Alzheimer classification using Deep Learning technique

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Abstract

A person with Alzheimer's disease may ultimately find it difficult to speak and react to their environment. A degenerative condition called Alzheimer's disease begins with minor memory loss. Recently, automated classification and early Alzheimer's disease diagnosis have drawn a lot of interest in deep learning. It has been demonstrated that convolutional neural networks (CNN) and other deep learning approaches outperform more conventional machine learning methods. Using mobility data and deep learning algorithms, this study seeks to determine a patient's stage of Alzheimer's disease. For classification research using machine learning, Feature selection, feature- based technique selection, dimensionality reduction and feature extraction are typically necessary four steps. These techniques may be time-consuming and call for specialist knowledge and several optimization stages. Among the recent studies, the Deep Learning approach has produced great results for picture classification. Medical imaging technology can be utilised to solve these issues, and neuroimaging methods like structural magnetic resonance imaging (SMRI) can be combined with deep learning algorithms to produce improved classification outcomes.

Keywords: *Alzheimer's disease, convolution neural network, Deep learning, Alexnet, Resnet.*

I. INTRODUCTION

According to the study, the deep learning-based methodology performed better than conventional machine learning techniques, delivering more accuracy and precision in the classification of Alzheimer's disease. The researchers also showed how deep learning algorithms may be effectively used with medical imaging equipment, such as structural magnetic resonance imaging (SMRI), to improve classification results. The results imply that deep learning algorithms can assist overcome some of the obstacles associated with classic machine learning approaches, such as feature selection and extraction, and deliver more accurate and trustworthy diagnostic tools for Alzheimer's disease.

The project intends to apply efficient and target-based characteristics in addition to deep learning methods to increase the accuracy of the results. The researchers aim to enhance the performance of the deep learning models by carefully choosing the elements that are most pertinent to the classification of Alzheimer's disease. Deep learning algorithms have showed promise in separating individuals with normal cognitive function from those with mild Alzheimer's disease dementia and moderate cognitive impairment using structural MRIs. Compared to conventional volume/thickness models, which call for the retrieval of volumes and thickness beforehand, our method is significantly faster.

The goal of the research is to categorize and segment the elements that will enable the machine to distinguish between photographs of patients who exhibit symptoms of Alzheimer's disease. In an effort to get very accurate findings, we have decided to employ 3 distinct designs. As the project's foundation, CNN is integrated with deep learning, effective and target-based features, and categorization to produce results that are more accurate. We select the model from a set of three that produces the best accurate results.

II. RELATED WORKS

Monika Sethi et al [1] The goal of this research is to examine cutting-edge CNN applications for the diagnosis of AD using both single-modality and multimodality brain scan data. More significant, however, is to determine how AD is classified from the earliest stage to the end stage. To fully understand all of CNN's work on single image or multimodality neuro-images we have examined a sizable corpus of research in this area. Moreover, we evaluated the CNN model's capability to extract characteristics that might enhance the model's effectiveness as a whole as well as its efficiency in identifying AD. but lack information, especially when it comes to locating the regions of interest (ROI) inside the cerebral cortex, uneven data collection, flaws in previously processed medical images, dataset accessibility concerns, and minimal variance across classes throughout various AD stages. The symptoms that distinguish AD, such as hippocampal atrophy, can occasionally be seen in an ageing, typically normal brain, although medical imaging are more sophisticated than those found in nature.

Shweta Madiwalar et al [2] In the current research, we have attempted to identify dementia in its early stages using machine learning approaches. For patients who are classified as having dementia or not, the investigation's data set includes details on their gender, age, education level, MMSE, CDR, hand strength, and number of hospital visits. We used many machine learning techniques, such as Neighbors Classifier, Logistic Regression, SVM, Random Forest Classifier, Decision Tree Classifier, and Extra Tree Classifier were used to analyse the data. Each algorithm is compared in a study. The most accurate algorithm will be employed to continue the examination of the data. In our suggested study, we used an additional tree classifier for a more thorough analysis of the data and six distinct machine learning(ML) methods to verify the accuracy of each model. The algorithms employed in research projects aid in the earlier diagnosis of Alzheimer's. The patients who choose to receive treatment at an early stage may profit from these forecasts. Although a definitive cure for the illness has not yet been discovered, early therapy is necessary to give the patient the best chance of battling the illness.

Y N Fu’adah et al[3] This paper suggests using AlexNet architecture and a convolutional neural network (CNN) to create an automated system for classifying Alzheimer's disease. Using MRI datasets, the investigation divides 664 datasets into groups for those who are not demented, are mildly, moderately, and extremely mildly demented. The experiment's findings in this investigation were 95% correct. Medical professionals may find it useful to use the automated Alzheimer's disease categorization to determine the illness' stage so that the right medical treatment can be given.

Sergio Grueso and Raquel Viejo-Sobera [4] the aim of this paper is avoiding or minimising cognitive decline are made possible by advancements in medical imaging and computer capability. Promising treatment for people with mild cognitive impairment includes computer supported picture analysis and early recognition of cognitive changes. Neuro- imaging data was examined using machine learning to forecast whether those with moderate cognitive impairment will have dementia due to Alzheimer disease or would remain stable. 116 studies were chosen for qualitative analysis after deleting duplicates and screening over 452 studies.

Osamah Ibrahim Khalaf and others[5] Many techniques, including Tree Structure, Support Vector Machine, Random Forest, Gradient Boosting, and Voting classifiers, have been used to find the most accurate variables for predicting Alzheimer's disease. Predictions for Alzheimer's disease are made using data from the Open Access Series of Imaging Studies, and the effectiveness of ML models is evaluated using metrics including Clarity, Recall, Accuracy, and F1- score. Clinicians can recognize these diseases using the indicated categorization method. These ML algorithms have the potential to significantly reduce the annual death rates of Alzheimer's disease in situations of early detection. The recommended approach produces superior results, with the AD test data's highest validation accuracy percentage of 83%. In comparison to past efforts, this test's accuracy score has greatly increased.

Suhuai Luo and others [6]. This study assesses the current state of deep learning-based AD detection. After carefully reviewing more than 100 publications in the literature, we provide the most recent findings and trends. We discuss fascinating biomarkers and characteristics (personal data, genetic data, and brain scans), crucial pre-processing steps, and various strategies with regard to managing neuroimaging data resulting from single-modality and multi-modality research. Performance of deep models is described in great detail. There are still a lot of issues with deep learning, notably with relation to the accessibility of datasets and training techniques, despite the fact that it has shown great success in detecting AD.

HabilKalkan and others [7] The objective of this work is to develop a precise artificial intelligence model that can identify AD patients who are at high risk based on a gene expression array from blood samples. 1D gene expression patterns are transformed into a discriminative two- dimensional (2D) picture in order to do this, which may then be classed using convolutional neural networks (CNNs). A total of 11,618 similar gene expression levels from three publically accessible datasets were combined. Using the Fisher distance, the genes were categorized based on their capacity to discriminate, and then a 2D picture was projected using linear discriminating analysis (LDA). Next, classification was performed using a 6-layer CNN model with 292,493 parameters.

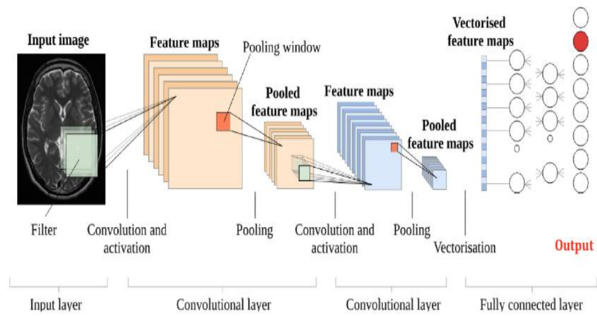
TABLE I. COMPARASION BETWEEN DIFFERENT FINDINGS

Authors	Adopted methodology	Findings	Limitation
SuhuaiLuo *al*[6]	• convolutiona lneural network	The accuracyof the model is 92%.	the medical images are complex
Shweta Madiwalar *al* [1]	Random forest classifier, Decision Tree Classifier, Extra Tree Classifier, Neighbors Classifier and Logistic Regression	accurateresults of93.14%.	time-consuming operation that could compromisethe algorithm's accuracy
Sergio Gruesoa*al* [2]	• SVM • CNN	Accuracyof 75.4% was achieved.	Methodological details are not included
C. Kavitha *al* [5]	• Decision Tree • Random Forest • SVM • XGBoost	Accuracy achieved is approx to 86%	Failed to identity relevant features and attributes to identify the issue at hand
Habil Kalkan*al* [7]	• CNN • LDA	Accuracy of 84.2% was achieved	Higher misclassification was observed while performing three-class classification

III. CONVOLUTIONAL NEURAL NETWORK

CNN is a multi-layer networking structure which was developed using the multi-layer perceptron neural network technique. It has two distinct components: first is the generative section, which extracts picture features. Convolution maps, which seem to be brand-new images, are created by putting the image through a sequence of filters or kernels. Some intermediary filters reduce the image resolution by a maximum local operation. The feature vector is then produced by combining the convolution maps. This vector is connected to the input of a second component, the multilayer perceptron classification component, which enables the division of the images into two classes.

Fig 1. CNN Architecture



The Convolution level: In this level, a filter is moved by dragging it across the entire image and a convolution (a matrix product) of the base image and this filter together. The filter will first be positioned at the upper left of the image, then it will shift many boxes (the pass) to the right. When the filter reaches the end of the image, it will descend a step to deduce until the entire image has been processed. This technique aims to highlight specific features of a given image as well as the filter's path on the image.

Pooling Layer: Minimises the image size while keeping important details. The "Max Pooling" approach is the most popular. It entails scaling down the image while retaining the pixels with the highest values. To accomplish this, a tile on the image's surface moves (much like a filter). The highest value is taken out of each tile place. This creates a brand-new image that has only the remarkable image values.

The correction layer: By adding a layer between the processing layers that will activate the output signals, processing efficiency will be increased. Neurons are compelled to produce positive values via this function.

Flattening: The task at hand is to combine all the image arrays into a single vector. By connecting each of its values to the neurons in the network's first layer, this vector will enable the development of the first layer of completely connected neurons.

The fully connected level: After a number of convolution and max pooling levels, classification reasoning is carried out using just levels that are completely connected. All of the neurons from the level above are interconnected with those in the level below. The Soft max function processes the level's outputs to produce the probability distribution vectors. In our picture classification problem, N is the number of classes, and this method outputs a vector of N-size. The likelihood that the input image fits into a particular category is represented by each component of the vector.

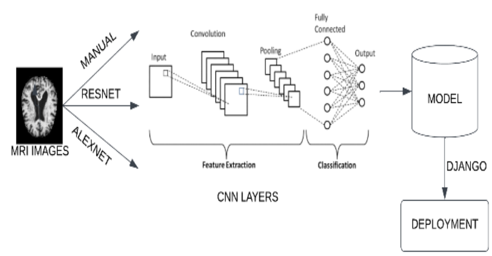
IV. EXISTING SYSTEM

Early Alzheimer's disease diagnosis is critical for prompt treatment to prevent further decline. It is very helpful clinically to visualise the physical characteristics of the early stages of AD. An innovative multi-directional perception generating adversarial network is used in this work to visualize the seriousness of AD for patients at various phases. In this study, the properties characterising the harshness of AD for patients at various stages are visualised using a multi- directional perception generating adversarial network (MPGAN). By including a cutting-edge multidirectional mapping method into the model, the suggested MPGAN may specifically capture the key global features with effectiveness.

V. PROPOSED WORK

The suggested study created a classifier for Alzheimer's disease to distinguish between Using different MRI image processing techniques, healthy and mentally ill people can be distinguished. The system compared the accuracy using three different architectures while employing the CNN method in deep learning. The architectures are Alexnet, Resnet50 and a manual architecture that consist of 5 layers. The model is fed with an obtained data set then classification and processing of the image is done by comparing against the Key features obtained during pre-processing and feature extraction. All the extraction part is done before training the mode at the convolution and pooling stages. The overall proposed system architecture is shown in fig 2.

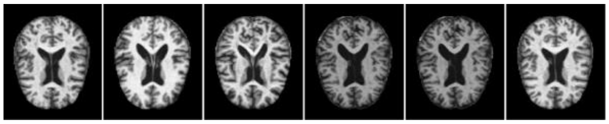
Fig 2. System architecture



A. Data Collection

The MRI datasets used in this investigation were obtained from Kaggle. The datasets are made up of MRI scans of the brain that have been labelled as dementia- or non-dementia related. Fig 1 displays an example of the data for both classes. The Alzheimer's MRI dataset comprises a total of 788 images, including both non-demented and demented images. Typically, this data is divided into training and testing sets, with 65% of the data used for training and the remaining used for testing. Figure 1 depicts that the input MRI image provided to the architecture is a grayscale image that measures 28 x 28 pixels, equaling 784 pixels in size.

Fig 3. MRI scan of demented and non-demented brain



B. Pre-Processing

Feature extraction

MRI image uploaded is made up of pixels whose height and width are to be determined. Each image is accessed from the database and stored in a list. the overall height and width (features) are determined by creating maximum and minimum height and width.

Fig 4. Feature extraction

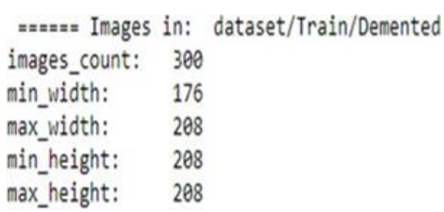

```
====== Images in:  dataset/Train/Demented
images_count:   300
min_width:      176
max_width:      208
min_height:     208
max_height:     208
```

TABLE II. FEATURE EXTRACTION ALGORITHM

Algorithm: Feature extraction Algorithm
1. Input: Data Repositories 2. Output: Raw Data 3. procedure Feature extraction 4. D ⇽ImageDetails(path) - Intialize data={} - Count the number of images and initialize min/max values for image width and height. - While(!endoffile) update min/max width and height. 5. D1 ⇽Images_details_Print_data() 6. return D1 7. end procedure

Data augmentation

Training a machine requires a large amount of data, so data needs to be augmented. The dataset will be expanded using the ImageDataGenerator class. Additionally, it is defined to be divided into two classes.

VI. MANUAL ARCHITECTURE

It is a user-defined architecture and can contain n number of layers as per our requirement. All the architecture contains the mandatory 4 layers i.e The Convolution layer, pooling layer, flattening layer and dense layer. Here 5 layers have been used

1. 1st Convolutional and MaxPooling layer:

classifier.add(Conv2D(16,(3,3),input_shape=(200,200,3),

activation=”relu”))

classifier.add(MaxPooling2D(2, 2))

In this process, we are training a total of 16 filters and subsequently utilizing Max Pooling to decrease the output volume's spatial dimensions. The dimension is set to 3x3, and the activation function is specified as relu(Rectified Linear Unit).

2. 2nd Convolutional and MaxPooling layer:

classifier.add(Conv2D(32,(3,3), activation=”relu”))

classifier.add(MaxPooling2D(2, 2))

We are utilizing a total of 32 filters and subsequently applying Max Pooling to decrease the output volume's spatial dimensions. Once again, the dimension is specified as 3x3, and the activation function is defined as relu(Rectified Linear Unit).

3. Fatten layer

classifier.add(Flatten())

The flattening process is employed to transform all the resulting 2-Dimensional arrays from the pooled feature maps into a singular, lengthy, continuous linear vector.

4. 1st Dense layer classifier.add(Dense(38,activation=”relu”))

5. 2nd Dense layer classifier.add(Dense(2,activation=”softmax”))

Softmax activation function is used when we have 2 or more than 2 classes. If we have total 2 classes, then the number of neurons in the output layer will be 2. Each neuron represents one class.

Fig 5. Manual architecture summary

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_2 (Conv2D)            (None, 198, 198, 16)      448
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 99, 99, 16)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 97, 97, 32)        4640
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 48, 48, 32)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 73728)             0
_________________________________________________________________
dense_2 (Dense)              (None, 38)                2801702
_________________________________________________________________
dense_3 (Dense)              (None, 2)                 78
=================================================================
Total params: 2,806,868
Trainable params: 2,806,868
Non-trainable params: 0
_________________________________________________________________
```

VII. MATHEMATICAL FORMULA

Accuracy depicts how well the machine has been trained. The accuracy is determined by dividing the number of correct predictions by the total number of predictions.

$$\textit{Accuracy} = \frac{\textit{True positive} + \textit{True negative}}{\textit{True positive} + \textit{True negative} + \textit{False positive} + \textit{False negative}}$$

Within the CNN architecture, validation loss and validation accuracy are metrics used to assess a neural network's performance on a validation set. This validation set is comprised of data that the model has not previously encountered during training.

Validation loss is an indicator of how effectively the model is functioning on the validation set, usually assessed using a loss function such as mean squared error (MSE) or cross-entropy. The validation loss evaluates the deviation between the predicted output and the actual output for the validation data. A lower validation loss implies that the model is performing better.

$$J=1/M \sum f(y\text{^}I,yi)$$

Where is the number of an epoch.

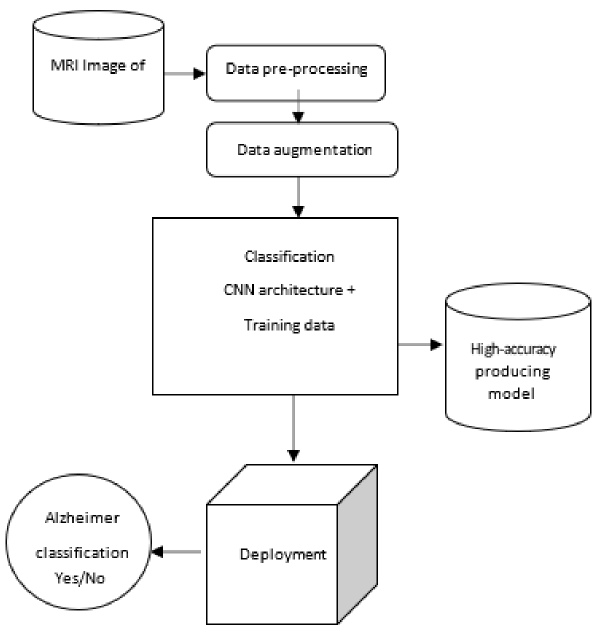
Validation accuracy, conversely, is a metric that assesses the model's ability to predict the appropriate class for the validation data. It is evaluated by dividing the number of accurately predicted data points by the total number of data points in the validation set. A higher validation accuracy indicates that the model is performing better.

Validation accuracy = (number of correctly predicted samples) / (total number of validation samples)

VIII. PROPOSED METHODOLOGY

In the proposed system there are 3 stages as shown in figure5. in the first stage. Data pre-processing happens where the image details will be extracted and data will be augmented. In this stage the machine will be fed with test data simultaneously. In the second stage the machine gets trained with 3 architectures. In 1st architecture I.e., manual architecture there are 5 layers. And the other two are Alex net and resent architecture. All the three architectures consist of convolution layer, max pooling layer, fully connected layer and finally dense layer. Once when the MRI scan from datasets goes through these layers u can train the machine and get the accuracy of how well the machine has been trained. Based on the obtained accuracy, the architecture that produced high accuracy will be chosen as the model. In the third stage, the model will be deployed using Django framework. Using Django, a user-friendly website is developed and the user can upload his/her MRI scan.

Block diagram of proposed methodology

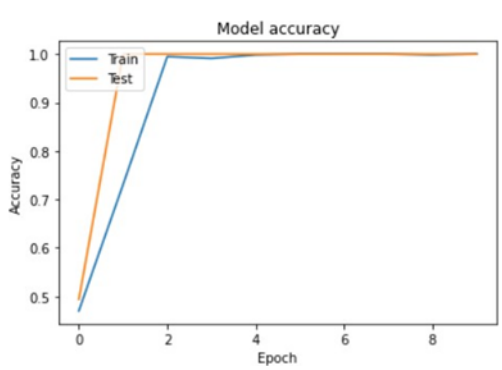


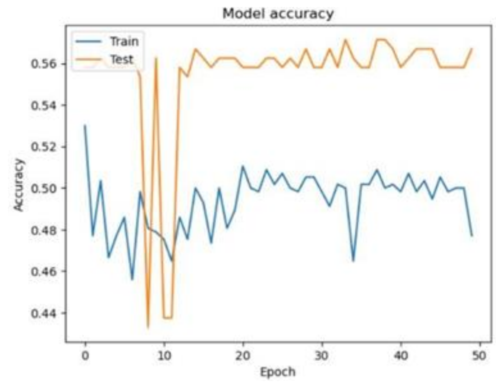
IX. RESULT AND DISCUSSION

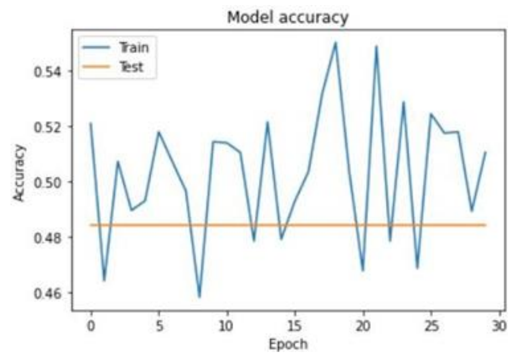
Accuracy produced by 3 different architecture were as follows :

- manual architecture: 100%
- AlexNet architecture: 54%
- ResNet architecture: 56%

Fig. 6 – Accuracy analysis graph of the three architecture







It was determined that the manual architecture produced the highest accuracy after training the machine. Accuracy produced by AlexNet architecture is 54%, ResNet is 56% and Manual is 100%. Hence, manual architecture was selected as the model, and we can now go on to the deployment. Deployment is done through Django framework. As the model is trained with 100% generating accuracy architecture, MRI classification will be effective.

Comparison between existing system and proposed system

Purpose: The existing system did not focus on identifying the Alzheimer's disease classification. It was only useful for segmentation. In the proposed system identifying and classifying Alzheimer disease is done.

Accuracy: Accuracy was not compared among different architectures in existing system. In the proposed system the model with high accuracy is chosen as the model.

Deployment: In the existing system, the model is not user friendly. Users don't have a way to interact with the model. But in the proposed system Django is used to build a interactive website where he/she can interact with the model.

X. FUTURE SCOPE

The application of deep learning to the classification of Alzheimer's disease is an intriguing field of study with enormous potential. For early detection and intervention, which can improve outcomes for patients and their families, the development of precise and trustworthy diagnostic techniques for Alzheimer's disease is essential. A promising field of research with enormous potential is the application of deep learning to the classification of Alzheimer's disease. For early detection and intervention, which can result in improved outcomes for patients and their families, it is critical to create accurate and trustworthy diagnostic methods for Alzheimer's disease. The integration of deep learning with other cutting-edge technologies, such as wearable technology and mobile applications, is another potential future use. Deep learning algorithms could offer real-time monitoring and early Alzheimer's disease identification by merging data from various sources with imaging biomarkers. This strategy might have a big impact on how well patients do and how much money the disease will cost in healthcare.

The application of deep learning to the study of Alzheimer's disease may yield fresh perceptions into the illness's basic mechanisms. Deep learning algorithms may be able to find patterns and links in vast volumes of data that may not be obvious to human researchers. This strategy might result in fresh understandings of the illness and new directions for study and therapy. Deep learning algorithms are still being developed and used, which has the potential to transform how we comprehend the condition, enhance patient outcomes, and finally find a cure.

XI. CONCLUSION

The CNN model is used to forecast the pattern of Alzheimer illnesses using images from a specified dataset (the training dataset) and historical data. This technique offers the following information regarding Alzheimer's disease prediction. One of the key benefits of the CNN classification framework is its ability to automatically classify images after sufficient training. Alzheimer disease is a brain disorder that gradually impairs one's memory and cognitive functioning. Early discovery can significantly impact a person's life because patients are frequently diagnosed too late, making a treatment rare. The collection of an Alzheimer's image data set, pre-processing procedures, feature extraction approaches, and classification schemes are just a few of the methods we've explored in this study to provide you an overview of how to discover anomalies in photographs taken by people with Alzheimer's disease. Deep learning models can beat traditional techniques in terms of diagnostic performance, according to an assessment of the use of deep learning techniques for classifying Alzheimer's disease. Deep learning models have considerable advantages in terms of accuracy and speed and are capable of autonomously learning image attributes for Alzheimer's disease categorization. Using 3D deep convolutional neural networks, it is possible to discriminate mild Alzheimer's disease with accuracy in the survey study on categorising Alzheimer's disease using deep learning techniques (CNNs). the application of deep learning algorithms for accurately diagnosing

Alzheimer's disease, as well as the use of feature extraction or classification techniques based on deep learning to obtain high accuracy for AD classification. The research also explains how to predict AD categorization with accuracy levels of up to 96.0% and 84.2%, respectively, using deep learning approaches. The article's conclusion urges the implementation of a thorough framework for the early detection of Alzheimer's disease and the coding of medical imaging for a variety of illnesses.

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