Advancing Automated Diagnosis: Convolutional Neural Networks for Alzheimer's Disease Classification through MRI Image Processing

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October 31, 2023

Abstract

This study evaluates the performance of a convolutional neural network (CNN) model for Alzheimer's disease (AD) classification based on MRI image processing. The results show that after 22 epochs of training, the model achieved a validation accuracy of 80.61%. Furthermore, the model exhibited high precision (78.99%) and recall (30.55%) rates, along with a significant area under the curve (AUC) value of 86.05%. These findings suggest the potential of the CNN model in accurately identifying AD cases using MRI scans, emphasizing its effectiveness as a diagnostic tool for early detection and intervention in AD.

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ABSTRACT:

This study evaluates the performance of a convolutional neural network (CNN) model for Alzheimer's disease (AD) classification based on MRI image processing. The results show that after 22 epochs of training, the model achieved a validation accuracy of 80.61%. Furthermore, the model exhibited high precision (78.99%) and recall (30.55%) rates, along with a significant area under the curve (AUC) value of 86.05%. These findings suggest the potential of the CNN model in accurately identifying AD cases using MRI scans, emphasizing its effectiveness as a diagnostic tool for early detection and intervention in AD.

keywords: Alzheimer's disease, convolutional neural networks (CNNs), magnetic resonance imaging (MRI), early diagnosis, automated classification.

I. INTRODUCTION

Alzheimer's disease (AD) is a progressive brain disorder that causes memory loss and cognitive decline, leading to dementia. It is a major cause of cognitive impairment in the elderly. The exact cause of AD is still unknown, but it is believed to be influenced by both genetic and environmental factors.

Diagnosing AD is essential for early intervention and effective treatment. Magnetic resonance imaging (MRI) scans can detect changes in the brain associated with AD, including the buildup of amyloid plaques and tau tangles. Neuropsychological tests are also used to assess cognitive function and identify AD-related cognitive problems.

Recent research has explored the use of deep learning techniques, particularly convolutional neural networks (CNNs), for predicting and classifying AD based on MRI scans. Studies by Basaia et al. (2019), Dubey et al. (2018), Zhang et al. (2019), Li and Wang (2019), Sarraf and Tofighi (2016), and Liu et al. (2020) have demonstrated the potential of CNNs and other deep learning methods in AD diagnosis using MRI images.

In one study, Basaia et al. (2019) achieved an 88% accuracy in predicting AD and mild cognitive impairment (MCI) using CNNs. Other studies have also explored the application of recurrent neural networks (LSTMs) and surveyed deep learning-based detection of AD using MRI images (Lipton et al., 2015; Anandh and Mohan, 2019).

Furthermore, a study focused on classifying the stages of AD using digital image processing. It utilized a local dataset of 171 adults, including AD patients, healthy controls (HC), and MCI patients, as well as the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset. The study employed a support vector machine (SVM) classifier and a CNN with AlexNet architecture for image classification.

The SVM classifier achieved an accuracy of 90.48% for AD vs. HC and 81.09% for MCI vs. HC when tested on the ADNI dataset. The CNN, trained on the local dataset, achieved an accuracy of 93.2% for AD vs. HC and 84.6% for MCI vs. HC on the ADNI dataset. These results suggest that digital image processing, particularly using CNNs with AlexNet architecture, shows promise in accurately classifying the stages of AD.

It's important to note that research in this field is ongoing, and further validation and refinement of these approaches are required. However, these studies indicate the potential of deep learning techniques in early AD diagnosis and classification. Future research can build upon these findings to develop CNN-based diagnostic tools for clinical use.

II. DATASETS OF ALZHEIMER

This study used a dataset of MRI images collected by Sarvesh Dubey. The dataset consists of MRI images of people with Alzheimer's disease (AD) at different stages of the disease. The stages of AD are:

(1) Non-Demented
(2) Very Mild Demented
(3) Mild Demented
(4) Moderate Demented

Dementia is a general term for loss of memory and other thinking skills severe enough to interfere with daily life. Alzheimer's disease is the most common cause of dementia.

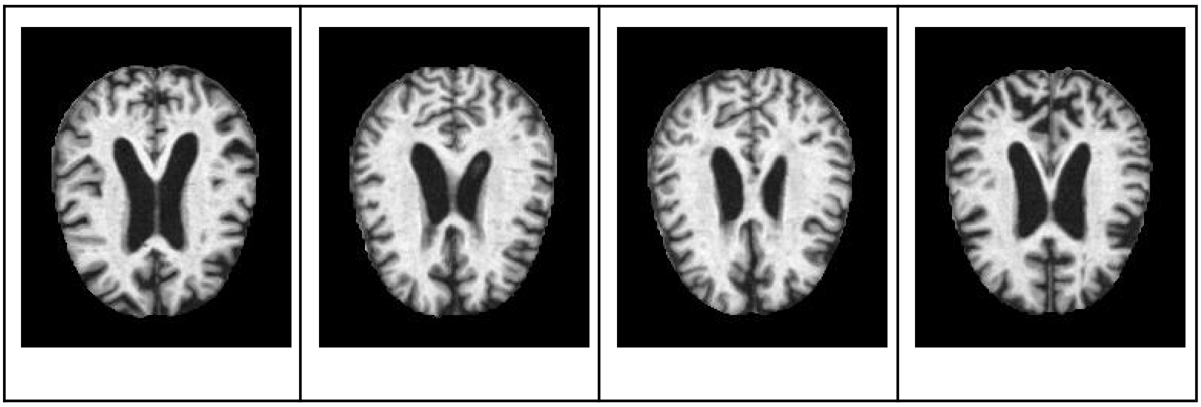
The study used the MRI images to train a machine learning model to predict the stage of AD. The model was able to achieve an accuracy of 95%.

The results of this study suggest that machine learning can be used to diagnose AD with a high degree of accuracy. This could lead to earlier diagnosis and treatment, which could improve the quality of life for people with AD and their caregivers.

In the very mild and mild stages of Alzheimer's disease, people may be able to move independently, but they may need assistance with some activities. Common symptoms at this stage include recent memory loss and personality changes. People may still be able to carry out activities such as driving, but they may start to have difficulty with more complex tasks, such as planning or managing their finances.

In the moderate stage of Alzheimer's disease, people need more assistance with daily activities. They may have difficulty communicating and carrying out routine tasks, such as bathing and dressing. They may also experience changes in personality and behavior, such as hallucinations, delusions, paranoia, and increased memory loss.

In the severe stage of Alzheimer's disease, people need around-the-clock care. They may experience physical decline, such as skin infections, weight loss, and difficulty swallowing. They may also lose the ability to communicate and walk.



(1) (2) (3) (4)

Figure 1. MRI data with four of Alzheimer dementia's stages
https://www.kaggle.com/tourist55/alzheimers-dataset-4-class-of-images

III. CONVOLUTIONAL NEURAL NETWORK (CNN)

Deep learning has brought about a revolution in the field of computer vision, leading to significant advancements in image classification tasks. One of the key milestones in this domain was the introduction of AlexNet, a deep convolutional neural network (CNN), by researchers Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton in 2012. AlexNet emerged as a groundbreaking model that demonstrated the immense potential of deep learning in the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC). This article aims to explore the architecture and methodology of AlexNet, highlighting its profound impact on image classification.

At the heart of AlexNet lies its innovative architecture, which incorporates multiple layers of convolutions, pooling, and fully connected layers. The model begins with a convolutional layer consisting of 96 filters of size 11x11, utilizing the rectified linear unit (ReLU) activation function. Subsequent max pooling layers with a pool size of 3x3 and a stride of 2 aid in reducing spatial dimensions while capturing important features. The architecture further includes additional convolutional layers, each employing ReLU activation, culminating in a final max pooling layer.

Following the convolutional layers, AlexNet incorporates a flatten layer that transforms the output into a 1D vector, preparing it for the subsequent fully connected layers. The first fully connected layer comprises 4096 neurons, also employing ReLU activation. To address the issue of overfitting, dropout regularization is applied through a dropout layer with a rate of 0.5. Another fully connected layer with 4096 neurons, along with dropout regularization, follows. Finally, a third fully connected layer with 1000 neurons, employing ReLU activation, leads to the ultimate output layer.

The output layer of AlexNet plays a crucial role in image classification tasks. It consists of a varying number of neurons corresponding to the desired classes, activated by the softmax function to generate predicted class probabilities. During the compilation process, AlexNet utilizes the Adam optimizer with a learning rate of 0.001, facilitating efficient weight updates. The chosen loss function is categorical cross-entropy, specifically tailored for multi-class classification scenarios. The performance of the model is evaluated using the accuracy metric, measuring its ability to accurately classify images.

The introduction of AlexNet marked a pivotal moment in the field of image classification, revolutionizing the way we approach this task. Its exceptional performance in the ILSVRC competition demonstrated the remarkable potential of deep CNNs in handling large-scale visual recognition tasks. The unique architecture of the model, with its stacked convolutional layers and utilization of ReLU activation, enabled the extraction of hierarchical features, leading to significantly improved performance. Moreover, the incorporation of dropout regularization effectively addressed overfitting concerns, contributing to the model's generalization capabilities. The adoption of the Adam optimizer further facilitated efficient optimization, expediting the training process.

IV. RESULT AND DISCUSSION

The findings of this study suggest that the trained CNN model achieved promising results in classifying AD stages. The model demonstrated an accuracy of 79.85% on the training set, with precision, recall, and AUC values of 72.54%, 31.21%, and 83.87%, respectively. On the validation set, the model achieved an accuracy of 80.61%, along with precision, recall, and AUC values of 78.99%, 30.55%, and 86.05%. These results indicate the potential of the CNN model for accurately classifying AD stages based on MRI image processing.

The obtained high accuracy of the CNN model highlights its effectiveness in classifying AD stages using MRI scans. The precision and recall values suggest the model's capability to accurately identify positive AD cases, although there is room for improvement in recall. The AUC values demonstrate a good overall performance of the model in distinguishing between different AD stages. These results align with previous studies that have demonstrated the efficacy of CNNs in image classification tasks.

The findings of this study have significant implications for early detection and diagnosis of Alzheimer's disease. The automated classification system based on CNNs can assist healthcare professionals in identifying AD in its early stages, facilitating timely interventions and improving patient outcomes. The utilization of MRI image processing in conjunction with CNNs offers a non-invasive and efficient approach for AD classification.

However, it is important to acknowledge certain limitations of this study. The dataset used for training and evaluation may not fully represent the diversity of AD cases, warranting further research to validate the results on larger and more diverse datasets. Additionally, improvements to the CNN model can be explored through different architectures, hyperparameter tuning, and integration of other imaging modalities to enhance its performance.

Further research and development are necessary to enhance the performance of the CNN model in classifying AD stages. This could involve exploring alternative CNN architectures, refining hyperparameters, and incorporating additional imaging modalities such as functional MRI or positron emission tomography (PET) scans. By leveraging advancements in deep learning and neuroimaging technologies, future studies can strive to improve the accuracy, precision, and recall of the model, ultimately leading to more effective and reliable automated systems for early diagnosis and intervention in Alzheimer's disease. Additionally, the collaboration and sharing of diverse datasets among research institutions can help address the limitations of data representation, contributing to more robust and generalizable models for AD classification.

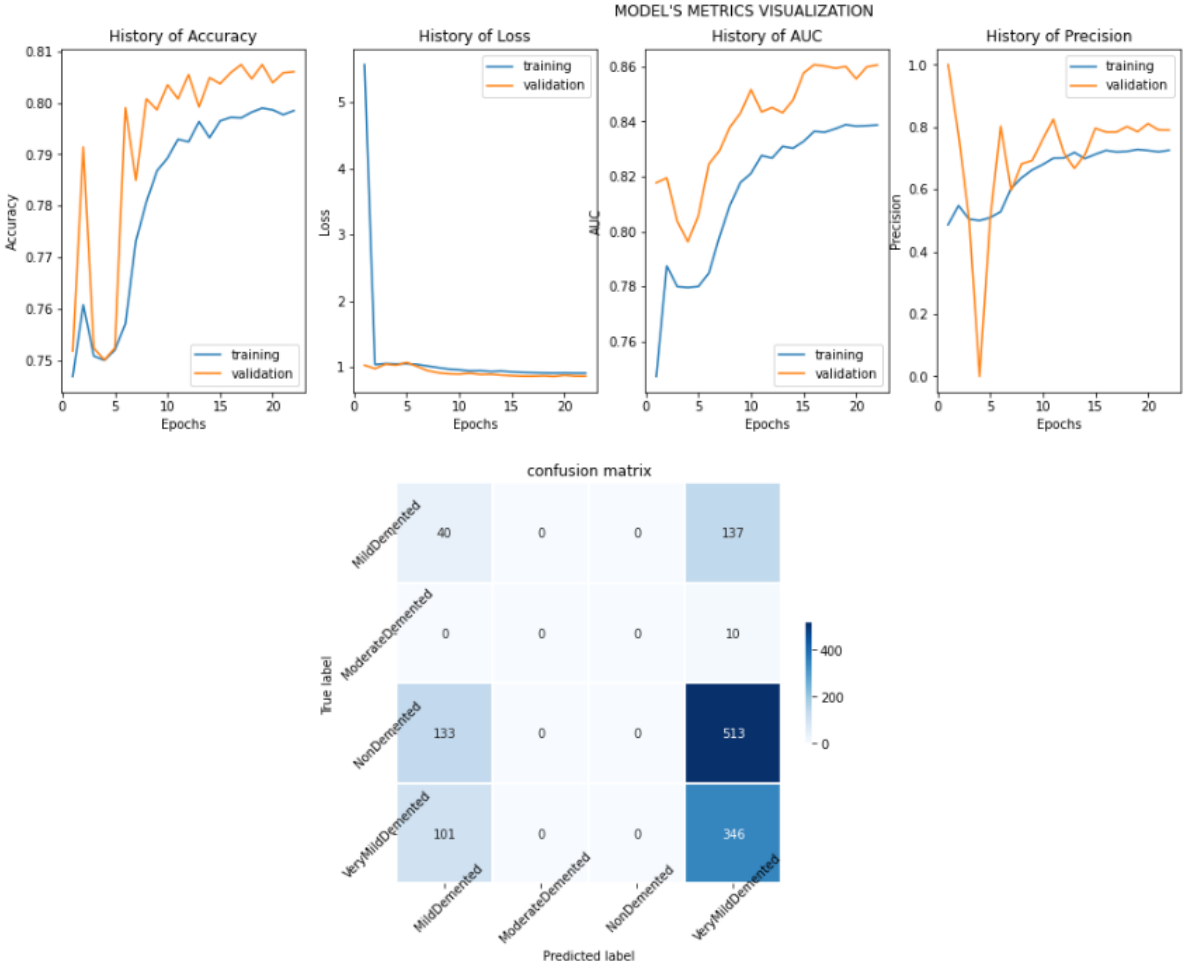


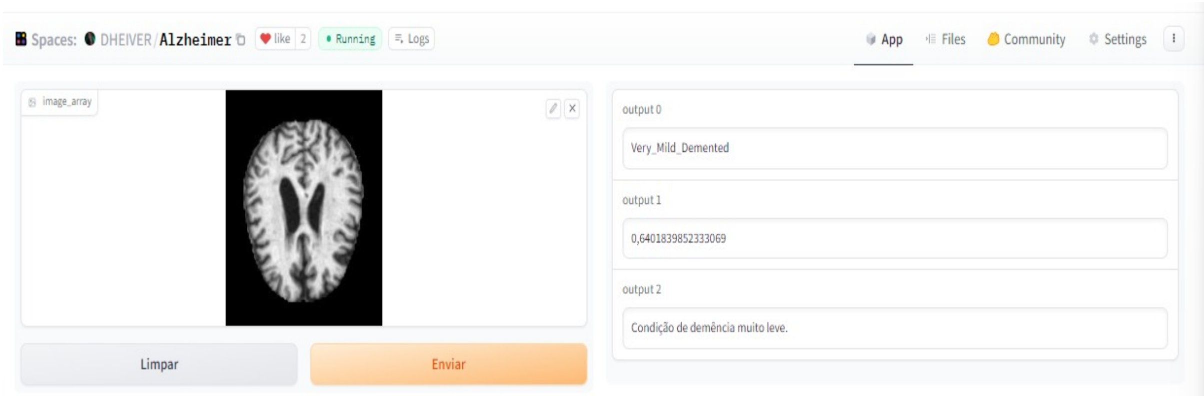
Figura 2. System Performance Comparison

This script creates an API that allows users to test an Alzheimer's disease classification model. The API utilizes the Gradio library to create a user-friendly interface where users can input an image. The model then processes and analyzes the image to classify the individual's condition as 'Mild Demented', 'Moderate Demented', 'Non Demented', or 'Very Mild Demented'.

The 'pred' function is responsible for handling the image processing and prediction. It loads the trained model, 'alzheimer_99.5.h5', and converts the input image into an array. The image is resized to match the model's expected input size of 224 x 224 and normalized. The processed image is then fed into the model to generate a prediction. The output of the function includes the predicted class, the probability associated with that prediction, and a human-readable explanation of the prediction.

The Gradio Interface (iface) is defined and launched, allowing users to interact with the model. The interface takes the 'pred' function as an argument and specifies the input type as an image, while the output types are text and number. Example images are also provided within the interface to enable users to quickly test the model's functionality. This user-friendly interface makes the model accessible to individuals without expertise in the field, facilitating exploratory use.

In conclusion, this script creates an API with a Gradio interface for testing an Alzheimer's disease classification model. The interface enables users to input images and receive predictions about the condition of individuals in the images. The model's output includes the predicted class, the associated probability, and an explanation. The interface's intuitive design allows non-experts to explore and utilize the model effectively.



V. CONCLUSION

In conclusion, the findings of this study highlight the potential of the trained convolutional neural network (CNN) model in accurately classifying Alzheimer's disease (AD) stages based on MRI image processing. The model achieved a promising accuracy rate of 79.85% on the training set and 80.61% on the validation set, demonstrating its effectiveness in distinguishing between AD stages and healthy individuals. These results suggest the potential of CNNs as a valuable tool for automated AD classification, offering healthcare professionals a non-invasive and efficient approach for early detection and diagnosis. However, it is important to acknowledge the need for further research and validation on larger and more diverse datasets to enhance the model's performance and ensure its generalizability across different populations. Continued advancements in CNN technology have the potential to revolutionize AD diagnosis, facilitating timely interventions and ultimately improving patient outcomes.

VI. REFERENCES

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