Classification of Mild, Very Mild, Moderate, and Non-Demented Alzheimer's Disease MRI Scans with SVM

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Abstract

Over 55 million people worldwide are affected by Alzheimer's disease (AD), which causes a substantial financial impact on society. The estimated expenses of health care and long-term care for individuals with forms of dementia are expected to approach around $360 billion in 2024. Recent developments in neuroimaging have yielded important insights into AD. Machine learning (ML) methods have become widely available as effective instruments for interpreting complex neuroimaging data. Previous studies on classifying magnetic resonance imaging (MRI) images found significant success in identifying neurological disorders. In this study, supervised learning is employed to investigate if ML models can distinguish between mild dementia, moderate dementia, very mild Dementia, and non-demented MRI images. The dataset was sourced from the Open Access Series of Imaging Studies (OASIS), a publicly available dataset that provides cross-sectional and longitudinal MRI data of the brain. We trained a linear support vector machine (SVM) classifier with stochastic gradient descent (SGD) on 75% of the dataset. To evaluate performance, we calculated the accuracy level from the testing data. This model produced an accuracy of 74.21%, demonstrating that SVM classification is a promising avenue to classify MRI images.

Keywords: Alzheimer's, MRI Scans, Machine Learning, OASIS, Support Vector Machine

1. Introduction

Alzheimer's Disease (AD) is a progressive disorder that impairs memory, cognitive function, and behavior [1]. Alzheimer's Disease (AD) is typically diagnosed in individuals who are 65 years of age or older. AD affects approximately 10%-30% of individuals over the age of 65. Individuals may begin with normal aging and then progress to mild cognitive impairment (MCI), which can lead to AD over time. AD symptoms such as difficulty recollecting information and behavior changes usually appear beyond 60. Over several years, a person gradually transitions from a healthy state to Alzheimer's disease, involving considerable changes in both brain structure and function. Ninety percent of AD diagnoses can be made depending on a general medical and psychiatric evaluation.

Diagnosis of AD begins with clinical assessment and an informant review. Clinical assessment includes direct observation from a physician of the patient's memory, attention, problem-solving skills, and ability to remember how to perform daily activities [2]. The informant review comes from family members and close friends. Family and friends report changes in daily activities like personal hygiene, handling finances, or cooking; all activities of daily living should be routine. Specific domains like arousal and focus, orientation, memory and recall, language, praxis, and visuospatial skills are all assessed in cognitive examinations. However, these tests alone are not enough to provide a conclusive diagnosis. Additional diagnostic procedures, including blood testing and neuroimaging, are required to exclude infections, vitamin deficiencies, and neurological illnesses as additional probable causes of cognitive impairment. Neuroimaging techniques, such as Magnetic Resonance Imaging (MRI), are used to identify structural alterations in the brain linked to Alzheimer's disease, namely brain shrinkage in regions such as the hippocampus (an area of the brain essential for memory formation) [3].

Furthermore, improvements in computer power and machine learning frameworks have made it possible to conduct more complex analyses and create models to identify minute patterns and alterations linked to Alzheimer's disease. These advancements may improve disease monitoring and early identification, ultimately improving patient outcomes and allowing for more individualized treatment plans. Given their capacity to automatically extract spatial information from MRI data, deep learning models—particularly convolutional neural networks (CNNs)—have demonstrated promise [4]. CNNs are a form of deep learning algorithms that are especially useful for image processing and recognition applications because of their ability to autonomously and adaptively learn spatial structures of features from images.

Depending on the particular diagnostic task being addressed, categorization models exhibit dramatically different levels of accuracy. For example, the most accurate diagnosis is often between control normal (CN) and Alzheimer's disease (AD) since the difference between healthy people and those with severe AD is more noticeable [5]. However, because of the more subtle and overlapping aspects of these disorders, distinguishing between AD and MCI or between CN and MCI presents a bigger challenge. Early Alzheimer's disease can mimic normal aging, which makes it more difficult for models to attain high precision in differentiating MCI patients from healthy controls.

Research in this area has significantly benefited from the availability of open-source databases such as the Alzheimer's Disease Neuroimaging Initiative (ADNI), the Australian Imaging,

Biomarkers, and Lifestyle (AIBL) project, and the Open Access Series of Imaging Studies (OASIS). The pharmaceutical industry has significantly benefited from ADNI's initiatives, including applying amyloid phenotyping to improve subject selection and trial design for AD trials [6]. More than 600 papers have been made possible by its open data-sharing policy, which has advanced the study of Alzheimer's pathology and genetics. Furthermore, ADNI has sparked comparable initiatives for other illnesses like Parkinson's and multiple sclerosis, demonstrating its wide-ranging impact on various medical research fields.

The predictive usefulness of β-amyloid imaging in predicting cognitive deterioration in older nondemented persons was assessed using the Australian Imaging, Biomarkers, and Lifestyle (AIBL) project database [7]. Over three years, data from 87 people with mild cognitive impairment and 183 healthy participants were evaluated in this study. To determine the chance of developing Alzheimer's disease or MCI, baseline cognitive tests and biomarker information, such as β-amyloid levels, hippocampal atrophy, and apolipoprotein E ε4 status, were employed. A thorough longitudinal picture of the influence of biomarkers on the course of disease was made possible by the AIBL data. An early prediction model for dementia was created in a prior study utilizing longitudinal data from the OASIS (Open Access Series of Imaging Studies) database, which included 373 instances and 15 features [8]. The dataset was evaluated with assistance from exploratory data analysis. Conventional machine learning models could not obtain more than 92.39% accuracy. The data was hierarchical. Thus, Capsule Networks were used; accuracy was increased using a modified version that included feature selection and optimized variables.

Support vector machines (SVMs) have proven themselves to be accurate in diagnosing Alzheimer’s disease and are famous for offering globally optimal solutions; in situations when class boundaries are apparent, they excel by identifying the hyperplane in the feature space that best divides classes [8]. Feature extraction is an essential component of both Support Vector Machines. To enable SVMs to separate classes, a feature space containing relevant characteristics must be created from the raw data. In one study, the essential characteristics of AD were extracted and used to analyze the disease using a computer-aided diagnosis (CAD) system [9]. Their process had three steps: feature extraction, feature selection, and classification. To determine which aspects are most pertinent to AD, the researchers first identified the elements that varied in intensity across photos, eliminating those that remained constant. In the last phase, they performed binary classifications using a linear SVM classifier to differentiate between AD patients and healthy people. The researchers observed that the SVM methodology obtained greater classification accuracy than conventional methods after testing this model on 120 structural MRI images from the OASIS database [9]. This encouraging outcome demonstrates how SVM may be used to diagnose Alzheimer's reliably using MRI data.

2. Methods

The OASIS (Open Access Series of Imaging Studies) brain MRI dataset, which has been prepared to facilitate neural network analysis-based Alzheimer's disease identification, is the dataset used in this study. The dataset includes 80,000 brain MRI pictures from 461 patients who were categorized as non-demented, very mild demented, mild demented, or moderately demented based on how their Alzheimer's disease was progressing. These classifications are based on the patients' Clinical Dementia Rating (CDR) scores, indicating the degree of cognitive

impairment [10]. The OASIS dataset includes the processed MRI images of 416 patients uploaded in phases to a GitHub repository after the original.img and.hdr files were transformed into the Nifti format (.nii) using FSL. The brain pictures in the dataset were divided into 256 segments to create 2D images for neural network training, with slices 100 to 160 being the focus for each patient. CDR values and metadata were used to classify patients into four groups: moderately demented, very mildly demented, mildly demented, and non-demented.

The first step involved downloading the dataset from Kaggle and organizing it into hierarchical folders labeled "Mild Dementia," "Moderate Dementia," "Very Mild Dementia," and "Non Demented" [11].

Table 1 shows the number of MRI images used for each dementia classification. To ensure image standardization, these images were scaled to a standard resolution and stored with their metadata indicating whether the subject had Alzheimer's disease. The dataset was then put into a pickle file format so that it could be quickly accessed while training the model.

Condition	Training Data	Testing Data
Mild Dementia	549 MRI Scans	183 MRI Scans
Moderate Dementia	366 MRI Scans	122 MRI Scans
Very Mild Dementia	549 MRI Scans	183 MRI Scans
Non-demented	549 MRI Scans	183 MRI Scans

Table 1. Distribution of MRI Images by Classification

The data includes 2,684 MRI images in total, with 2,013 images in the training dataset and 671 images in the testing dataset. The full dataset is divided into a training and testing set with a 75% and 25% split. To prevent bias, we ensured that the same subjects did not overlap between the training and testing datasets.

The Histogram of Oriented Gradients (HOG) technique was used for feature extraction from an image. First, the size of the brain is reduced in an MRI. HOG computes the gradient for a predetermined number of directions after splitting the image into tiny blocks, each consisting of 14x14 pixels [12]. This produces an image representation that preserves important structural details while minimizing data, simplifying the image for additional examination. The total number of pixels in the original image is much greater than the number of HOG features, which reduces the data to approximately 15% of the original size while maintaining sufficient information for object detection.

The data was processed, and the models were implemented using Python 3.7 with the sci-kit learn library. Three primary changes are made in the preprocessing: standardizing the data, extracting features from the Histogram of Oriented Gradients (HOG) characteristics, and converting RGB images to grayscale. To facilitate processing, we first developed a new

transformer class called RGB2GrayTransformer, which transforms RGB images into grayscale by lowering the dimensionality. This transformer can be used in scikit-learn pipelines because it is built on the BaseEstimator and TransformerMixin classes from scikit-learn. While the transform method converts each image in the dataset to grayscale, the fit method leaves the data unchanged.

The HOGTransformer class is then implemented to determine the HOG characteristics for every grayscale picture. The HOG technique breaks a picture into smaller cells, calculates the gradient direction and magnitude for each pixel, and then combines all of this data to create a feature vector representing the image's key structural elements. Parameters that affect the detail recorded in the HOG features are given during setup. These parameters include the number of orientations, pixels per cell, and cells per block. The HOG feature vectors were scaled using the scikit-learn StandardScaler transformer, guaranteeing that each feature has a zero mean and a unit variance. Models sensitive to feature magnitudes, such as Support Vector Machines (SVM), require this scaling step.

The procedure of testing and training comes next. Initially, an instance of the Stochastic Gradient Descent (SGD) Classifier, a linear SVM classifier trained by gradient descent optimization, was implemented. This classifier's effectiveness and respectable results on big datasets led to its selection. The preprocessed training data (i.e., grayscale, HOG-transformed, and scaled pictures) and the associated labels are fed into the classifier during training via the fit technique.

We apply the classifier to the test set to assess its performance. Before predictions are made, the test data is preprocessed using the same methods as the training data: scaling, grayscale conversion, and HOG feature extraction. We then predict the class using the trained SGD classifier. The percentage of accurate predictions is determined by comparing the outcomes with the true labels.

3. Results

This model produced an accuracy of 74.21%. The confusion matrix in Figure 1 illustrates how the predictions match the proper labels for each class, offering a more thorough examination of the classifier's performance. In this matrix, the projected class is represented by each column, while each row represents the actual class.

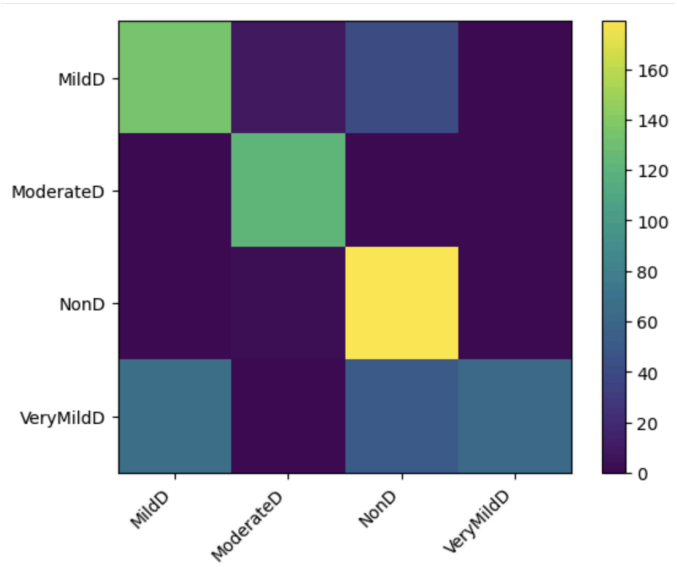

Figure 1. Confusion Matrix Showing the Performance on this Multi-class Classification of Mild Dementia, Moderate Dementia, Non Demented, and Very Mild Dementia.

4. Discussion

Compared to other studies that utilized an OASIS dataset, the 74.21% accuracy achieved by this model shows room for improvement in AD classification. A study leveraging an OASIS dataset achieved an SVM model accuracy of 74%, similar to our model [13]. The OASIS dataset they used had a male-female ratio of 60% to 40%, and all patients were over 60. Logistic regression, decision trees, and random forest were also used to achieve predictions. After fine-tuning the SVM model, their accuracy was significantly higher, at 92%. The study shows that the potential for improvement exists, and with fine-tuning, better predictions can be achieved. Another SVM model that utilized an OASIS dataset had an accuracy of 81.5% [14]. This study proposed different ML algorithms to classify AD patients using T1-weighted MRI data. The MRI scans dataset includes a longitudinal collection of 150 patients between the ages of 60 to 96 years old. A convolutional neural network (CNN) model achieved an accuracy of 83.3% [15]. The dataset used included 1,098 patients who were 42 to 95 years of age. The model was built using five convolutional slabs covered with convolutional layers. The study utilized a backpropagation algorithm to stop the model automatically once it reached its maximum accuracy.

These papers suggest that machine learning applications can be highly successful in classifying Alzheimer's disease scans.

A limitation of this study is the relatively small amount of data used for training and testing the model. Due to technical limitations, only a small portion of the total OASIS dataset was able to be used to train and test the model. The model's accuracy might also be constricted because of its dependence on 2D slices of 3D MRI data [10]. This could have led to the loss of some spatial information needed to classify the MRI scans into each of the four AD categories.

In future work, increasing the number of MRI scans utilized in the data would improve the model's performance and ability to generalize. More data would lead to better pattern detection and possibly a higher accuracy score. Incorporating more advanced machine learning techniques like convolutional neural networks (CNNs) may improve the classification of the MRI data by automatically learning the patterns in the data.

5. Conclusion

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that primarily affects memory, thinking, and behavior. It is a major social and economic burden that affects more than 55 million people worldwide. AD usually begins with mild memory loss and worsens with time, causing significant impairments in language, thinking, and day-to-day functioning. The identification of neurological illnesses has been made easier by the interpretation of complex brain data made possible by advancements in machine learning (ML) and neuroimaging. This work used supervised learning with a linear support vector machine (SVM) and stochastic gradient descent (SGD) to classify MRI images from the OASIS dataset. The model used a Linear SVM classifier with stochastic gradient descent for classification after extracting features using the Histogram of Oriented Gradients (HOG) approach. Following preprocessing the data to scale the HOG features and convert images to grayscale, the model was trained and tested, yielding a 74.21% accuracy rate.

The results of this study show that significant performance on multi-class classification of healthy controls, MCI, very mild dementia, and moderate dementia can be accomplished using linear SVM with SGD. This research is important because it may help diagnose Alzheimer's disease and other associated disorders early and accurately, which is essential for prompt intervention and treatment. This method also sets the stage for future study because it can significantly increase the predictive potential of the model by adding more complex machine learning algorithms or refining it with larger datasets. This may lead to more timely diagnosis, individualized treatment plans, and improved handling of neurodegenerative illnesses.

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