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Predicting Alzheimer’s Disease with Deep Learning Techniques

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Abstract

Alzheimer's disease (AD) represents the most common type of dementia, advancing from mild to severe stages and ultimately necessitating full-scale care. The increasing incidence of the disease is attributed to aging and late-stage diagnosis. Conventional diagnostic techniques, such as medical history assessments, cognitive assessments, and MRI scans, are marred by inconsistencies and limitations. This research investigates the utilization of a convolutional neural network (CNN) to identify MRI abnormalities related to AD, taking into account four stages of dementia using visually interpretable models in addition to addressing class imbalance. The DenseNet264 model is employed to classify MRI scans, ranging from "not demented" to "moderately insane." MRI data from Kaggle reveals a significant class imbalance, thereby emphasizing the need for a good classification model. The model's ability to distinguish between dementia stages is assessed by predictions derived from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset.

Keywords: *Magnetic Resonance Imaging, Alzheimer’s disease, Demented, Convolutional Neural Network.*

1. Introduction

The application of computational neuroscience for translational goals has significantly enhanced epidemiological research of mental illness. This cross-disciplinary approach may allow a greater understanding of the mechanisms of clinical symptoms through modeling the biological processes occurring in the human brain, both normal and pathological. Neurodegenerative and neuropsychiatric diseases in the past decade have been enhanced by the growth of machine learning (ML) techniques and large biological datasets. One of the main motivations for this is the application of magnetic resonance imaging (MRI), which is simple to learn and enables precise localization of calcifications and foreign bodies. MRI is the gold standard for imaging Alzheimer's disease (AD) and related disorders. Alzheimer's disease is a form of dementia that can develop suddenly and have a devastating effect. A new case of Alzheimer's disease is diagnosed every four seconds, causing a devastating loss to the diagnosed individual and their relatives. Dementia is characterized by the loss of cognitive abilities, including reasoning, social and emotional skills, and the capacity for independent living, with Alzheimer's disease being the most common. As the disease advances, individuals can lose all memory of previous experiences, beginning with recent ones. Early detection is therefore imperative. A good model could analyze an MRI of the brain and provide a diagnosis of dementia, classifying it as mild, moderate, very mild, or absent. Dementia is characterized by significant impairment in daily life that prevents independence, while mild dementia is characterized by cognitive impairment and decreased performance on objective cognitive tests compared to baseline. At the intermediate phase of AD, patients are generally more confused and forgetful and require more support with activities of daily living and personal care. Intermediate-stage dementia AD patients might show declining judgment and more confusion. Other Alzheimer's patients who do not have dementia will have a related illness. [1-5]

2. Literature Survey

Arya, A. D. et al. (2023) – Conducted a systematic review of machine learning and deep learning techniques for Alzheimer’s diagnosis. Identified promising approaches and challenges. (Brain Informatics). Bass, C. et al. (2023) – Introduced ICAM-Reg, an interpretable classification and

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regression method for mapping neurological phenotypes in MRI scans. Focused on feature attribution and model interpretability. (IEEE Transactions on Medical Imaging). Bellenguez, C. et al. (2022) – Provided new insights into the genetic etiology of Alzheimer's disease and related dementias. Analyzed genetic risk factors using large-scale datasets. (Nature Genetics). Bogdanovic, B. et al. (2022) – Explored Alzheimer's disease through explainable machine learning approaches. Focused on improving model interpretability and diagnosis accuracy. (Scientific Reports). Borovkova, M. et al. (2022) – Investigated Alzheimer's screening using multiwavelength Stokes polarimetry in a mouse model. Proposed a novel imaging technique for early detection. (IEEE Transactions on Medical Imaging). Cheung, C. Y. et al. (2022) – Developed a deep learning model for detecting Alzheimer's disease using retinal photographs. Conducted a retrospective, multicenter case-control study. (ARTICLES). Cummings, J. et al. (2023) – Analyzed the Alzheimer's disease drug development pipeline, focusing on current clinical trials and future treatment prospects. (Alzheimer's & Dementia: Translational Research & Clinical Interventions). Dara, O. A. et al. (2022) – Surveyed machine learning techniques for Alzheimer's disease diagnosis. Discussed the strengths and limitations of different approaches. (Applied Sciences). Gupta, M. et al. (2024) – Proposed an adversarial network-based classification method for Alzheimer's detection using multimodal brain imaging. Evaluated performance across different datasets. (IEEE Access).

3. Methodology

Here we focus on using deep studying (DL) algorithms to encounter Alzheimer`s disease (AD) through scientific image analysis. In particular, the approach employs convolutional neural networks. (CNN) and switch studying fashions to classify various stages of Alzheimer`s—Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. We use an available public dataset. obtained from Kaggle, including MRI scans of Alzheimer's patients, with a total of 86,000 photos. Similarly distributed under the four categories. The dataset contains 21,500 images that are labeled accordingly. undergo preprocessing, whereby all MRI images are resized to 224x224 pixels to give a uniformity for version enter. Following preprocessing, we exercise two Prominent switch learning trends: DenseNet and VGG16. These fashions are pre-skilled on large photograph datasets and are enormously green for function Extraction and classification. Transfer research. permits us to evolve those fashions for our Alzheimer's prediction mission with the assistance of using editing the very last layers to fulfill our particular needs. DenseNet and VGG16 assist in function studying via their deep convolutional layers, which seize tricky details from the MRI photos. In our architecture, we built a convolutional series version skilled over thirty periods. The variant accommodates a number Convolutional layers pulling out abilities from the Enter images that were observed with the help of a Flatten layer, that Directly converts the multidimensional output into one-dimensional form vector. Then this flattened output is outperformed by A dense layer, that transforms the dimensionality of the records to make the very last category one of the 4 levels of dementia. We define the ReLU (Rectified Linear Unit) activation function in the convolutional and dense layers are defined. Non-linearity enables the version to examine intricate styles withinside the records. The very last Dense layer utilizes a SoftMax activation property to return a probability distribution among the four classes to facilitate accuracy degree prediction of Alzheimer`s disease. This collection of CNN-mainly based fully function extraction, switch studying, and punctiliously tuned layers forms the basis of our method of affirmatively identifying Alzheimer's onset. [6-10]

3.1. Architecture Diagram

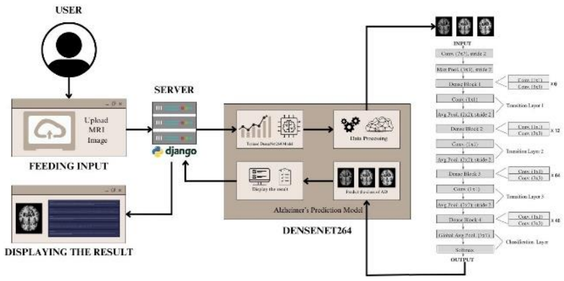

Figure 1 **Proposed Architecture**

3.2. Data Acquisition

The first thing is to gather photos. In order to create class version, the pc have to examine by doing. To apprehend an object, the computer has to look at a huge variety of images. Deep learning Fashions can also learn how to use various types of statistics, which also include time collection statistics and voice statistics. Pictures are crucial facts had to perceive AD in the context of the works discussed in this article. This Step produces images intended for the purpose of informing the version later. Figure 1 shows Proposed Architecture Figure 2 shows Representation of Data Acquisition

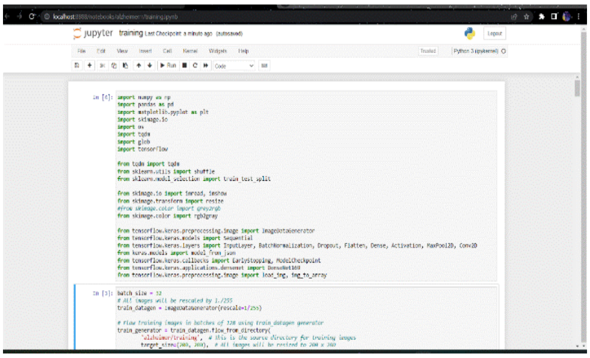

Figure 2 Representation of Data Acquisition

3.3. Data Preprocessing

The picture type activity gives a category to a given MRI picture. It is a simple high-stage picture A comprehension exercise that can be split into two different groups. multi-type duties. The picture is classified in accordance with the requirements of the output layer following a few convolution and fusion operations through CNN. The greatest difference between binary and multiclassification duties is characteristic of activation of the output layer. The procedure in relation to image type for MRI picture evaluation is effortlessly recognized, allowing the required steps to be taken for in order to establish the nature of dementia for which natural photograph type is high, which include the utilization of Convolutional Neural Network (CNN) to categories JPG/PNG images. [11-16]

3.4. Feature Extraction

Feature extraction is finished to lessen capabilities withinside the dataset, on this module, we carry out a few additional operations at the segmented image. In this module, we are able to use function extraction to acquire all of the particular statistics approximately a mind image. In the fields of laptop imaginative and prescient and system learning, function extraction and discount have performed a critical position withinside the type of tumor areas. The foremost hassle with function extraction is determining which capabilities are the maximum lively or sturdy for type, ensuing in a green performance Feature extraction is utilized in dimensionality discount. Figure 3 shows Representation of Data Preprocessing Figure 4 shows Representation of MRI Image Classification

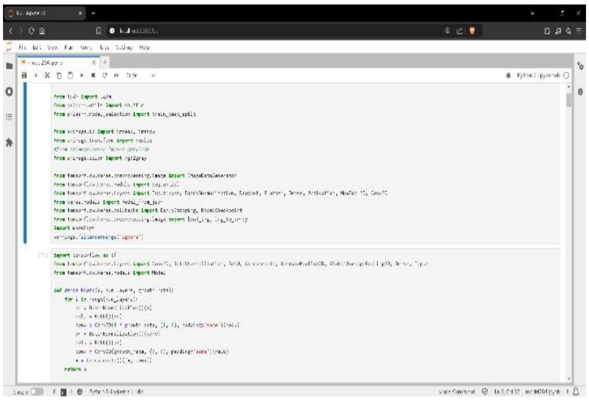

Figure 3 Representation of Data Preprocessing

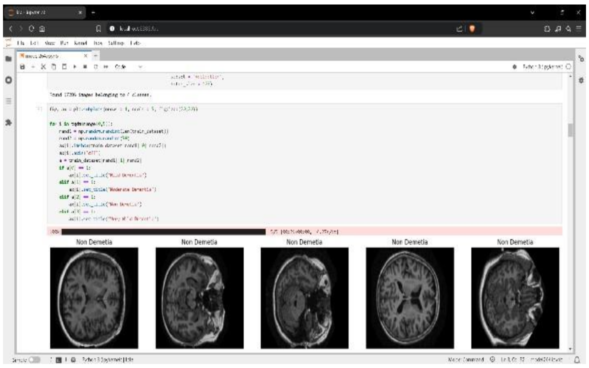

Figure 4 Representation of MRI Image Classification

3.5. CNN Model

Image classification involves extracting features from images in order to perform operations that identify records of datasets. Other approaches involve great parameter training for NN, which make image classification computationally intensive. For example, a neural network may have been trained to

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distinguish between a 50 × 50 cat and a dog image using width and height. – (50*50) * a hundred photograph pixels instances hidden layer + a hundred bias + 2 * a hundred output neurons + 2 bias = 2,50,30 Filter use a local connection pattern throughout neurons that affords certain spatial localization of the image. This is genuinely wise multiplication of features and formation of a third one by convolution. Hence, the filter and the matrix of image pixels are features. Sliding the filter across the image gives the dot produced by the matrices. This matrix is called the "Activation Map" or the "Feature Map."

- **Step 1:** Choose a Dataset

You may choose a dataset of interest or construct your own picture dataset to solve your own image classification challenge. On kaggle.com, selecting a dataset is simple. The dataset I will be using may be found here. 12,500 enhanced photos of (JPEG) There are roughly 3,000 photos for each of the four categories of AD organized into four distinct files (according to AD type). The categories include Mild, Moderate, Very Mild, and No Dementia. In this context, we utilize several libraries that require their respective import statements.

- **Step 2:** Prepare Training Dataset Assigning paths, labels, and resizing photographs will prepare our dataset for training. Resizing photographs to 224x224
- **Step 3:** Training data is an array of picture pixel values and the image's CATEGORIES index.
- **Step 4:** Shuffle Dataset
- **Step5:** Label and Feature
- NEURAL NETWORKS will classify these listings.
- **Step 6:** Normalizing X and categorizing labels.
- **Step 7:** Separate CNN-use X and Y.
- **Step 8:** Define, build, and train CNN Model
- **Step 9:** Model score and accuracy. The Dense net and VGG16 models classify AD type.

3.6. Dense Networks (Dense Net)

A huge challenge facing deep neural networks today is the disappearance or explosion of gradients. It has been suggested that this problem may be solved by creating a bypass link that feeds the activation unit of a layer to a deeper one. This is where dense networks come in. As neural networks gain layers, training error should be monotonically decreasing. Yet, a simple neural network may eventually increase training error. Dense Nets are not built that way. Dense nets can even train networks with 1,000 layers. Before moving to the Dense net for image classification, let's build a 50-layer Keras Dense net for image classification. Keras is compatible with TensorFlow, CNTK, and Theano. It was designed for quick experimentation. Figure 5 shows Pseudocode Representation of the Algorithm

```
Input: The new ID sensor signal (S) with size of 5625
Output: Gray level image (Im) with size of 125 x 45

count = 1
for i=1 to 125 do
for j=1 to 45 do
Im(Ij) = S(count);
count = count + 1;
end for j
end for i
Normalize Im by using min-max normalization
```

Figure 5 Pseudocode Representation of the Algorithm

3.7. VGG16 Implementation

The entire architecture uses convolution and max-pooling layers. Two fully connected layers and a SoftMax output conclude it. The VGG16 method has weighted layers 16. This broad community contains 138 million parameters. Here, we import all the libraries for VGG16. To create a sequential version, the Sequential method is used. The Sequential version arranges version layers in a stack. Keras preprocessing loaded Image Data Generator. The image Data Generator labels the input data. This class has many important techniques to resize, rotate, zoom, and flip. This class does not change disk-saved data. Instead, it changes the data being fed to the model. Figure 6 shows VGG16 Architecture Diagram

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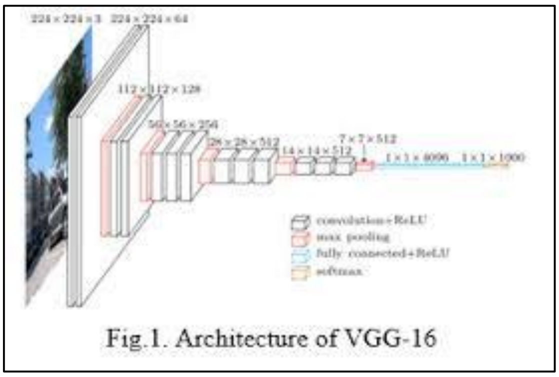

Figure 6 **VGG16 Architecture Diagram**

4. Results

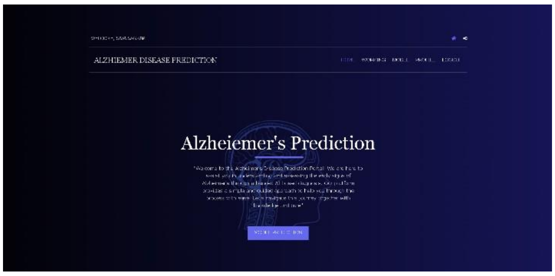

Figure 7 **Homepage**

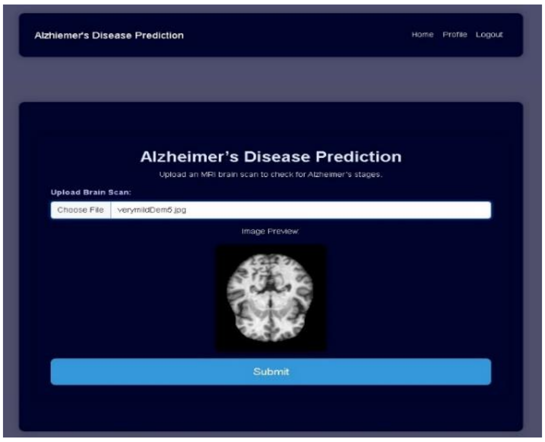

Figure 8 **Input Page**

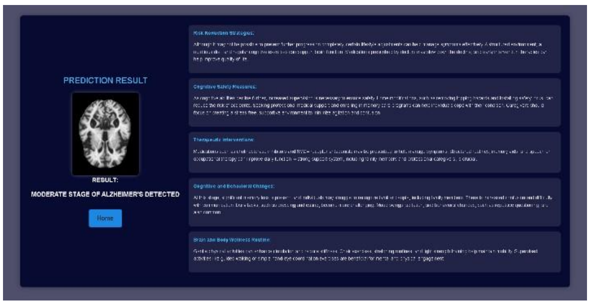

Figure 9 **Result Page**

5. Experiment Analysis

Part of the cross-validation testing was conducted to assess how well the classifiers anticipated the demographic status of adult patients with AD since it was to be depicted by a fuzzy credibility matrix. The machine-learning-based classifiers Adult-onset Dementia would have caused unbearable suffering because cellular involution was a factor affecting cognition and consciousness. AD accounts for about 60 to 70% of dementia cases in the adult world and is said to be the most common type of dementia. As mentioned in the introduction, the actual diagnosis of AD was purely speculative using clinical and exclusion criteria, possible only post mortem. On the other hand, early diagnosis of AD is very essential for the early institution of treatment for the purpose of ameliorating the health of the brain. It is also notable that the existing AD were to use the MRI charts or sample collections for diagnosis. Figure 10 shows Graphical Analysis

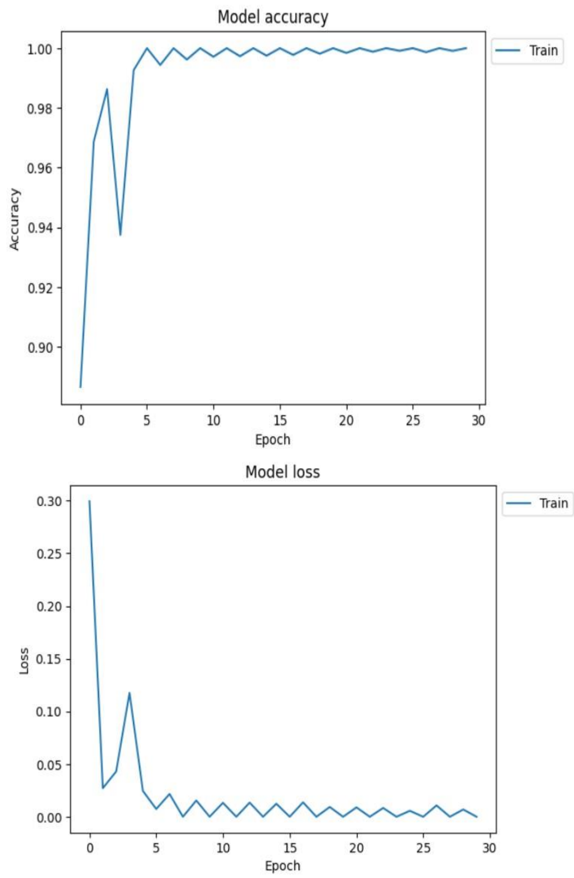

Figure 10 **Graphical Analysis**

Conclusion

In this paper, we proposed a model spectrum technique for Alzheimer's disease MRI scans that was simultaneously honest and dependable. The techniques are mostly based on a visual content description of hippocampal regions, a brain area correlated with AD. In particular, we suggest fusing the classification results of the hippocampus with the CSF considering them as two biomarkers of interest. Studies found that this combination might significantly enhance the performance of the AD versus MCI separation compared with using either traits from the hippocampus or CSF volume-based classification alone. A comparison of the proposed method with other volumetric techniques showed that it offers a definite better stage of classification accuracy. In this work, we would like to incorporate different ROIs and MRI techniques into our pre-existing classification framework.

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