**DeepCurvMRI: Deep Convolutional Curvelet Transform based MRI Approach for Early Detection of Alzheimer’s Disease**

**Alternate Title:**

 Survey on Detection and Classification of Alzheimers disease from MRI Images

**Aim:**

To detect and identify the Alzheimers disease detection using Deep-Learning techniques

**Abstract:**

Alzheimer's disease is a neurodegenerative disorder that affects memory, thinking, and behavior. Detecting the disease early is crucial for effective management and treatment. Transfer learning is a technique where a pre-trained neural network, such as Inception V3, which was originally trained on a large dataset for image recognition tasks, is fine-tuned for a specific task, such as medical image analysis.

**Introduction:**

Alzheimer's disease, a progressive neurodegenerative disorder, poses a significant global health challenge. The difficulty in diagnosing the disease in its early stages underscores the importance of advanced diagnostic tools. This article delves into the integration of transfer learning techniques with the Inception V3 model to develop a robust and accurate Alzheimer's disease detection system.

**Existing System:**

There are several existing of techniques are available for Alzheimers disease detection and classification to detect the early detection. There are many techniques available presents a study of existing techniques for Alzheimers disease detection and their advantages and limitations. To overcome these limitations, propose a Convolution Neural Network (CNN) based classifier. CNN based classifier does the comparison between trained and test data, from this to get the simplest result.

**Disadvantages:**

CNNs can be computationally intensive, especially with deep architectures and large datasets. The extensive number of layers and parameters can lead to longer training times and resource-intensive computations, requiring powerful hardware like GPUs or TPUs. Effective training of CNNs often demands substantial amounts of labeled data. Insufficient data can lead to over fitting, where the model learns to perform well on the training data but struggles to generalize to new, unseen data. Over fitting occurs when a CNN learns to recognize noise and irrelevant patterns in the training data, resulting in poor performance on validation or test data. Regularization techniques, data augmentation, and early stopping can help mitigate over fitting. CNNs are often treated as "black-box" models, making it challenging to understand how and why they make certain predictions. The complex hierarchical features learned in deeper layers can be difficult to interpret, limiting insights into decision-making. While data augmentation can enhance model generalization, it's not always straightforward to apply to all types of data. For instance, generating realistic variations in medical images might be more complex than in natural images. CNN performance can be sensitive to hyper parameters such as learning rate, batch size, and architecture choices. Finding optimal values often requires extensive experimentation.

**Proposed System**

The diagnosis of Alzheimers disease detection at the early stages is very important. Our proposed methodology is based on Deep Neural Network Model which trains on the Dataset and detects the image with a classification and in such image the disease gets segmented. Then we are using flask web framework to detect a Disease classification.

**Advantages:**

Transfer learning, a technique in deep learning, involves leveraging pre-trained models on one task to enhance performance on a different but related task. The Inception V3 model is a prime example of a deep neural network that excels in transfer learning due to its versatile architecture and broad pre-training. Inception V3 Architecture: Inception V3 is a convolutional neural network (CNN) architecture known for its efficiency in image analysis. It features various "Inception modules," which consist of parallel convolutional operations of different sizes and pooling operations. This design enables the model to capture features at multiple scales, aiding in recognizing complex patterns within images. Pre-Training on ImageNet: Before transfer learning, Inception V3 undergoes pre-training on massive datasets, such as the ImageNet dataset. This phase imparts the model with a diverse set of features, including edges, textures, and higher-level object parts, learned from a wide range of images. Fine-Tuning for Task-Specific

**Objectives:**

After pre-training, Inception V3 is fine-tuned for a specific task. Fine-tuning typically involves modifying the final layers of the network to align with the new task's objectives. For example, if the task is medical image classification, the output layer might be changed to accommodate the number of classes in the medical dataset.

**Module Description:**

* Dataset collection
* Transfer Learning (**Inception V3 Model**)
* Detection

**Dataset Collection:**

A curated dataset of brain MRI scans is collected, comprising both Alzheimer's disease-affected and healthy individuals. Each scan is associated with the appropriate label.

**Transfer Learning (Inception V3 Model):**

Inception V3 is a convolutional neural network (CNN) architecture that has garnered attention for its efficiency in image classification tasks. Developed by Google researchers, this architecture is part of the Inception family known for their innovative designs to extract hierarchical features from images.

**Architecture Overview:**

Inception V3's architecture is characterized by its utilization of various "Inception modules." These modules consist of parallel convolutional operations of different sizes and pooling operations, allowing the model to capture features at multiple scales. This design choice enhances the model's ability to recognize intricate patterns within images.

**Pre-Training on ImageNet:**

Before fine-tuning for a specific task, Inception V3 undergoes pre-training on massive datasets, most notably the ImageNet dataset. This pre-training phase imparts the model with a wide array of features that are relevant to general image recognition tasks.

**Fine-Tuning for Task-Specific Objectives:**

Once pre-trained, Inception V3 can be fine-tuned for a target task. Fine-tuning involves modifying a few layers of the model while retaining the knowledge gained during pre-training. For instance, in medical imaging applications, the model can be fine-tuned to detect specific diseases from scans.

**Detection:**

Once user login to the Web-application, User should give an image as the input. If the model predicts that the given image disease or not.

**Software Requirements:**

* Operating System : Windows 10 (64 bit)
* Software : Python
* Tools : Anaconda (Jupyter Note Book IDE)

**Hardware Requirements:**

* Hard Disk : 500GB and Above
* RAM : 4GB and Above
* Processor : I3 and Above

**Architecture Diagram**:

User

Web interface

 MRI Images

Image Pre-processing

Inception V3

Diseases

Detection

Mild Demented

Moderate demented

Data Acquisition

Very Mild Demented

 Non Demented

**Conclusion:**

The potentiality of the proposed Deep- CurvMRI to efficiently identify brain regions associated with AD MRI images, serving as a fast and easy to implement the tool for assisting physicians in AD diagnosis. As for future work, Deep CurvMRI will be trained and tested on various datasets for Alzheimer’s disease diagnosis. Moreover, meta-data such as clinical biomarkers and demographics can be included and combined to create a holistic approach to AD diagnosis.