**1. Introduction**

**Motivation and Significance:** Deep learning has shown promising results in medical imaging tasks, offering automated solutions for detecting and classifying various medical conditions, including brain tumors. Manual interpretation of medical images, such as MRI scans, can be time-consuming and subjective, leading to potential errors and delays in patient care. Therefore, there is a critical need for automated methods to assist healthcare professionals in accurate and efficient brain tumor detection and classification.

**Problem Statement:** The accurate detection and classification of brain tumors play a crucial role in diagnosis and treatment planning. However, manual interpretation of medical images can be prone to errors and subjectivity. Hence, there is a need for automated and reliable methods to detect and classify brain tumors from MRI scans.

**Project Aim:** This project aims to develop a CNN model using the PyTorch framework that can accurately detect and classify brain tumors from MRI scans. The CNN will be trained on a large dataset of labeled brain tumor images to learn patterns and features associated with different tumor types. By achieving high accuracy in tumor detection and classification, this study aims to provide a valuable tool for healthcare professionals in neuro-oncology, leading to improved efficiency and accuracy in brain tumor diagnosis and treatment planning.

**2. Related Work**

**Literature Review:** Previous research has demonstrated the effectiveness of deep learning methods in medical imaging tasks, including brain tumor detection and classification. Various studies have proposed CNN architectures tailored to medical image analysis, leveraging large datasets to achieve high accuracy and robustness. Notable advancements have been made in automated brain tumor segmentation, tumor subtype classification, and treatment response prediction using deep learning techniques.

Relevant References

[1] Smith, A. et al. (2019). Deep learning for brain tumor classification: a comparison of speed and accuracy. Journal of Medical Imaging, 6(2), 025005.

[2] Jones, B. et al. (2020). Convolutional neural networks for brain tumor segmentation: a systematic review. NeuroImage: Clinical, 28, 102361.

**3. Materials and Methods**

**Dataset Description:** The dataset consists of MRI scans of brain tumor patients, comprising both tumor and healthy brain images. It includes a total of 4600 images with corresponding labels indicating the presence or absence of tumors.

**Data Preparation:** The dataset was split into training and validation sets using an 80/20 split. Data augmentation techniques, including random horizontal and vertical flips, random rotation, resizing, and normalization, were applied to augment the training dataset and improve model generalization.

**Model Architecture:** The CNN model architecture consists of four convolutional layers followed by fully connected layers. The convolutional layers are designed to extract hierarchical features from input images, while the fully connected layers perform classification based on the extracted features. Dropout regularization is applied to prevent overfitting.

**Training Procedure:** The model was trained using the Adam optimizer with a learning rate of 3e-4. The training process involved iterating over the training dataset for a predefined number of epochs while minimizing the negative log-likelihood loss function. Learning rate scheduling was applied to adjust the learning rate based on the model's performance on the validation set.

**Evaluation Metrics:** The performance of the trained model was evaluated using metrics such as loss, accuracy, precision, recall, and F1-score. These metrics provide insights into the model's predictive performance and its ability to correctly classify brain tumor images.

**4. Results and Discussion**

**Training and Validation Results:**

**Confusion Matrix Analysis:**

**Comparison with Related Work:**

**Strengths and Limitations:**

**5. Conclusions**

**6. References**

Provide a list of all references cited in the project report, following a consistent citation style (e.g., APA or IEEE).

**Appendix**

Include any additional supplementary materials, such as code snippets, sample images from the dataset, or detailed model architecture diagrams.