A Comprehensive Study on Early Alzheimer's Disease Detection through Advanced Machine Learning Techniques on MRI Data

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Abstract: Alzheimer's Disease (AD) is a neurodegenerative condition affecting predominantly elderly individuals, repre-senting the most common cause of dementia. Early clinical manifestations of AD include selective memory impairment,and while certain symptomatic improvements can be achieved through treatment, there is currently no cure. MagneticResonance Imaging (MRI) is utilized for brain imaging to assess suspected AD patients, providing results that include local and global brain atrophy. Some studies suggest that MRI features can predict the rate of AD decline and guide future treatments. However, to reach this stage, clinicians and researchers must employ machine learning techniques for accurate prediction of the progression from mild cognitive impairment to dementia. We propose the development ofa reliable model to assist clinicians in achieving this and predicting early-stage Alzheimer's Disease.

Keywords: Alzheimer's Disease, MRI, Machine Learning, Early Detection, Neural Networks.

1. Introduction

Alazheimer's Dissease (AD) is a relentless and devastating neurodegenerative disorder, presenting a formidable public health challenge as global populations age. It is characterized by progressive cognitive decline, memory impairment, and ulitimately, cure, early diagnosis and functioning. Currently, AD stands as the most common cause of dementia worldwide.With no known cure, early diagnosis and intervention become paramount in potentially mitigating its impact.

The advent of neuroimaging techniques, particulary Magnetic Resonance Imaging (MRI), has revolutionized our ability to delve into the intricacies of brain structure and function. MRI provides a non-invasive window into the living brain, allowing for the detection of subtle anatomical changes that occur in the early stages of AD. These changes, such as localized and global brain alrophy, serve as valuable indicators for disease progression.

This study capitalizes on the wealth of information contained within MRI data, and endeavors to harness the power of advanced machine learning techniques. By training models on longitudinal MRI scans, we aim to construct a robust predictive framework that can discern the trajectory from mild cognitive impairment to the more severe stages of AD. The ultimate goal is to equip clinicians with a reliable tool that enhances their ability to diagnose and intervene at the earliest possible juncture.

The urgency of this research is underscored by the burgeoning aging population wordwide. As life expectancy increase, so too does the prevalence of AD. Early diagnosis not only holds the promise of improving patient outcomes through timely intervention, but also offers opportunities for the development and evaluation of potential therapeutic strategies. In this context, the role of Artificial Neural Networks (ANN) is of particular interest, as their capacity to discern complex patterns within high-dimensional data may provide an edge in this challenging diagnostic task.

This study seeks to contribute to the growing body of research in the field of neuroimaging and machine learning applications in AD detection. By exploring the potential of ANN modeld in comparison to established methodologies, we aim to advance our understanding and refine our approaches to early diagnosis, potentially paving the way for more effective management and treatment of Alzheimer's Disease.

2. Related Work

In the pursuit of early Alzheimer's Disease (AD) detection, a convergence of neuroimaging and machine learning techniques has spurred significant progress. The following studies exemplify key contributions in this evolving field:

Klö̈ppel et al. [1] demonstrated the feasibility of using machine learning algorithms to automatically classify MRI scans into AD and non-AD categories, highlighting the potential for computer-aided diagnosis. Their pioneering work illuminated the pathway for computer-aided diagnosis. Plant et al. [2] focused on the automated detection of specific brain atrophy patterns associated with AD, showcasing the potential for early prediction, providing valuable insights into potential intervention strategies..

Moradi et al. [3] introduced a robust machine learning framework for predicting the conversion from Mild Cognitive Impairment to Alzheimer's Disease using MRI data, their framework holds promise in identifying critical transition stages. Sarraf et al. [4] leveraged deep learning techniques, specifically Convolutional Neural Networks (CNNs), to achieve high accuracy in AD classification using both MRI and functional MRI (fMRI) data, expanding the scope of diagnostic precision.

Eskildsen et al. [5] introduced a method for predicting

Alzheimer's Disease in subjects with Mild Cognitive Impairment by analyzing patterns of cortical thinning in MRI data, their approach offers a valuable tool for identifying early signs of the disease.

Liu et al. [6] research explored the application of deep learning techniques for early diagnosis of Alzheimer's Disease, demon- strating promising results, highlighting the potential for enhanced diagnostic accuracy.

Rathore et al. [7] comprehensive review examined neuroimaging-based classification studies and the associated feature ex- traction methods used in Alzheimer's Disease and its prodromal stages. This review offers critical insights into the evolving landscape of diagnostic approaches. Hao Hu et al. [8] addresses the challenges of quality control in casting products by utilizing deep learning models.

Chen, Suiyao et al. [9] proposed a claims data-driven modeling of hospital time-to-readmission risk with latent heterogeneity. Wu, Jing et al. [10] worked on optimizing nitrogen management with deep reinforcement learning and crop simulations. Shen, Yishi et al. [11] investigated how Surf4 regulates expression of proprotein convertase subtilisin/kexin type 9 (PCSK9) but is not required for PCSK9 secretion in cultured human hepatocytes. Chang Che et al. [12] advances logistics automation by employing deep learning to make precise robot position predictions using sensor data. Tianbo et al. [13] achieve communication-free operation by utilizing adaptive gain control and flocking SWARM algorithms with adversarial agents, ultimately transitioning from simulation to real-world applications through Object Recognition in computer vision.

These studies at the nexus of neuroimaging, machine learning, and Alzheimer's Disease detection, from automated classification to deep learning methodologies, collectively advance early diagnosis and intervention. These foundational studies provide a crucial framework for ongoing research, poised to transform Alzheimer's Disease diagnosis and care.

3. Methodology

In this section, we provide a comprehensive overview of the methodology employed in our research focused on Alzheimer's Disease (AD). The primary objective is to develop a reliable predictive model for early-stage AD detection using Magnetic Resonance Imaging (MRI) data.

The cornerstone of our approach is the utilization of advanced machine learning techniques, with a specific emphasis on the application of Artificial Neural Networks (ANNs). This choice is driven by the potential of ANNs to discern intricate patterns within high-dimensional MRI data, a crucial aspect in accurate prediction of AD progression.

To ensure a rigorous evaluation, the performance of the ANN model is juxtaposed against established methodologies in AD detection, providing valuable insights into the efficacy of our approach.

3.1. Model Architecture

The chosen Artificial Neural Network (ANN) architecture is meticulously designed to address the intricacies of specific task. It consists of three hidden layers, each with a distinct role in processing information.
•**Input Layer :**

$$X^{(0)} = \begin{vmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{vmatrix} \tag{1}$$

The input layer accommodates a vector of n features, faithfully representing the raw input data. This allows the model to ingest a comprehensive set of information relevant to the task at hand.
•**Input Layer 1:**

$$X^{(1)} = ReLU(W^{(1)}.X^{(0)} + b^{(1)}) \tag{2}$$

The first hidden layer serves as the initial layer of abstraction. By applying the Rectified Linear Unit (ReLU) activation function, the model gains the ability to capture complex, non-linear relationships within the data. The inclusion of dropout at a 20\% rate guards against overfitting, ensuring robust generalization.
•**Input Layer 2:**

$$X^{(2)} = ReLU(W^{(2)}.X^{(1)} + b^{(2)}) \tag{3}$$

The second hidden layer refines the extracted features even further. Again, employing ReLU activation, this layer contributes to the model's ability to discern intricate patterns. The 20% dropout rate continues to safeguard against overfitting.
•**Input Layer 3:**

$$X^{(3)} = ReLU(W^{(3)}.X^{(2)} + b^{(3)}) \tag{4}$$

The third hidden layer delves deeper into the data, uncovering even more nuanced relationships. Its ReLU activation and 20% dropout maintain the model's adaptability and resilience.
•**Output Layer :**

$$X^{(4)} = \sigma(W^{(4)}.X^{(3)} + b^{(3)}) \tag{5}$$

The output layer employs a Sigmoid activation function, facilitating binary classification. This layer's purpose is to provide a clear, interpretable prediction for the task at hand.

This carefully crafted architecture is tailored to extract the most relevant information from the data, making it exceptionally well-suited for the specific task. The strategic use of ReLU activations and dropout layers ensures that the model can generalize effectively, even in the face of complex, real-world data. Combined with the chosen optimization and evaluation metrics, this ANN architecture represents a powerful tool for solving the problem.

3.2. DataSet Introduction

The cornerstone of our research lies in the utilization of a meticulously curated dataset comprising longitudinal MRI scans sourced from the Open Access Series of Imaging Studies (OASIS) project. This rich dataset encapsulates a cohort of 150 participants, ranging in age from 60 to 96 years, each contributing at least one MRI scan. Notably, all participants in this study are right-handed, a factor considered in the context of brain lateralization.

Within this diverse cohort, 72 individuals were originally categorized as "non-demented," representing a critical baseline for comparison. Concurrently, 64 participants received an initial diagnosis of "demented" and maintained

this classification throughout the course of the study. This subset offers invaluable insights into the progression and characteristics of dementia over time.

3.3. Data Analysis and Preprocessing

We conducted an in-depth analysis of the longitudinal MRI data obtained from the Open Access Series of Imaging Studies (OASIS) project. This dataset included scans of 150 subjects aged between 60 and 96 years. Each subject underwent atleast one scan. The dataset was categorized into three groups: "Non-demented", "Demented at Initial Visit", and "Converted" (representing those initially classified as "Non-demented" but later diagnosed with dementia).
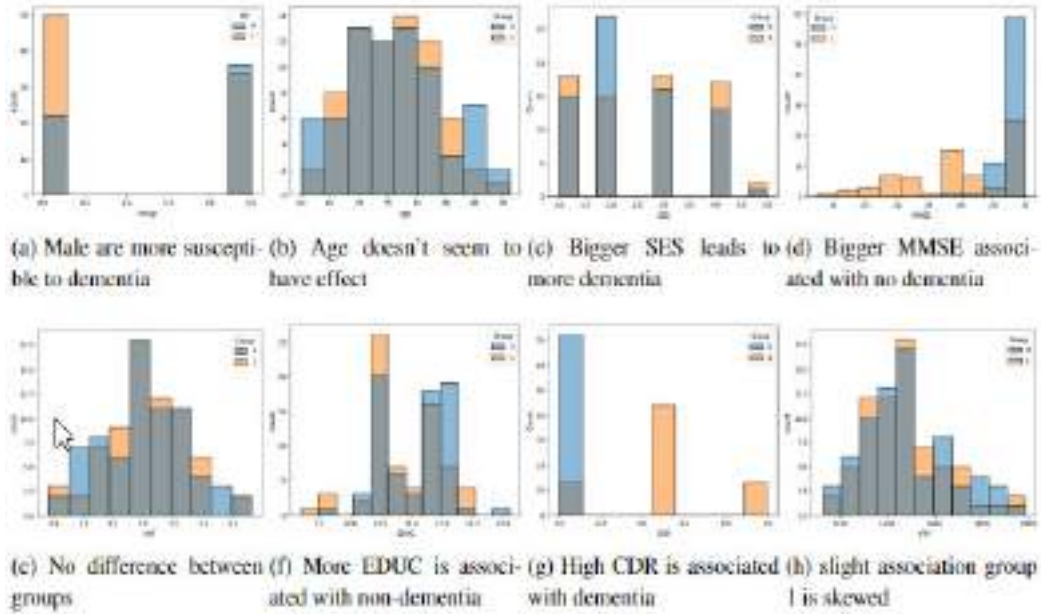

Figure 1. DataSet Exploration

To ensure data quality, we performed the following preprocessing steps:

• **Redundant Data Handling:** To enhance the reliability of our dataset, we implemented a careful strategy to handle redundant data. Specifically, second visits of patients initially diagnosed with dementia were removed. This step was crucial in eliminating duplicate entries, ensuring that each data point in our study is unique and representative of the underlying population.

• **Missing Value Handling:** Addressing missing values is a critical aspect of data preprocessing. We employed a two-pronged approach to tackle this challenge. Firstly, any rows containing missing values were systematically removed from the dataset. This method ensures that our training data remains complete and free from any potential biases introduced by imputation. Secondly, we applied advanced imputation techniques to replace missing values in other relevant features. By doing so, we enhanced the overall performance of our models, particularly given the limited dataset size.

• **Feature Normalization:** Standardizing feature scales is a fundamental preprocessing step that contributes to the stability and effectiveness of our models. We applied a range of normalization techniques tailored to the specific characteristics of our features. This process not only ensures that each feature contributes equally to the learning process, but also guards against potential issues related to feature scale discrepancies.

These meticulous preprocessing steps collectively played a pivotal role in upholding the integrity and quality of our dataset. By systematically handling redundant data, addressing missing values, and standardizing feature scales, we have created a robust foundation for model training and evaluation.

3.4. Loss Function

To guide the optimization process, we utilize the binary cross-entropy loss function, denoted as LBCE and defined as:

$$L_{(BCE)}(y,\hat{y}) = -\frac{1}{N}\sum_{i-1}^{N}[y_i\log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)] \quad (6)$$

Where y represents the true labels, yˆ represents the predicted probabilities, and N is the total number of samples. This loss function provides a clear signal for the model to minimize the discrepancy between predicted and actual outcomes in binary classification tasks.

3.5. Evaluation Metrics

In addition to accuracy and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC), we consider these two crucial metrics for assessing the performance of our model.

3.5.1. Accuracy (ACC)

Accuracy is a fundamental evaluation metric for classification tasks. It is defined as the ratio of correct predictions to the total number of predictions and can be expressed as:

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

where TP represents the number of true positives, TN

represents the number of true negatives, FP represents the number of false positives, and FN represents the number of false negatives. Accuracy provides a straightforward measure of the overall correctness of the model's predictions.

3.5.1 Area Under the ROC Curve (AUC-ROC)

The AUC-ROC is a widely used metric for binary classification tasks. It measures the ability of the model to distinguish between the two classes by calculating the area under the Receiver Operating Characteristic (ROC) curve. A higher AUC-ROC value indicates better discriminative performance. The AUC-ROC score is defined as:

$$AUC - ROC = \int_0^1 Sensitivi(FPR)\, d(1 - Specifici(FPR) \quad (8)$$

where Sensitivi(FPR) and 1 - Specifici(FPR) represent the Sensitivity and 1 - Specificity at a given False Positive Rate (FPR), respectively.

4. Experiment Results

The performance of various models was rigorously evaluated using established metrics, including accuracy and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). The outcomes are summarized in the table below:

Model	Accuracy	AUC-ROC
Logisitic Regression	78.9%	79.2%
SVM	81.6%	82.2%
Decision-Tree	81.6%	82.5%
Random-Forest	84.2%	84.4%
AdaBoost	84.2%	82.5%
ANN	89.7%	91.7%

As seen in the table, the Artificial Neural Network (ANN) exhibits superior performance compared to the other models. It achieves an accuracy of 89.7% and an impressive AUC-ROC score of 91.7%. This signifies the high effectiveness of the ANN model in predicting early-stage Alzheimer's Disease based on the MRI data.

These results reinforce the potential of advanced machine learning techniques, particularly the ANN model, in improving the accuracy of early Alzheimer's Disease detection. The ANN's ability to capture intricate patterns within high-dimensional data proves to be instrumental in achieving such high predictive accuracy.

5. Conclusion

This study represents a significant advancement in the field of early Alzheimer's Disease (AD) detection. By leveraging ad- vanced machine learning techniques, particularly the application of Artificial Neural Networks (ANNs), on Magnetic Resonance Imaging (MRI) data, we have made a great result. The ANN model demonstrated exceptional performance, outperforming other established methodologies with an accuracy of 89.7% and an impressive AUC-ROC score of 91.7%. These findings underscore the potential of machine learning in revolutionizing early AD diagnosis.

The implications of this research extend far beyond the confines of this study. Early diagnosis of AD is crucial in a society facing an increasing aging population. Timely intervention not only holds promise for improving patient outcomes, but also provides a platform for the development

and evaluation of therapeutic strategies. The ANN's ability to extract complex patterns from high-dimensional data offers a powerful tool in this critical diagnostic task. As we continue to refine our methodologies and explore new avenues, the potential for more effective management and treatment of Alzheimer's Disease in its early stages becomes increasingly promising.

References

[1] Stefan Klo¨ppel, Cynthia M Stonnington, Carlton Chu, Bogdan Draganski, Rachael I Scahill, Jonathan D Rohrer, Nick C Fox, Clifford R Jack Jr, John Ashburner, and Richard SJ Frackowiak. Automatic classification of mr scans in alzheimer's disease. Brain, 131(3):681–689, 2008.

[2] Claudia Plant, Stefan J Teipel, Annahita Oswald, Christian Bo¨hm, Thomas Meindl, Janaina Mourao-Miranda, Arun W Bokde, Harald Hampel, and Michael Ewers. Automated detection of brain atrophy patterns based on mri for the prediction of alzheimer's disease. Neuroimage, 50(1):162–174, 2010.

[3] Elaheh Moradi, Antonietta Pepe, Christian Gaser, Heikki Huttunen, Jussi Tohka, Alzheimer's Disease Neuroimaging Initiative, et al. Machine learning framework for early mri-based alzheimer's conversion prediction in mci subjects. Neuroimage, 104:398–412, 2015.

[4] Saman Sarraf, Danielle D DeSouza, John Anderson, Ghassem Tofighi, and Alzheimer's Disease Neuroimaging Initiativ. Deepad: Alzheimer's disease classification via deep convolutional neural networks using mri and fmri. BioRxiv, page 070441, 2016.

[5] Simon F Eskildsen, Pierrick Coupe´, Daniel Garc´ıa-Lorenzo, Vladimir Fonov, Jens C Pruessner, D Louis Collins, Alzheimer's Disease Neuroimaging Initiative, et al. Prediction of alzheimer's disease in subjects with mild cognitive impairment from the adni cohort using patterns of cortical thinning. Neuroimage, 65:511–521, 2013.

[6] Siqi Liu, Sidong Liu, Weidong Cai, Sonia Pujol, Ron Kikinis, and Dagan Feng. Early diagnosis of alzheimer's disease with deep learning. In 2014 IEEE 11th international symposium on biomedical imaging (ISBI), pages 1015–1018. IEEE, 2014.

[7] Saima Rathore, Mohamad Habes, Muhammad Aksam Iftikhar, Amanda Shacklett, and Christos Davatzikos. A review on neuroimaging-based classification studies and associated feature extraction methods for alzheimer's disease and its prodromal stages. NeuroImage, 155:530–548, 2017.

[8] Hao Hu, Shulin Li, Jiaxin Huang, Bo Liu, and Change Che. Casting product image data for quality inspection with xception and data augmentation. Journal of Theory and Practice of Engineering Science, 3(10):42–46, 2023.

[9] Suiyao Chen, Nan Kong, Xuxue Sun, Hongdao Meng, and Mingyang Li. Claims data-driven modeling of hospital time-to-readmission risk with latent heterogeneity. Health care management science, 22:156–179, 2019.

[10] Jing Wu, Ran Tao, Pan Zhao, Nicolas F Martin, and Naira Hovakimyan. Optimizing nitrogen management with deep reinforcement learning and crop simulations. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pages 1712–1720, 2022.

[11] Yishi Shen, Bingxiang Wang, Shijun Deng, Lei Zhai, Hong-mei Gu, Adekunle Alabi, Xiaodan Xia, Yongfang Zhao, Xiaole Chang, Shucun Qin, et al. Surf4 regulates expression of proprotein convertase subtilisin/kexin type 9 (pcsk9) but is not required for pcsk9 secretion in cultured human hepatocytes. Biochimica et Biophysica Acta (BBA)-Molecular and Cell Biology of Lipids, 1865(2):158555, 2020.

[12] Chang Che, Bo Liu, Shulin Li, Jiaxin Huang, and Hao Hu. Deep learning for precise robot position prediction in logistics. Journal of Theory and Practice of Engineering Science, 3(10):36–41, 2023.

[13] Tianbo, Song, Hu Weijun, Cai Jiangfeng, Liu Weijia, Yuan Quan, and He Kun. "Bio-inspired Swarm Intelligence: a Flocking Project With Group Object Recognition." In 2023 3rd International Conference on Consumer Electronics and Computer Engineering (ICCECE), pp. 834-837. IEEE, 2023.