A PROJECT REPORT

ON

Brain Tumor Segmentation

Maanya Gupta (E23CSEU0728)

Jashanpreet Kaur (E23CSEU0736)

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Description automatically generatedSandeep (E23CSEU0850)

SUBMITTED TO

Mr. Nitin Arvind Shelke

**Objective:**

The objective of this project is to develop **a deep learning-based solution** that can **automatically segment brain tumors** from MRI images. Accurate segmentation of brain tumors is crucial in medical imaging for diagnosis, treatment planning, and monitoring. Traditional manual segmentation is time-consuming and prone to human error, making automation a valuable tool for radiologists.

To tackle this problem, we use a **U-Net architecture**, which has shown remarkable success in biomedical image segmentation tasks due to its ability to learn from relatively few training samples and deliver precise pixel-level predictions.

**Tools & Libraries Used:**

|  |  |
| --- | --- |
| **Category** | **Libraries** |
| Data Handling | numpy, pandas |
| Visualization | matplotlib, seaborn |
| Image Processing | OpenCV, scikit-image |
| Machine Learning | scikit-learn |
| Deep Learning | TensorFlow, Keras |

**Understanding the Problem Domain:**

MRI (Magnetic Resonance Imaging) scans provide detailed images of the brain, which are used to detect abnormalities such as tumors. A **tumor mask** highlights the region of the image where the tumor is located.

The goal of segmentation is to create a **binary mask** (black and white) that separates tumor areas from normal tissue, thus identifying the shape and location of the tumor.

**Dataset Description:**

Dataset Link: https://www.kaggle.com/datasets/mateuszbuda/lgg-mri-segmentation

* The dataset comprises **MRI scans** of brains and their corresponding **binary masks.**
* Each image has a corresponding mask with the same dimensions, where:
  + 1 (white) indicates the presence of tumor
  + 0 (black) indicates background or non-tumor regions

A custom function is used to:

* Read paths of images and corresponding masks
* Match them accurately
* Store them in a structured format using a Pandas DataFrame

**Data Split:**

The dataset is divided into:

* **Training Set (80%)**: Used to train the model
* **Validation Set (10%)**: Used to tune hyperparameters and prevent overfitting
* **Test Set (10%)**: Used to evaluate model performance on unseen data

**Preprocessing Pipeline:**

**1. Resizing:**

All images and masks are resized to **256×256 pixels** to standardize the input size for the neural network.

**2. Normalization:**

Pixel values are scaled to a range of **[0, 1]** by dividing by 255. This improves model convergence during training.

**3. Binarization of Masks:**

* Mask values are converted to binary (0 or 1) using a threshold of 0.5.
* This ensures clear segmentation of tumor vs. non-tumor regions.

**4. Data Augmentation:**

To improve generalization, Image Data Generator is used to apply random transformations such as:

* Rotation
* Zoom
* Horizontal/vertical flip

This helps simulate a more diverse dataset.

**U-Net Architecture Explained:**

The U-Net is a **convolutional neural network** specifically designed for **semantic segmentation**. It consists of two main parts:

**1. Encoder (Contracting Path):**

* Series of convolutional layers followed by max-pooling
* Captures the *context* of the image (what is present)

**2. Decoder (Expanding Path):**

* Series of upsampling (transposed convolutions)
* Reconstructs the image to original resolution
* Combines with features from the encoder (skip connections)

**Skip Connections:**

* Help retain fine-grained spatial information lost during downsampling
* Improve model's ability to accurately segment smaller or complex shapes

**Training the Model:**

The model is compiled with:

* **Loss Function**: Binary Crossentropy (suitable for binary classification)
* **Optimizer**: Adam (adaptive learning rate optimization)

**Callbacks Used:**

* Model Checkpoint: Saves the best model during training based on validation loss
* Early Stopping: Stops training if validation loss doesn’t improve for several epochs

**Evaluation Metrics:**

Once trained, the model is evaluated using the test set on the following metrics:

| **Metric** | **Explanation** |
| --- | --- |
| **Accuracy** | Proportion of correctly classified pixels |
| **IoU (Intersection over Union)** | Measures overlap between predicted and actual masks |
| **Dice Coefficient** | 2×(Intersection) / (Union of predicted and true masks) |

These metrics are essential in medical image segmentation where even a few pixels of error can lead to incorrect diagnosis.

**Visualization of Results:**

The model predictions are visualized using triplets:

* Original Image
* Ground Truth Mask
* Predicted Mask

This visual inspection helps in qualitatively analyzing the model’s performance.

**Conclusion:**

* The U-Net architecture proves to be an effective solution for **medical image segmentation** tasks like **brain tumor detection**.
* The model is capable of accurately learning the structure and location of tumors from MRI images.

**Future Work:**

* **Deploy the model as a web app** for real-time tumor segmentation.
* Integrate with hospital systems for clinical use.
* Improve performance with transfer learning or ensemble models.