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Implementation of Alzheimer Disease Detection using Structural Images

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ABSTRACT: Early detection of Alzheimer's disease (AD) is important so that preventative measures can be taken. Current techniques for detecting AD rely on cognitive impairment testing which unfortunately does not yield accurate diagnoses until the patient has progressed beyond a moderate AD. Alzheimer's disease considered being one of the acute diseases that cause the human death especially in people above 60years old. Many computer-aided diagnosis systems are now widely spread to aid in Alzheimer diagnosis. Therefore, an automated and reliable computer-aided diagnostic system for diagnosing and classifying the brain diseases has been proposed. MRI (Magnetic resonance Imaging) is one source of brain diseases detection tools, but using MRI in Alzheimer classification is considered to be difficult process according to the variance and complexity of brain tissue. This project presents a survey of the most famous techniques used for the classification of brain diseases based on MRI. The Alzheimer detection and classification systems consist of four stages, namely, MRI pre-processing, Segmentation, Feature extraction, and Classification respectively. In the first stage, the main task is to eliminate the medical resonance images (MRI) noise which may cause due to light reactions or any inaccuracies in the imaging medium. The second stage, which is the stage where the region of interest is extracted (Alzheimer region). In the third stage, the features related to MRI images will be obtained and stored in an image vector to be ready for the classification process and finally the fourth stages, where classifier will take place to specify the Alzheimer kind Image segmentation is a significant research field in medical engineering. Segmented brain images are used to visualize volume and quantitatively analyze anatomical and cortical structures. Segmented brain tissues provide an anatomical frame work for visualization which has a potential use in neuroscience research and neurosurgical planning owing to advances in Magnetic Resonance Imaging (MRI). Segmentation refers to the labeling of pixels into different regions.

KEYWORDS: Brain segmentation, skull stripping, threshold, Seed region growing.

I. INTRODUCTION

The early detection of Alzheimer's disease (AD) is of utmost importance for implementing preventive measures. However, the current methods relying on cognitive impairment testing often fail to provide accurate diagnoses until the disease has progressed to a moderate stage. Alzheimer's disease is a significant cause of mortality, particularly among individuals aged 60 years and older. To aid in the diagnosis of Alzheimer's and other brain diseases, computer-aided diagnostic systems have gained widespread usage. In line with this, we propose an automated and reliable computer-aided diagnostic system for diagnosing and classifying brain diseases. While Magnetic Resonance Imaging (MRI) is a valuable tool for detecting brain diseases, its utilization in Alzheimer's classification poses challenges due to the complex and variable nature of brain tissue. Presently, machine learning and pattern classification methods are extensively employed in the development of computeraided diagnosis systems that utilize various neuroimaging techniques, including MRI, Positron Emission Tomography (PET), functional MRI (fMRI), and Diffusion Tensor Imaging (DTI). Among these techniques, structural MRI is widely regarded as the most standardized imaging modality in clinical practice and is particularly useful for tracking different clinical phases of AD. Hence, our proposed method is specifically evaluated on structural MR images.

II. RELATED WORK

A. Detection of Alzheimer's Disease with Shape Analysis of MRI Images

A study was conducted to detect Alzheimer's disease by analyzing the shape of MRI images. The researchers employed various descriptors as features and used a support vector machine for classification. They achieved an accuracy of 87.5%, surpassing the accuracy of conventional volume ratio evaluation.

B. Alzheimer's Disease and Dementia Detection from 3D Brain MRI Data Using Deep Convolutional Neural Networks This paper presents an alternative approach using deep convolutional neural networks (CNNs) for detecting Alzheimer's disease and dementia from 3D brain MRI data. CNNs, known for their image processing capabilities, offer a fast, cost-effective, and reliable method. The authors introduced a state-of-the-art CNN model specifically designed for Alzheimer's disease and dementia detection.

C. Alzheimer's Disease Diagnosis Model Based on Three-dimensional Full Convolutional DenseNet Proposing an increment method for dataset augmentation and a learning method for small sample sizes, the authors established a 3D full convolutional DenseNet classification model. This model utilizes the advantages of DenseNet architecture to extract comprehensive image feature information and improve generalization ability.

D. An Optimal Decisional Space for the Classification of Alzheimer's Disease and Mild Cognitive Impairment In this study, MRI data was combined with the Mini-Mental State Examination (MMSE) test results for classifying Alzheimer's disease and mild cognitive impairment. The authors constructed a multi-dimensional decisional space by selecting statistically significant features through careful ranking and selection. Support vector machines (SVM) were employed for classification, achieving promising results.

E. Classification of Patients with Alzheimer's Disease and Healthy Subjects from MRI Brain Images Using the Existence Probability of Tissue Types Using the existence probability of different tissue types obtained through image segmentation, this study aimed to classify patients with Alzheimer's disease from healthy subjects based on MRI brain images. Quantitative evaluation of structural changes using existence probabilities led to the creation of a feature matrix for classification. The study reported promising results, with the highest accuracy achieved when considering specific structural changes.

F. Detection of Alzheimer's Disease with Shape Analysis of MRI Images This study focused on the effectiveness of utilizing brain shape information for classifying healthy subjects and Alzheimer's disease patients. The authors used a P-type Fourier descriptor as shape information and analyzed the lateral ventricle excluding the septum lucidum. Classification using a support vector machine yielded an accuracy of 87.5%, outperforming traditional morphological evaluations based on volume ratio.

III. METHODOLOGY

A) System Architecture

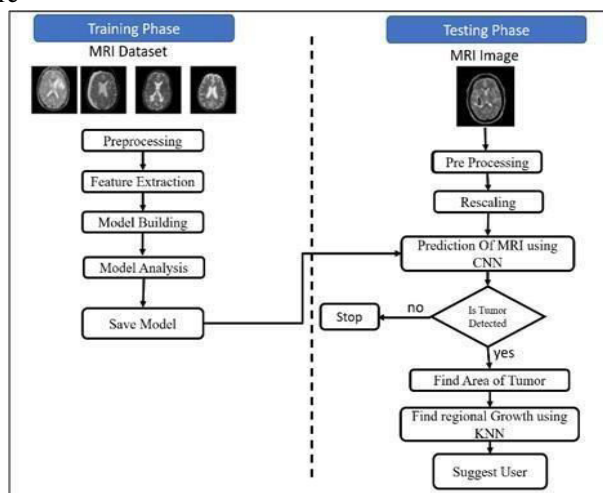


Fig1: System Architecture



B) MODULES

- **Testing:** Magnetic Resonance Imaging (MRI) scans are utilized as the input for testing in the system. MRI scans can produce activation maps that show the affected areas of the brain. They detect changes in blood oxygenation and flow in response to neural activity.
- **Pre-processing:** Image pre-processing is performed at the lowest level to enhance image features and suppress undesired distortions. This module includes operations such as image resizing, conversion, and intensity adjustment.
- **Prediction of Alzheimer's Disease:** This module employs a CNN (Convolutional Neural Network) algorithm for predicting Alzheimer's disease. It involves segmenting the volumes of the overall brain and obtaining the white and gray matter. The ratio of gray to white matter is calculated to predict the presence of Alzheimer's disease.
- **Region of Growth:** This module is responsible for detecting the location and overall area of tumors using the KNN (KNearestNeighbors) algorithm.

The algorithm for region-based segmentation consists of the following steps:

1. Selection of a set of seed points based on user criteria.
2. Growth of regions from the seed points based on adjacency and region membership criteria.
3. Determination of a suitable threshold value for region growth.
4. Calculation of brain volume.

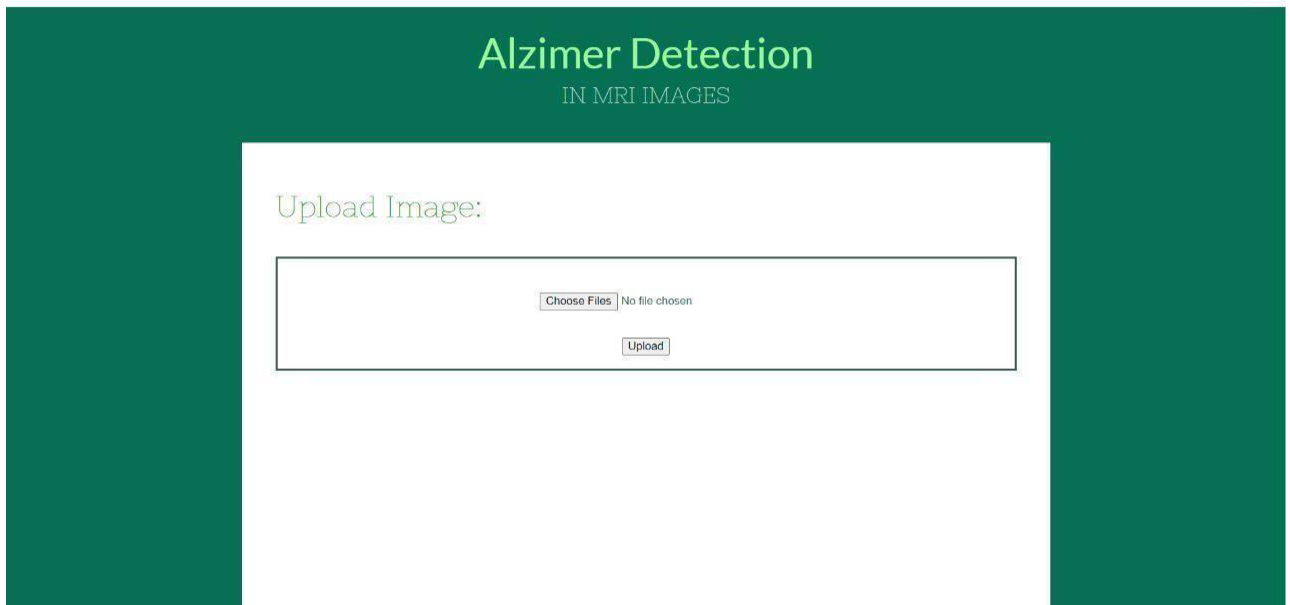
IV. RESULT ANALYSIS

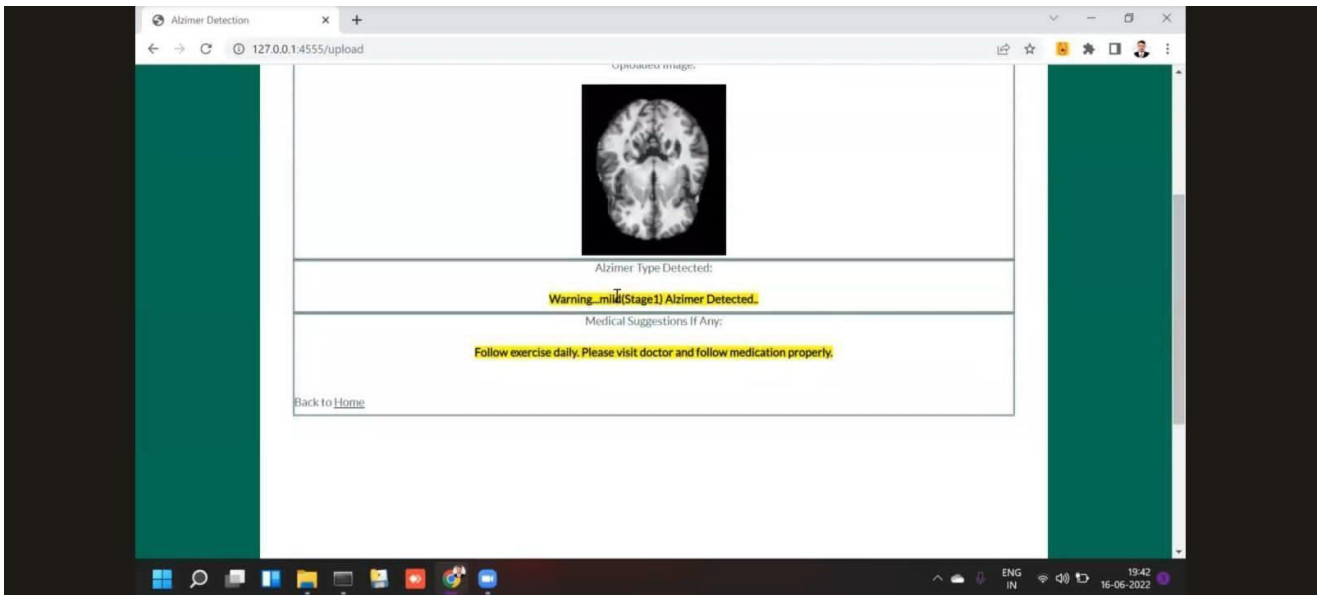
```

1 # -*- coding: utf-8 -*-
2
3 # Part 1 - Building the CNN
4
5 # Importing the Keras Libraries and packages
6 from keras.models import Sequential
7 from keras.layers import Convolution2D
8 from keras.layers import MaxPooling2D
9 from keras.layers import Flatten
10 from keras.layers import Dense
11 from keras.models import model_from_json
12
13 # mobile.css
14 # style.css
15 # style1.css
16
17 batch_size = 32 #32 number of images to be pass to algo in batch wise
18
19 from tensorflow.keras.preprocessing.image import ImageDataGenerator
20
21 # ALL images will be rescaled by 1./255
22 train_datagen = ImageDataGenerator(rescale=1/255)
23
24 # Flow training images in batches of 128 using train_datagen generator
25 train_generator = train_datagen.flow_from_directory(
26     'dataset/train/', # This is the source directory for training images
27     target_size=(200, 200), # All images will be resized to 200 x 200
28     batch_size=batch_size,
    
```



```
File Edit Selection View Go Run Terminal Help Alzimer_Detection
result.html model.py x
MultiClass-Image-Classification-master > model.py > IDIR
26 batch_size=batch_size,
27 # Specify the classes explicitly
28 classes = ['mild','moderate','non','verymild'],
29 # Since we use categorical_crossentropy Loss, we need categorical labels
30 class_mode='categorical')
31
32 import tensorflow as tf
33
34 model = tf.keras.models.Sequential([
35 # Note the input shape is the desired size of the image 200x 200 with 3 bytes color
36 # The first convolution
37 tf.keras.layers.Conv2D(16, (3,3), activation='relu', input_shape=(200, 200, 3)),
38 tf.keras.layers.MaxPooling2D(2, 2),
39 # The second convolution
40 tf.keras.layers.Conv2D(32, (3,3), activation='relu'),
41 tf.keras.layers.MaxPooling2D(2,2),
42 # The third convolution
43 tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
44 tf.keras.layers.MaxPooling2D(2,2),
45 # The fourth convolution
46 tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
47 tf.keras.layers.MaxPooling2D(2,2),
48 # The fifth convolution
49 tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
50 tf.keras.layers.MaxPooling2D(2,2),
51 # Flatten the results to feed into a dense layer
```





V. CONCLUSION

In this system, we have implemented an Alzheimer's disease identification system using Python programming language, developed as a Windows application. The system showcases the application of image processing techniques in healthcare. It can not only assist in personal healthcare but also contribute to the betterment of society. In the future, we plan to incorporate techniques such as PCA (Principal Component Analysis) and FLDA (Fisher Linear Discriminant Analysis) for dimensionality reduction and presentation, respectively. Additionally, we aim to introduce more efficient algorithms and utilize methods like LLR (Local Linear Regression) for obtaining virtual frontal images and DCT (Discrete Cosine Transform) for illumination normalization. By expanding the system's capabilities, we can further enhance its effectiveness in Alzheimer's disease.

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