# Detection of Alzheimer's Disease Using CNN Model

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**ABSTRACT**

Alzheimer's disease (AD), a progressive neurodegenerative illness, are dementia and a marked reduction in cognitive function because of brain cell destruction. The disease is multifaceted, and two major contributing hypotheses are the amyloid hypothesis, which links the buildup of β-amyloid plaques as a basic disease mechanism, and the cholinergic theory, which links cognitive impairment with the death of cholinergic neurons. There are several risk factors that have been found to affect the onset and course of AD, including ageing, genetics, head trauma, and lifestyle. NMDA antagonists and cholinesterase inhibitors are the only available medications that can alleviate symptoms; they cannot stop the disease's progression. To provide hope for more successful future interventions, ongoing research attempts to create disease-modifying medications that target biological mechanisms such tau protein dysfunction and inflammatory pathways. To effectively manage and maybe reverse the course of Alzheimer's disease, this study emphasizes the need for a holistic strategy that targets both symptomatic treatment and the underlying disease pathology.[1]

The main focus of this study is the considerable difficulties in accurately and early diagnosing Alzheimer's disease from MRI scans using traditional techniques, which frequently rely on complex feature extraction by clinical professionals. In addition to requiring a great deal of time and experience, these conventional methods run the risk of producing inconsistent diagnostic results because of human error and the subjective character of the study. The paper suggests using a pre-trained Convolutional Neural Network (CNN) model in conjunction with sophisticated deep learning approaches to address these problems The objective of this model is to improve the efficiency and accuracy of Alzheimer's disease diagnosis by automating the feature extraction process from brain MRI images. This strategy uses deep learning to standardize the diagnostic procedure, lessen reliance on specialized human knowledge, and maybe improve the scalability of Alzheimer's diagnosis in a variety of healthcare contexts. In order to open the door for more dependable and easily available diagnostic tools in the field of neurodegenerative illnesses, the main objective is to confirm that the CNN-based model outperforms conventional techniques. This is especially important for Alzheimer's research because early diagnosis is directly related to improved patient outcomes and the effectiveness of treatment treatments.[2]

Alzheimer's disease (AD), the most prevalent type of dementia, gradually deteriorates memory and other cognitive abilities. It is frequently discovered too late to be effectively treated. The improvement of care and treatment results depends on early identification. This work suggests a deep learning-based pipeline that uses 2D T1-weighted MR brain images and shallow Convolutional Neural Networks (CNN) for precise AD diagnosis and staging. Both global and local classifications are provided by the pipeline, which not only provides a quick and accurate AD diagnostic tool but also differentiates between normal, mild cognitive impairment (MCI), and various stages of dementia, such as very mild dementia (VMD), mild dementia (MD), and moderate dementia (MoD).[3]

Alzheimer's disease (AD) is a severe neurological illness that requires accurate diagnosis to be effectively managed and treated. The Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset's MRI data is used in this study to categories AD using a convolutional neural network (CNN) architecture. A classification layer of the suggested network combines two different CNN models, each with its own filter sizes and pooling layers. These findings demonstrate how well the network can extract pertinent information from MRI pictures, allowing for precise classification of AD stages and subtypes. The network efficiently pulls both general and detailed patterns from the input by employing the hierarchical structure of convolutional, pooling, and fully connected layers, enabling precise AD classification. Early detection, customized treatment planning, continuous monitoring, and prognosis evaluation are just a few of the significant clinical advantages that come with this precision. The CNN model's proven accuracy indicates that it has a great deal of promise to assist researchers and medical professionals in making well-informed decisions for AD patients.[16]

**Keywords:** Convolutional Neural Network (CNN), Deep Learning, Alzheimer's Disease (AD), MRI scans, Early Diagnosis, Feature Extraction

**1.Introduction:**

As the world's population ages, Alzheimer's disease (AD) is becoming more common and causing significant financial and health problems. From concentrating only on managing symptoms, AD research has expanded to look into possible disease-modifying treatments. Pharmacological therapies like cholinesterase inhibitors and the continuous search for novel molecular targets are noteworthy developments. Researchers are identifying possible treatment avenues that could greatly lessen the effects of AD on people and society by integrating clinical and genetic data.[4]

Cognitive decline has grown in importance as the world's population ages, with Alzheimer's disease standing out for its dramatic effects on both individuals and society. While cognitive decline is a normal aspect of ageing, AD causes considerably more severe and incapacitating symptoms, such as behavioural abnormalities, disorientation, and memory loss. Since millions of people are now impacted by AD and estimates suggest that the number will increase dramatically by 2050, early detection is now essential. For those impacted, early management can help control symptoms, decrease the disease's course, and enhance quality of life. Recent developments in machine learning (ML) present a viable path ahead in this regard. In particular, convolutional neural networks (CNNs), which have demonstrated notable efficacy in processing medical imaging data, offer a fresh chance to identify AD in its early stages. CNNs may detect minute alterations in brain structure or function by processing brain imaging data, including MRI and CT scans. This helps medical professionals diagnose AD more quickly and precisely.[5]

A neurodegenerative condition called Alzheimer's disease results in the progressive death of brain cells and the shrinkage of brain tissue. Cognitive faculties, such as memory, thinking, and the capacity to do daily tasks, deteriorate as a result. With more than 60% of dementia cases being caused by AD, it is the most prevalent cause of dementia and primarily affects people 65 and older. However, younger people, typically in their 40s or 50s, can develop early-onset forms of AD. The illness progresses slowly but steadily, eventually affecting one's capacity for independent living, critical thought, and communication. Although the exact origins of Alzheimer's disease remain unclear, scientists think a mix of lifestyle choices, environmental factors, and genetics have a role in the disease's incidence and progression. Although a number of indicators have been found, AD is still difficult to diagnose, particularly in its early stages when symptoms could be mild or confused with typical ageing.[6]

Improving treatment outcomes and giving patients better management techniques depend on early detection of Alzheimer's disease, particularly when it is still in the Mild Cognitive Impairment (MCI) stage. There is a chance for prompt intervention during this stage, which lies in between more severe forms of dementia and typical age-related cognitive decline. Using magnetoencephalography (MEG) signals, which record brain activity with great temporal and spatial precision, this study presents a novel deep learning model for the early identification of MCI. To address the issue of the dataset's large feature-to-sample ratio—it comprises 25,755 features from 132 patients—the suggested model employs an ensemble of randomised convolutional neural networks (CNNs). A typical issue in machine learning when there are significantly more features than training samples is overfitting, which is made more likely by this imbalance. To combat this, the model uses strategies like feature permutation and weight-sharing across sub-models to improve generalisation and lessen overfitting. In comparison to other deep learning models and more conventional machine learning classifiers (such random forests and support vector machines), the model's remarkable F1-score of 0.92 is superior. This demonstrates how the suggested approach may be able to provide more precise and trustworthy MCI detection, which is essential for early Alzheimer's disease treatment.[7].

Early detection of AD, especially at the MCI stage, has attracted a lot of attention in light of these developments. There is a greater need than ever for precise, effective diagnostic techniques as the world's population ages and the frequency of AD increases. In the analysis of intricate neuroimaging data, deep learning techniques—particularly CNNs—have demonstrated promise in detecting minute alterations in the brain that conventional approaches frequently overlook. Early and more accurate identification of AD may be possible with the integration of these models into clinical practice. This would enable therapies that enhance patient outcomes and lessen the financial burden of AD on healthcare systems.[8]

**2.Literature Review:**

In the NIH Research Matters article, the revolutionary influence of machine learning techniques is emphasised in relation to the use of computer technologies for Alzheimer's disease detection. Neuroimaging data analysis has been greatly improved by deep learning models, especially support vector machines. Early detection of Alzheimer's disease is now feasible thanks to technical advancements that have not only increased diagnostic accuracy but also sped up the detection process. Traditional, manual diagnostic techniques have given way to more automated, effective, and accurate ones thanks to developments in machine learning. By combining these computer models, scientists and medical professionals can more accurately distinguish between early Alzheimer's symptoms and typical aging-related brain changes, which could result in better patient outcomes through earlier intervention techniques.[9]

The review of the MDPI publication "MRI Deep Learning-Based Solution for Alzheimer’s Disease Prediction" covers the development and implications of deep learning technologies in the use of MRI images for early Alzheimer’s disease diagnosis. It examines several research that have improved the precision of Alzheimer's diagnosis through machine learning, highlighting the advantage of deep neural networks in interpreting the complex patterns found in neuroimaging data. The transition from traditional diagnostic techniques to sophisticated automated systems that use deep learning to evaluate MRI data for predictive insights is also covered in this paper. It also covers current issues including data diversity and computing demands, as well as possible advancements in the future for improving algorithmic performance and reaching more extensive clinical applications.[10]

Convolutional neural networks (CNNs) provide a substantial advance over conventional diagnostic methods, which you would address in a literature review on their use for Alzheimer's disease detection utilising MRI scans. CNNs are excellent at picking up on minute patterns in MRI pictures that could point to Alzheimer's, resulting in a more precise and timely diagnosis. MRI data variability and the requirement for large training datasets to improve CNN model accuracy are two issues that would be covered in the review. Future studies could also focus on improving CNN models to handle a variety of data sets and increase its generalisation in various clinical contexts. This strategy is essential for improving the ability to diagnose Alzheimer's patients and providing prompt treatment alternatives.[11]

The article "Conventional Machine Learning and Deep Learning in Alzheimer's Disease Diagnosis Using Neuroimaging" describes how Alzheimer's disease is being detected using both contemporary deep learning (DL) and conventional machine learning (ML). It highlights DL models like convolutional neural networks and various machine learning approaches like random forests and support vector machines. The paper also highlights the significance of ML and DL in enhancing Alzheimer's diagnosis through the analysis of neuroimaging data, while addressing issues such imbalanced datasets and preprocessing needs.[12]

Focussing on important pathological components such as tau proteins and beta-amyloid plaques, the article "Alzheimer’s Disease: Targets You Need to Know" thoroughly examines important therapy targets for Alzheimer's. Therapy development attempts to decrease beta-amyloid synthesis or increase its clearance because it builds up to create plaques that impair neurone function. Similar to this, aberrant phosphorylation of tau proteins causes neurofibrillary tangles, which ultimately lead to neurone death; several strategies, such as tau aggregation inhibitors, are being researched to address this pathology. Another important aspect is neuroinflammation, whereby activated glial cells release inflammatory cytokines that exacerbate neurodegeneration. Researchers are looking into treatments that lessen inflammation in order to lessen the harm. Additionally, cholinergic dysfunction is discussed in the paper, where cognitive impairment is a result of the death of cholinergic neurones. Cholinesterase inhibitors are one type of treatment that is frequently used to alleviate this impairment. Improving antioxidant defences is regarded as a possible therapeutic, and oxidative stress is also emphasised as a factor in the development of disease. The use of neuroprotective drugs and innovative tactics that aim to simultaneously modulate several pathogenic pathways are among the multi-target therapeutic approaches that are gaining popularity, according to the article. Although a lot of research has been done, there are still issues, such as the need for reliable biomarkers for early diagnosis and therapy monitoring and the limited efficacy of direct amyloid targeting. It emphasises the value of precision medicine and promotes tailored treatment plans based on the pathology unique to each patient. The complex character of Alzheimer's disease necessitates that future research prioritize personalized and multi-target therapies [13].

**3.Data and Methods:**

**3.1 Dataset:**

The collection includes details on medical imaging and how they are classified in relation to dementia. A distinct filename in the Image name column, which appears to follow a particular pattern and may encode information like patient ID or scan settings, identifies each item as corresponding to a distinct image. Additionally, each image's dementia condition is labeled in the Class column using categories like "Non-Demented" and "Mild Dementia." By differentiating between people with moderate symptoms of dementia and those without, these categories show the cognitive health state of the individuals. Because it provides a direct correlation between each image and its dementia, this dataset may be particularly helpful for creating machine learning models or medical image analysis tools intended to identify or evaluate the severity of dementia based on imaging data.

Research on Alzheimer's disease and our understanding of aging are intended to be supported by the brain imaging data from the OASIS-1 dataset. Cross-sectional MRI images of people between the ages of 18 and 96—both healthy people and those with Alzheimer's disease—make up this collection. This dataset includes high-resolution MRI scans, clinical evaluations of cognitive function, and comprehensive demographic data (e.g., age, sex, and educational attainment). Four classes—Non-Demented, Very Mild Dementia, Mild Dementia, and Moderate Dementia—are represented by the more than 86,000 MRI slice pictures in this dataset. These data are useful for examining the structural alterations in the brain linked to Alzheimer's and aging, offering insights into cognitive decline, and locating disease biomarkers. The OASIS-1 dataset is especially helpful for creating machine learning models that can forecast Alzheimer's disease and monitor its progression since it combines imaging and clinical data.[14]

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A close-up of a brain scan

Description automatically generated

Figure 1: MRI Scans of Non-Demented Brain Samples

A close-up of a brain

Description automatically generated

Figure 2: MRI Scans of Very Mild Demented Brain Samples

A close up of a circular object

Description automatically generated

Figure 3: MRI Scans of Mild Demented Brain Samples

A close up of a skull

Description automatically generated

Figure 4: MRI Scans of moderate Brain Samples

**3.2 Data Pre-Processing:**

The offered code focuses on getting the image dataset ready for training deep learning models. It first iterates over the corresponding folders to load the paths for each class (Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented) before concatenating these routes into a single list. In order to map the photographs to their appropriate categories, labels are made and assigned in accordance with each class. A bar plot is used to display the class distribution and draw attention to any disparities. Train\_test\_split is then used to divide the dataset into training and testing sets, with stratification to preserve the same class distribution in both sets. The pre-trained VGG16 model is then used to extract features from the photos after each image has undergone pre-processing (resizing, converting to an array, and normalizing) to conform to the input format required by VGG16. By creating synthetic samples for the minority classes, SMOTE is used on the training set to balance the distribution of classes. To make multi-class classification easier, the labels are additionally one-hot encoded. The CNN model can now be trained using this pre-processed data.

**3.3 Deep Learning Model:**

Convolutional Neural Networks (CNNs) are used to analyze neuroimaging data by learning spatial patterns that can signal the existence or progression of Alzheimer's disease, according to the article. CNNs use convolutional, pooling, and fully connected layers to process MRI images, identifying intricate patterns in the anatomy of the brain that aid in differentiating between healthy and pathological conditions. In order to guarantee dependable and clinically significant findings, model evaluation is essential in this situation. Metrics like accuracy, precision, recall, F1 score, and the AUC-ROC curve are used. By confirming the model's capacity to differentiate between various stages of dementia with few errors, these measures evaluate the model's effectiveness in correctly detecting Alzheimer's and bolster its potential as a diagnostic tool.[15]

Convolutional Neural Networks (CNNs) are used to categorize MRI brain scans into different dementia stages. In order to extract features from the MRI images and help identify crucial visual patterns for diagnosis, the model architecture makes use of transfer learning with the VGG16 pre-trained model. A dense neural network classifier that generates class probabilities for dementia stages is subsequently trained using the retrieved characteristics. By applying SMOTE (Synthetic Minority Over-sampling Technique) to the training data, more samples for underrepresented classes are produced in order to address class imbalance. The data is divided into training and testing sets for evaluation, and important measures like accuracy and a confusion matrix are used to gauge the model's performance. Together with precision, recall, F1-score, and a classification report, the confusion matrix offers a thorough assessment of the model's ability to differentiate between various stages of dementia, facilitating accurate diagnosis.

**3.4 Methodology:**

In order to produce an easily accessible resource for researching aging and Alzheimer's disease, the methods outlined in the article "Open Access Series of Imaging Studies (OASIS): Cross-sectional MRI Data in Young, Middle-Aged, Nondemented, and Demented Older Adults" includes gathering and processing MRI data. To determine their cognitive health status, participants of all ages—young, middle-aged, and elderly—as well as those with dementia and those in good cognitive health—went through extensive clinical exams. To guarantee consistency amongst subjects, brain MRI scans were then carried out utilizing a standardized imaging methodology. These photos were standardized for uniformity and treated to eliminate artifacts. The project places a strong emphasis on data accessibility and quality, offering the scientific community publicly accessible, high-quality imaging data that can be utilized to investigate neurodegeneration and brain aging.[14]

This project's methodology is centered on using cross-sectional MRI data to identify Alzheimer's disease. Data gathering, preprocessing, model construction, training, and evaluation are all steps in the process. The Open Access Series of Imaging Studies (OASIS) provided the dataset, which includes more than 86,000 MRI slice pictures from four different classes: Moderate Dementia, Very Mild Dementia, Mild Dementia, and Non-Demented. To lessen the computational burden, MRI pictures were preprocessed to grayscale. The dataset was then divided into subgroups for training (70%), validation (20%), and testing (10%). Dropout and other regularization approaches were used to prevent overfitting because of the class imbalance (e.g., 67,000 non-Demented samples vs. fewer than 500 Moderate Dementia samples). The model architecture is a 2D Convolutional Neural Network (CNN) called SCNN4, which consists of a fully connected linear layer after four convolutional layers with increasing channel numbers (8, 16, 32, 64). A dropout layer is inserted before the last linear layer to reduce overfitting, and each convolutional layer is succeeded by a batch normalization layer and a ReLU activation function. Following each convolutional layer (except from the first two), feature maps were further reduced in size using max pooling layers. A One Cycle Learning Rate scheduler, a weight decay of 0.0001, and the Adam optimizer with a maximum learning rate of 0.003 were used to train the model. The model's performance was assessed using the test dataset and measures like accuracy, confusion matrix, and a classification report that included precision, recall, and F1-score for every class. The training procedure had both training and validation stages. To evaluate the model's capacity to distinguish between the four categories of dementia, a confusion matrix was plotted. By implementing a helper function to predict labels for MRI slices, the trained model was preserved and utilized to make predictions, confirming the model's dependability in practical applications.

This project, which focuses on Alzheimer’s disease detection using deep learning techniques, involves several key steps. Initially, necessary libraries such as Keras, TensorFlow, and various image-processing packages are imported to facilitate data handling and model construction. Data for different dementia stages (Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented) is gathered from specific folders, with each category assigned a unique label. The dataset is then examined to assess the distribution of classes, and sample images from each class are visualized for verification. Next, the dataset is split into training and testing sets. Feature extraction is performed using the VGG16 model, a pre-trained convolutional neural network, which serves as a foundation for identifying key features. To correct for class imbalances, the Synthetic Minority Over-sampling Technique (SMOTE) is applied, generating a more balanced dataset for training. A custom CNN model is built with fully connected layers and dropout layers for regularization to prevent overfitting. This model is trained on the enhanced dataset, utilizing callbacks for early stopping and saving the best model based on validation loss. After training, model performance is evaluated on the test set, generating metrics such as precision, recall, and F1-score, which are displayed in a confusion matrix. Lastly, cross-validation with SMOTE is employed to verify the model’s reliability, computing average accuracy scores across multiple folds to ensure robustness.

**A graph of class distribution

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Figure 5: Distribution of Samples Across Dementia Stages in the Dataset

**4. Result:**

Using convolutional neural networks (CNNs) on MRI data, an Alzheimer's disease detection model was created that demonstrated remarkable accuracy in recognizing different stages of dementia. The effectiveness of the model was strong, with a test accuracy of approximately 95%. Precision, recall, and F1-score—three important evaluation metrics—all supported the model's dependability, especially in the Non-Demented and Mild Demented groups, where F1-scores were roughly 0.97 and 0.95, respectively. With F1-scores of 0.87 and 0.98, the model demonstrated good performance even with fewer samples in the Very Mild Demented and Moderate Demented classes. The model successfully decreased misclassifications across categories, according to the confusion matrix. The model's consistency and robustness were further confirmed by cross-validation accuracy, highlighting its potential as a useful tool for the early diagnosis and categorization of Alzheimer's disease. These results demonstrate CNNs' ability to analyze complex neuroimaging data and improve neurodegenerative disease detection tools, especially when paired with data balancing techniques like SMOTE.

**5. Conclusion:**

This project illustrates the effectiveness of using a convolutional neural network (CNN) model to detect and classify different stages of Alzheimer’s disease from MRI data. By balancing the dataset with SMOTE to address class imbalances, the model achieved strong accuracy in distinguishing between Non-Demented, Very Mild Dementia, Mild Dementia, and Moderate Dementia categories. Utilizing a pre-trained VGG16 network for initial feature extraction, followed by a customized CNN architecture, enabled the model to effectively identify critical patterns in brain structure associated with each dementia stage. Evaluation metrics such as accuracy, precision, recall, and F1-score confirm the model’s reliability and its potential as a valuable diagnostic tool for early Alzheimer’s detection. The application of cross-validation also underscores the model’s consistency across diverse data subsets, supporting its readiness for use in real-world clinical settings. Future directions may include exploring more advanced architectures or integrating multimodal data to further enhance accuracy, advancing early diagnostic capabilities and the overall management of Alzheimer’s disease.

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