

Deep Learning Classification using MRI for Alzheimer's Disease Detection

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Abstract

Alzheimer's disease is an incurable, progressive brain disorder that gradually destroys memory and cognitive function, and eventually the ability to perform even the most basic tasks. It is now considered to be one of the most common illnesses worldwide. Furthermore, there is no known cure for Alzheimer's disease. Convolutional Neural Networks (CNNs), a type of deep learning technique, are used to work on interaction for the identification of Alzheimer's infection. CNN has made great strides recently in the analysis of MRI images and medical research. Much research has been done to determine the exact location of Alzheimer's disease based on brain MRI images that are processed by CNN. However, a fundamental limitation is that there was no demonstration of a valid link between a suggested model and pre-trained models. Thus, utilizing the ADNI MRI dataset, we present a 6-layer CNN model for binary classification in this study to identify Alzheimer's. Our model's presentation is compared to a few other CNN-based models in terms of review, F1 score, ROC bend, and accuracy, precision, and accuracy on the Alzheimer Disease Neuroimaging Initiative (ADNI) dataset. The focus of the paper is our CNN model, which has an accuracy of 98.83%, better than the other previously proposed CNN-based models that are provided on the ADNI. The trial output demonstrates our model's supremacy over the other models.

Keywords: CNN, MRI, ADNI, Alzheimer, Deep Learning, Machine Learning.

Introduction

ADNI Datasets

The ADNI datasets are an essential resource in the field of neuroscientific research, specifically in the study of Alzheimer's disease (AD) and related neurodegenerative disorders. Since its launch in 2004, ADNI has been dedicated to collecting, validating, and sharing data to expedite the development of effective treatments for AD. These datasets contain a comprehensive range of clinical, imaging, genetic, and biomarker data from participants at different stages of cognitive health, mild cognitive impairment (MCI), and AD. The meticulous curation and standardization of these datasets enable researchers worldwide to make cross-study comparisons and investigate various aspects of AD pathology, progression, and potential interventions. By utilizing the ADNI datasets, researchers can identify biomarkers that indicate the onset and progression of the disease, uncover neuroimaging patterns associated with AD pathology, and create predictive models for early diagnosis and personalized treatment approaches. Furthermore, the ADNI datasets play a crucial role in advancing computational methods in neuroscience, fostering innovation in machine learning, data mining, and artificial intelligence techniques for analysing complex

multidimensional datasets. Through collaborative efforts and the sharing of open data, ADNI continues to drive breakthroughs in our understanding of AD, leading to the development of more effective diagnostic tools and therapeutic interventions to mitigate the devastating impact of this neurodegenerative disease.

Deep Learning

Deep learning is a branch of artificial intelligence in which artificial neural networks—layers of interconnected nodes that imitate the structure of the human brain—help algorithms identify patterns and make judgments. To train and perform better on tasks like image recognition, natural language processing, and autonomous driving, these networks consume enormous volumes of data. Deep learning models maximize predictions and reduce mistakes by adjusting parameters using techniques like gradient descent and backpropagation. Advances in technology and creativity have been fuelled by popular architectures like convolutional neural networks (CNNs) and recurrent neural networks (RNNs), which have changed sectors including computer vision, speech recognition, and healthcare.

CNN Algorithm

Convolutional Neural Networks (CNNs) are a type of deep learning algorithms that are mainly utilized for the analysis of visual data, such as images and videos. CNNs are specifically designed to learn spatial hierarchies of features from the input data in an automatic and adaptive manner. By employing convolutional layers, they apply filters across the input data to extract relevant features through convolutions. Additionally, pooling layers are employed to reduce spatial dimensions while preserving crucial information. The advent of CNNs has brought about a significant transformation in tasks like image classification, object detection, and image segmentation, rendering them indispensable in various fields, including computer vision, medical imaging, and autonomous driving. The six phases of a typical Convolutional Neural Network (CNN) algorithm are:

1. **Input Layer:** The network receives input data, usually images or other multidimensional arrays.
2. **Convolutional Layers:** These layers are made up of multiple filters that slide over the input data, carrying out convolution operations. Each filter identifies different features in the input, capturing patterns like edges, textures, or shapes.
3. **Activation Function:** Following each convolution operation, an activation function such as ReLU (Rectified Linear Unit) is applied element-wise to introduce non-linearity into the network, allowing it to learn more intricate patterns.
4. **Pooling Layers:** Pooling layers downsample the feature maps generated by the convolutional layers, decreasing their spatial dimensions while preserving the most important information. Common pooling operations include max pooling or average pooling.
5. **Fully Connected Layers:** These layers combine the high-level features extracted by the convolutional layers and make predictions based on them. Each neuron in a fully connected layer is linked to all the neurons in the previous layer.
6. **Output Layer:** The final layer generates the network's output, which could be class probabilities for classification tasks or continuous values for regression tasks. The

selection of activation function in this layer depends on the problem's nature, such as softmax for classification or linear for regression.

These phases collectively form the fundamental architecture of a Convolutional Neural Network, which has demonstrated significant effectiveness in various tasks, particularly in computer vision.

Algorithm

```
from keras.models import Sequential

from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense

# Step 1: Input Layer
input_shape = (32, 32, 3) # Example input shape for an image of size 32x32 with 3 channels
model = Sequential()

# Step 2: Convolutional Layers
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=input_shape))
model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))

# Step 3: Activation Function (ReLU)
# Activation functions are typically applied implicitly after convolutional layers in Keras.

# Step 4: Pooling Layers
model.add(MaxPooling2D(pool_size=(2, 2)))

# Step 5: Fully Connected Layers
model.add(Flatten())
model.add(Dense(128, activation='relu'))

# Step 6: Output Layer
num_classes = 10 # Example number of classes for a classification task
model.add(Dense(num_classes, activation='softmax'))
```

The World Health Organization (WHO) states that Alzheimer's is the most serious infection globally. It is estimated that 50 million people worldwide suffer from dementia, including Alzheimer's disease and other types. The total number of cases of dementia that occur annually is close to 9 million, indicating an additional case every few years. The number of people who have Alzheimer's is predicted to increase to 83 million in 2031 and 153 million in 2051. Cognitive deterioration is the primary cause of Alzheimer's disease. Over time, patients lose the ability to remember their own personalities, which are comparable to names and become mature. Because this is an ongoing cycle, patients eventually lose the ability to remember their family members.

Review of Literature

Deep learning methods have been used increasingly recently to classify patients with Alzheimer's disease (AD) utilizing multimodal brain imaging data. Using the rich data from many imaging modalities, several research have proposed enhanced deep convolutional neural networks (CNNs) for the categorization of Alzheimer's disease.

Khagi et al. [1] used pre-made CNN models in 2019—specifically, Alexnet, GoogleNet, and Resnet50—to distinguish between Alzheimer's patients (e.g., Unhinged) and solid patients (e.g., non-demented). They employed 27 Alzheimer's patients and 27 Normal Controls in their evaluation. Wang et al. [2] discussed the issue of Alzheimer's disease in 2019 when considering a 9-layer CNN. For their assessment, they used 99 AD patients and 99 Normal Controls. The accuracy of the CNN with seven layers was 98.75%. In 2018, Hosseini et al. [3] used motion learning to understand Alzheimer's disease. Additionally, Islam et al. set up a major mind association to perceive at roughly the same time. A CNN model called "Alzheimer Network" (AlzNet) was proposed by Al-Khuzai et al. [4] to aid in the binary classification of AD and CN. The AlzNet model consists of a max-pooling layer with a kernel size of 2×2 , and five convolution layers, each with a ReLU activation function. A total of 15,200 200×200 image datasets from OASIS were used to train and evaluate their model. To solve the overfitting issue, the model was optimized using the Adadelta optimizer with a ratio of 0.2 dropouts. To get the greatest performance, the model was trained with varying numbers of dense units in the hidden layer; this was accomplished at 121 units. 99.53% testing accuracy and 97.99% training accuracy are attained by the model. Two models, VGG16 and VGG19, were proposed by Antony et al. [5] for the diagnosis of AD. The 780-image dataset from the ADNI was used to train their model. Prior to training the model, the skull underwent augmentation and decomposition during the preprocessing phase. The size of the input image is 224×224 . Two classes were classified in VGG16 models using the sigmoid activation function in the last layer. Two classes were classified in VGG19 models using the SoftMax activation function in the last layer. In contrast, VGG19 has 64, 128 and 256 kernel sizes, whereas VGG16 has 64 and 128 kernel sizes. Both models' accuracy (81% for VGG-16 and 84% for VGG-19) was insufficient. A 3D multi-scale CNN (3DMSCNN) model was created by Ge et al. [6] 3DMSCNN was a revolutionary architecture for AD diagnosis. They also suggested feature fusion and an enhancement technique for multi-scale features. Song et al. [7] proposed the Graph Convolutional Neural Network (GCNN) classifier, which is based on graph-theoretic methods. Structural connection graphs representing a multi-class model were used to train and evaluate the network to categorize the AD spectrum into four groups. Liu et al. [8] put up a unique model for AD categorization. First, a CNN model was created from the ground up. It has two fully connected layers, three convolutional layers, three pooling layers, and SoftMax as the activation function in the final layer. Furthermore, transfer learning was used to address overfitting problems and enhance classification accuracy in AlexNet and GoogLeNet models. The models did not, however, produce notably high categorization accuracy. It should be noted that 500 training iterations and 5-fold cross-validation are used by both the AlexNet and GoogleNet models during transfer learning. The CNN, AlexNet, and GoogleNet models all achieved classification accuracy rates of 78.02%, 91.4%, and 93.02%, in that order. Given that GoogleNet contains deeper layers and more convolutions than AlexNet it achieves a higher classification accuracy rate. Impedovo et al. [9] introduced a protocol. To assess the connection between cognitive processes and handwritten processes in both healthy subjects and patients with cognitive impairments, this methodology provided a cognitive

model. The main objective was to develop a simple, non-invasive method for monitoring and diagnosing neurodegenerative dementia during screening and follow-up. Harshit et al. [10] identified four AD stages (AD, EMCI, LMCI, and NC) using a 3D CNN architecture on 4D FMRI images. Silvia et al. [11] and Dan et al. [12] have also proposed additional CNN structures that deal with 3D MRI for distinct AD stage categorization. In 3D MRI photographs, a 3D Densely Connected Convolutional Network (3D DenseNets) is used for 4-way classification by Juan Ruiz et al. [13]. Savaş et al. [14] classified the 2182 picture objects that were collected from the ADNI database using several CNN models. The research provided a thorough methodology for evaluating the effectiveness of 29 models that had previously undergone image training photos were subjected to preprocessing, which involved dividing the photos, cleaning the data, and converting the image format. The models receive image input after preprocessing procedures have been applied. The EfficientNetB0 model had the greatest accuracy rate of 92.98% during the test phase. The EfficientNetB2 and EfficientNetB3 models, with rates of 94.42% and 97.28%, respectively, acquired the highest accuracy, sensitivity, and specificity values for the Alzheimer's disease class, according to the confusion matrix during the comparative evaluation stage. Sahumbaiev et al. [15] presented a HadNet architecture to investigate Alzheimer's spectrum MRI. For improved training, the MRI image collection is skull-stripped and spatially normalized using the Statistical Parametric Mapping (SPM) toolbox. It is anticipated that sensitivity and specificity would increase in tandem with improvements in HadNet architecture. Payan et al. [16] employed 3D convolutional neural networks and a sparse autoencoder. They developed an algorithm that uses a brain magnetic resonance imaging (MRI) scan to determine the disease state of an affected individual.

Proposed Methodology

To fully address the research objectives, the proposed methodology for this study uses a mixed-methods approach that integrates both qualitative and quantitative techniques. First, semi-structured interviews with important stakeholders will be used to collect qualitative data, enabling a thorough examination of their viewpoints, experiences, and ideas pertaining to the topic. To find repeating themes and patterns in the qualitative data, thematic analysis will also be used. Second, surveys with a bigger sample size will be used to gather quantitative data, which will provide statistical insights into more general trends and relationships. To get useful conclusions, this data will be evaluated statistically using both descriptive and inferential techniques.

This section looks at a suggested approach that includes an additional 6-layer CNN model, and compares the model's display to the pre-made models. The underlying steps of the proposed methodology are as given below:

1. Dataset Collection
2. Data Pre-processing
3. Data Labelling
4. Applying CNN Algorithm
5. Loading pre-trained CNN models
6. Comparison

A block diagram illustrating our proposed approach is presented, showcasing the workflow of the technique from start to finish. This block diagram also highlights the seven main stages of our proposed strategy.

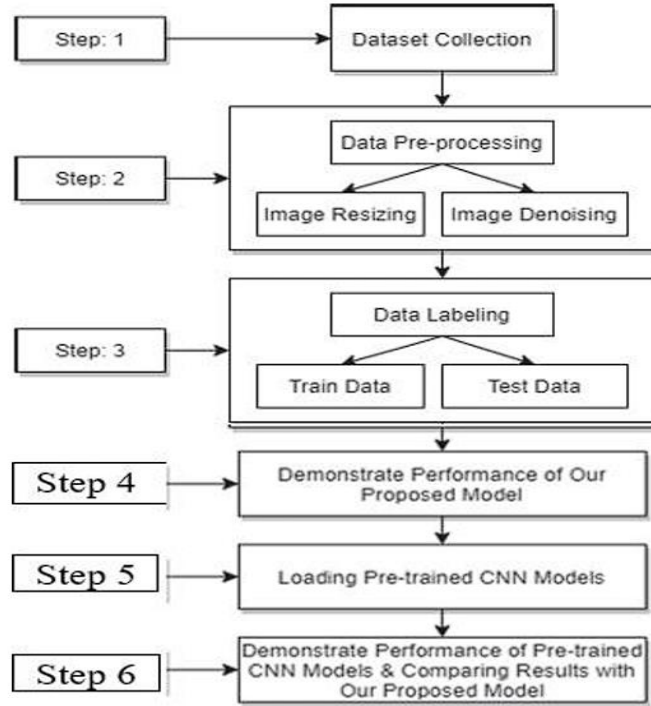


Fig 1: Block diagram of proposed methodology

A. Dataset Collection

The Dataset has been collected from **ADNI** (Alzheimer's Disease Neuroimaging Initiative). The Alzheimer's Disease Neuroimaging Initiative (ADNI) is a groundbreaking project that uses **neuroimaging, genetics, and clinical data** to improve our understanding of Alzheimer's disease (AD). Since its inception over 10 years ago, this successful public-private partnership has been dedicated to advancing AD research by facilitating data sharing among researchers worldwide. The main objectives of ADNI are:

- Identifying biomarkers for the early detection and tracking of Alzheimer's disease (AD) progression
- Describing the course of AD and mild cognitive impairment (MCI) through longitudinal studies
- investigating the connections between clinical, cognitive, imaging, genetic, and biochemical biomarkers
- developing better techniques for AD clinical trials
- providing information to researchers globally to expedite AD research and foster collaboration.

The all-encompassing strategy of ADNI encourages cooperation between scientists and medical professionals, leading to improvements in Alzheimer's disease diagnosis, treatment, and prevention.

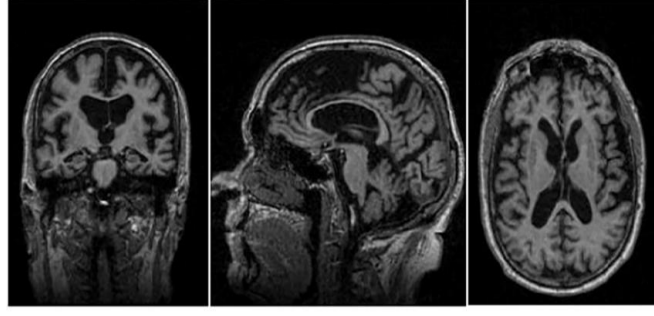


Fig 2: Sample MRI image from ADNI dataset

B. Data Pre-processing

The raw images collected from the ADNI dataset are available in various formats and sizes. These images used directly would lead to low accuracy and sometimes inaccurate results. Hence preprocessing is done to make the data ready to use. Three main steps are followed during data pre-processing. These are:

- Conversion and Formatting: MRI machines often produce their own proprietary formats for the acquisition of MRI pictures. To enable interoperability with various analytic software, the initial step is to transform these pictures into standard formats like as DICOM or NITI (Neuroimaging Informatics Technology Initiative).
- Noise reduction: MRI scans can contain artifacts from the scanner and thermal noise, among other kinds of noise. Filtering and denoising algorithms are two examples of noise reduction techniques that are used to increase signal-to-noise ratio and enhance image quality. This is accomplished through Median filters which is a digital filtering technique.
- Image Resizing: Resizing images shortens the training processing time. With CV2 Python, resizing is accomplished.

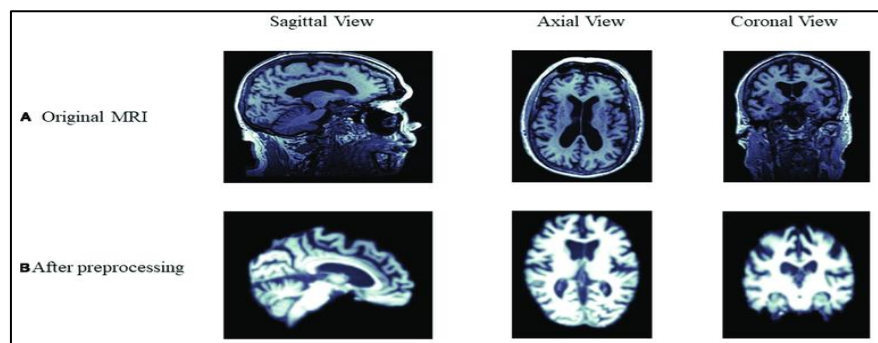


Fig 3: Comparison image of MRI images before and after pre-processing

C. Data Labelling

Following preprocessing, we name our data for a double request and set the model size. Because we use twofold presentation, the dataset's images are labeled with a Clinical Dementia Ratio (CDR) of either 0 or 1. Considering that CDR 1 denotes severe Alzheimer's disease and CDR 0 indicates strong, or no dementia. With CDR 1, there are 27 patients. We

had 27 individuals with Alzheimer's and 27 people without the disease. We take two photos to accomplish this. After that, we separated the photos into an 8:2 extent while taking inconsistent decisions into account. This implies that a maximum of 80% of the data is used as training data and the remaining portion is used for testing.

D. Proposed CNN Model

The CNN model proposed by us consists of 5 layers. These are:

- 1) Input Layer: In the case of CNNs, this layer typically represents the input data, which are images. Every image is represented as a grid of pixels, with intensity values for each colour channel (red, green, blue, etc.) assigned to each pixel.
- 2) Convolution Layer (Convolution + Activation): Convolutional filters are used in this layer to extract features from the input image. To introduce non-linearity and enable the network to learn intricate relationships in the data, the activation function (such as ReLU) is implemented.
- 3) Pooling Layer: The feature maps by the convolutional layers are down sampled by the pooling layers. Pooling lowers the computational cost of the network and aids in making the representations invariant to slight distortions and translations in the input data. MaxPool2D is used for this purpose.
- 4) Flatten Layer: Convolutional and pooling layers create multi-dimensional feature maps, which the CNN's flatten layer transforms into a one-dimensional vector. This conversion makes it possible for the extracted features to be seamlessly integrated into fully linked layers for further classification or regression tasks, which speeds up information processing within the network.
- 5) Fully Connected Layer (Dense Layer): This layer connects a classic feedforward neural network to the flattened feature maps from the preceding layers. Because every neuron in this layer is connected to every other neuron in the layer before it, the network can understand intricate correlations between different features. In classification tasks, the output of this layer is frequently run through a softmax activation function to generate class probabilities.

The Rectified Linear Unit (ReLU) activation function is defined mathematically as:

$$f(x) = \max(0, x)$$

In this formula, x represents the input to the function, and $f(x)$ represents the output. The ReLU function returns the input value if it is positive, and zero otherwise, effectively introducing non-linearity to the network's activations.

Leaky ReLU is used to address the "Dying ReLU" issue, providing a small negative slope when $x < 0$.

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}}$$

σ = SoftMax

$\vec{Z}$ = input vector

e^{z_i} = exponential function of input vector

K = numbers of classes in classifier

e^{z_j} = exponential function of output vector

E. Loading Pre-trained CNN Models

We load our pre-prepared CNN models in this stage, including VGG19 and InceptionV3. It is evident that we added two thick layers and a straight layer to each pre-prepared model after stacking them. With every thick layer, initial capacities ReLU and softmax have also been used.

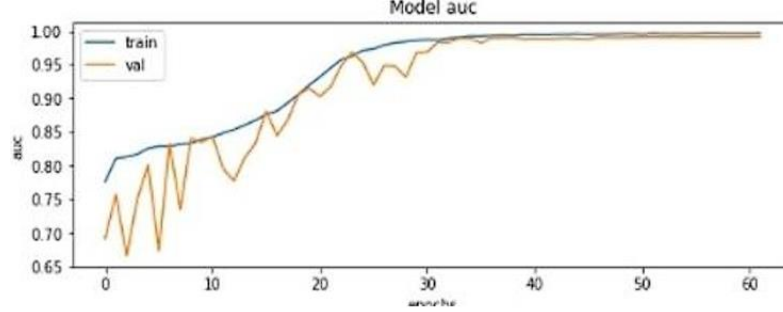


Fig 4: Accuracy of the model

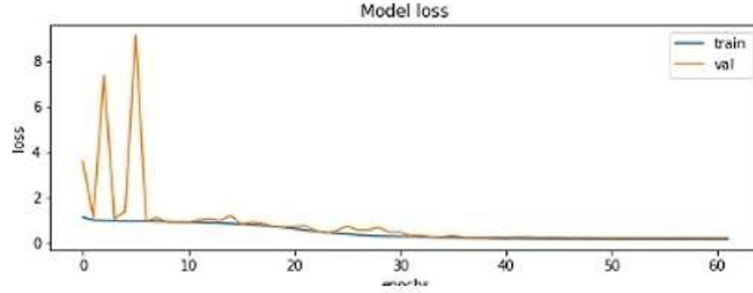


Fig 5: Loss of Data

The graph illustrating the data's accuracy and loss is displayed in the figure. In figure 4, a straight line is produced after the accuracy continues to rise with the number of iterations until it reaches the stable point. Figure 5 shows how the loss decreases as the number of repetitions increases until it reaches a stable position, at which time a straight line is produced.

F. Execution and Comparison

On executing pre-prepared CNN models, we observed varying outcomes in terms of accuracy, computational efficiency, and generalization performance. In contrast, our proposed model exhibits superior performance, achieving higher accuracy, faster execution times, and improved robustness, highlighting its efficiency in addressing the task at hand.

Experimental Results

The goal is accomplished by employing 6-layer CNN to achieve an accuracy of 98.87% in the identification and portrayal of Alzheimer's disease across all dimensions. Please take note that the ADNI dataset helps us accomplish our goal of the maximum accuracy. Evidently, 98.67% accuracy is now the highest achievable precision for a 6-layer CNN model on the OASIS dataset. As a result, we conclude that, in terms of survey and accuracy, our suggested CNN model performs better than the predetermined models. We may conclude from the exploratory results that the suggested 6-layer CNN model performs better than all other pre-trained models and standards that we evaluated. Patient-provided MRI brain scans serve as the input in this case.

An input image can be one or more pictures taken from various perspectives. After processing the provided image, the type of dementia is identified. Mild Dementia, Moderate Dementia, Severe Dementia, and Non-Dementia are the classifications.

Mild Dementia: MCI, or mild cognitive impairment, lies between the more official sort of dementia and the common mental corrosion of natural aging. It manifests as problems with thinking, language, memory, or judgment. In the elderly, mild dementia and mental weakness are common problems. Important things to think about. Most patients with these issues primarily rely on their suppliers, who should be fully informed on their findings, visualizations, and the board. Genuine evidence of mental impairment can be used to characterize both mild mental disability and gentle dementia.

Moderate Dementia: Mild dementia is characterized by transient memory loss, character changes, such as fury or melancholy, forgetting things, being absent-minded, having difficulty completing challenging homework, or having difficulty expressing emotions or ideas.

Severe Dementia: In older adults, modest cognitive impairment and mild dementia are common problems. Important to keep in mind: Since suppliers are most patients with these issues' main source of support, they should be fully aware of their resolve, judgment, and executives. True evidence of mental weakness characterizes both mild mental disability and mild dementia.

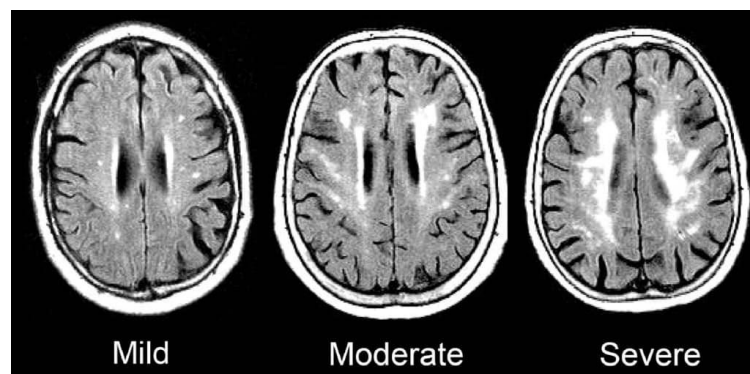


Fig 6: Comparison of Mild, Moderate and Severe Dementia

Non-Dementia: Conditions such as depression, nutritional deficiencies, medication side effects, and localized pain can all produce symptoms that resemble early signs of dementia, such as difficulties with correspondence and memory and behavioural abnormalities. The important components of the brain MRI image that are extracted during pre-handling are displayed.

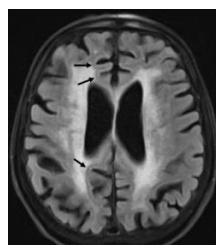


Fig 7: Early Onset of Dementia

Following feature analysis, a result based on the dementia kinds previously described is provided. This result is displayed below. If the patient needs any additional criteria or

confirmations, they can also obtain the report. The report includes the name of the dementia that was identified and the acquired brain MRI image.



Fig 8: Final output

Conclusion

AD is one of the most prevalent forms of irreversible dementia in the world, with a high fatality rate that ultimately results in death. Improved medication outcomes and increased patient survival rates may result from early identification of AD. We looked closely at the use of deep learning models with various architectures in AD diagnosis in this study. Here, we suggested using a 5-layer CNN algorithm to identify dementia symptoms and provide equal request. Our attention was fully engaged with the ADNI dataset. Therefore, the dataset used is not only freely available to us but also it is vast and provides for a variety of input images which leads to the best accuracy. Provided CNN model is dependent on AI estimations and substantial learning. In comparison to four pre-arranged models and a continuing 8 CNN model, our suggested model performs better. We will be doing numerous inspections as part of our planned inquiry.

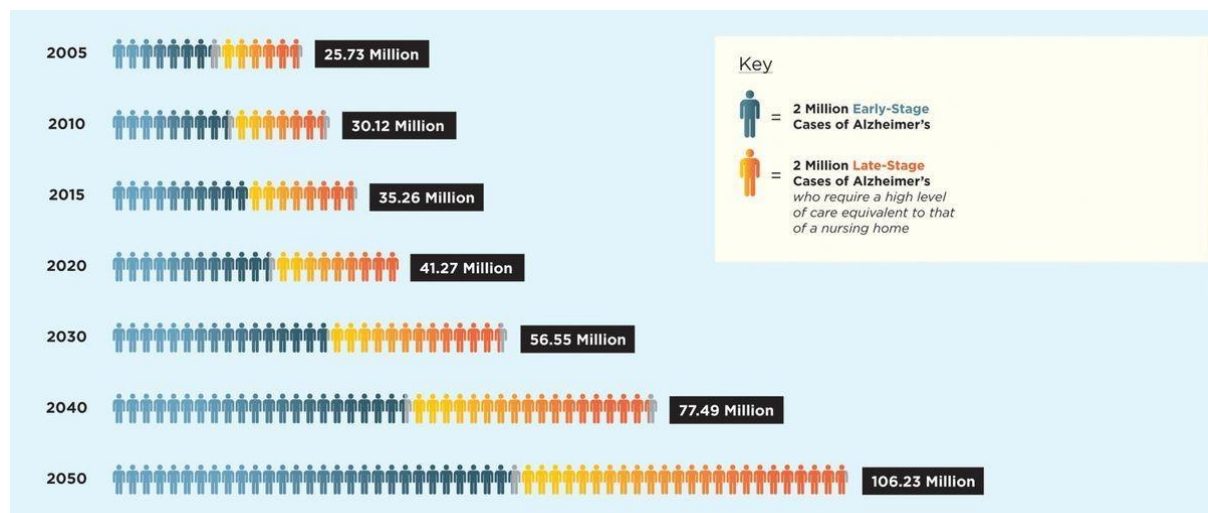


Fig 9: World-wide projection of Alzheimer's prevalence for the years 2005-2050

Future Scope

Deep Learning in AD research is always being upgraded for better efficiency and openness. Deep learning algorithms are being used exclusively in a model that replaces hybrid techniques in research on the diagnostic categorization of AD. One of the main challenges is getting sufficient, reliable, and cognitively balanced information about Alzheimer's disease. Nevertheless, methods for integrating completely other types of data into a deep learning network still need to be developed. Given that high-quality, noise-free data is a major challenge, we suggest the following strategies for further research:

- Research techniques that emphasized the use of feature selectors prior to CNNs.
- Methods utilizing deep learning algorithms based on manifolds.
- Using sparse regression models to classify AD.
- Techniques that identify the areas of activity by introducing deep learning segmentation into the process.

The previously mentioned approaches may all pave the way for novel developments in the prediction and classification of AD.

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