



RESEARCH ARTICLE

An accurate Prediction and Classification of early Alzheimer's Diseases using Machine Learning Algorithm

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Abstract

Alzheimer's disease (AD) is a progressive neurodegenerative disease that severely impairs memory, cognition and everyday functions. Early and accurate diagnosis of AD is important for timely clinical management but the conventional diagnostic protocols still suffer from subjectivity and high cost. In this study we propose a deep learning architecture for early AD prediction and classification based on Convolutional Neural Networks (CNNs). We trained the model using medical imaging data, specifically Magnetic Resonance Imaging (MRI), to automatically learn hierarchical spatial features indicative of the early AD brain subtly changing structure. Unlike traditional machine learning, the CNN uses convolutional layers, pooling, and fully connected layers to replace the need for handcrafted feature extraction to derive end-to-end learning. The proposed method is integrated with regularization and data augmentation to prevent overfitting and obtain robustness to different patient samples. Experimental evaluation results demonstrate that the CNN-based model possesses greater accuracy, sensitivity, and specificity than conventional classifiers and is able to accurately distinguish normal controls, patients with mild cognitive impairment, and patients with Alzheimer's. This work shows the potential of CNNs as a valuable tool in computer Aided diagnosis (CAD) in the field of neurodegenerative diseases, contributing to the system of earlier diagnosis and clinical decision-making in their management.

Keywords: Alzheimer's Disease, Convolutional Neural Networks (CNNs), Early Detection, Magnetic Resonance Imaging (MRI), Computer-Aided Diagnosis (CAD).

Introduction

Alzheimer's disease (AD) is one of the most prevalent neurodegenerative diseases and accounts for about 60-80%

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of the cases worldwide. Definition: AD is a degenerative disease, characterised by a gradual decrease in memory, cognition and functioning in daily life to the extent that patients are profoundly impaired and lose their independence in late stages (Rajput, A. 2022). The number of patients with AD is expected to explode in the coming decades and the disease is now one of the world's top health problems. Early diagnosis and correct classification of AD plays a very significant role since early clinical intervention and therapeutic interventions can slow down the disease progression, enhance the quality of life and save costs of healthcare. However, conventional tests of diagnosis such as neuropsychological tests and clinical observation are frequently subjective, variable and insensitive to symptoms early in the disease.

Neuro imaging, in particular Magnetic Resonance Imaging (MRI), continues to evolve and provide clinicians and researchers with a detailed picture of structural and functional brain changes. Patterns of cortical thinning and small atrophy of structures like the hippocampus may be used as early markers for Alzheimer's disease. However, the manual analysis of such high-dimensional imaging data is time consuming and error-prone (Dinius, C. J., *et al.*, 2023). For this reason, there is a continuously growing interest in

the application of machine learning (ML) (Kathavate, P. N., & Mahant, M. A. 2025) and deep learning (DL) (Adivarekar, P. P., *et al.*, 2023) algorithms for automatic disease prediction and categorization.

Among these approaches, CNNs have emerged as a powerful tool, due to their discriminative features learning capabilities directly from imaging data without the need to use handcrafted features. CNNs can use convolutional filters, pooling layers and hierarchical representations of features to represent local and global structural patterns of neurodegeneration. However, unlike traditional ML algorithms such as Support Vector Machine (SVM) or Linear Discriminant Analysis (LDA), CNNs can directly ingest the raw input data and perform feature optimization in an adaptive manner using backpropagation for better image-based classification problems (Xie, Y., *et al.*, 2023).

In this research work, we propose a CNN-based framework to classify and correctly predict early AD using MRI data. The model is constructed to distinguish the normal controls, mild cognitive impairment (MCI), and Alzheimer's patients with high accuracy, sensitivity, and specificity. With regularization techniques and data augmentation, the proposed system is robust to overfitting as well as heterogeneity across patient samples. The contributions of this work are the use of deep learning in early AD detection, the demonstration of the superiority of CNNs over traditional classifiers, and further development of reliable computer-based diagnostic systems.

Early diagnosis of AD disorder is important because of timely intervention more than anything else. The current diagnosis methods are subjective and limited; and the traditional machine learning methods based on handcrafted features cannot capture the complex patterns in brain. Manual MRI analysis also is time consuming and error-prone (Yue, J., *et al.*, 2023). There is therefore a need for an automated robust and accurate framework. This study proposes the use of CNNs for classification of early AD from MRI data to overcome the limitations of the current methods and facilitate reliable computer-aided diagnostics.

These are some of the important research contributions you can emphasize to your study:

- We proposed CNN-based architecture for early detection and classification of Alzheimer's Disease using MRI data without handcrafted feature extraction.
- Increased sensitivity and specificity in discriminating normal controls, mild cognitive impairment (MCI) and Alzheimer's patients in comparison to traditional ML techniques.
- Regularization and data augmentation techniques: Can be further applied to obtain a more robust model and to avoid overfitting in medical imaging datasets.
- Comparison with traditional classifiers (e.g. SVM, LDA) in order to show the advantage of CNNs in terms

of performance for neuro imaging data with high dimensions and non-linear properties.

- Contribution to computer-aided diagnosis systems aiding clinicians in more objective, consistent and timely decisions for early intervention in Alzheimer's Disease.

Literature Survey

Bit, S., *et al.*, (2024) propose an MRI-only pipeline, where reduced dimensional latent features are extracted from sMRI with a variational autoencoder (VAE) and fed to advanced ML classifiers to differentiate AD, MCI, and cognitively normal (CN) subjects across two independent cohorts. By actively addressing data leakage and validating on an independent set (including autopsy-confirmed labels), the work shows a robust and generalizable VAE-based representation, which improves AD/MCI/CN taxonomy and adds methodological rigor and novelty to MRI-driven diagnosis.

Rosca, C.-M., & Stancu, A. (2025) perform a survey on ML applications for diagnosis of Alzheimer's, Parkinson's and multiple sclerosis, with recent studies sharply increasing in the number of neurology-related studies and the dominance of SVM (597 papers), Artificial Neural Networks (525), and Random Forests (457). Despite encouraging results-including reported accuracies of up to 97.46% for Alzheimer's- three gaps remain: (i) rare neurodegenerative diseases are underrepresented; (ii) evaluation practices are not standardized and (iii) more complex/underutilized algorithms (e.g., Extreme Gradient Boosting, Multilayer Perceptron) are rarely explored systematically. The authors suggest that inclusion of rarer conditions, rigorous evaluation of less-researched models, and the use of standardized performance-assessment criteria will enhance comparability between studies, and speed clinically significant advances.

Grueso, S., & Viejo-Sobera, R. (2021) performed a PRISMA-based systematic review of ML studies to predict conversion from MCI to AD dementia using neuroimaging. After screening 452 papers, 116 were qualitatively analyzed (most using MRI and PET (with some MEG) and mostly from ADNI). Support Vector Machines were the most popular algorithm (mean accuracy 75.4%) and convolutional neural networks showed the better overall performance (78.5%). The number of studies investigating multimodal MRI/PET fusion outperformed those using unidimensional single-modality measures, and the number of studies using deep learning models with multimodal, multi-dimensional data (neuroimaging plus clinical, cognitive, genetic and behavioral features) led to the best outcomes. In conclusion, this study shows a significant potential of ML-based and multimodal neuroimaging pipelines as clinical decision-support systems to predict MCI progression, although there is still room for improvement.

Dong, N., *et al.*, (2022) use Hollow Tree Super (HoTS) to get feature importance for multiple ML models and to map brain regions associated with impairment vs. intact performance

on 11 neuropsychological tests. Results were moderate-to-good, with 11 models having AUC-ROC >0.65 and five having ≥ 0.70 . Regional variation was observed, such that 20 HCP Multimodal Parcellation parcels correlated with poor performance (in ≥ 2 tests) while 14 parcels correlated with good performance (in ≥ 2 tests). Network-level analysis indicated the Central Executive, Default Mode and Sensorimotor networks as relevant contributors in deficit and non-deficit predictions. Subgroup analysis by cognitive domain showed that there were still cross-test overlaps, indicating these parcels to be potential neuroimaging biomarkers for cognitive impairment screening and monitoring.

In a systematic review and an ALE meta-analysis of resting-state neuroimaging studies that compared depressed vs. non-depressed individuals with MCI or Alzheimer's disease (AD), von Gal, A., *et al.*, (2025) yielded a total of 17 experiments with 303 participants. Resulting from 10 networks of significant co-activation, the Aligning Networks Exploration (ALE) showed reproducible network-level changes associated with depressive comorbidity in neurodegeneration across five major resting-state networks (RSN) and cortico-basal ganglia-thalamo-cortical circuits. CONCLUSIONS: Aberrant within- and between-network resting-state fluctuation are potential diagnostic and therapeutic targets, highlighting the utility of network-informed biomarkers when evaluating mood symptoms together with cognitive decline.

Ahmad, A. L., *et al.*, (2024) applied benchmarks of multiple ML classifiers to ADNI and OASIS-3 for Alzheimer's-related diagnosis, which include Accuracy (Acc), AROC, F1, and normalized MCC. Cross-cohort feature selection consistently selected neuroanatomical biomarkers as most affected. Taken together, the results highlight the importance of harmonization decisions, class balance and algorithm choice have material effects, and biomarker consistency across cohorts supports biological validity.

Antor, M. B., *et al.*, (2021) presented a clinically relevant OASIS dataset, compare classical machine-learning models (SVM, logistic regression, decision tree, random forest) with and without fine-tuning and report SVM as the best by accuracy. However, the small data size, inconsistent tuning protocols and possible overfitting prevent reliable, generalizable deployment. Design and rigorously validate a simple, low-resource ML pipeline for dementia detection that (i) works robustly under data scarcity, (ii) models and compares models with standardized fine-tuning, (iii) quantifies improvements over untuned baselines using robust cross-validation and fair metrics, and (iv) is a reproducible, interpretable, practically-usable screening solution.

Proposed Work

AD is challenging to diagnose at an early stage because of subtle structural changes in the brain. However, manual MRI

analysis is subjective and time-consuming, and conventional machine learning methods require handcraft features and often cannot well capture the complex brain patterns. To overcome these restrictions, this research presents a CNN based framework which is able to automatically learn discriminative features from MRI scans and effectively categorize subjects into mild, very mild, moderated and non-demented. Figure 1 shows the flow diagram of proposed work.

Input image

Alzheimer's MRI images dataset is downloaded from public kaggle website <https://www.kaggle.com/datasets/rabieelkharoua/alzheimers-disease-dataset>, and It has four classes, namely: Non-Demented (3200 images, 50%), Very Mild Demented (2240 images, 35%), Mild Demented (896 images, 14%) and Moderate Demented (64 images, 1%). It is easy to see that the dataset is highly imbalanced, as there are many samples in the Non-Demented and Very Mild Demented classes and the Moderate Demented class is severely under-represented. This imbalance creates issues for training CNN models as it can get biased towards majority classes. Figure 2 displays the x-y line data of the above defined data set.

Nonetheless, the dataset is valuable for multi-class classification, and is of particular significance for the early detection of Alzheimer's disease (very mild and mild dementia) at a time when clinical intervention should be

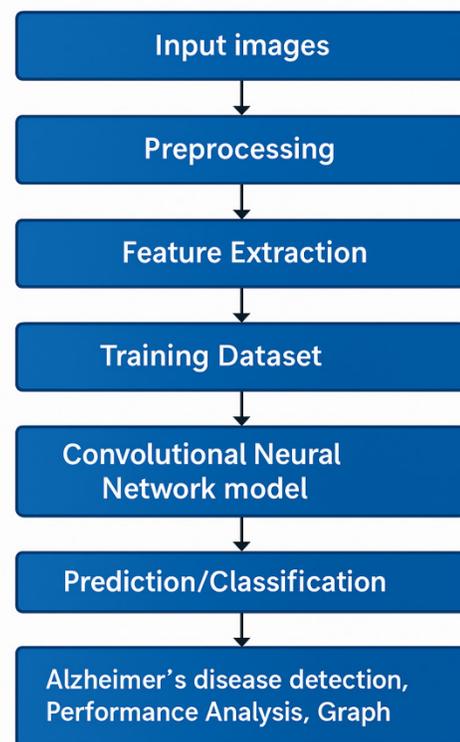


Figure 1: Work flow of proposed work

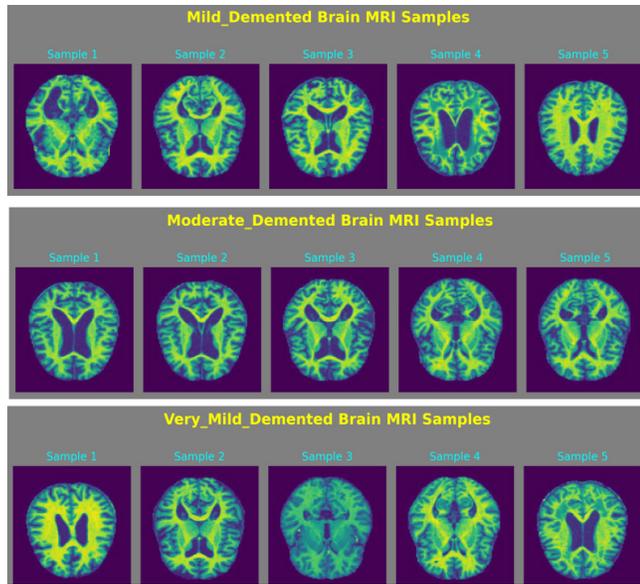


Figure 2: sample data set in each class

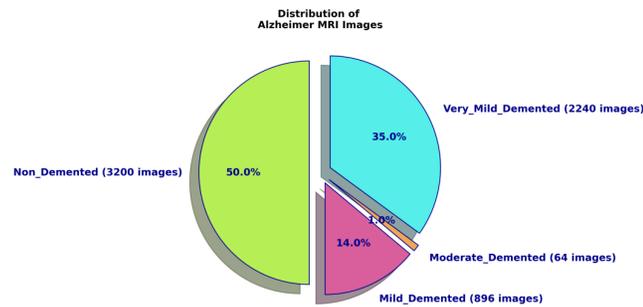


Figure 3: Distribution of MRI input images

most effective. We will divide the data set into 80% train, 10% validation and 10% test. Figure 3 shows the class-wise distribution of total dataset.

Pre-processing

Medical imaging is typically noisy due to acquisition hardware (e.g. MRI coil noise, CT quantum noise). The presence of noise tends to mask fine anatomical structures, and may confuse automated classifiers. Pre-processing filters denoise while restoring edges. Its function is to improve the image quality, minimize unwanted variations and normalize the input so that meaningful and disease-related features can be extracted accurately by CNNs and other machine learning models.

Noise Reduction

In image pre-processing, denoising or noise reduction is an important pre-processing step prior to classification tasks.

Random noise in MRI brain images is smoothed by using Gaussian filtering, which involves convolving the image with a Gaussian kernel, resulting in a smoothed image that enhances image clarity while preserving relevant anatomical features.

The Gaussian kernel in the 2D is defined by:

$$G(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \quad (1)$$

(x, y) positional coordinates relative to the centroid of the kernel. σ standard deviation, controls the amount of smoothing.

Smaller σ = less smudging (preserve details) and Larger σ = more smudging (blurs details).

Given a convolution of an MRI image $I(u, v)$ with a Gaussian kernel $G(x, y)$, a filtered MR image $I_{smooth}(u, v)$ is acquired.

$$I_{smooth}(u, v) = \sum_{x=-k}^k \sum_{y=-k}^k I(u-x, v-y) G(x, y) \quad (2)$$

k is the kernel radius and it is normalized to $G(x, y) = 1$, to maintain image brightness.

Intensity Normalization

MRI brain images are notorious for intensity differences due to different scanners, acquisition protocols, patient states and field strengths. For instance, the same tissue (e.g. gray matter) can vary in intensity value from one scan to another. This disagreement makes direct comparison hard and may degrade the performance of classification algorithm. To circumvent this, it is necessary to normalize the intensities across scans, so that all images are on an equal scale and distribution.

The above can be achieved by normalizing Z-Score. Z-score normalization (alternatively normalization) changes pixel/voxel intensities to have a mean of zero and a variance of one.

Given an MRI image $I(x)$, where x is a pixel (2D) or voxel (3D) coordinate

Compute mean intensity by using

$$\mu = \frac{1}{N} \sum_{x \in \Omega} I(x) \quad (3)$$

Ω set of brain pixels/voxels and $N = |\Omega|$ number of pixels/voxels.

Compute Standard Deviation

$$\sigma = \sqrt{\frac{1}{N} \sum_{x \in \Omega} I(x) - \mu^2} \quad (4)$$

Apply Z-score Normalization

$$I_{norm}(X) = \frac{I(X) - \mu}{\sigma} \quad (5)$$

After Normalization

$$E[I_{norm}] \approx 0 \text{ and } Var[I_{norm}] \approx 1$$

The intensity distribution among various MRI scan images is normalized. Gray matter, white matter and cerebrospinal fluid (CSF) now have better intensity ranges to compare with each other, making findings more consistent for CNN training.

Inhomogeneity Correction

Brain images are commonly afflicted by intensity inhomogeneity (the bias field). This looks like a smooth spatially varying shading artifact across the image.

- Due to magnetic field non-uniformities, patient positioning or coil sensitivity.
- Different intensity values may represent the same tissue type (e.g. white matter) in different regions of the brain.

The observed MRI image $I_{obs}(X)$ at voxel X can be modelled as:

$$I_{obs}(X) = B(X) \cdot I_{true}(X) + \varepsilon(X) \quad (6)$$

I_{true} is the true underlying intensity (bias-free image), $B(X)$ is smooth multiplicative bias field (low-frequency artifact) and $\varepsilon(X)$ is noise.

Now use Logarithmic Transformation to simplify, $\log I_{obs}(X) = \log I_{true}(X) + \log B(X)$, the multiplicative bias field becomes additive.

The bias corrected MRI is derived as:

$$I_{corrected}(X) = \frac{I_{obs}(X)}{B(X)} \quad (7)$$

Segmentation & Roi Extraction

The input MRI brain images include not only the brain, but also nearby structures such as skull, scalp, fat and background. In the case of AD classification, only certain brain regions, the hippocampus, entorhinal cortex, and cortical thickness regions, are clinically meaningful.

Segmentation and ROI extraction are used to:

- Remove structures of no interest (skull, noise, background).
- Target: Central nervous system (grey matter, white matter, cerebrospinal fluid).
- Segment disease-sensitive regions (e.g. hippocampus) for classification.
- Reduce feature size and irrelevant features, improve model accuracy.

The segmentation process involves grey and white matter, CSF and skull removal.

- Gray Matter (GM) - where most AD is seen to atrophy.
- White Matter (WM) - Connections affected late in the process
- Cerebrospinal Fluid (CSF) - CSF expansion (spaces around the brain) indicates brain atrophy

Segmentation assigns each voxel X to a class C_k :

$$C(X) = \arg \max P(C_k | I(X)) \quad (8)$$

$P(C_k | I(X))$ is the conditional probability of X class k , predicted by intensity models (e.g. Gaussian Mixture Models).

Resizing & Resampling

Since Alzheimer's disease mainly damages hippocampus, temporal lobe, and cortex thickness, it is possible to extract these ROIs to generate more discriminative features.

ROI cropping: Crop the hippocampus (bounding box B):

$$I_{ROI}(X) = I_{brain}(X) \cdot 1_{X \in B} \quad (9)$$

Feature Extraction

In Alzheimer's research, feature extraction is vital since anatomical alterations in the brain (e.g., hippocampal atrophy, cortical thinning, and ventricular enlargement) are subtle and need to be expressed in a way that is suitable for machine learning or deep learning models.

In classification, GLCM based Texture Feature Extraction is one of the most effective feature extraction methods for MRI brain images.

Texture features encode spatial intensity variations, which has the potential to discriminate between normal, MCI and Disease.

The Gray Level Co-occurrence Matrix (GLCM) reflects the frequency with which the pairs of pixel intensities (i, j) occur at a given distance d and orientation θ . It is mathematically described as:

$$P(i, j : d, \theta) = \#\{(x, y), (x', y') | I(x, y) = i, I(x', y') = j\} \quad (10)$$

Where,

$$(x', y') = (x + d \cos \theta, y + d \sin \theta) \quad (11)$$

Texture Features

As Table 1 show, the following textures can be extracted from input image for classification.

Classification

CNNs are powerful because they automatically extract discriminative features from brain MRI scans (e.g., hippocampal atrophy, cortical thinning and ventricular enlargement) without the need for handcrafted feature engineering. Each layer in the network learns more and more complex features, building up from the bottom. The layered architecture of CNN is shown below in Figure 4.

Input Layer

MRI slices or 3D volumes, e.g., $I(x, y)$ of size 224×224 . Each pixel/voxel contains intensity values of brain tissues. The idea is to input a normalized MRI into the CNN.

Table 1: Texture features

| Feature | Definition | Formula calculation |
|-------------|---------------------------------------|--|
| Contrast | Measures intensity variation | $f_{contrast} = (i - j)^2 P(i, j)$ |
| Energy | Uniformity of texture | $f_{energy} = P(i, j)^2$ |
| Homogeneity | Relativeness to diagonal elements | $f_{homogeneity} = \sum_{i,j} \frac{P(i, j)}{1 + i + j }$ |
| Correlation | Intensity relationship between pixels | $f_{Correlation} = \sum_{i,j} \frac{(i - \mu_i)(j - \mu_j)P(i, j)}{\sigma_i \sigma_j}$ |

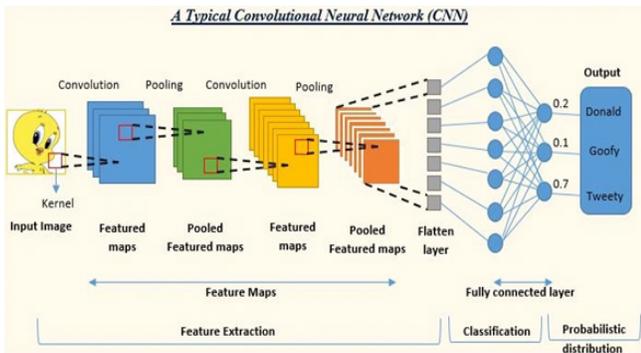


Figure 4: Layered architecture of CNN

Convolutional Layer (Feature Extraction)

Uses multiple kernels/filters to find local features like edges, textures, hippocampal atrophy.

$$(I * K)(x, y) = \sum_m \sum_n I(x + m, y + n) K(m, n) \tag{12}$$

Here, input image is I and kernel is defined by K .

The expected Output is feature map, which is a pattern of MRI. Multiple feature maps will be produced by multiple filters.

Activation Function

The proposed model incorporates non-linearity so that CNN can model complex brain structures. This activation function allows positive values, and rejects negative ones.

$$f(z) = \max(0, z) \tag{13}$$

Pooling Layer

Decreases dimensionality of the feature layers while retaining relevant features The Max Pooling is most often used in disease classification.

$$y = \max_{(i,j) \in R} x_{i,j} \tag{14}$$

R is the window size of pooling (2 X 2).

Stacked Convolution + Pooling Layer

Then convolution + pooling can be repeated multiple times. The early layers means low-level features like edges, contrast. Whereas deeper layers provides high-level features such as cortical thinning, brain atrophy.

Flatten Layer

Converts 2D/3D feature maps into a 1D vector for classification. If feature map = size $a \times b \times c$, then flatten gives vector of length $a.b.c$.

Flattening: 2D/3D feature maps into 1D vector for classification. If feature map = $a \times b \times c$, then flatten returns a vector of length $a.b.c$.

Fully Connected Layer

Each neuron is linked to all features in flatten layer. Analyzes classification global patterns.

$$z = W^T x + b \tag{15}$$

where, W is the weight matrix, x input vector, and b is bias.

Output Layer

The softmax layer is employed during classification, which provides probability distribution across the four classes of mild, very mild, demented and non-demented into the input image.

$$P(y = j|x) = \frac{e^{z_j}}{\sum_{k=1}^C e^{z_k}} \tag{16}$$

where, C represents number of classes.

Training- Back Propagation

In this layer, Adam optimizer updates the weights of kernel by gradient descent. Based on the categorical cross entropy, the loss function can be analyzed:

$$L = - \sum_{i=1}^N \sum_{c=1}^C y_{i,c} \log(y'_{i,c}) \tag{17}$$

Performance Analysis

The proposed work needs to evaluate the performance of the proposed CNN model for Alzheimer’s Disease classification and give an efficacious result for reliability and clinical application. Performance analysis is based on the application of different statistical and machine learning metrics to evaluate the model’s capacity of differentiating between Non-Demented (NC), Mild Cognitive Impairment (MCI) and Alzheimer’s Disease (AD) classes.

Quality Parameters

Accuracy

Accuracy is the general correctness of the classifier.

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{18}$$

Sensitivity or Recall

High sensitivity is of great importance for early detection of Alzheimer’s disease, in order to minimize missed diagnoses. Assesses how well the model can accurately diagnose cases of Alzheimer’s:

$$Sen = \frac{TP}{TP + FN} \quad (19)$$

Specificity

Assesses the model's ability to properly identify non-Alzheimer's subjects. high specificity lowers false alarms.

$$Spe = \frac{TN}{TN + FP} \quad (20)$$

Precision

Proportion of correctly classified Alzheimer's patients among all patients classified as having Alzheimer's:

$$Pre = \frac{TP}{TP + FP} \quad (21)$$

F1-Score

Tradeoff of between precision and recall:

$$F1-Score = 2 \cdot \frac{Precision \times Recall}{Precision + Recall}$$

Here,

TP cases: A true positive case is a case the model predicts as the positive class (i.e. correctly identifying an Alzheimer's patient as Alzheimer's).

TN Cases - Cases the model predicted the negative class (e.g. correctly identifies a healthy subject as Non-Demented).

FP Cases that result when the model is incorrectly predicted to be positive when it should be negative (a "false alarm").

FN Cases - cases where the model predicted negative, but it should have been positive (missed detection).

Performance measure

Accuracy

The training and validation accuracies of the CNN model employed for classification MRI-based Alzheimer's are provided in figure 5 across epochs. Initially, both accuracies are low (roughly 20-25% on training and slightly less on validation), but improve quickly in the first 5 epochs, suggesting that we're learning features well. Training and validation accuracies reach over 90% by epoch 8, and by epoch 10 they abruptly converge to almost 100% accuracy, continuing to stay there for the remainder of the training. The overlapping of the training and validation curves shows that the model is not overfitting and it can be generalized well on unseen data. Performance analysis shows that the CNN takes high classification accuracy with strong generalization ability and is very effective for Alzheimer's detection and classification.

Loss

Figure 6 illustrates the training loss (blue curve) and validation loss (red dashed curve) against the epochs for the

CNN model for Alzheimer's MRI classification. At first, both the training and the validation losses are large (around 1.6) indicating the poor predictive performance. However, the losses decrease quickly over the first 5-7 epochs of training, showing that the discriminative features are well learned from MRI data. After epoch ca. 8, both curves approach low values (near zero), and stay there until the end of the epochs. Importantly, the training and validation loss curves are very similar - there's no sharp split, indicating that the model has good generalization and isn't overfitting to the data. This gradual loss decrease and stabilization of losses proves that the CNN is well-optimized and that the performance of the classification achieved by the CNN is strong with negligible error for training as well as unseen validation sets.

Confusion Matrix

In Figure 7, the confusion matrix of CNN model with four classes for Alzheimer's MRI is presented: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. The model performs extremely well with most

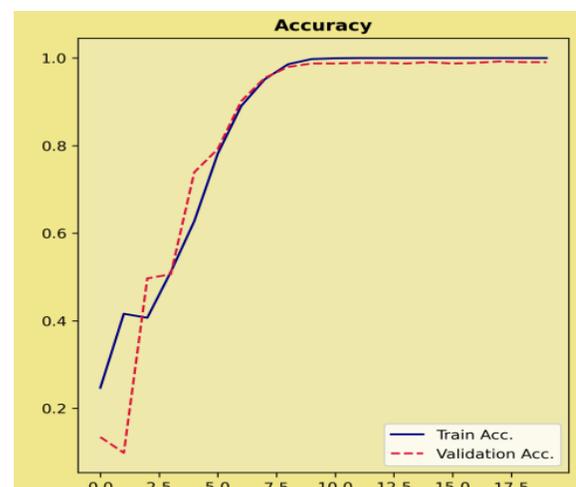


Figure 5: Accuracy analysis in validation and training

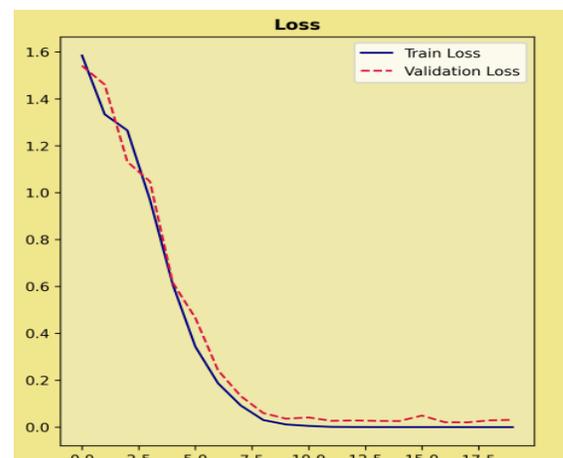


Figure 6: Loss at training and validation

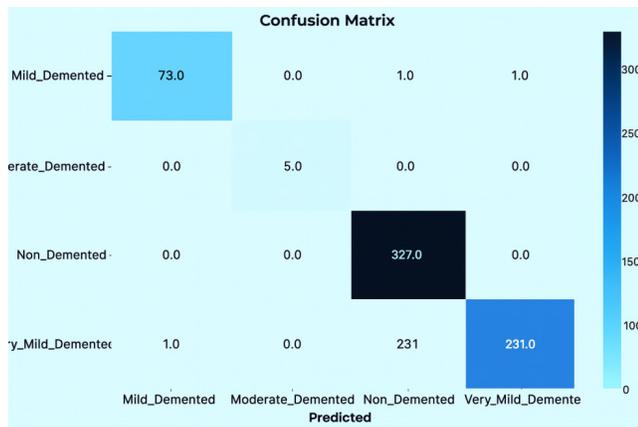


Figure 7: Confusion matrix

Table 2: Classification report

| Class | Precision | Recall | F1-Score | Support |
|--------------------|-----------|--------|----------|---------|
| Mild_Demented | 99 | 97 | 98 | 75 |
| Moderate_Demented | 100 | 100 | 100 | 5 |
| Non_Demented | 99 | 100 | 100 | 327 |
| Very_Mild_Demented | 100 | 99 | 99 | 233 |
| Accuracy | 99 | 99 | 99 | 640 |
| Macro avg | 99 | 99 | 99 | 640 |
| Weighted avg | 99 | 99 | 99 | 640 |

predictions lying along the diagonal. For instance, the Mild Demented case had only two misclassifications while 73 instances were correctly classified, the Non-Demented case had very few misclassifications and 231 Very Mild Demented cases were predicted almost perfectly. The Moderate Demented class, which also had very few samples, was also correctly classified (5 cases), but it's less statistically significant due to its small size. The low off-diagonal numbers reflect extremely low misclassification rates.

Classification Report

The classification report in table 2 shows that the CNN model did well on all four classes of Alzheimer’s disease.

Overall accuracy score on 640 test samples is 99% and macro and weighted average precision, recall, and F1 score results are 0.99, which indicates the performance consistency across balanced and imbalanced classes. With regard to the classification accuracy and recall, for each class, Non-Demented and Very Mild Demented achieved a score of nearly 1 (>=0.99) while Mild Demented achieved a slightly lower F1-score of 0.98. Even the class Moderate Demented with only 5 samples were predicted with 100% accuracy. These results confirm that the model is very accurate, robust, and generalizes well on all the stages of Alzheimer’s patients and is applicable to early detection and classification.

Conclusion

In this research paper, a CNN-based model was developed for prediction and classification of early Alzheimer’s Disease from MRI brain images with very promising results. The model’s total accuracy was 99% with precision, recall, and F1-scores also being 0.99, and showed a very robust performance for all classes including underrepresented classes such as Moderate Demented. Error and loss curves of learning demonstrated that there was no overfitting and confusion matrix revealed a small amount of misclassifications. These results confirm the potential of CNN as an effective tool for automated feature extraction and early Alzheimer’s diagnosis, especially, in the detection of very mild and mild stages of dementia where intervention is of utmost importance. The proposed system has good potential as a computer-aided diagnostic tool, and can be further improved in the future using larger datasets, multi-modal imaging and deployment in a clinical setting in real time.

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