Classifying Alzherimer's from MRIs Using CNN/CNN for Early Alzheimer's Detection

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Abstract

Early detection of Alzheimer’s is crucial for many reasons; it allows early intervention which can slow down its progression, it can provide patients access to clinical studies for treatment testing, and it allows families/caregivers to think ahead, which can include care plans, financial options, and legal logistics. This project focuses on using Convolutional Neural Networks (CNNs) to classify Alzheimer's disease from brain imaging data – in addition to CNN, other machine learning models such as Support Vector Machines (SVM), Random Forests, and K-Nearest Neighbors (KNN) are implemented for comparison. By leveraging deep learning techniques, the aim is to develop a model that can accurately distinguish between different stages of Alzheimer's. This project addresses overfitting utilizing techniques such as dropout, early stopping, and regularization during model training. Model performance will be evaluated using metrics such as accuracy, precision, recall, and F1-score. Cross-validation ensures generalization across unseen data. By exploring these methods, the project aims to not only enhance diagnostic accuracy but also pave the way for more effective integration of machine learning models in medical diagnostics, ultimately contributing to improved patient care and early intervention strategies.

Introduction

What is Alzheimer's?

Alzheimer's disease (AD) is a progressive neurodegenerative disorder and the leading cause of dementia globally. It leads to the destruction of brain cells and eventually causes the brain to shrink over time. Common symptoms of dementia include cognitive decline and memory loss, significantly impacting an individual’s ability to perform daily activities and maintain independence.

How is it being studied or attempted to be diagnosed?

Currently, Alzheimer's is studied and diagnosed through a combination of methods, including reviewing a patient’s medical history, physical evaluations, neurological exams, and utilizing lab tests, psychiatric evaluations, and psychological assessments. However, these methods are often inconclusive and can only estimate the likelihood of Alzheimer’s. Definitive diagnosis is only possible post-mortem through an autopsy.

In terms of treatment, Alzheimer’s cannot be cured, but its progression can be slowed through medications like cholinesterase inhibitors and NMDA receptor antagonists. These drugs help manage symptoms but do not stop the disease entirely. Supportive care, like cognitive therapy and lifestyle modifications, also plays a role in improving the quality of life for patients.

Why is it important to optimize the accuracy of MRI predictions?

Although MRI scans are not a definitive diagnostic tool for Alzheimer’s, they play an important role in identifying structural changes in the brain, such as atrophy and reductions in gray matter. Optimizing the accuracy of interpreting MRI scans can provide earlier indications of Alzheimer’s, enabling interventions that can slow the disease's progression. Since Alzheimer’s can only be confirmed post-mortem, MRI scans serve as the best available method to monitor brain changes associated with the disease.

Improving the reliability of MRI scan interpretations not only aids in earlier and more accurate diagnoses but also enhances the ability to differentiate Alzheimer's from other neurodegenerative diseases. This is important because early detection allows patients to begin treatment sooner, manage symptoms more effectively, and plan for the future.

What purpose does our model serve?

Since Alzheimer's is a disease that, unfortunately, cannot be determined with absolute certainty until after death—when an autopsy provides definitive confirmation—it is essential to optimize the tools available to physicians. Brain imaging techniques such as Magnetic Resonance Imaging (MRI) and Computer Tomography (CT) scans are among the closest methods available to visualize brain activity. CT scans take cross-sectional images of the body, while MRIs use magnetic fields and computer-generated waves to create detailed images of the brain's structure, providing critical insights into areas affected by Alzheimer's.

This project focuses on enhancing the interpretation of MRI scans through machine learning techniques, particularly CNNs. The goal is to improve the accuracy of classifying Alzheimer's-related changes in the brain into four categories: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. By refining these classifications, our model aims to support physicians in making better-informed decisions and potentially diagnosing Alzheimer's earlier.

This project is not only about improving diagnostic tools but also about leveraging technology to provide hope for millions of individuals at risk of Alzheimer's. By enhancing the interpretation of MRI scans, our model seeks to address a critical gap in Alzheimer's diagnosis and facilitate early intervention, which can significantly impact patient outcomes and quality of life.

Related Work

CNNs have shown significant promise in the early and accurate diagnosis of Alzheimer's disease using medical imaging techniques like MRIs. Recent advancements, such as the approach outlined in a 2024 study by El-Assy et al., demonstrate the efficacy of tailored CNN architectures in addressing multi-class classification tasks for AD. The proposed architecture utilized two complementary CNN models, each with distinct filter sizes and pooling configurations, to analyze MRI scans from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset. This approach achieved remarkable accuracy rates—99.43%, 99.57%, and 99.13% for three-way, four-way, and five-way classifications, respectively—underscoring its ability to differentiate between various stages of AD. These advancements highlight the potential of CNN-based solutions to enhance early detection, personalized treatment planning, and prognosis monitoring in clinical settings.

Proposed Method

This project utilizes a publicly available Alzheimer's MRI dataset from Kaggle, which classifies MRI images into four categories: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The dataset includes both original and augmented images to enhance variability and size for training and testing machine-learning models. The data will be split into training, testing, and validation sets and undergo preprocessing to ensure compatibility with the models. Preprocessing steps include batching, resizing images to 224x224 pixels, normalizing pixel values to a range of 0 to 1, and applying data augmentation techniques such as flipping, shuffling, brightness adjustments, and contrast modifications. These techniques aim to improve model robustness and generalization by simulating variations found in real-world data.

The main model for this project is a Convolutional Neural Network (CNN), a deep learning architecture designed for image classification tasks. The CNN will include multiple convolutional layers to extract spatial features, Batch Normalization to stabilize and accelerate training, and regularization techniques such as Dropout and L2 regularization to reduce overfitting. A softmax output layer can be used to classify MRI images into one of the four categories.

Additionally, the project incorporates transfer learning by using pre-trained models such as ResNet50. These models, trained on large-scale datasets like ImageNet, are ideal to adapt to the Alzheimer's dataset. By freezing their convolutional base layers and adding custom dense layers, the project capitalizes on the high-level features already learned by these models, reducing training time and improving performance.

Models such as K Nearest Neighbor (KNN) and Random Forest were implemented to provide a baseline comparison. This allowed a direct comparison between traditional machine learning and deep learning approaches.

Furthermore, regularization techniques such as L2 regularization (Ridge), Dropout, and Batch Normalization will be used to optimize the performance of all deep learning models. Dynamic learning rate adjustment using the ReduceLROnPlateau callback and Early Stopping mechanisms will ensure optimal convergence while preventing overfitting.

By combining CNNs, transfer learning, and machine-learning models, this project aims to evaluate and enhance the accuracy of Alzheimer's classification, offering an improved tool for interpreting MRI scans and identifying early signs of neurodegeneration.

Experiments

How was the data processed?

The size and nature of the dataset necessitated optimizing the process of constructing and training the convolutional neural network. Parallelization techniques were employed to accelerate this process, leveraging multiple CPUs to distribute the computational workload efficiently.

Preprocessing the dataset

To standardize input dimensions, all images were resized to 224x224 pixels during loading. The images were processed in batches of 32, ensuring computational efficiency while maintaining manageable memory usage.

Labeling

The data labeling is automated by using labels='inferred', where labels are derived from the dataset's directory structure. Each subdirectory represents a class, and integer labels are assigned based on the alphabetical order of the subdirectory names. For example, folders like

MildDemented, ModerateDemented, NonDemented, and VeryMildDemented, would be labeled as 0, 1, 2, and 3 respectively. The label_mode='int' ensures labels are integers, making them ready for model training. This approach simplifies labeling, ensures consistency, and leverages a well-organized dataset structure.

Dataset Splitting and Organization

The training dataset was shuffled to enhance model generalization by presenting the data in a varied order during training. Conversely, the testing dataset was not shuffled to maintain a consistent evaluation sequence, ensuring reliable and reproducible performance assessment.

Data augmentation

To improve the robustness of the model and reduce overfitting, data augmentation was applied exclusively to the training dataset. The augmentation transformations included:

- Random Horizontal Flip: Mirrors the image horizontally with a random probability.
- Random Vertical Flip: Mirrors the image vertically with a random probability.
- Random Brightness Adjustment: Introduces variations in image brightness by a factor of up to ± 10%
- Random Contrast Adjustment: Modifies image contrast within a range of ± 10%

These augmentations simulate natural variations in the data, enhancing the model's ability to generalize across diverse input patterns.

Normalization

Both the training and testing datasets underwent normalization to scale pixel values to the range [0,1], ensuring numerical stability during training. The images were converted to floating point tensors by dividing intensities by 255.

The testing dataset, being an already augmented set, did not undergo further augmentation in this program. This decision was made to ensure that the testing images were not excessively distorted, preserving their integrity for accurate evaluation. By maintaining the original augmented testing dataset, the evaluation results more reliably reflected the models performance under realistic conditions.

Data Optimization

Intermediate results were cached to avoid redundant computations in subsequent epochs. The training dataset was shuffled with a buffer size of 1,000 to introduce randomness and promote generalization. Using `tf.data.experimental.AUTOTUNE`, prefetching allowed data loading and preprocessing to overlap with model training, reducing bottlenecks.

Base CNN

The model is a basic CNN. It contains four convolutional layers that are used to extract features from the images. The number of filters goes from 16 to 32 allowing the model to learn complex patterns. Furthermore, each convolutional layer is followed by a max pooling layer to reduce dimensions and computational complexity while maintaining important features. Then, in the flattened layer the feature map is transformed into a one-dimensional vector to be inputted in the fully connected layer. One dense layer with 512 nodes and a ReLU activation function is used. The final dense layers contain four neurons with a softmax activation function suitable for output multi-class probabilities. Adam optimizer was used, as it combines benefits from Momentum and RMSProp. It leads to faster training as it adjusts the learning rate for each parameter.

This design was chosen because it provides a baseline comparison for more complex deep learning pre-built models implemented later. Moreover, the use of convolutional layers allows the model to learn features within images. To prevent overfitting a dropout layer was used to randomly drop 20% of nodes in the dense layer during training.

The training and validation plots indicate that the basic CNN model learns quickly with a high improvement in accuracy and reduction in the loss within the first few epochs. By epoch six, the model reaches high accuracy and low loss. The plots suggest that the model generalizes well to unseen data as both training and validation accuracy converge near 100% indicating it performed well on both training and validation sets. Moreover, the training and validation loss plot suggests that the validation and training loss converge at the end of the 10th epoch, indicating that the model does not overfit the training data.

Some limitations of this basic CNN model is that it is simple compared to other pre-built architectures like ResNet and VGG16 so this simplicity might limit its performance on more complex data sets. Furthermore, this model does not use batch normalization, which could speed up the training process by normalizing the activations of each layer within a mini-batch.

MobileNet

The second model implemented is MobileNet. Custom layers followed the base architecture. The MobileNet base architecture is efficient and lightweight. Transfer learning was implemented using ImageNet pretrained weights and depthwise separable convolution which breaks down a convolution operation into two parts to reduce the number of parameters. This reduces the computational costs while maintaining good accuracy. The custom layers include global average pooling to reduce a feature map into a vector, hence reducing dimensions. Furthermore, the model includes three dense layers for the model to learn complex patterns. Batch Normalization is also implemented to speed up training by normalizing the activations of each layer. Lastly, dropout layers are used after each dense layer to reduce overfitting by randomly dropping neurons during the training process. Adam optimizer was used because it combines the benefits of Momentum and MPSProp, which allows adaptive learning rates for faster training and convergence.

The training and validation accuracy plot indicates that the model obtains a high accuracy on both the training and validation datasets. This suggests that the model learns the important features without overfitting the data. The training and validation loss plot shows that the validation loss decreases and follows the training loss closely after the 9th epoch. This suggests that the model has good generalization.

The MobileNet model achieved higher accuracies than the basic CNN model on both the training and validation sets. However, since transfer learning was used in the MobileNet model, it converged faster than the basic CNN model. Furthermore, compared to the first model, the batch normalization and dropout layers increased the model's generalization to new data.

Some limitations of this model are seen in the training and validation loss plot. The minor fluctuations in validation could be an indication that the model would benefit from using regularization techniques. Additionally, although MobileNet is lightweight, the added custom dense layers increase computational costs.

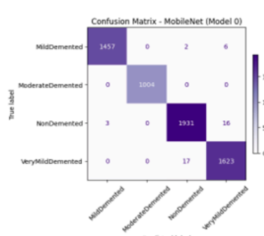
Results and Discussion

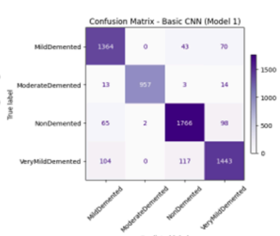
Models	Performance Based on Accuracy	Precision (Micro Avg)
KNN	0.76	0.75
Random Forest + PCA	0.79	0.81
MobileNet	0.99	0.99
CNN	0.91	0.92
CNN L2 + Learning Rate of 0.01	0.75	0.90
CNN L2 + Learning Rate of 0.001	0.89	0.77
CNN with Batch Normalization	0.90	0.91

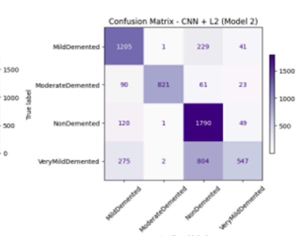
Results

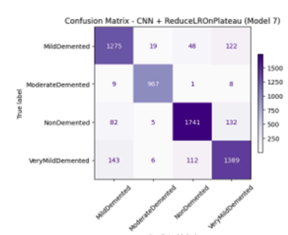
The results of our Alzheimer's classification project highlight the effectiveness of CNN models compared to traditional machine learning approaches. Among the models tested, MobileNet achieved the highest accuracy and precision, both at 99%, demonstrating its robustness for this task. Our basic CNN model followed, with an accuracy of 91% and a precision of 92%, showcasing the capability of custom CNN architectures. Models incorporating L2 regularization and varying learning rates showed mixed results, with performance ranging from 75% to 89% accuracy, indicating that hyperparameter tuning significantly impacts CNN outcomes. Batch normalization improved performance slightly, yielding a precision of 91% and accuracy of 90%.

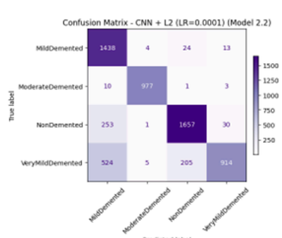
The K-Nearest Neighbors (KNN) model and Random Forest with PCA, though useful as baselines, lagged behind CNN-based models, achieving accuracies of 76% and 79%, respectively. The confusion matrices highlight the superior performance of MobileNet in classifying all categories, while other models exhibited occasional misclassifications, especially between Mild Demented and Very Mild Demented categories

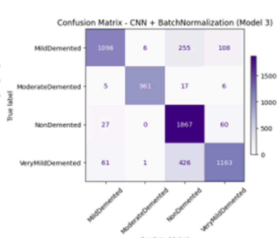


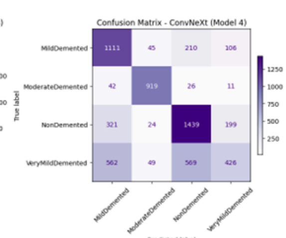










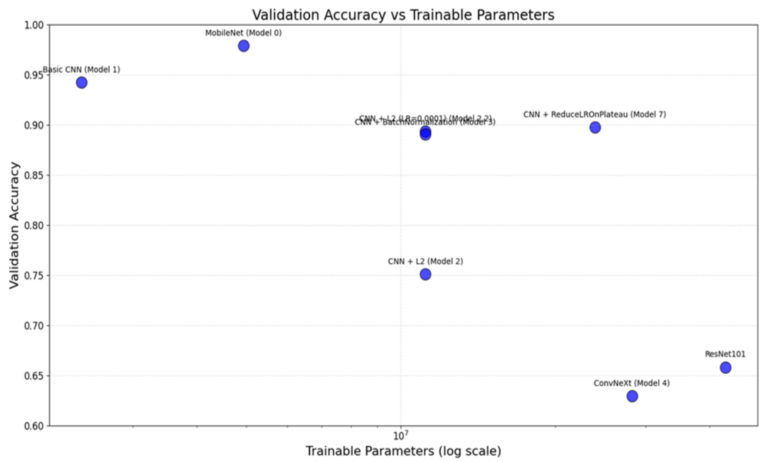


Discussion

Machine learning models are generally better suited for smaller datasets, unlike the large image dataset used in this project. Techniques like

PCA proved effective for reducing dimensionality while retaining significant variance. Among the models tested, MobileNet emerged as the top performer, outperforming other pre-built models. Interestingly, custom CNNs also outperformed more complex pre-built models, which are typically optimized for larger datasets with pre-tuned hyperparameters like Adam. However, the complexity of these pre-built models can hinder gradient flow, negatively impacting their learning capacity. These findings suggest that model architectures should be designed to avoid excessive complexity, ensuring efficiency and effective learning.

Conclusions



After evaluating various models on our dataset, lightweight models like MobileNet and custom CNNs (<10M parameters) outperformed more complex models like ResNet101 and ConvNext, emphasizing the importance of balancing complexity and efficiency. We also found that high learning rates can cause overfitting and exploding gradients, highlighting the importance of careful hyperparameter tuning. These applications can further improve efficiency so that early intervention can be provided with much more accurate results with higher precision to reduce the number of false negatives. These findings suggest that focusing on lightweight, efficient models could enable earlier intervention with more precise results, reducing the prevalence of false negatives. Future work should explore optimizing such architectures to further enhance their applicability in real-world scenarios.

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