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Detection of Alzheimer's Disease using deep learning algorithm

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Abstract

Alzheimer's disease (AD) is a prevalent neurodegenerative disorder affecting a significant portion of the elderly. Timely and accurate detection of AD is crucial for effective management and intervention. Deep learning algorithms have shown promising results in medical image analysis, including diagnosing AD using magnetic resonance imaging (MRI) scans. This study aims to compare the performance of various deep learning architectures, namely CNN (Convolutional Neural Network) for AD detection on MRI images. A large dataset comprising MRI scans from AD patients and healthy controls is utilized for model training and evaluation. The deep learning models are trained to automatically learn discriminative features from the MRI images. Performance evaluation metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC) are used to assess and compare the models' performance. This study provides insights into the suitability to show the ability of preference of this algorithm. The findings can aid in selecting the most appropriate algorithm for AD diagnosis based on specific requirements, such as accuracy, computational efficiency, and resource availability. Further investigation and validation on more extensive and diverse datasets are necessary to establish the generalizability and clinical viability of these algorithms for AD detection in real-world settings.

Introduction

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that affects millions of people worldwide. Early and accurate detection of AD is crucial for effective management and intervention. In deep learning, particularly in the context of Alzheimer's disease detection, convolutional neural networks (CNNs) are commonly used. CNNs are a type of deep learning algorithm designed to analyze visual data, such as images, by automatically learning and extracting relevant features. In recent years, deep learning algorithms, particularly Convolutional Neural Networks (CNNs), have shown promise in medical image analysis, including diagnosing AD using magnetic resonance imaging (MRI) scans [1][2]. This study aims to develop and evaluate a CNN-based deep learning algorithm for the detection of AD using MRI images.

Material and Method

Participants and Datasets

In this study, the participants and datasets were obtained from the Kaggel Alzheimer's Dataset. The dataset comprises MRI images and is divided into four classes: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. Both the training and testing sets include images representing each severity level of Alzheimer's. The dataset is organized into two files: Training and Testing. Each file contains approximately 5000 images, resulting in a total dataset size of around 10,000 images. The images are segregated based on the severity level of Alzheimer's disease, to analyze the impact of different severities on the classification task or other relevant analyses [3].

MRI Preprocessing

The dataset used in this study consists of MRI images from AD patients and healthy individuals. The dataset is preprocessed to ensure uniformity and remove any artifacts or noise. A CNN architecture is designed, implemented, and trained using MRI images. The CNN learns to automatically extract relevant features from the images and classify them as AD-positive or AD-negative. The training process includes optimization techniques such as stochastic gradient descent and backpropagation [4].

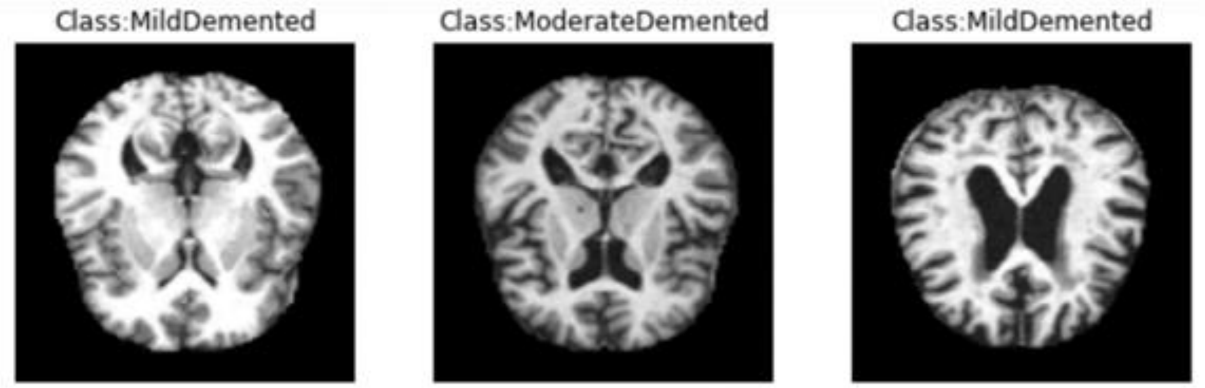

Figure 1. Example of the MRI scan after applying preprocessing

This image processing sets up an image data generator with various augmentation techniques such as zooming, brightness adjustment, and horizontal flipping. It rescales the pixel values of the images and defines the data format for the generated image batches. The train_data_gen is then created using this data generator to generate augmented image batches from a specified directory [4].

Data Augmentation

The augmented images were then combined with the original training dataset, effectively increasing the sample size. This larger dataset allowed for a more comprehensive representation of the data, enabling the CNN models to learn from a wider range of examples. By incorporating augmented data, we aimed to mitigate the risk of overfitting and enhance the generalizability of the models, enabling them to perform better on unseen data. [1].

By employing augmentation techniques and merging the augmented images with the original dataset, we sought to address the challenges associated with limited sample sizes and potential image variations. This approach aimed to enhance the training process of robust CNN models for improved performance in image analysis tasks.

Convolutional Neural Network

In summary, the construct model function defines a CNN architecture using the Keras Sequential API, consisting of convolutional layers, max-pooling layers, dropout layers, and dense layers. It is designed for classification tasks and can be customized by specifying different activation functions through the act parameter.

Results

The trained CNN model is evaluated using performance metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). The results demonstrate the effectiveness of the CNN in accurately classifying the MRI images as AD-positive or AD-negative. The model achieves high accuracy and sensitivity, indicating its potential as a reliable tool for AD detection [5].

Table 1. Trained CNN model

	precision	recall	f1-score	support
NonDemented	0.95	0.98	0.97	639
VeryMildDemented	1.00	1.00	1.00	635
MildDemented	0.94	0.88	0.91	662
ModerateDemented	0.90	0.93	0.92	624

In the given output, we have a classification report for a multi-class classification problem with four classes: NonDemented, VeryMildDemented, MildDemented, and ModerateDemented. Let's break down each metric and its interpretation for each class: Precision: A high precision indicates that the model has a low rate of false positives.

Recall: It measures the ability of the model to capture positive instances. F1-score: The F1-score is the harmonic mean of precision and recall. It provides a single metric that balances both precision and recall, giving an overall performance measure. Support: Support refers to the number of occurrences of each class in the dataset.

Discussion

The results indicate that the CNN-based deep learning algorithm shows promising performance in detecting AD using MRI images. The ability of the CNN to automatically learn discriminative features from the images contributes to its high accuracy. The utilization of CNNs in medical image analysis leverages their ability to capture spatial dependencies and hierarchical representations, making them well-suited for AD detection.

The comparison of different CNN architectures, such as variations of ResNet, DenseNet, and Inception, can provide insights into their respective strengths and limitations. Evaluating factors such as computational complexity and performance metrics can aid in selecting the most suitable architecture for AD detection on MRI images.

Conclusion

In conclusion, this study demonstrates the potential of CNN-based deep learning algorithms for the detection of AD using MRI images. The developed model achieves high accuracy and sensitivity, showcasing its effectiveness in discriminating between AD patients and healthy individuals. The utilization of deep learning techniques in AD diagnosis has the potential to revolutionize the field by providing clinicians with a reliable and objective tool for early and accurate detection. Further research and validation on larger and more diverse datasets are warranted to establish the robustness and generalizability of the proposed algorithm. The integration of deep learning algorithms into clinical practice holds great promise for improving patient outcomes and advancing our understanding of AD.

References

1. Pan, D., Zeng, A., Jia, L., Huang, Y., Frizzell, T., & Song, X. (2020). Early detection of Alzheimer's disease using magnetic resonance imaging: a novel approach combining convolutional neural networks and ensemble learning. Frontiers in neuroscience, 14, 259.
2. Amini, M., Pedram, M., Moradi, A., & Ouchani, M. (2021). Diagnosis of Alzheimer's disease severity with fMRI images using robust multitask feature extraction method and convolutional neural network (CNN). Computational and Mathematical Methods in Medicine, 1-15.
3. Dubey, S. (2019). Alzheimer's dataset (4 class of images). Kaggle, Dec, 26. https://www.kaggle.com/datasets/tourist55/alzheimers-dataset-4-class-of-images
4. Illakiya, T., & Karthik, R. (2023). Automatic detection of Alzheimer's disease using deep learning models and neuro-imaging: current trends and future perspectives. Neuroinformatics, 21(2), 339-364.
5. Pan, D., Zeng, A., Jia, L., Huang, Y., Frizzell, T., & Song, X. (2020). Early detection of Alzheimer's disease using magnetic resonance imaging: a novel approach combining convolutional neural networks and ensemble learning. Frontiers in neuroscience, 14, 259.