

DACN-NET: ALZHEIMER'S DISEASE DETECTION USING DATA AUGMENTED CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT

Alzheimer's disease develops progressively and leads to irreversible cognitive decline as well as memory impairment. Therefore, the importance of early and accurate diagnosis cannot be overstated. Hence, the need for clinical intervention and disease management is well established. In this paper, we evaluate the efficacy of various deep learning-based techniques to classify patients with Alzheimer's using structural magnetic resonance imaging (MRI) data. Our study includes the assessment of the performance of multiple CNN (Convolutional Neural Network) architectures, including two of the most popular architectures in the transfer learning approach (i.e., ResNet50 and GoogLeNet). In addition, we developed a new deep learning architecture, DACN-Net, specifically for classifying patients with AD using MRI images, which were preprocessed to grayscale and resized to $128 \times 128 \times 1$ pixels. When comparing the performance of the different models, we found that DACN-Net achieved the best performance, with an accuracy of 93.6%, when classifying patients with AD from the OASIS MRI dataset that included four clinically relevant categories of AD. Our results demonstrate that DACN-Net can accurately classify early-stage cases of AD and suggest that the use of deep learning-based approaches could be a viable tool for the early detection of AD.

Keywords: Alzheimer's disease, MRI, CNN, DACN-Net, ResNet50, Deep Learning.

1. INTRODUCTION

Alzheimer's Disease is characterized as having a slow but predictable course of decline in cognitive function (i.e., the ability to remember), socialization ability, and ultimately an individual's ability to complete basic daily living tasks without assistance. As Alzheimer's Disease typically occurs in elderly individuals, it serves as the number one cause of dementia worldwide. It is estimated that currently, over 55 million people have dementia according to the World Health Organization, with Alzheimer's Disease representing between 60-70% of all cases of dementia. Despite the high prevalence and growing prevalence of this disease, one of the most difficult clinical issues surrounding Alzheimer's Disease is the ability to diagnose the disease early and with

accuracy. The most common means for diagnosing the disease relies heavily on conducting a clinical examination (e.g., physical exam, neurologic assessment), conducting neuropsychological testing, and obtaining imaging studies of the brain. Of the available imaging modalities currently utilized, MRI has proven to be one of the primary imaging modalities for visualizing MRI brain structure changes; however, the expertise of radiologists in interpreting the resulting images can be time-consuming and subject to variation due to different radiologist training backgrounds and experience levels.

Due to the limitations of existing diagnostic methods, many in the healthcare field have turned to Artificial Intelligence (AI), particularly deep

learning (DL), to improve accuracy and efficiency. Deep learning is a type of machine learning that helps create models based on large data sets and that help to identify the hierarchy of features present in an image. Deep convolutional neural networks (CNN) form the basis of deep learning by allowing automatic learning of feature hierarchies within images. CNNs have been used successfully in the detection of tumors, diabetic retinopathy diagnosis, and brain abnormality classification, among countless medical uses. The model divides the input images of OASIS dataset as four classes, namely: (1) Non-Demented, (2) Very Mild Dementia, (3) Mild Dementia, (4) Moderate Dementia.

Pretrained models like VGG16, VGG19, GoogLeNet, and Res Net initially designed to work on large-scale image classification problems like ImageNet have been found to be promising within the transfer learning paradigm in medical images. These models can be fine-tuned on custom datasets to achieve domain-specific tasks like AD detection. The advantage in using pretrained models is that they get to utilize the learning experience, for which they require much smaller amounts of labeled datasets but manage to maintain high performance. For instance, ResNet employs residual connections to address the vanishing gradient issue and enables deeper networks to be trained efficiently. GoogLeNet maximizes computational efficiency through its inception modules, and VGG models, even though they are deep, provide simple and uniform architecture that is simple to fine-tune. Here, we seek to employ and compare a number of CNN-based models such as a DACN-Net and pre-trained networks such as GoogLeNet, and ResNet for the classification of Alzheimer's Disease from structural MRI images. The reason is the demand for an accurate, automated, and scalable diagnostic tool that enables early detection and classification of AD severity.

The goals of this research are:

1. To suggest a technique that helps clinicians identify Alzheimer's Disease by MRI-based image classification.
2. To create a system that differentiates between different stages of Alzheimer's progression utilizing deep learning.
3. To find the best performing deep learning model for AD identification based on thorough performance assessment metrics.

With this work, we aim to further integrate AI-assisted diagnosis into clinical practice, thereby enabling improved patient care and earlier intervention for Alzheimer's Disease.

2. Literature Review

In [1], the MRI data is collected from two independent sources ADNI and OASIS datasets. The data included T1-weighted MRI scans obtained from two common MRI protocols: MPRAGE and IR-SPGR. Structural features were extracted from MRI scans. Several machine learning algorithms were trained to diagnose conditions, including Support Vector Machines (SVM), Random Forest (RF), Decision Trees (DT), and others. These classifiers were trained to differentiate between: (HC) vs. MCI, MCI vs. AD, HC vs. AD, HC vs. MCI vs. AD (multi-diagnostic). Performance was measured using metrics like Balanced Accuracy (BAC) and Matthews Correlation Coefficient (MCC). Performance was robust across different datasets, achieving a balanced accuracy of 62.1% for diagnosing HC, MCI, and AD, and an AUC of 77.7%.

The authors in [2] and [8] presented an approach that uses machine learning algorithms, such as Support Vector Machine (SVM) and Decision Trees, to predict Alzheimer's disease based on psychological factors. In [2], the OASIS dataset is trained on SVM, Random Forest classifier, Decision tree classifier, XG Boost and Voting classifier to effectively distinguish the affected individuals with a high degree of efficiency and speed. 5-fold Cross Validation is performed where the Random Forest classifier attains the highest accuracy of 86.92%. In study [8], the dataset is split into training and testing sets (70% and 30%, respectively). SVM with a linear kernel and Decision Trees are implemented for classification. Using cross-validation to evaluate the model's performance and compare different algorithms. The SVM classifier achieved an accuracy of 85%, while the Decision Tree classifier achieved 83%. Study [4], using the ADNI dataset, was cleaned by selecting the most relevant 22 features (like age, gender, MMSE score, brain volume) and converting all categorical data to a numeric format. Several supervised ML models were tested for accuracy, including: Logistic Regression, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Naive Bayes, Decision Tree, Linear Discriminant Analysis. The data was split into training and test sets using 5-fold cross-validation for evaluation.

The best-performing models were: Logistic Regression with an accuracy of 99.43% on the ADNI dataset. Support Vector Machine with 99.10% accuracy. On the OASIS dataset, Logistic

Regression and Random Forest achieved 84.33% and 83.92% accuracy, respectively. In [7], the authors use a Graph Convolutional Network (GCN) to model brain connectivity. They convert brain imaging data into graph structures where nodes represent regions of interest (ROIs) in the brain, and edges represent functional or structural connectivity between these regions.

The GCN processes these graph representations to predict whether a subject has Autism Spectrum Disorder (ASD) or Alzheimer's Disease (AD). The dataset includes functional Magnetic Resonance Imaging (fMRI) data for ASD and structural MRI data for AD. The investigations in [1] demonstrate how to use MRI data gathered from two distinct locations, ADNI and OASIS. The developed models for the study also tested accurate models on multiple stages of progression toward developing Alzheimer's disease (AD) using cerebrospinal fluid (CSF) samples taken from dementia patients. The CSF samples were tested for the three major biomarkers associated with AD: amyloid-beta ($A\beta_{42}$), total tau (t-tau) and phosphorylated tau (p-tau). All of the CSF biomarker concentrations were statistically correlated with the incidence of AD and used for predicting AD from machine learning predictive models about AD progression using the concentrations of biomarkers measured.

In another paper, [10] by Zhou et al., a further evaluation of CSF testing's value as a tool for diagnosing AD is presented; machine learning algorithms have achieved up to 85% prediction accuracy in differentiating early stages of AD from stable patients based upon CSF biomarker concentrations. An Area Under Curve (AUC) score of about 0.89 was achieved using these CSF concentration machine learning models, thus further supporting the role of these three biomarker concentrations in diagnosing Alzheimer's Disease very early. Thus, the testing of CSF concentrations can be an important tool for identifying Alzheimer's Disease and providing treatment decisions even before a patient's diagnosis of Dementia.

The research [12] suggests an enhancement to ResNet-50 with a Mish activation function to enhance gradient flow and accuracy, instead of the classic ReLU that is used. The authors developed a model incorporating Spatial Transformer Networks (STN's) to offer spatial invariance while including a non-local architecture to capture long-range dependencies from the feature domain. Trained and validated on ADNI dataset with all MRI images being pre-processed for consistency. All the classifiers were evaluated using K-fold cross-validation against the baseline ResNet-50 model with an accuracy rate of 97.1% and macroscopic precision, recall, and F1 scores of 95.5%, 95.3%, and 95.4%, respectively.

The article [15] provides 3 new models that utilize 2D CNN techniques (Alex Net, LeNet-5, VGG, GoogLeNet, Respects to Dense Net) that focus on both the level of pixel detail as well as the analysis of the brain slices to improve AD classifications. As for the 3 models created in this paper, sBPCNNs reach an accuracy of 88.55%, SACNNs reach 91.68%, and MSCNNs reach 93.75%, respectively. The study [16] proposed a deep learning method to classify patients suffering from Alzheimer's disease into four categories: Non-Dementia, Very Mild Dementia, Mild Dementia, and Moderate Dementia using two deep learning tools, DenseNet-169 and ResNet-50 CNN architectures. It was determined that DenseNet-169 produced more accurate results than ResNet-50, with training and testing accuracies of 97.7% and 83.82%, respectively. Therefore, the DenseNet-169 version of this model is ideal for evaluating individuals with real-time AD diagnosis. Table 1 compares and contrasts existing studies on the classification of Alzheimer's disease based on the model type, the dataset used, the reported performance, and limitations. The comparison shows how the traditional machine learning models have evolved to the sophisticated deep learning models.

Table 1: Comparative Analysis of Existing Literature on Alzheimer's Disease Classification

Ref. No.	Study Focus	Model / Method Used	Dataset Used	Reported Performance	Limitations
[1]	Early AD diagnosis using ML	SVM, Random Forest, Decision Tree	ADNI + OASIS	Balanced Accuracy: 62.1%, AUC: 77.7%	Depends on extracted structural features; limited performance for multi-class classification; not end-to-end deep learning

[2]	Early-stage AD prediction	SVM, Random Forest, Decision Tree, XG Boost, Voting Classifier	OASIS	Accuracy: 86.92% (Random Forest best)	Requires feature engineering; does not capture deep spatial features from MRI images
[4]	ML-based AD detection	Logistic Regression, SVM, Random Forest	ADNI and OASIS	ADNI: up to 99.43%, OASIS: ~84%	High-performance dataset-specific; relies on selected features, not image-based deep learning
[7]	Brain connectivity modeling	Graph Convolutional Network (GCN)	fMRI (ASD) + structural MRI (AD)	Not explicitly stated	Requires graph construction and non-imaging relationships; more complex pipeline
[10]	Biomarker-based prediction	Machine learning on CSF biomarkers	CSF biomarker data	Accuracy ~85%, AUC ~0.89	Depends on biomarker availability; not purely MRI-based; clinical data dependency
[12]	Improved deep learning model	Enhanced ResNet with Mish, STN, and non-local architecture	ADNI	Accuracy: 97.1%	High computational complexity; requires advanced architecture and tuning
[15]	CNN-based AD classification	2D CNN models (Alex Net, VGG, GoogLeNet, Dense Net variants)	MRI brain slices	Accuracy up to 93.75%	Slice-based learning may miss full 3D brain structure
[16]	Deep CNN comparison	DenseNet-169 and ResNet-50	MRI dataset	Dense Net: 83.82% testing accuracy	Deep models prone to overfitting on limited data; higher computational cost

Based on the comparison one can note that traditional machine learning methods are heavily dependent on handcrafted features and demonstrate little ability to capture complex patterns of space based on MRI data. Deep learning models have made progresses but they tend to consume complicated models and intense computing resources. The proposed DACN-Net addresses these shortcomings by offering a lightweight CNN architecture along with GAN-based augmentation to deal with the issue of class imbalance without compromising on accuracy.

3. DATASET DESCRIPTION

The OASIS (Open Access Series of Imaging Studies) database provides neuroimaging resources for Alzheimer's Disease research that are publicly available. The high-resolution T1-weighted MRI images are taken from healthy individuals and patients who have an Alzheimer's Disease diagnosis across a wide range of ages. Each subject in this database has been assigned a Clinical Dementia Rating (CDR) Score, where CDR = 0 indicates non-demented subjects, CDR = 0.5 refers to very mild dementia or mild cognitive impairment, CDR = 1 refers to mild dementia, and CDR = 2 refers to moderate dementia. The illustration of the

classification and labelling system used in creating this dataset is shown in Fig. 1.

In addition to MRI images, the OASIS database also contains demographic and clinical characteristics of subjects such as age, gender, education level and Mini-Mental State Examination (MMSE) scores.

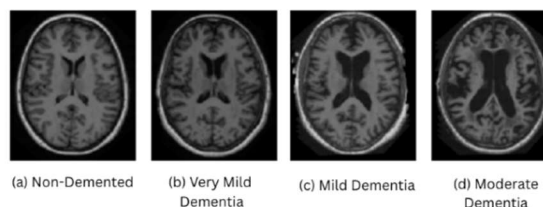


Fig. 1: Growing severity of Neuron Degeneration

All MRI images were obtained using standard imaging protocols to ensure consistency in the MRI scan results. The OASIS database provides the ability to analyse both cross-sectional and longitudinal data, allowing researchers to track the progression of Alzheimer's Disease. Despite the fact that OASIS is a small dataset compared to some of the other databases available today for training Deep Learning models, the dataset has been thoroughly vetted and used extensively in academic studies; therefore, when Deep Learning models are used with

OASIS, researchers will often apply data augmentation techniques to improve generalization in Deep Learning models. Finally, because OASIS contains publicly available data and info relevant to clinical Alzheimer's Disease practice, it is often considered the benchmark for automated prediction research in Alzheimer's Disease.

The OASIS dataset consists of MRI scans from 461 subjects, which were preprocessed and converted into 2D image slices for deep learning purposes. Each MRI volume was divided into multiple slices, resulting in approximately 80,000 images. These slices were categorized into four classes based on Clinical Dementia Rating (CDR) values, leading to an imbalanced distribution across classes. The dataset exhibits significant class imbalance, with a larger number of non-demented slices compared to moderate dementia cases, which necessitates the use of GAN-based augmentation techniques.

4. METHODOLOGY

The framework consists of the proposed DACN-Net along with transfer learning models such as ResNet50 and InceptionV3. These models were selected due to their strong performance in image classification tasks and their ability to effectively extract hierarchical features from MRI data. To alleviate the class imbalance in our dataset we are proposing an approach using a Generative Adversarial Network (GAN), which consists of Generative and Discriminative Neural Networks in conjunction with other traditional Data Augmentation methods. The Generative network's primary function is to create counterfeit data samples that are as closely matched to actual data points of the less frequent or minority class as possible while the Discriminative network's role is to assess whether or not the samples produced by the Generative Network are real versus counterfeit. By using the same method to continually produce counterfeit examples for the minority class in this approach, we are effectively creating new samples that will allow us to achieve a balanced dataset. The images are loaded in grayscale mode in order to simplify the data, and then the images are scaled to (128,128) pixels in order to standardize input shapes for all models.

4.1 Data Augmentation

Traditional Data Augmentation processes consisting of horizontal flips, random rotations (within ± 20 degrees), shear transformations, horizontal shifts (up to 20% of width), vertical shifts

(up to 20% of height), and replacing blank pixel values with the value of the nearest pixel were used. These methods were used to produce many more synthetic & real images of each class, therefore increasing the diversity of the sample data for the underrepresented classes. After applying data augmentation techniques to create additional images, the augmented dataset increases the model's exposure to diverse sets of visual patterns associated with the classification of each stage of the disease and increases the robustness and generalization of the resulting output. The Alzheimer's disease dataset, used in this classification tasks, suffers from class imbalance, particularly between categories such as Non-Demented and Moderate Demented. This imbalance can bias deep learning models toward majority classes, reducing their generalization ability and degrading performance on minority classes. To mitigate this, a Deep Convolutional Generative Adversarial Network (DCGAN) along with other traditional data augmentation techniques were implemented to generate synthetic samples for underrepresented classes, effectively balancing the dataset and enhancing model robustness. The architecture of the DCGAN consists of two parts generator and a discriminator. The DCGAN model was trained with a latent space dimension of 100. The model was trained for 50 epochs with a batch size of 32 using the Adam optimizer with a learning rate of 0.0002. The synthetic images were created for underrepresented classes, with about 1000 images per class to balance the dataset. The images generated were visually checked to make sure that they were structurally similar with real MRI scans. Even though GAN-based augmentation enhances class balance, possible risks, including the cross-entropy as the artifacts, were taken into consideration during assessment.

The input to discriminator consists of images with shape (128,128,1) which is consistent with the Alzheimer's disease dataset. It consists of stacked Conv2D layers which gradually reduce spatial dimensions while increasing depth, enabling the model to learn both local and global image features. It consists of Leaky ReLU activation function which avoids the 'dying ReLU' problem and supports better gradient flow. A 40% dropout rate is used before the dense layer to 18 reduce overfitting, especially important due to the adversarial nature of training. Finally it outputs a probability score indicating whether an image is fake or real using a sigmoid activation function. As the classification between real and generated images is binary, we use binary cross-entropy as the loss function. The input

to the generator includes a 100-dimensional noise vector, which is the cause of the diversity of the generated image, a set of Conv2DTranspose layers, which incrementally upscale the image to 128*128 resolution & Leaky ReLU layers. The tanh activation in the last Conv2D layer which gives output of pixel values within the range $[-1,1]$. The

generator is compiled using the binary_crossentropy loss function and the Adam-based optimizer.

4.1.1 Training configuration

The models were all trained with a batch size of 32 using the Adam optimizer with a learning rate of 0.0002 and 50 epochs. In case of

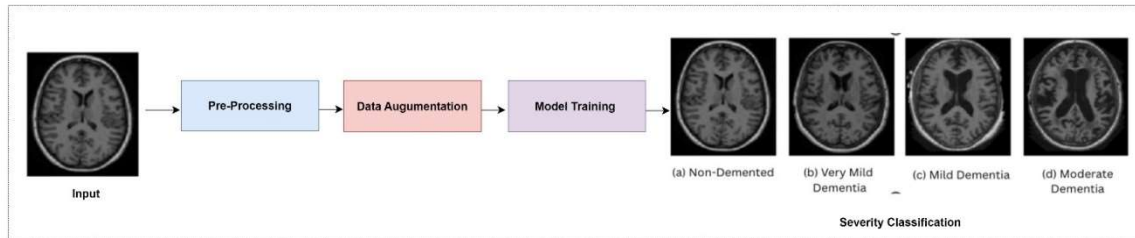


Fig. 2: Block diagram of DACN-Net

the transfer learning models, including ResNet50 and InceptionV3, the pretrained ImageNet weights were employed, and the top classification layers were removed. The convolutional base was frozen, and only the recently added dense layers were trained. The block diagram of the proposed architecture is shown in Fig.2.

4.2 Deep Learning Models

To enhance the accuracy and reliability of the neuroimaging-derived diagnosis of Alzheimer's Disease, a proposed system utilizing strong, deep-learning architectures GoogLeNet is recommended. These models have been chosen based on their unique structural elements, established effectiveness in image classification problems, and transferability through transfer learning. The configuration of the pretrained models is given in Table 2 and the work flow of the model is shown in Fig.3

4.2.1 ResNet Architecture

Res-Net is the short form for Residual Networks. This addresses the problem of depth in the neural networks through the use of shortcuts, which are referred to as residual connections. These connections help in preserving or 'carrying' the gradients during the backpropagation process, thus diminishing the vanishing gradient problem that is rife in deep networks. This makes it possible to construct very deep networks on the ResNet architecture contrary to what it could be seen that the depth reduces performance. In this system, ResNet was used as it is a deep neural network with the

ability to learn high-level features, and due to residual connections, the learning is fast. This model is highly applicable for image classification purposes and, as such, has been confirmed suitable for use in the proposed system.

4.2.2 GoogLeNet Architecture

Also known as Inception v1, GoogLeNet introduces inception modules that allow the network to choose from multiple filter sizes in each block, enhancing its ability to extract diverse features. It uses fewer parameters compared to similarly performing networks by combining multiple types of convolutions in parallel. GoogLeNet is effective in managing computational complexity while still achieving high classification accuracy, making it well-suited for medical image analysis tasks such as AD detection.

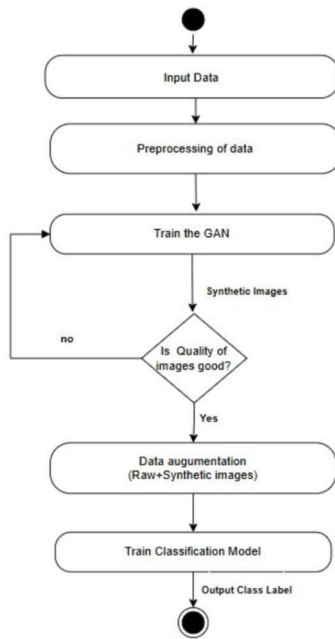


Fig. 3: Workflow of GAN-Based Data Augmentation and Classification

Table 2: Pretrained Configuration of Transfer Learning Models

Model	Pretrained Dataset	Input Size	Layers Used (Base)	Layers Frozen	Trainable Layers	Classification Head	Output Classes
ResNet50	ImageNet	128 × 128	Convolutional base	All base layers	Dense layers only	Global Average Pooling + Dense (512, ReLU) + Dense (128, ReLU) + Softmax	4
InceptionV3	ImageNet	128 × 128	Convolutional base	All base layers	Dense layers only	Global Average Pooling + Dense (512, ReLU) + Dense (128, ReLU) + Softmax	4

4.2.3. Proposed Architecture for Alzheimer's disease Detection: DACN- Net

The proposed DACN-Net as shown in Fig.4 is a tailor-made Convolutional Neural Network (CNN) that has been developed to classify the MRI images of the Alzheimer's Disease. The input of the model is grayscale images with the size of 128 × 128 × 1. The architecture is designed with a series of convolutional layers with larger filter sizes to capture hierarchical features. ReLU activation follows each convolutional layer, and Max Pooling layers reduce spatial dimensions and computational complexity. This network will start with two convolutional layers, each with 32 filters, with a pooling layer in between. Later layers expand filter depth to 64, 128, and allow more complex features

to be extracted. The feature maps are then flattened into a one dimensional vector and passed through a fully connected dense layer with 128 neurons, followed by a dropout layer with a rate of 0.5 to prevent overfitting. The ultimate output layer will have four neurons with SoftMax activation that corresponds to the four classes of Alzheimer's disease. The architecture is designed to balance performance and computational efficiency, making it suitable for medical image classification tasks. Table 3 demonstrates the Layer-wise Architecture of DACN-Net with Output Shapes

The mathematical formulation of the proposed DACN-Net model, which shows the process of extracting the features and classifying them, is stated as follows:

$$P(i, j, k) = \max_{(m, n) \in \Omega} [\max(0, \sum_c \sum_u \sum_v X(i + u, j + v, c) \cdot K(u, v, c, k) + b_k)] \quad (1)$$

$$L = - \sum_{(c = 1 \text{ to } 4)} y_c \log (\exp(W_c \cdot x + b_c) / \sum_{(k = 1 \text{ to } 4)} \exp(W_k \cdot x + b_k)) \quad (2)$$

The input feature map, denoted by $X(i,j,c)$, is combined with ReLU activation and max-pooling operations to extract features of the input data.

$X(i,j,c)$ can be used to represent the feature of the input data. $K(u,v,c,k)$ is used to represent the convolution kernel. The feature map results are then pooled over a local window Ω to generate $P(i,j,k)$, the most important spatial features. The pooled feature maps are flattened into a vector x and fed through a fully connected layer characterized by weights W_c and bias b_c , producing class scores. The Softmax function is used to convert these scores into probabilities, and the categorical cross-entropy loss L is computed in terms of the ground truth labels y_c and predicted probabilities

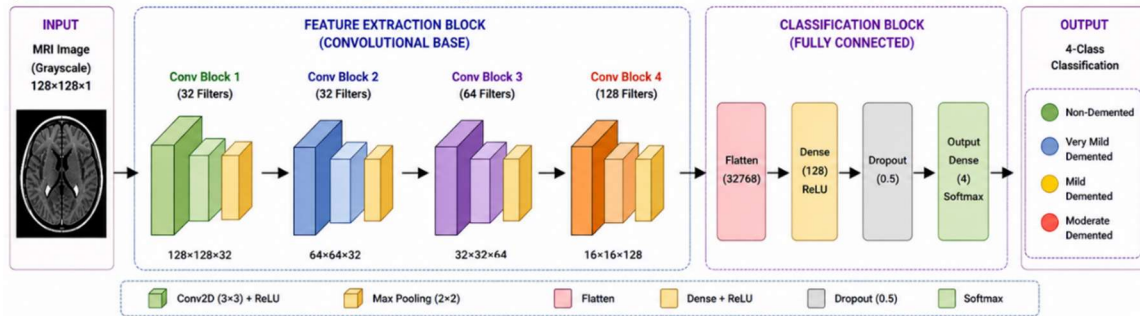


Fig. 4: Architecture of the Proposed Model DACN-Net

Table 3: Layer-wise Architecture of DACN-Net with Output Shapes

Layer	Type	Filters	Kernel	Output Shape
Input	-	-	-	128x128x1
Conv1	Conv2D	32	3x3	128x128x32
Conv2	Conv2D	32	3x3	128x128x32
Pool1	MaxPool	-	2x2	64x64x32
Conv3	Conv2D	64	3x3	64x64x64
Pool2	Max Pool	-	2x2	32x32x64
Conv4	Conv2D	128	3x3	32x32x128
Pool3	Max Pool	-	2x2	16x16x128
Flatten	-	-	-	32768
Dense	FC	128	-	128
Dropout	-	-	-	-
Output	FC	4	-	4

Each convolutional layer uses a kernel size of 3×3 with ReLU activation and ‘same’ padding. The 2×2 window of max pooling layers has stride 2. An artificial dropout layer (rate: 0.5) is placed in front of the fully connected layer. Table 4 shows the architectural comparison of the models to the proposed model

5. RESULTS

5.1 Experimental Setup

Python is used to build and execute the experiments in a cloud-based Jupyter Notebook environment called Google Colab, where 12 GB of available RAM and free GPU access allow for faster training and testing of models through the use of various Machine Learning frameworks such as TensorFlow and Keras (ML) and Flask, Streamlit for deployment.

5.2 Performance Metrics

Performance metrics, such as accuracy, precision, recall, and F1-score, are used to evaluate the models' performance. The metrics of the proposed model are represented in Table 5 below, indicating optimal results for the proposed work.

Table 5: Results of Alzheimer's Detection classification on the Proposed Model

Label	Precision (%)	Recall (%)	F1-score(%)
Non-Demented	88%	90%	89%
Very Mild Dementia	100%	100%	100%
Mild Dementia	98%	97%	97%
Moderate Dementia	89%	88%	88%

Table 4: Architectural and Performance Comparison of DACN-Net, ResNet50, and InceptionV3 Models

Feature	DACN-Net (Proposed)	ResNet50	InceptionV3
Model Type	Proposed Model	Transfer Learning (Residual Network)	Transfer Learning (Inception Architecture)
Pretrained Weights	No	Yes (ImageNet)	Yes (ImageNet)
Input Size	$128 \times 128 \times 1$	$128 \times 128 \times 1 \rightarrow 3$	$128 \times 128 \times 1 \rightarrow 3$
Architecture Depth	Shallow-Moderate	Very Deep (50 layers)	Deep (Inception modules)
Feature Extraction	Learned from MRI data	Pretrained generic features	Multi-scale pretrained features
Convolution Type	Standard Conv2D	Residual blocks	Inception modules
Pooling	Max Pooling	Global Average Pooling	Global Average Pooling
Fully Connected Layers	128 neurons	512 \rightarrow 128 neurons	512 \rightarrow 128 neurons
Dropout	Yes (0.5)	Optional / Not explicit	Optional / Not explicit
Trainable Layers	All layers	Only top layers	Only top layers
Computational Complexity	Low	High	High
Training Time	Fast	Slow	Slow
Overfitting Risk	Moderate (controlled via dropout)	Lower due to pretraining	Lower due to pretraining
Dataset Compatibility	Highly suitable for small medical datasets	Requires fine-tuning	Requires fine-tuning
Accuracy	93.60%	57.80%	88.60%

The model's metrics indicate its optimal performance on the problem statement. These metrics were selected to assess each model's precision in image categorization and ability to mitigate the effects of the supplemented data. The

Fig.5 shows how the training and testing accuracy of the proposed DACN-Net model change over different epochs.

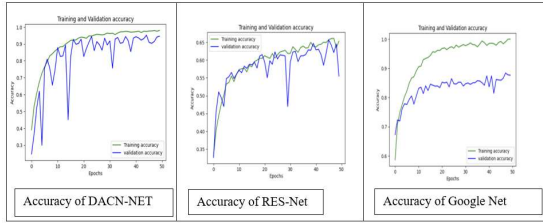


Fig. 5: Training and Accuracy Validation curves of the Proposed Models to RES-Net and GoogLeNet

It can be seen that the training accuracy gradually increases as the model learns meaningful features from the MRI images. The testing accuracy follows a similar pattern and stays close to the training curve, indicating that the model performs well on unseen data. The small difference between the two curves suggests that the model generalizes effectively and does not exhibit significant overfitting.

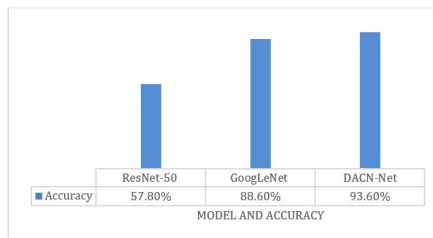


Fig. 6: Accuracy comparison of ResNet-50, GoogLeNet and DACN-Net (proposed model)

Each model was evaluated on a separate test set using accuracy, precision, recall, and F1-score metrics. The best accuracy was 93.6% of the proposed DACN-Net model, and then GoogLeNet (88.6%) and ResNet50 (57.8%). The results, as shown in Fig. 6, demonstrate that DACN-Net is well-suited for this dataset and classification task.

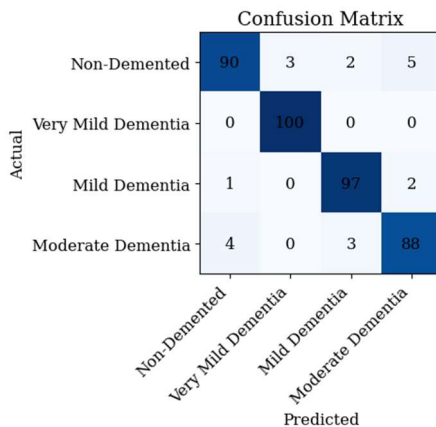


Fig. 7: Confusion matrix of the proposed DACN-Net model illustrating classification performance across Alzheimer's disease categories.

The confusion matrix as in Fig. 7 provides a clear view of how well the proposed DACN-Net model performs across the four Alzheimer's disease categories. Most predictions lie along the diagonal, indicating that the model correctly classifies the majority of samples. The Very Mild Dementia class is identified with perfect accuracy, while minor misclassifications are observed between Mild and Moderate Dementia classes, reflecting the challenge of distinguishing intermediate disease stages

6. CONCLUSION

In this work, we investigated the use of deep learning models to automatically detect and classify Alzheimer's Disease from brain MRI images. A specially designed Convolutional Neural Network (CNN) was proposed and contrasted with two established models: GoogLeNet and ResNet. To improve generalization and reduce overfitting, data augmentation strategies were incorporated into the preprocessing pipeline.

The proposed model proved to be competitively accurate and relatively simple to interpret. GoogleNet and ResNet, with their deep structures and architectures specifically designed for feature extraction, achieved decent classification accuracy. Batch normalization and dropout layers significantly improved the stability of training and model robustness in all the architectures. In general, the combination of data augmentation, transfer learning, and architectural optimization successfully improved model performance on limited medical imaging data. The promising results indicate that deep learning can be a valuable tool in aiding early and correct diagnosis of Alzheimer's Disease, and therefore potentially aiding clinicians in making timely decisions.

The proposed DACN-Net model is highly effective in classifying the stages of the Alzheimer's Disease based on the MRI images. The combination of data augmentation and a DACN-Net architecture helped to achieve a better accuracy. The study is however restricted by the fact that only one dataset has been used. Future research will aim to on evaluating the model on larger and more diverse datasets and exploring explainability techniques to increase clinical trust.

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