Intelligent Alzheimer's Disease Diagnosing Using a Deep Learning Model

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ABSTRACT

Alzheimer's Disease (AD) is a significant global health concern. As a progressive neurological disorder, AD, a common cause of dementia, leads to a gradual decline in the cognitive function and the ability to perform daily activities. Since early intervention is crucial for helping patients maintain a higher quality of life, researchers are increasingly turning to new technologies for early detection. Artificial Intelligence (AI) and Deep Learning (DL) are proving to be powerful allies in the effort to identify AD sooner, due to their ability to analyze complex medical data, like Magnetic Resonance Imaging (MRI) scans, uncovering patterns that may be missed by the human eye. To contribute to this growing field, this paper proposes two distinct DL models that leverage the brain MRI data. The first approach utilizes a Convolutional Neural Network (CNN) for a binary classification task to distinguish between the healthy individuals and those with dementia. Building on this, the second model offers a more detailed, four-tiered classification system to identify the specific stage of the disease: Non-Demented (ND), Very Mild Demented (VMD), Mild Demented (MD), and Moderate Demented (MOD).

Keywords-Alzheimer's disease; convolutional neural network; deep learning; VGG16 model; EfficientNetB0

I. INTRODUCTION

AD poses a significant and escalating public health concern, accounting for approximately 60% of all dementia cases, and is characterized by the progressive deterioration of memory, cognition, and language functions, while its prevalence rises sharply with age [1]. For those affected, early and accurate diagnosis is paramount, as timely intervention can help manage symptoms and lead to a better patient life quality [2]. Clinicians typically assess the progression of the disease using distinct stages: ND, VMD, MD, and MOD [3].

A critical tool in identifying the subtle neurological changes associated with AD is the MRI. This non-invasive technique provides detailed anatomical images of the brain's soft tissue without using ionizing radiation, making it a safe and powerful diagnostic aid [4]. However, the sheer volume and complexity of the MRI data present a significant challenge for manual analysis. This is where the intersection of AI and computer visional field, which trains machines to interpret visual data, offers a transformative solution [5]. By leveraging AI, specifically Machine Learning (ML) algorithms, systems can be created that are able to detect patterns in medical images that might otherwise be missed. Rather than being explicitly programmed, these ML models are trained on vast datasets to identify the markers of a disease, enhancing the diagnostic decision support for clinicians and improving the patient care [6-8].

DL, a sophisticated subset of ML, has driven many of the recent breakthroughs in this area. Using complex neural networks with many layers, DL models can learn intricate, hierarchical features directly from raw data, such as MRI scans [9]. The power of this approach has led to a surge in the development of DL algorithms tailored specifically for AD diagnosis, promoting the fight against the disease [10, 11]. Research highlights a variety of DL approaches for AD classification. For instance, authors in [1] investigated a transformer-based architecture, the Compact Convolutional Transformer for Alzheimer's Disease (CCTAD), to classify patients into different stages of impairment using brain MRI. The CCTAD model demonstrated high overall accuracy on both the Alzheimer's Disease Neuroimaging Initiative (ADNI) and Kaggle datasets, showing strength in early-stage identification. Similarly, authors in [2] utilized a pretrained ResNet-50 model for a four-class classification (ND, VMD, MD, MOD), achieving a testing accuracy of 80.14%.

Authors in [11] used an ADNI dataset to address multi-class and binary classification problems, reporting a four-class classification accuracy of 41.1% and a binary classification accuracy of 60.3% for distinguishing patients with mild

cognitive impairment. Authors in [12] developed a custom CNN model composed of three Conv2D and MaxPooling layers, which reportedly achieved an accuracy of 96.43% after 40 epochs. In comparison, their implementation of a modified ResNet-50 yielded a lower accuracy of 55.41%. Furthermore, authors in [13] compared the DenseNet-169 and ResNet-50 architectures, concluding that DenseNet-169 performed better for both the training (97.7%) and testing (83.82%) accuracy compared to ResNet-50 (88.70% and 81.92%, respectively).

This work introduces two unique DL models that analyze MRI data, focusing on AD. The first approach utilizes a custom CNN to perform a high-precision binary classification between dementia and non-dementia cases. The second, more granular model expands on this by classifying the four distinct stages of the disease (ND, VMD, MD, and MOD). Together, these models form a robust framework intended to improve the accuracy of both the detection and classification of AD.

II. PROPOSED ALZHEIMER'S DISEASE DETECTION AND CLASSIFICATION MODELS

For the training and testing of the proposed DL models, data were sourced from Kaggle, a widely used data science and ML platform offering over 50,000 publicly available datasets, including brain MRI scans. Two datasets were utilized, the first dataset, consisting of 11,000 MRIs (6,200 non-dementia and 4,700 dementia cases) of size 256×256 pixels [14], is used for the AD diagnosis, whereas the second dataset, consisting of 35,206 MRIs of the same size [15], is employed for the classification of the various stages of AD. From both datasets, 20% of the data were used for model validation and 80% for model training.

To enhance the model generalization and mitigate the overfitting, data augmentation techniques were applied to the training set. As illustrated in Figure 1, these techniques included random horizontal flipping, rotation, rescaling, zooming, and adjustments to image width and height. Artificially increasing the training dataset through these transformations is a crucial step in improving the robustness and accuracy of the DL models.

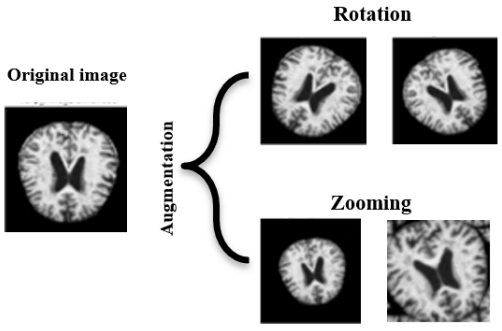


Fig. 1. Preprocessing dataset sample techniques.

A. Detection Model

The general framework for the proposed detection model is displayed in Figure 2.

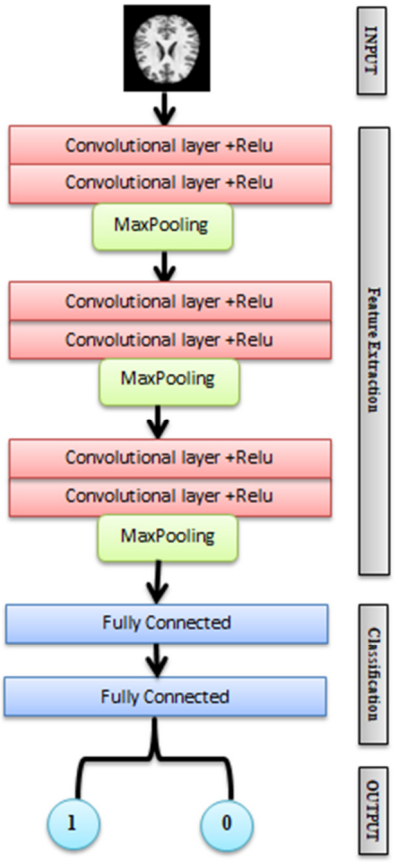


Fig. 2. General framework of the proposed AD detection model.

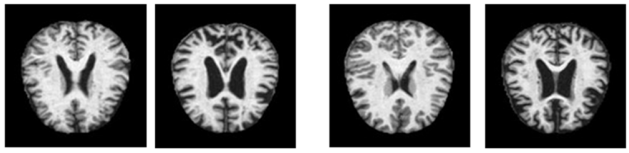
The proposed CNN architecture begins with an input layer that accepts the preprocessed MRI scans, which contain critical information about anatomical changes associated with AD [16]. The core of the model consists of three sequential convolutional blocks responsible for feature extraction. Each block contains a Conv2D layer that applies a set of kernels (filters) to its input, creating feature maps that capture increasingly complex patterns. The number of filters in the convolutional layers is 32, 64, and 128, respectively. Following each Conv2D layer, a MaxPooling2D layer with a pool size of (2, 2) is employed. This max-pooling operation downsamples the feature maps, reducing the number of parameters and computational complexity while retaining the most salient features [17]. After the final convolutional block, a Flatten layer transforms the two-dimensional feature maps into a one-dimensional vector. This vector is then processed by a fully connected dense layer before being passed to the output layer. The output layer consists of a single neuron with a sigmoid activation function, which produces a probability score to classify the input as either dementia or non-dementia. To validate the efficacy of the proposed custom architecture, its performance was benchmarked against the pretrained VGG-16 model [20] using the same dataset.

B. Classification Model

The distribution of MRI images in the second dataset [15] across the four classification categories, ND, VMD, MD, and MOD, is detailed in Table I. To illustrate the visual characteristics of each stage, representative MRI scans from the dataset are presented in Figure 3.

TABLE I. DATASET DISTRIBUTION FOR AD CLASSES

AD class	Number of MRIs
VMD	11,200
MOD	6,528
MD	4,674
ND	12,800



(a) (b) (c) (d)

Fig. 3. Examples of MRI scans for each classification case: (a) MD, (b) MOD, (c) ND, and (d) VMD.

The architecture of the proposed multi-class classification model, depicted in Figure 4, is based on a sequential CNN framework. It is designed to process the input MRI scans, which have been preprocessed into single-channel images of 180×180 pixels. The core feature extraction is performed through two convolutional blocks: the first block comprises a Conv2D layer with 16 filters, and the second block a Conv2D layer with 32 filters. Both convolutional layers utilize a kernel size of 3×3 and the ReLU activation function. To reduce the spatial dimensions and enhance the translation invariance, each block concludes with a MaxPooling2D operation with a pool size of 2×2.

Following the feature extraction, the resulting two-dimensional maps are flattened into a vector and passed to a classification head composed of two sequential, fully connected (Dense) layers. These layers are responsible for interpreting the learned features to make a final classification. The network terminates in a Dense output layer that uses a SoftMax activation function to produce a probability distribution across the four classes, with the highest probability yielding the final prediction.

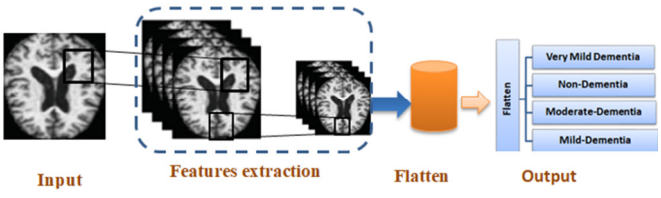


Fig. 4. Proposed AD classification model.

C. Training and Evaluation

The performance of the proposed DL models is assessed using a standard set of evaluation metrics (accuracy, recall, precision, F1-score), which are essential for quantifying their effectiveness in diagnosing AD. These metrics are derived from the confusion matrix components: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). Accuracy represents the proportion of all correctly classified MRI scans, providing an overall measure of the model's performance:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (1)$$

Recall evaluates the model's ability to correctly identify the positive cases. It measures the proportion of the actual positives that are correctly predicted:

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (2)$$

Precision quantifies the proportion of the positive predictions that are correct, reflecting the model's reliability in identifying AD [19]:

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (3)$$

The F1-score is the harmonic mean of precision and recall, offering a balanced metric that is particularly informative when dealing with class imbalance [1]:

$$\text{F1} - \text{score} = \frac{2(\text{Precision}\cdot\text{Recall})}{\text{Precision} + \text{Recall}} \quad (4)$$

The training process for both models was governed by the hyperparameters detailed in Table II.

TABLE II. THE MOST IMPORTANT PARAMETERS FOR THE TWO PROPOSED MODELS

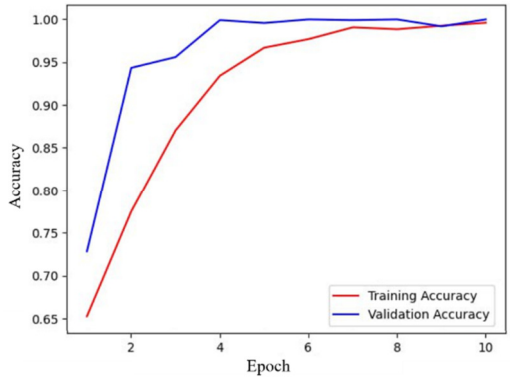
Parameters	Classification model	Detection model
Optimizer	Adam	Adam
Classes	4	2
Activation function	SoftMax	Sigmoid
Loss function	Categorical Cross Entropy	Binary Cross Entropy
Learning rate	0.0001	0.0001

III. RESULTS

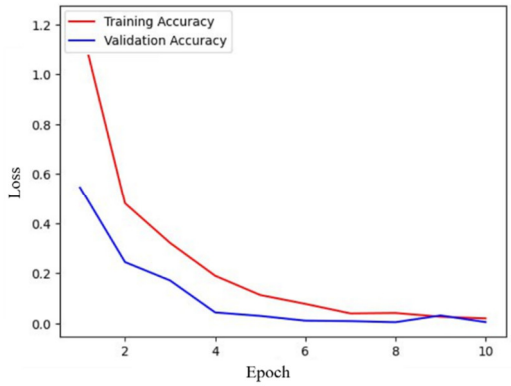
A. Results of the AD Detection Model

The proposed DL model for AD demonstrated robust performance across the training and validation phases. The model's learning dynamics, specifically, the progression of accuracy and loss over time, are illustrated in Figure 5 for both the training and validation sets, confirming a stable learning behavior and minimal overfitting. After 10 training epochs, the model attained a final training accuracy of 99.4% with a corresponding loss of 2.5%, indicating an effective convergence and low training error, a validation accuracy of 99.97%, and validation loss of 0.57%.

As presented in Table III, the proposed CNN-based model outperforms the benchmark VGG16 architecture [17, 19], achieving superior accuracy in the classification of AD-related MRI scans.



(a)



(b)

Fig. 5. Results of proposed AD detection model: (a) accuracy, (b) loss.

TABLE III. COMPARISON OF THE PROPOSED MODEL AGAINST VGG16

Model	Accuracy	Loss
Proposed model	99.40%	2.5%
VGG16 [17, 19]	91.64%	27.69%

The confusion matrix of the proposed model is presented in Figure 6, where class 1 corresponds to dementia cases and class 0 to non-dementia cases.

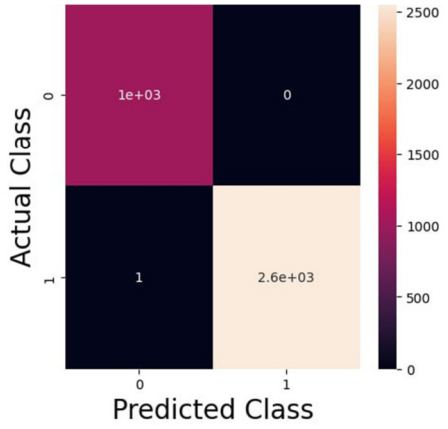


Fig. 6. Confusion matrix of the proposed AD detection model.

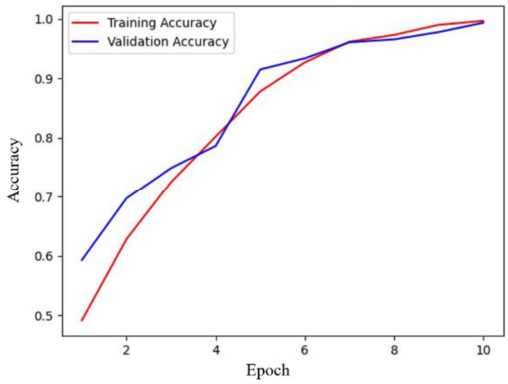
Additionally, Table IV summarizes the key evaluation metrics derived from this matrix. These results demonstrate the model's strong capability to accurately distinguish between the two cases.

TABLE IV. AN ASSESSMENT OF THE PROPOSED ALZHEIMER'S DETECTION MODEL

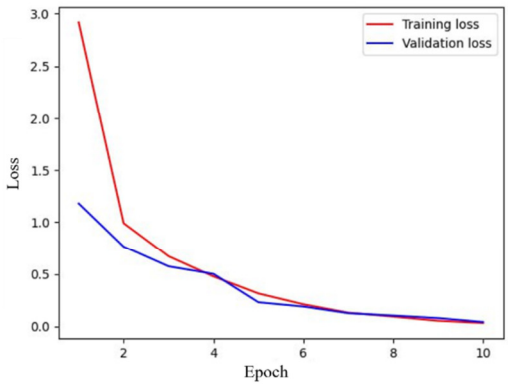
	Precision	Recall	F1-score
Non-dementia	1.00	1.00	1.00
Dementia	1.00	1.00	1.00
Test-accuracy	1.00	1.00	1.00

B. Results of the AD Classification Model

The proposed AD classification model was trained over 10 epochs, achieving a final training accuracy of 99.00% and a training loss of 3.66%, indicating an excellent convergence and minimal overfitting. Additionally, the validation accuracy achieved was 99.34% and the validation loss 4.2%. The full learning progression for both the training and validation sets is portrayed in Figure 7. To benchmark the performance, a comparative analysis was conducted against EfficientNetB0, a well-established CNN architecture [22]. Both models were trained and validated on the same dataset under identical experimental conditions. The comparative results, outlined in Table V, demonstrate that the proposed model consistently outperforms EfficientNetB0 in terms of classification accuracy and computational efficiency.



(a)



(b)

Fig. 7. Results of the AD classification model: (a) accuracy, (b) loss.

TABLE V. COMPARISON OF THE PROPOSED AD CLASSIFICATION WITH EFFICIENTNETSB0

Model	Accuracy	Loss
Proposed classification model	99.00%	3.66%
EfficientNetsB0 [22]	84.75%	53.57%

Figure 8 depicts the confusion matrix [21] of the proposed AD classification model, where class 0 represents the MD cases (717 MRIs), class 1 represents the MOD cases (52 MRIs), class 2 represents the ND cases (2,533 MRIs), and class 3 represents the VMD cases (1,792 MRIs). The comprehensive evaluation metrics for each classification case for the proposed model are presented in Table VI. The proposed model correctly identified 700 out of the 717 cases as MD, 49 out of 52 as MOD, 2,500 out of 2,533 as ND, and 1,400 out of 1,779 as VMD. The overall accuracy achieved was 90.8%.

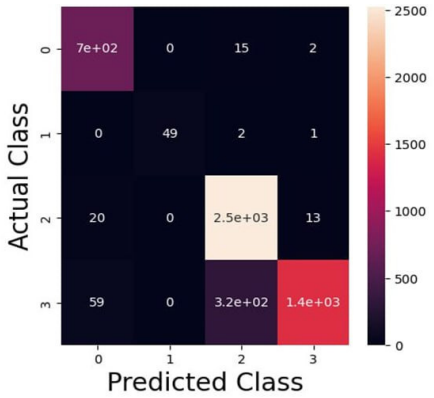


Fig. 8. Confusion matrix of the proposed AD classification model.

TABLE VI. EVALUATION METRICS OF THE PROPOSED AD CLASSIFICATION MODEL

Class	Precision	Recall	F1-score
MD	0.89	0.97	0.93
MOD	1.00	0.94	0.97
ND	0.88	0.98	0.93
VMD	0.98	0.78	0.87
Total	0.94	0.92	0.93

TABLE VII. A SUMMARY OF THE LITERARY WORKS

Ref.	Dataset from	Model used	Accuracy %
[2]	Kaggle	ResNet-50-pretrained CNN	80.14%
[3]	Kaggle	ResNet-50	95%
[12]	ADNI	CNN inspired by VGG19	Classification: 41.1% Detection: 60.3%
[18]	From the AFAC daycare	CNN	90.91%
[23]	Open Access Series of Imaging Studies (OASIS)	(AlexNet, VGG16, ResNet18, ResNet50 and MobileNetV2)	96.8%
[24]	Kaggle	Inception V2	above 90%
Proposed model	Kaggle	CNN	90-99%

The combination of high classification accuracy, computational efficiency, and architectural simplicity positions the proposed CNN models as promising diagnostic tools for AD. As shown in Table VII, the model's performance is not only highly competitive with, but in some instances superior to previously reported methods in the literature.

IV. CONCLUSION AND FUTURE WORK

This research has effectively demonstrated the potential of custom-designed Deep Learning (DL) architectures for the diagnosis of Alzheimer's Disease (AD) using Magnetic Resonance Imaging (MRI) data. Through a two-pronged approach, the study achieved compelling results across distinct diagnostic tasks. In the binary classification of dementia versus non-dementia cases, the proposed custom Convolutional Neural Network (CNN) achieved a notable accuracy of 99.40%, outperforming the well-established VGG16 model. For the more complex task of multi-stage AD classification, the second DL model achieved an impressive accuracy of 99%, surpassing the performance of the widely recognized EfficientNetB0 architecture. The robustness and generalizability of both models were further supported by high F1-scores, indicating a well-balanced performance between precision and recall.

While these results are promising, the path toward clinical implementation presents several important directions for future work. The diagnostic capabilities of the proposed models could be further enhanced through multi-modal integration, combining MRI with additional biomarkers, such as Positron Emission Tomography (PET) imaging or Cerebrospinal Fluid (CSF) analysis. Beyond algorithmic advancements, an essential next step involves the translation of these models into practical tools. For example, the development of a secure and user-friendly mobile application could facilitate early, accessible screening, empowering individuals and caregivers to seek timely medical evaluation, an essential factor in slowing the disease progression and improving the patient outcomes.

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