VISUAL GEOMETRY GROUP 19 METHOD FOR ALZHEIMER DISEASE CLASSIFICATION

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Abstract. The term "dementia" refers to a wide range of symptoms associated with cognitive impairment, of which Alzheimer's disease is responsible for about two-thirds. There is currently no treatment for this ailment; therefore, the only way to prevent any medical, financial, or economic impacts or losses is through early discovery and robust engagement with suspect persons. In this study, we propose using deep learning to label the various stages of Alzheimer's disease. Preprocessing with an example pyramid and bi-linear interpolation is the first stage in the four-step methods, followed by feature extraction with a grey level co-occurrence matrix and a local binary pattern, feature concatenation, and classification with VGG19.On the MPRAGE structural MRI dataset from the Alzheimer's Disease Neuron Imaging Initiative (ADNI), our proposed strategy outperformed state-of-the-art methods in a head-to-head comparison. Both grey and white matter (GM and WM) were accurately identified across numerous classes for cognitive normality, early mild cognitive impairment, late mild cognitive impairment, and Alzheimer disease, with a total accuracy of 89.80. Data classification into binary categories was an area where both GM and WM excelled. We found that GM was 96.43% accurate when compared to CN and EMCI, 90.91% accurate when compared to EMCI and AD, and 95.24% accurate when compared to LMCI and AD.We also found that WM could differentiate between CN and LMCI (with 95.6% accuracy) and EMCI and LMCI (with 95.6% accuracy). The accuracies of WM and GM were identical, at 96.15 percent.

Keywords: Alzheimer's Disease, Deep Learning, VGG19, MRI, Cognitive Impairment, Feature Extraction, Classification Accuracy

1 Introduction

The percentage of dementia that can be attributed to Alzheimer's disease is reportedly between 60% and 70%. It is characterised by a cluster of symptoms, chief among them being a decline in cognitive abilities over time that far exceeds what would be expected from normal ageing. Deductive thinking, concentration, memory, learning, mathematics, language, understanding, and the ability to make sound decisions are just few of the areas where difficulties can develop. When one's cognitive abilities decline, it's all the more crucial to exercise self-control over one's feelings, connections, behaviour, and desires. Sixty percent of the fifty million persons aged 60 and up who have dementia live in low and middle-income nations. By 2030, the World Health Organisation estimates that number to have increased to 82 million, and by 2050, to have increased to 150 million. The effects of this massive increase on people's health will be felt on many different fronts. There could be physical, mental, or emotional fallout. The United States likely spent $818 billion in 2015 on healthcare and related social expenses.Dementia is a progressive disease that may initially manifest with mild symptoms but eventually lead to profound cognitive decline. Dementia symptoms often go through three stages. It's possible to divide the first two years, the next five years, and everything after that into three distinct time frames. through define the stages of dementia and Alzheimer's disease, researchers use a wide range of terminology, from "healthy controls" (HC) or "cognitive normal" (CN) at the beginning, through "mild cognitive impairment" (MCI) in the middle, and finally to "advanced" AD at the end.

During this time of change, you may hear the following acronyms: People with mild to moderate Alzheimer's disease or dementia; translators for those with MCI-NC (mild cognitive impairment in non-believers). There are two types of mild cognitive impairment: early-onset (EO) and late-onset (LO). The progressive form of moderate cognitive impairment (pMCI) is associated with ageing. sMCI, or stable moderate cognitive impairment, has been identified.

2 Objective

Alzheimer's disease is associated with the loss and degradation of neurons across multiple brain regions. The hippocampus serves as the brain's memory and learning centre, but this process spreads throughout the brain. Depending on the patient's age, level of education, and gender, a neurologist may recommend laboratory testing such as the Mini-Cog Test, the Mini-Mental State Examination, and thyroid and vitamin B12 levels.The FSBi-LSTM extension prioritises inputting 1 pixel of each feature at each step to the relevant location in order to extract high-level spatial and semantic information. The sickness stage is categorised by the Soft Max activation mechanism based on user input and gathered information. Accuracy was found to be 86.36 percent when comparing speed to CN, but only 65.35 percent when comparing semi to CN.

2.1 Problem Statement

Most people think of Alzheimer's disease when they hear the word "dementia." The most common form of dementia, Alzheimer's disease, is still incurable, making a prompt diagnosis crucial. The academic community is making greater use of computer-assisted methods for diagnosis than ever before. In recent years, the use of convolutional neural networks (CNNs) has exploded in the field of computer vision due to their impressive results in tasks including object recognition, detection, and segmentation.

Using deep learning to examine MRI brain scans for indicators of Alzheimer's disease has showed encouraging results in recent research. One type of deep learning architecture, convolutional neural networks (CNNs), has the drawback of needing a lot of data to train properly. The PFSECTL mathematical model is introduced in this research paper. A convolutional neural network (CNN) is used in transfer learning as a feature extractor after being trained on one classification job, such as Alzheimer's

disease diagnosis. The CNN was initially trained using a large dataset, such as ImageNet (a library of images useful in a variety of contexts).
Despite its potential, the current approach has a few significant shortcomings that must be addressed. Because it employs a big CNN with several parameters, training this method first takes a considerable amount of time. It is also difficult for neural networks to correctly identify the locations and orientations of objects in the images they are given to examine. Incorporating max-pooling procedures into CNNs can drastically cut down on processing times.

2.2 Existing System

Alzheimer's disease, the most prevalent form of dementia, is a neurodegenerative brain disease for which there is currently no cure. Experts are devoting significant resources to developing methods for using computers to make accurate, early diagnoses of this illness.

Due to its effectiveness in visual object categorization, detection, and segmentation, convolutional neural networks (CNN) are quickly becoming a popular topic of computer vision.

Recent experiments combining deep learning with brain MRI images have shown encouraging results in the diagnosis of Alzheimer's disease. However, the huge amount of training data required to successfully train CNN and comparable deep learning systems is a considerable barrier to entry. In this study, a transfer-learning based mathematical model (PFSECTL) is trained on the Image-Net dataset to extract features for classification.

Disadvantage of Existing System

- Training its settings is time-consuming because the network is so extensive.
- They can't encode spatial relationships between items.
- Procedures like max-pool can significantly increase the time required.

2.3 Proposed System

Alzheimer's disease is associated with the loss and degradation of neurons across multiple brain regions. The hippocampus serves as the brain's memory and learning centre, but this process spreads throughout the brain.

Researchers and scientists have proposed novel methodology that make use of Machine Learning (ML) and Deep Learning (DL) techniques in response to the increasing number of cases of Alzheimer's disease, the catastrophic effects of these cases on individuals, communities, and economies, and the lack of a solution.
It is crucial that ML and DL techniques can aid neurologists in early detection and arrest the course of Alzheimer's disease given the shortage of specialists and the expanding number of patients with the condition.

Advantages of Proposed System

- The Image Net database, which contains millions of images organised into thousands of categories, was used to teach Vgg19.
- Due to the multiple 3x3 filters used in each convolutional layer, this technique has become widely used for image classification.

3 Related Works

Using deep learning on a single MRI cross-section, [18] developed a CNN model that performed exceptionally well on Alzheimer's disease diagnostics. Accuracy rates of 87.7 and 76.1% were achieved, respectively, when comparing healthy controls (HC) to those with clinically defined MCI (c-MCI) and HC to people with suspected MCI (s-MCI). We used 229 images from the Milan dataset alongside 3D T1-weighted images from ADNI-1, ADNI-2, and ADNI-Go.

After processing, 361 magnetic resonance imaging (MRI) scans formed the basis for a novel approach proposed in [19]. After deciding on 90 separate brain regions to map onto the GM images using the Automated Anatomical Labelling (AAL) template, they used Principal Component Analysis (PCA) to identify the features. To do classification, support vector machines (SVMs) were combined with switching delayed Particle Swarm Optimisation (PSO). When comparing CN to pMCI, the method had an accuracy of 85.7143%, and when comparing CN to sMCI, it had an accuracy of 76.9231%.

Fully Stacked Bidirectional Long Short-Term Memory (FSBi-LSTM) networks were used alongside 3D-CNNs to analyse 397 MRI and PET imaging datasets from ADNI in the study by [20]. Using FSBi-LSTM with the SoftMax activation function, we were able to categorise complex geographical and semantic data. In 86.36% of pMCI cases and 65.35% of sMCI cases, we were able to rule out CN using this technique.

Both progressive and stable MCI, also known as cognitive decline (MCI-C) and non-declining MCI (MCI-NC), have been the principal foci of MCI research. Anatomical Landmarks and landmark-based deep multi-instance learning (LDMIL) are used in the feature extraction method described in [21]. They were able to discriminate between pMCI and sMCI with an accuracy of 76.9% on the ADNI-2 and MIRIAD datasets. When compared to CN, AD fared noticeably better overall (91.09% vs. 92.75%).

Adaptive patch-based fusion, a local confidence criterion, and 3D Gabor filter-based multi-directional texture grading are all part of the novel approach suggested in [22]. In a trial using 800 T1-weighted MRIs from the ADNI dataset, the accuracy of sMCI vs pMCI was 72.2% and that of CN versus AD was 91.3%.

4 Methodology

Bi-linear interpolation and the example pyramid method were used to create the interpolated MRI and its subsamples in this research. When the original image's size was reduced by a factor of three, the best results were obtained in terms of accuracy, recall, and specificity. Excellent GM and WM accuracy was found after applying GLCM and LBP texture analysis to the problem of early identification of Alzheimer's disease in this study. When it comes to grouping information into distinct classes, GM and WM perform comparably. By contrast, the WM excels when data is divided into binary classes that differentiate between the CN and LMCI, which is the optimal classification for the GM. Both GM and WM are equally accurate when trying to distinguish between CN and AD. Combining the structural MRI segmented pictures did not improve upon the findings obtained from using each image alone. We were also unsatisfied with the claimed results of information transfer between GM and WM.

Modules Name:

- Dataset
- Importing the necessary libraries
- Retrieving the images
- Splitting the dataset
- Building the model
- Apply the model and plot the graphs for accuracy and loss
- Accuracy on test set
- Saving the Trained Model

Module Description:

1) Data Collection:

To get the dataset needed for training and testing, we constructed a method in the first module. The MRI of the brain has been employed as a detection dataset.
There are currently 5121 brain MRIs stored there.

2) Importing the necessary libraries:

To accomplish this, we will be utilising Python. To begin, we'll bring in the necessary libraries, which include keras (for building the main model), sklearn (for splitting training and test data), PIL (for converting images to numerical arrays), numpy (for analysing the data), matplotlib (for plotting), and tensor flow (for visualisation)..

3) Retrieving the images:

Metadata associated with the photos will also be obtained. As a result, you'll want to resize your photos to (176X208) so that they're all the same size for easy comparison. The images should then be converted into a numpy array.

4) Splitting the dataset:

Generating test and training datasets. The ratio of training data to test data is typically 80:20.

A. VGG19

The cutting-edge VGG model for object recognition can have as much as 19 layers. VGG performs better than the baselines on a number of tasks and datasets despite not being designed as a deep CNN. When it comes to image identification, VGG is one of the most popular architectures out there right now.

5) Building the model:

Several CNN models are now available to the general audience. These models were created with multi-layered processors with exceptional processing capability and memory bandwidth. This article will discuss several different models, one of which is VGG19. VGG19 classifies your image into one of a thousand different categories.
Therefore, we will use this framework to develop a model for classifying images in the Intel Image Classification dataset. This database divides its information into six distinct categories: street, building, mountain, glacier, and sea.

6). Apply the model and plot the graphs for accuracy and loss:

The model will be built, and the fit function will be applied it before. Two separate lots are planned. After that, we'll plot the accuracy and loss graphs. The average accuracy during training was 99.3 percent, whereas during validation it was 97.5 percent.

7). Accuracy on test set:

The accuracy we achieved on the test set was 99.7 percent.

8). Saving the Trained Model:

The first step is to export your model from the development setting into the production setting for finalisation.h5 file
Make sure Pickle is installed and running in your setting.
Putting the model into the module is the next step.h5 file.

5 Algorithm Used in Project

VGG19:

The Visual Geometry Group, or VGG, created the widely used Vgg19 multi-layer deep convolutional neural network (CNN) architecture.
VGG-19 has 16 and 19 convolutional layers because "deep" refers to the total number of layers. To create state-of-the-art ocr models, researchers turn to the VGG architecture.
The layers in the advanced CNN VGG19 don't need to be taught, and it has a profound comprehension of image shape, colour, and structure.
Deep VGG19 has been prepared for challenging classification tasks by being trained on millions of images.

7

6 Data Flow Diagram

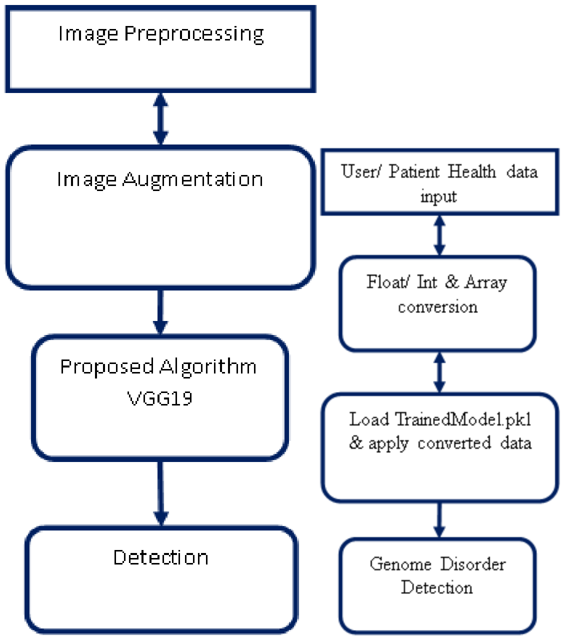


Fig. 1. Data Flow Diagram

7 System Architecture

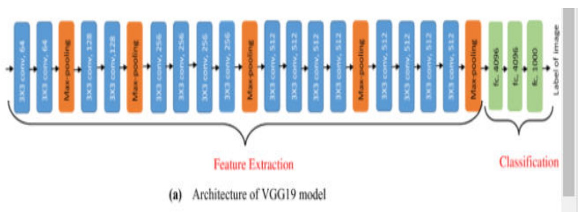
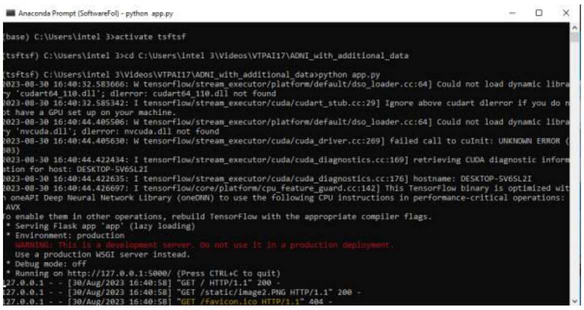
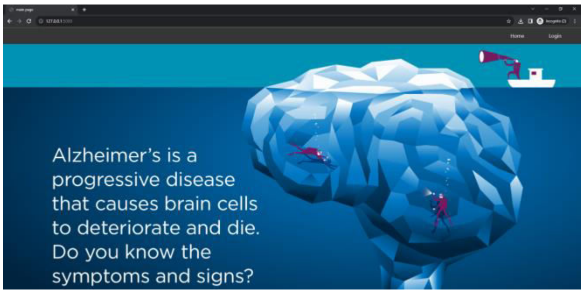


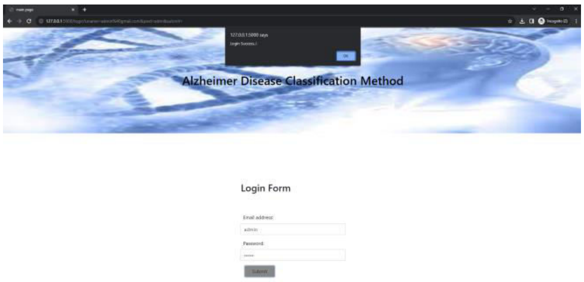
Fig. 2. System Architecture Of Project

8

8 System Architecture







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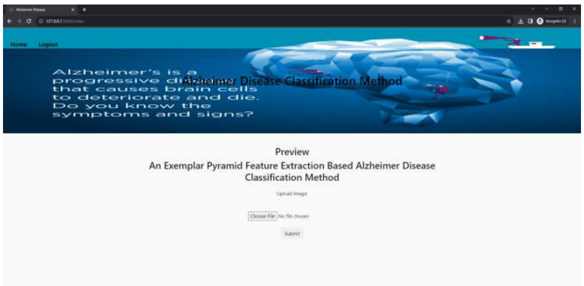
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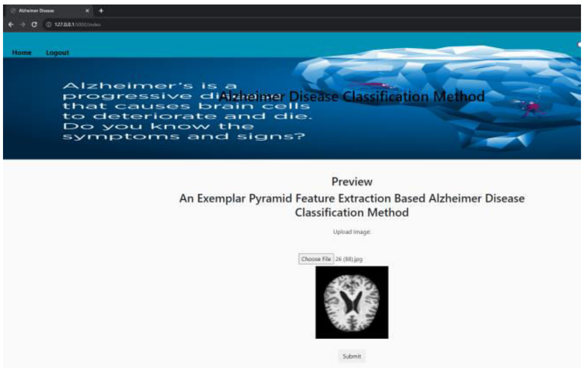
Logout
Alzheimer Disease Classification Method
Preview
An Exemplar Pyramid Feature Extraction Based Alzheimer Disease Classification Method
Upload Image
Submit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Alzheimer Disease Classification Method
Preview
An Exemplar Pyramid Feature Extraction Based Alzheimer Disease Classification Method
Upload Image
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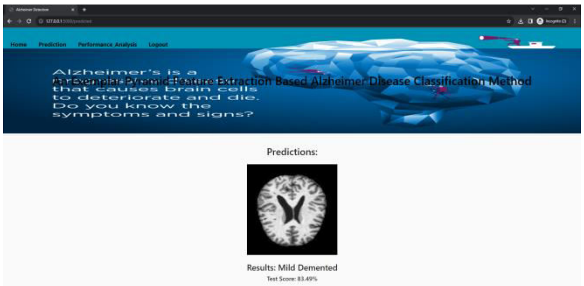
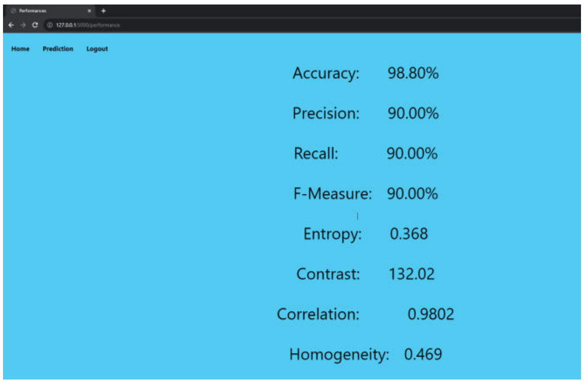
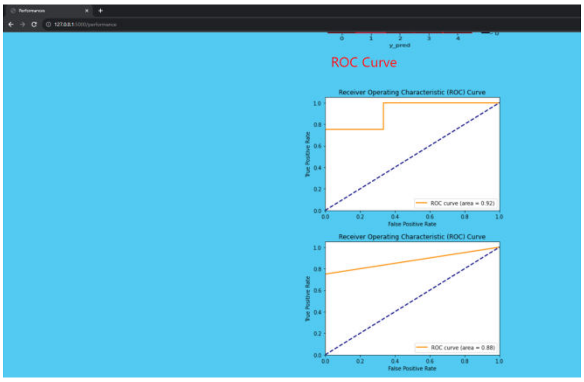
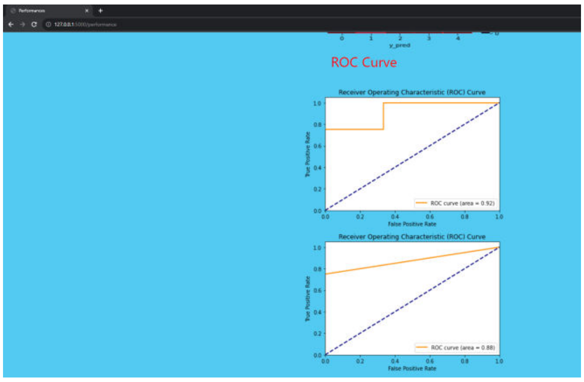

Home
Prediction
Performance Analysis
Logout
Predictions:
Results: Mild Demented

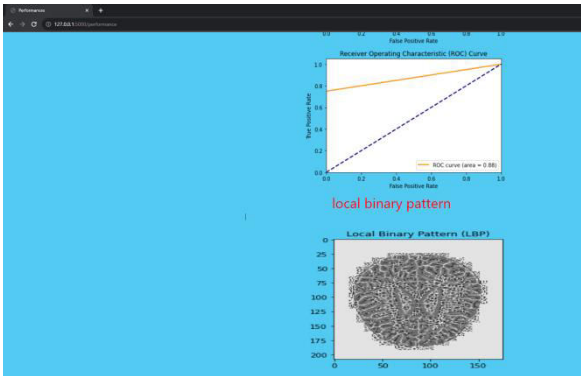
10


Home
Prediction
Logout
Accuracy: 98.80%
Precision: 90.00%
Recall: 90.00%
F-Measure: 90.00%
Entropy: 0.368
Contrast: 132.02
Correlation: 0.9802
Homogeneity: 0.469


Confusion Matrix


ROC Curve





9 Future Enhancement

We were able to classify using all the information we had acquired by employing a multilayer perception. We used CN (a binary system), EMCI (a multi-class system), LMCI (a latent-variable classifier), and AD (an attribute-based classifier). We applied our suggested technique to an ADNI dataset, segmented the MRI into Grey Matter, White Matter, and CSF, and presented the results clearly. We reported extremely accurate findings for the GM in binary class classification for CN and EMCI, highly accurate results for the WM in binary class classification for CN and LMCI, and identical results for the GM and the WM in binary class classification for CN and AD. The findings point to the potential value of early diagnosis of Alzheimer's disease in slowing the deterioration of the disease and protecting against its severe effects.

10 Conclusion

For downscaling MRI pictures by a factor of three, we suggested using a bi-linear interpolation technique and a sample pyramid approach. We analysed four texture qualities (Entropy, Contrast, Correlation, and Homogeneity) using Grey Level Co-Occurrence Matrix and extracted a number of features using Local Binary Pattern. When we pooled the information, we were able to classify on multiple levels.We used CN (a binary system), EMCI (a multi-class system), LMCI (a latent-variable classifier), and AD (an attribute-based classifier). We applied our suggested technique to an ADNI dataset, segmented the MRI into Grey Matter, White Matter, and CSF, and presented the results clearly. We reported extremely accurate findings for the GM in binary class classification for CN and EMCI, highly accurate results for the WM in binary class classification for CN and LMCI, and identical results for the GM and the WM in binary class classification for CN and AD. The findings show promise for early diagnosis of Alzheimer's disease and the potential to arrest the illness's progression and the related losses.

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