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ALZHEIMER'S CLASSIFICATION USING DEEP LEARNING TECHNIQUE

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Abstract

Alzheimer's disease is characterized by the decline of memory and cognitive abilities, which affects brain regions responsible for language, thought processes, and memory. A DL algorithm based on CNN has been developed to detect this disease, with the potential for further improvements by integrating more techniques for feature extraction. Solution can be shared through a webpage using the Django Framework. The CNN-based approach with added feature extraction methods can have a significant impact on this disease diagnosis.

Keywords: ALZHEIMER, DEEP LEARNING

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Introduction:

Alzheimer's disease is a prevalent disorder globally, and currently, there is no cure available for advanced stages. This condition is the leading cause of dementia and leads to a gradual decline in cognitive, social, and behavioral skills, ultimately impacting an individual's ability to function independently. In beginning of this disease, individuals may exhibit memory lapses and struggle to recall recent events or conversations. As the disease advances, patients may experience more pronounced memory impairment and struggle to complete routine tasks. While medicines can provide temporary relief, DL methods can significantly enhance the speed, accuracy.

Problem Statement:

The brain regions associated with memory, such as the hippocampus and entorhinal cortex, are the first to be affected by Alzheimer's disease, before affecting other areas involved in language, reasoning, and social behavior in the cerebral cortex. As the disease progresses, it can cause difficulties in performing daily activities, such as driving, cooking, or managing finances. Patients may repeat questions, misplace belongings, or become easily confused. Furthermore, some individuals may experience emotional distress and even exhibit aggressive behavior.

This paper aims to investigate the impact of different CNN methods on prediction accuracy for Alzheimer's disease. Specifically, our research focuses on classifying images into two categories: Alzheimer's-defected and normal images. In addition, we explore the use of handcrafted features extracted from raw images after various processing techniques to enhance the accuracy of forcast of illness. This strategy's objective is to discover distinct quality that are accountable for predicting the occurrence for Alzheimer's disease. By incorporating different CNN methods and feature extraction techniques, our research aims to improve early diagnosis and treatment planning for Alzheimer's disease.

Project Objectives:

- The aim is to employ convolutional neural network techniques in developing a DL model capable of categorizing images related to Alzheimer's disease, and to compare various CNN architectures to determine the one that yields the highest accuracy.

- Additionally, a user-friendly web application will be developed to display the prediction results.

Related Works:

[7] In a recent study, the researchers set out to create and validate a DL algorithm capable of accurately predicting the sease, mild cognitive impairment, or neither of these, by examining fl 18 (18F) (FDG) PET brain images. The study used a collection of 2,1091002 patients from the ADNI and imaging studies, collected between 2005 and 2017, as well as an independent test set of 40 imaging studies and 40 patients from 2006 to 2016. At the subsequent visit, the final clinical diagnosis was noted and the algorithm was compared to radiologic readers. The InceptionV3 architecture convolutional neural network was tested using the remaining 10% of the ADNI data set and the independent test set after training on 90% of the data set. Model performance was evaluated using sensitivity, specificity, t-distributed stochastic neighbour embedding, ROC, and saliency map.

[8] Here, author introduced a DL approach for distinguishing between healthy control data and Alzheimer's disease (AD) in

magnetic resonance imaging (MRI) and functional MRI (fMRI) data. They utilized a high-performance computing platform for precise data preprocessing and a convolutional neural network (CNN) architecture to extract invariant features from a vast number of training images. This study is the first to employ fMRI data in DL models for medical image analysis and AD prediction. The proposed pipelines showed superior classification results compared to other studies, achieving reproducible results around 99.9% to fMRI and 98.84% to MRI . The findings highlight the potential of DL methods in advancing the diagnosis and treatment of AD.

[9] The current diagnosis method for Alzheimer's disease involves structural MRI image analysis by experienced radiologists, which is time-consuming, subjective, and prone to misdiagnosis. To address this issue, CNNs have been used to classify MRI images of patients and controls using DL by transfering learning techniques. The study examined the effectiveness of the VGG 16 and MobileNet CNN models, and the findings revealed that MobileNet performed better than VGG 16. This approach provides an efficient and accurate method for diagnosing Alzheimer's disease compared to traditional MRI image analysis by radiologists. DL techniques have the potential to revolutionize medical image analysis and improve patient outcomes in the future.

[10] In this study, the authors utilized a convolutional neural network (CNN) to differentiate between Alzheimer's disease-affected brains and healthy brains. The aim was to develop a predictive model or system capable of distinguishing the disease from normal subjects or estimating the stage of the disease. Clinical data classification, particularly for Alzheimer's disease, has been a challenging task, with selecting the most distinguishing features being the most difficult aspect.

Proposed Methodology:

In this study, a classification task was performed on a dataset of MRI images, which included both Alzheimer and non-Alzheimer images. The images were categorized into input and output classes based on their classification as normal or abnormal. A DL method based on CNN was proposed to predict Alzheimer's disease, with the expectation that this method will achieve higher accuracy. The results were presented in a web application hosted on a local server.

Methodology:

To prepare the MRI brain image dataset for CNN model training, a preprocessing step is carried out, which involves reshaping, resizing, and converting the images to an array format. Additionally, the dataset is categorized into demented and non-demented groups, and separate test images are prepared for the software.

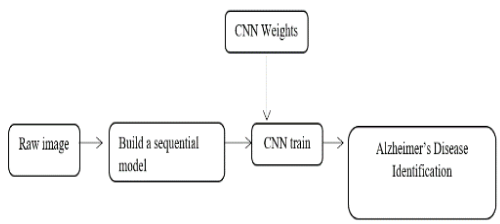

Figure 1: Methodology

Once the dataset and test image have been preprocessed, the CNN model is trained by train dataset. This comprises several layers. After training, the model can distinguish between Alzheimer's and normal images. Finally, image is evaluated against the trained model to predict the presence of Alzheimer's.

CNN Model steps:

Conv2d:

The process of 2D convolution is relatively simple. It involves using a small matrix of weights, known as a kernel, to perform an element-wise multiplication with a portion of the input data, followed by adding the results to create an individual output pixel. For each location that the kernel "slides", this is repeated, effectively converting a 2D matrix into another 2D matrix of features. How many input features are combined to create a new output feature depends on the size of the kernel. Unlike fully connected layers, convolutional layers use far fewer parameters to achieve this transformation, which is essential to understand their relative strengths and weaknesses in DL. For instance, a fully connected layer would require 225 parameters to connect 25 input features with 9 output features, whereas a convolutional layer only needs 9 parameters. Furthermore, each output feature considers only input features from a specific area of the input layer.

MaxPooling2D layer:

The MaxPooling2D layer is a feature in DL that minimizes the spatial dimensions (height and width) of the input data by selecting the maximum value within a specific window size for each channel. The window's displacement is determined by the number of strides along each dimension. If "valid" padding is used, the output shape (rows or columns) is calculated using the formula Given that input_shape >= pool_size, output_shape is equal to math.floor((input_shape - pool_size) / strides) + 1. The output shape is determined as output_shape = math.floor((input_shape - 1) / strides) + 1 when using "same" padding, in contrast. This layer helps reduce the model's parameters and computational complexity, which can aid in avoiding overfitting.

Image Data Generator:

The Image Data Generator performs various operations such as image rescaling, shear, zoom, and horizontal flipping. These operations allow for various orientations of the image to be included in the dataset.

Training Process:

To prepare the train dataset directory, the function is utilized, with the image size specified by target_size. Similarly, test_datagen.flow_from_directory is used to prepare the test data. The data is then fit into the model using fit_generator.

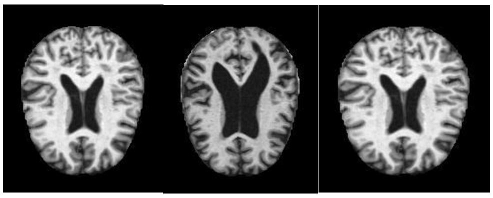

Figure 2: Brain MRI Images with Alzheimer's

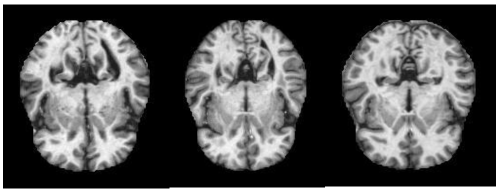

Figure 3: Brain MRI Images without Alzheimer's

ResNet:

ResNet is a CNN model widely used in computer vision with hundreds or thousands of convolutional layers. Traditional CNNs faced the "vanishing gradient" problem with an increase in the number of layers leading to poor performance. However, ResNet overcomes this problem with the use of "skip connections". These connections enable the reuse of the prior layer's activations by stacking several identity mappings and skipping those layers. It condenses the network into fewer layers, which helps in speeding up initial training. ResNet's innovative solution has made it a highly effective model for DL in computer vision.

AlexNet:

AlexNet is a popular deep CNN that consists of eight layers, including five convolutional layers and three fully connected layers. The first layer of AlexNet uses 96 11x11 filters and has a stride of 4.

After the first layer in AlexNet, a max-pooling layer is applied with a stride of 2 and a filter size of 3x3. Subsequently, the second and third convolutional layers of the model use 256 filters with a size of 5x5, followed by max-pooling layers with 3x3 filters and a stride of 2. The fourth and fifth convolutional layers of AlexNet each use 384 3x3 filters, with the fifth layer being followed by another max-pooling layer. To introduce non-linearity to the model, ReLU activation functions are applied to all the convolutional layers.

The fully connected layers of AlexNet have 4096 neurons each, and a dropout layer with a 0.5 probability of retaining a neuron follows each fully connected layer. The final layer of AlexNet is a softmax layer with 1000 outputs, which corresponds to the 1000 classifications of the ImageNet dataset. To prevent overfitting, AlexNet's architecture also uses data augmentation techniques such as cropping and horizontal flipping, which increase the size of the training set. These techniques, combined with AlexNet's deep architecture, have significantly improved image classification accuracy.

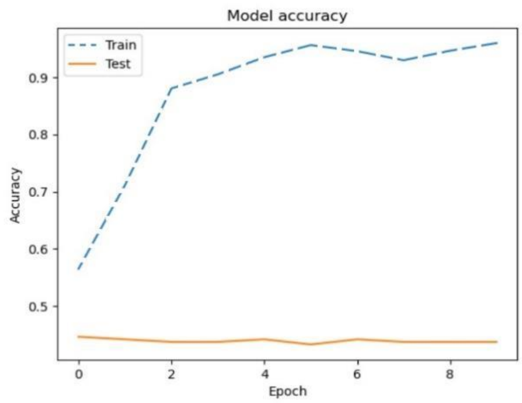

Figure 4: RESNET Accuracy Curve Graph

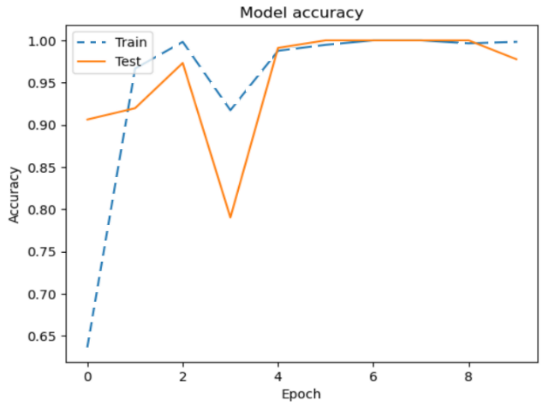

Figure 5: AlexNet Accuracy Curve Graph

Results:

With the aid of CNN, ResNet and AlexNet we concentrated on Alzheimer's classification through MRI images in this study. Through this we are accurately able to detect if a an MRI image shows the signs of Alzheimer's. To make this process a little bit more streamlined a website was designed which gives the user an opportunity to upload the image of the MRI scan and then get an result for the image. Doctors can also study the brain scan and give a more detailed analysis for future treatments and decisions.

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