# 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 gives families/caregivers the opportunity 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, including normal, mild cognitive impairment, and severe 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. 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.

## Background

The primary goal of this project is to leverage Convolutional Neural Networks (CNNs) to classify MRI brain scans, distinguishing between healthy brains and those affected by Alzheimer's disease. Alzheimer's, a neurodegenerative disease, affects millions worldwide, causing cognitive decline, memory loss, and significant emotional and psychological distress for patients and their families. The increasing prevalence of this disease poses immense challenges to individuals and the healthcare system alike.

Despite advances in medical research, the exact causes and progression of Alzheimer's remain unclear, complicating early diagnosis and treatment. Early detection is critical, as it offers the potential for more effective interventions and improved patient outcomes. However, traditional imaging techniques like CT and MRI scans, while valuable, often fail to detect early-stage Alzheimer's, leading to missed opportunities for timely care.

This project aims to address these challenges by applying CNNs, which excel in pattern recognition and anomaly detection. By training and evaluating a deep learning model tailored to MRI data, we hope to identify subtle abnormalities indicative of Alzheimer's at its earliest stages.

## Methods

**Data Acquisition and Preprocessing**

The Kaggle Alzheimer's MRI dataset (34,000+ images, four classes) was split into training (70%), validation (15%), and testing (15%) sets. Three preprocessing methods were tested:

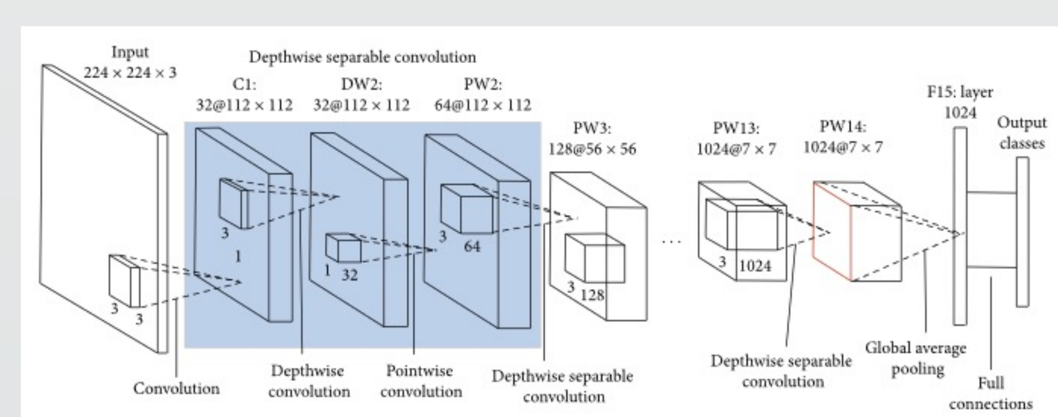
- **Method 1**: Resized to 128x128 pixels without data augmentation or normalization.
- **Method 2**: Resized to 224x224 pixels; normalized to [0, 1] using ImageDataGenerator; no additional augmentation.
- **Method 3**: Resized to 224x224 pixels; applied random flips, brightness/contrast adjustments, and normalized to [0, 1]. Data was sharded for parallel processing.

**Model Architectures**

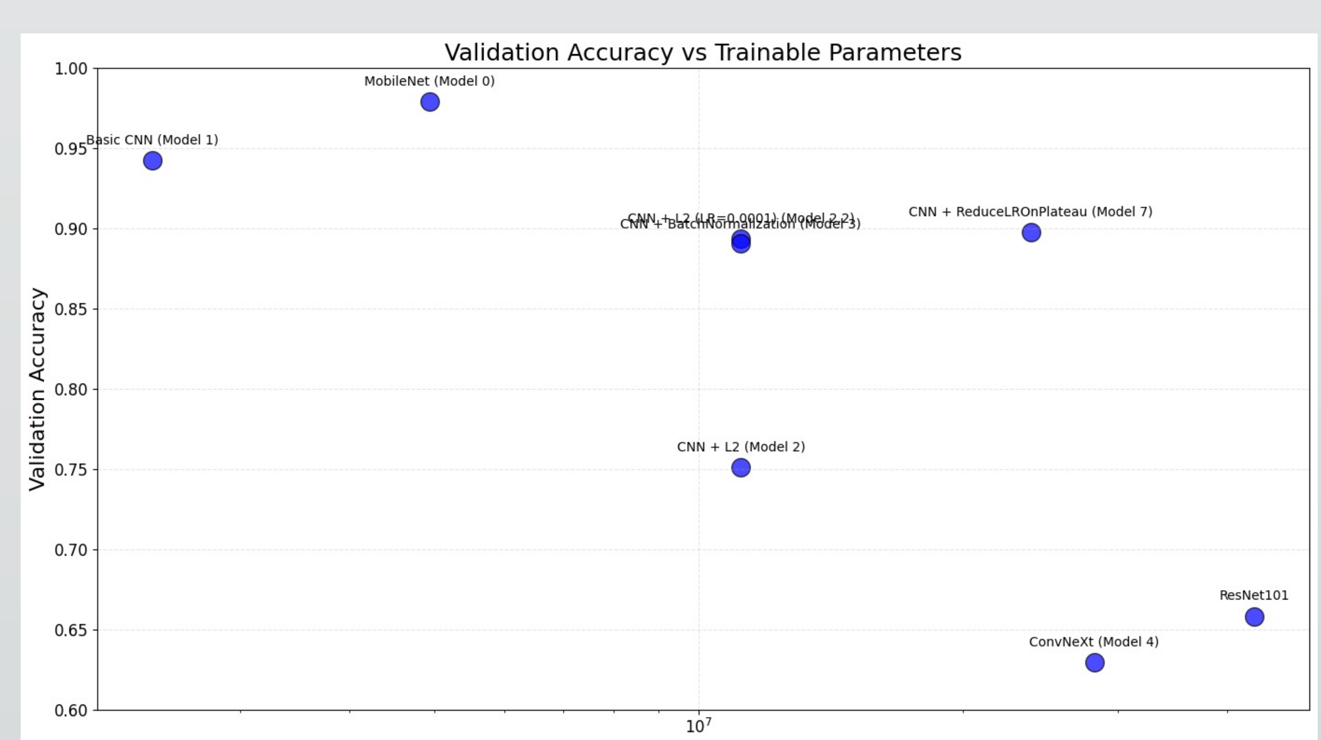
- **Method 1**: VGG16 pre-trained on ImageNet for feature extraction, followed by an SVM classifier.
- **Method 2**: Custom CNN with batch normalization, max-pooling, dropout layers; trained with Adam optimizer and categorical cross entropy loss.
- **Method 3**: Custom CNNs with L2 regularization, batch normalization, dropout layers, and transfer learning using ResNet50. ResNet50's base layers were frozen, with added custom layers for classification.
- **Method 4**: MobileNet with global average pooling, batch normalization, dropout layers, and dynamic learning rate.

**Training and Evaluation**

Models were trained for up to 10 epochs, evaluated using validation accuracy and F1-scores. Method 3 employed early stopping and learning rate reduction to prevent overfitting.




**MobileNet Model**




## Results

| Models | Performance Based on Accuracy | Precision (Micro Avg) | Insights |
|---|---|---|---|
| KNN | 0.76 | 0.75 | The model struggles with false positives but performs slightly better in balancing precision and recall. |
| Random Forest + PCA | 0.79 | 0.81 | PCA aids in dimensionality reduction enabling it to perform reasonable well applying Random Forest. |
| MobileNet | 0.99 | 0.99 | MobileNet showed superior ability to detect true positives with minimal false predictions. |
| CNN | 0.91 | 0.92 | CNN with convolution, max pooling and drop out layer combat overfitting by reducing the model's complexity. |
| CNN L2 + Learning Rate of 0.01 | 0.75 | 0.90 | Prioritized precision, thus making highly selective leading to an in-balance. |
| CNN L2 + Learning Rate of 0.001 | 0.89 | 0.77 | Showed robustness but precision was compromised. |
| CNN with Batch Normalization | 0.90 | 0.91 | Achieved a balanced with training stability. |

## Conclusion

- Deep learning models with a lower number of parameters (< 10 million) such as MobileNet and CNN performed better than models with a higher number of parameters (ResNet101 and ConvNext).
- Increasing the learning rate will result in an overfitting model and thus lead to an exploding gradient.

## Future Direction

**Balancing dataset**: To prevent the models from favoring majority class, so it performances improve across all categories.

**Optimizers Tuning**: Try difference optimizers instead of Adam to see if they yield a better performance.

**Cross Validation**: Train and validate using k-fold validation to get better estimate of the model performance.

**Early Stopping**: To prevent overfitting by halting training at the right time

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