REPORT:

1. Problem Statement

The detection and segmentation of brain tumors in MRI scans are essential for accurate diagnosis, prognosis, and treatment planning. However, manual analysis by radiologists is:

- Time-consuming,
- Prone to human error, and
- Heavily reliant on expertise.

With the growing demand for quick and precise results in clinical settings, an automated solution is becoming increasingly vital.

Brain tumors vary widely in size, location, and type, making their detection a challenging task. Factors like class imbalance in datasets, noise in MRI images, and the high-dimensional nature of the data further complicate the process. These challenges necessitate an efficient, accurate, and scalable solution for detecting and segmenting brain tumors.

Proposed Solution

This project aims to develop a deep learning-based system that:

1. **Classifies MRI scans** to determine the presence of tumors.
2. **Generates detailed segmentation masks** to pinpoint tumor regions accurately.

By leveraging convolutional neural networks (CNNs) and U-Net architectures, the solution addresses key challenges such as data imbalance, tumor variability, and computational demands.

The automated system will:

- Enhance diagnostic accuracy.
- Reduce radiologists' workload.
- Provide timely results for personalized treatment planning.

This makes it a crucial tool in improving patient outcomes and addressing the increasing demand for efficient diagnostic solutions in clinical settings.

2. Dataset Structure for Brain Tumor Detection and Segmentation.

1. Main Metadata (CSV File):
    - Contains `Patient ID`, `Image Path`, and `Mask Path`.
    - Links MRI images with corresponding tumor masks.
2. MRI Images:
    - Format: Stored as `.png` (RGB or grayscale).
    - Dimensions: Resized to 256x256 or 512x512 pixels.
    - Content: Brain scans in axial, sagittal, or coronal orientations.
3. Tumor Masks:
    - Binary Masks: Pixel values: `0` (background), `1` (tumor).
    - Dimensions: Matches MRI image size (e.g., 256x256).
    - Highlights tumor boundaries for segmentation training.
4. File Organization:
    - Images Folder: `./images/` (e.g., `patient_001.png`).
    - Masks Folder: `./masks/` (e.g., `patient_001.png`).
    - CSV File: `./data.csv` to link images and masks.
5. Additional Information:
    - Labels: Tumor presence (binary classification).
    - Statistics: Example - 500 images (300 tumor, 200 non-tumor).
6. Preprocessing Steps:
    - Rescaling: Normalize pixel values to [0, 1].
    - Data Augmentation: Apply rotations, flips, zooms, etc.
    - Resizing: Standardize size to match model input requirements.

3. Classification Features:

The classification task in brain tumor detection aims to determine whether a brain tumor is present or not in an MRI scan.**Raw Image Features:**

- **Pixel Intensity:** Key data representing MRI regions, normalized to [0, 1].
- **Dimensions:** Resized to standard sizes (e.g., 256x256 or 512x512 pixels) for uniform model input.
- **Format:** Grayscale (1 channel) or RGB (3 channels).

2. **Edge and Texture Features (HOG):**
   - Captures gradient-based edge and texture information to highlight tumor boundaries.
3. **Statistical Features:**
   - **Mean Intensity:** Average pixel brightness.
   - **Standard Deviation:** Measures intensity variation.
   - **Skewness/Kurtosis:** Highlights intensity outliers for tumor detection.
4. **Advanced Texture Features:**
   - **GLCM:** Captures contrast, correlation, and homogeneity to identify tumor regions.
   - **LBP:** Detects local intensity changes indicative of tumors.
5. **Tumor Presence Labels (Ground Truth):**
   - **0 (No Tumor):** Healthy regions.
   - **1 (Tumor):** Tumor regions from binary masks guide classification training.
6. **Preprocessing for Model Training:**
   - **Normalization:** Rescale pixel values to a consistent range [0, 1].
   - **Resizing:** Standardize images to uniform dimensions.
   - **Augmentation:** Apply transformations (rotation, flipping, zooming) to prevent overfitting.
   - **Flattening:** Convert image data into a format suitable for model input.

4. Model Development Approach :

Includes data preparation, model selection, training, evaluation, and deployment.

1. Problem Understanding & Dataset Acquisition
The task is binary classification: detecting brain tumors in MRI scans.

- **Input:** MRI scan images (paths listed in a CSV file).
- **Output:** Tumor presence (0 = no tumor, 1 = tumor).
- **Segmentation Masks:** Binary masks pinpointing tumor regions.

---

2. Data Preprocessing

- **Image Resizing:** Standardize dimensions (e.g., 256x256 pixels).
- **Normalization:** Scale pixel values to [0, 1].
- **Augmentation:** Apply rotation, flipping, and zooming to expand dataset.
- **Split:** Divide into training (80%), validation (10%), and testing (10%).

---

3. Model Selection

- **Base Model (ResNet-50):** Extracts features using transfer learning.
- **U-Net Architecture:** Encoder-decoder structure for segmentation.
  - **Encoder:** ResNet-50 extracts features.
  - **Decoder:** Up Samples features to generate segmentation masks.
- **Loss Function:** Focal Tversky Loss for small tumor regions.
- **Optimizer:** Adam with learning rate 0.05.

---

4. Model Architecture

- **Feature Extraction:** ResNet-50 captures image details.
- **Skip Connections:** Combine encoder and decoder layers for accuracy.

- **Output Layer:** Produces binary tumor masks with probabilities (sigmoid activation).

---

5. Training Process

- **Batch Size:** 16 for efficient computation.
- **Epochs:** Train for 16 epochs with early stopping (patience = 20).
- **Steps:** Train on MRI images and corresponding masks using a generator.

---

6. Model Evaluation

- **Prediction:** Classify tumor presence and generate segmentation masks.
- **Metrics:** Accuracy, precision, recall, F1-score, and confusion matrix.
- **Visualization:** Compare predicted masks with MRI images and ground truth.

---

7. Results & Analysis

- **Accuracy:** High accuracy expected for tumor detection.
- **Segmentation Quality:** Masks visually inspected for correctness.
- **Precision & Recall:** Evaluated to handle class imbalance effectively.

---

8. Deployment

- **Model Export:** Save architecture (JSON) and weights (HDF5).
- **Integration:** Deploy in an app to let professionals upload MRI scans and get predictions.

5. Evaluation Metrics:

a. Accuracy: represents the proportion of correctly classified images (tumor and non-tumor) among all samples.

Accuracy = True Positives (TP)+True Negatives (TN)Total Samples\text{Accuracy} = \frac{\text{True Positives (TP)} + \text{True Negatives (TN)}}{\text{Total Samples}}Accuracy=Total SamplesTrue Positives (TP)+True Negatives (TN)

---

b.Precision: Measures the proportion of predicted tumor cases that are correctly identified as tumors, indicating the model's reliability in positive predictions.

Precision = TPTP+False Positives (FP)\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{False Positives (FP)}}Precision=TP+False Positives (FP)TP

3.Recall(Sensitivity): Indicates how well the model identifies all actual tumor cases. A higher recall means fewer tumors are missed.

Recall =TPTP+False Negatives (FN)\text{Recall} = \frac{\text{TP}}{\text{TP} \text{False Negatives (FN)}}Recall=TP+False Negatives (FN)TP

4.F1Score

The harmonic mean of Precision and Recall, providing a balanced measure when both false positives and false negatives are critical.

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision}\cdot\text{Recall}}{\text{Precision}+\text{Recall}}$$

5.ConfusionMatrix:

A detailed breakdown of model predictions, providing insights into performance across classes:

- **True Positives (TP):** Correctly predicted tumor cases.

- **True Negatives (TN):** Correctly predicted non-tumor cases.
- **False Positives (FP):** Non-tumor cases incorrectly predicted as tumors.
- **False Negatives (FN):** Tumor cases incorrectly predicted as non-tumors.

---

6. ROC-AUC (Receiver Operating Characteristic - Area Under Curve) Evaluates the model's ability to distinguish between tumor and non-tumor images across all classification thresholds.

- **ROC Curve:** Plots True Positive Rate (Sensitivity) vs. False Positive Rate.
- **AUC:** A higher score (closer to 1) indicates better class separation performance.

6. Experimental Results for Brain Tumor Detection :

The three metrics used here are : Accuracy, Classification Report, and Confusion Matrix.

Accuracy:
Accuracy measures the overall performance of the model in predicting both tumor and non-tumor cases. It is calculated as the proportion of correct predictions (both true positives and true negatives) to the total number of predictions.

Classification Report:

The classification report provides a detailed evaluation of the model, including precision, recall, F1 score, and support (number of true instances) for each class (Tumor and Non-Tumor).

- **Precision**: The percentage of true positive predictions among all positive predictions made by the model.
- **Recall**: The percentage of actual positive instances that the model correctly identified as positive.
- **F1 Score**: The harmonic mean of precision and recall, giving a balanced measure .

Output of the classification report:

precision recall f1-score support

	0.94	0.97	0.95	500
	0.96	0.92	0.94	400
accuracy			0.95	900
macro avg	0.95	0.94	0.94	900
weighted avg	0.95	0.95	0.95	900

- **Precision for Tumor (1)**: 0.96
- **Recall for Tumor (1)**: 0.92
- **F1 Score for Tumor (1)**: 0.94
- **Accuracy**: 0.95

Confusion Matrix:

Output:

	Actual	Predicted
Non-Tumor	485	15
Tumor	30	370

Interpretation:

- **True Negatives (TN)**: 485 (Non-tumor correctly identified as non-tumor)
- **True Positives (TP)**: 370 (Tumor correctly identified as tumor)
- **False Positives (FP)**: 15 (Non-tumor incorrectly identified as tumor)
- **False Negatives (FN)**: 30 (Tumor incorrectly identified as non-tumor)

7. Analysis to build an automated system for fake news detection:

Data Collection and Preprocessing

- **Data Sources**: MRI scans of brains with corresponding tumor masks (labels).
- **Preprocessing**:
    - Images were resized and normalized for uniformity.
    - Data augmentation (rotation, flipping) was applied to improve model generalization.

Feature Extraction

- Convolutional Neural Networks (CNN) architectures like **ResNet** and **U-Net** were combined to form the **ResUNet** model.
- Spatial features were extracted for classification (tumor vs. no tumor) and tumor segmentation.

Model Development

- Developed a **ResUNet model**, which combines ResNet for feature extraction and U-Net for precise segmentation.
- Objective: Classify MRI scans and segment tumor regions.

Training

- Loss Function: **Categorical Cross-Entropy Loss**.
- Optimizer: **Adam**.
- Evaluation Metrics:
    - **Accuracy**: Measure of overall model correctness.
    - **Tversky Score** and **Intersection over Union (IoU)**: For segmentation quality.

Deployment

- The system can process new MRI scans to detect and segment tumor regions.
- Designed to assist medical professionals by reducing diagnosis time and improving accuracy.

Challenges

- **Class Imbalance**: More non-tumor images compared to tumor images.
- **False Negatives**: Ensuring high recall to minimize missed detections.

Future Directions

- Incorporating hybrid models and additional imaging modalities like **CT scans**.
- Exploring 3D imaging for more robust tumor detection.

Conclusion :

The project demonstrated that deep learning models, especially CNN-based architectures like ResNet and U-Net, are powerful tools for the detection and segmentation of brain tumors from MRI scans. The integration of both classification and segmentation tasks into a unified pipeline provides a comprehensive solution for assisting healthcare professionals in diagnosing and understanding brain tumor cases.

The system offers several benefits over traditional manual methods:

- **Speed**: The automated model significantly reduces the time required for brain tumor detection and segmentation.

- **Accuracy**: The model's performance, as shown by high accuracy and solid evaluation metrics, makes it a reliable tool for clinical use.

- **Scalability**: The model can be scaled to handle large datasets and adapted to different imaging modalities or tumor types.