features layer by layer.
  - ❖ I used it because its pre-trained knowledge and architecture make it highly effective for detecting brain tumors from MRI scans.

Classification

- ➢ Support Vector Machine (SVM):
  - ❖ Support Vector Machine is a machine learning algorithm, that selects the best possible hyperplane (a line to divide data).
  - ❖ I used it to classify extracted features and PCA
  - ❖ It learned to classify images by finding patterns in these features that distinguish tumor vs. no-tumor
- ➢ Artificial Neural Network (ANN):
  - ❖ An ANN is a machine learning algorithm, build on the concept of a human brain neuron that is trained to transfer and processes information like a human brain..
  - ❖ I used it to classify extracted feature

Result Metrics

	Accuracy	Precision	Recall	F1-Score
CNN	**92%**	**89%**	**98%**	**93%**
VGG16	85%	79%	96%	87%
SVM	89%	84%	**98%**	89%
ANN	85%	88%	86%	85%

Figure 18: Classification Performance

Results

- ➢ **CNN** achieved the highest overall accuracy of 92%, with strong precision 89%, excellent recall 98%, and an F1-score of 93%.
- ➢ **VGG16** reached an accuracy of 85%. While its precision was lower (79%), it achieved a very high recall of 96%, meaning it was highly sensitive to detecting tumor cases
- ➢ **SVM** performed competitively with 89% accuracy and balanced metrics across the board of 84% precision, 98% recall, and 89% F1
- ➢ **ANN** achieved 85% accuracy with balanced precision of 88%, recall of 86%, and F1-score of 85%.

- ❖ Precision: How many predicted tumors were actually tumors. True Positives / (True Positives + False Positives)
- ❖ Recall (Sensitivity): How many real tumors did it catch. True Positives / (True Positives + False Negatives)
- ❖ F1-Score: The balance between precision and recall. 2 × (Precision × Recall) / (Precision + Recall)

Conclusion

- Among all the models, the CNN achieved the highest overall performance, demonstrating its superior ability to correctly classify both tumor and no-tumor MRI images.
- This improve early and accurate detection of brain tumors with the outcome of supporting clinical decision-making, enhancing diagnostic accuracy and contributing to better treatment planning and patient outcomes
- Future work will focus on expanding the dataset, testing more advanced deep learning architectures, and integrating the model into real-time clinical systems to further improve accuracy and practical applicability in healthcare.