Deep learning for Alzheimer’s detection: A CNN-Based approach using MRI scans

This report details the use of Convolutional Neural Networks (CNNs) for Alzheimer’s detection from MRI brain scans. It covers data processing, model architecture, training, evaluation, and obtained results. Additionally, it discusses challenges, future improvements, and key considerations for applying deep learning in medical diagnosis.

Introduction

Alzheimer's disease is a progressive neurodegenerative disorder that affects memory, cognition, and daily life activities. Early detection is crucial for effective treatment and management. This report presents a detailed explanation of the deep learning approach used in this project to classify MRI brain scans for detecting Alzheimer's disease at different stages.

This study employs **Convolutional Neural Networks (CNNs)** to analyze MRI brain images and classify them into four categories:

- **Non-Demented**
- **Very Mild Demented**
- **Mild Demented**
- **Moderate Demented**

We leverage a dataset stored in **Parquet format**, preprocess the images, design a CNN model, and train it using appropriate techniques. The trained model is evaluated and used to make predictions on new MRI scans. This document provides an in-depth look at each step involved.

Data description

Data source

The dataset consists of MRI brain scans stored in **Parquet files**. This format allows efficient storage and retrieval of large datasets.

Data distribution

The dataset is divided into **training, validation, and test sets** to ensure robust evaluation of the model.

Data preprocessing

Before feeding the images into the CNN, several preprocessing steps are performed:

1. **Loading the data**: The data is read from Parquet files using Pandas and stored in a structured DataFrame.
2. **Image conversion**:
    - The MRI scans are stored as byte data and need to be converted into a usable image format.
    - Each image is decoded and transformed into an array format.
3. **Image resizing**: All images are resized to a standard size (e.g., **224x224 pixels**) to ensure uniformity.
4. **Normalization**: Pixel values are normalized between 0 and 1 to stabilize and improve model convergence.
5. **Channel conversion**: Images are converted to **RGB format** if required.

Deep learning model architecture

A **Convolutional Neural Network (CNN)** is used for feature extraction and classification. The CNN architecture consists of:

Convolutional Layers

- Extract spatial features from images using **kernel filters**.
- Employ **ReLU activation** to introduce non-linearity.

MaxPooling Layers

- Reduce the spatial dimensions while preserving important features.
- Prevent overfitting and improve computational efficiency.

Flatten Layer

Converts the feature maps into a 1D vector to be fed into fully connected layers

Dense Layers

- Fully connected layers perform the final classification.
- **Softmax activation** is used in the output layer to produce class probabilities.

Model training

Data splitting

The dataset is split into **training (80%)**, **validation (10%)**, and **test (10%)** sets.

Training process

- The model is trained using the **Adam optimizer** and **categorical cross-entropy loss**.
- **Batch size and number of epochs** are chosen based on experimentation.

Monitoring training

- Training and validation **accuracy** and **loss** are monitored using plots.
- Early stopping is used to prevent overfitting.

Model evaluation

Metrics used

- **Accuracy**: Measures the percentage of correctly classified images.
- **Precision, Recall, and F1-score**: Provide a deeper insight into model performance.
- **Confusion Matrix**: Visualizes misclassifications.

Performance analysis

- The trained model is evaluated on the test set.
- Insights from evaluation metrics guide further improvements.

Prediction process

Once trained, the model can classify new MRI scans. The process includes:

1. **Loading the trained model**: The saved model is loaded for inference.
2. **Preprocessing new images**: The same preprocessing pipeline (resizing, normalization) is applied.
3. **Making predictions**: The image is passed through the CNN to obtain class probabilities.
4. **Displaying results**: The predicted class and probability scores are shown.

Results and observations

Sample predictions

- The model correctly classifies most images.
- Some misclassifications occur due to **overlapping features** in different dementia stages.

Challenges faced

- **Limited dataset size**: More data could improve generalization.
- **Data imbalance**: Certain categories have fewer samples.
- **MRI image variability**: Differences in imaging techniques affect model performance.

Future improvements

To enhance model performance, we propose:

1. **Experimenting with different architectures**: Testing deeper CNNs such as **ResNet, VGG, or EfficientNet**.

2. **Data augmentation**: Introducing transformations such as rotation, flipping, and contrast adjustments.

3. **Fine-Tuning with pretrained models**: Using transfer learning to leverage existing models trained on medical images.

4. **Collecting more data**: Expanding the dataset to improve generalization.

Conclusion

This project showcases the power of deep learning in **medical imaging**. By leveraging **CNNs**, we have developed a model capable of detecting Alzheimer's disease from MRI scans. The insights from this project contribute to advancing automated diagnosis techniques.

However, it is crucial to note that this is an **educational project** and should not be used for real medical diagnoses. Further refinements and clinical validation are required for real-world applications.