Alzheimer's Disease Detection Using Deep Learning

1. Introduction

Alzheimer's Disease (AD) is a long-term brain disorder that causes memory loss, confusion, and changes in behavior, especially in elderly people. It progresses slowly and severely affects a person's ability to carry out daily activities. Early diagnosis is extremely important so that treatment can begin at the right time.

Thanks to advancements in Artificial Intelligence (AI), we can now use deep learning methods to help detect Alzheimer's early by analyzing brain MRI scans. This approach can support doctors in identifying the disease faster and more accurately.

2. Datasets

Here are 2–3 popular Kaggle datasets ideal for deep learning-based AD detection:

OASIS Alzheimer's Detection:
http://kaggle.com/code/kirollosashraf/oasis-alzheimer-s-detection
The dataset on Kaggle contains T1-weighted MRI brain images labeled into four categories: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. It is designed to aid early detection of Alzheimer's using deep learning. The images are preprocessed and suitable for training CNN-based models.

Early Alzheimer's Detection Dataset:
https://www.kaggle.com/datasets/yasserhessein/dataset-alzheimer
comprises longitudinal MRI data from 150 subjects aged 60 to 96, each scanned at least once. It is designed to facilitate the analysis and early detection of Alzheimer's Disease by providing a valuable resource for researchers and practitioners

Alzheimer's Disease Dataset:
https://www.kaggle.com/datasets/rabieelkharoua/alzheimers-disease-dataset
contains over 5000 MRI brain images categorized into four classes: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The images are well-organized and suitable for training deep learning models for multi-class classification. It's an excellent dataset for building CNN-based Alzheimer's detection systems.

3. Algorithms & Models to Use

1. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are specially designed to handle image data, making them highly effective for analyzing medical images like brain MRIs. CNNs automatically detect patterns, edges, and textures that are important for recognizing abnormalities in brain structures—features that may not be immediately obvious to the human eye. In the case of Alzheimer's detection, CNNs can classify MRI images into different stages of the disease (such as non-demented, mild, or moderate dementia) by learning from large datasets. Their layered architecture allows them to extract deep hierarchical features, which significantly boosts the accuracy of diagnosis compared to traditional machine learning methods.

2. Transfer Learning Models

Transfer learning is a technique where pre-trained models, such as VGG16, ResNet50, and InceptionV3, are adapted for a new but related task—in this case, Alzheimer's detection. These models have already been trained on massive image datasets like ImageNet and have learned to recognize a wide variety of features. Instead of training a model from scratch, researchers fine-tune these pre-trained models using MRI images, which reduces the time and computational resources needed for training. Transfer learning also helps improve accuracy, especially when working with limited medical data, by allowing the model to apply previously learned patterns to identify signs of Alzheimer's in brain scans.

3. Hybrid Models (CNN + LSTM)

Hybrid models that combine CNNs with Long Short-Term Memory networks (LSTMs) are particularly useful for analyzing time-series or longitudinal MRI data. While CNNs handle the spatial features of each image, LSTMs are capable of processing sequences and learning temporal dependencies. This combination allows the model to understand how a patient's brain changes over time, which is crucial for tracking the progression of Alzheimer's Disease. For instance, if a patient undergoes multiple MRI scans over several months or years, a CNN+LSTM model can analyze not just individual images, but also how the features evolve across those images, resulting in more accurate and insightful diagnoses.

4. Methods and Processing Steps

Preprocessing

MRI images are resized (e.g., 128×128) and normalized (pixel values scaled) to make training easier. Data augmentation techniques like rotation, flipping, and zoom are used to create more training samples and avoid overfitting.

Dimensionality Reduction

To reduce complexity:

- Layers like **Global Average Pooling** or **Flatten** shrink data size.
- **PCA** is used if combining image features with clinical data, helping the model focus only on important features.

Training Process

- **Data is split** into training (70%), validation (20%), and testing (10%) sets.
- **Early stopping** and **dropout** are used to prevent overfitting.
- The model uses the **Adam optimizer** and **categorical cross-entropy loss** for learning.

Evaluation Metrics

To measure performance:

- **Accuracy:** Overall correctness
- **Precision & Recall:** Focus on how well the model detects the disease
- **F1-Score:** Balance between precision and recall
- **ROC-AUC:** Measures how well the model separates different classes

5. Possible Results

When using deep learning for Alzheimer's Disease detection, **CNN models** have shown impressive performance, achieving **accuracy levels between 88% to 95%** in classifying different stages of the disease. By using **transfer learning** techniques with pre-trained models like **VGG16** or **ResNet50**, even better results can be obtained, often outperforming standard CNNs due to their ability to reuse learned features from large datasets. Additionally, applying **data augmentation** (e.g., rotating or flipping images) and **regularization methods** (like dropout) significantly helps the model **generalize better** to new, unseen data, improving reliability in real-world applications.

6. Conclusion

Deep learning models, especially CNNs, offer a powerful solution for early and accurate Alzheimer's Disease detection using brain MRI scans. Kaggle datasets provide a solid foundation for experimentation. With proper preprocessing, model selection, and evaluation, students can build effective diagnostic tools and use this report as a reference for their case study.