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Development of a Deep Learning Model for the classification of Alzheimer's Disease from Magnetic Resonance Imaging

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Abstract
Alzheimer's disease (AD) is a disorder in which the nervous system slowly declines progressively which affects reasoning, forgetting, balancing, daily activities and memory. The early recognition and diagnosis help to manage and treat the disease effectively. Magnetic Resonance Imaging (MRI) especially 3D scan brain imaging which provides detail structural format and information that can aid in recognizing anomalies linked to the various stages of Alzheimer's disease (AD). The problem face with manual interpretation of MRI scans is enormous in terms of accuracy and time consuming with clinical experts. In this study, we propose a deep learning approach for the multi classification of Alzheimer's disease from 3D MRI images. The framework uses Convolutional Neural Networks (CNNs) for developing intelligent model for effective 3D image analysis and interpretation. To enhance classification performance, the extracted region of interest is modified with deep learning classifiers including Efficient Net, SE-ResNet and Dense Net. These architectures improve feature representation, enhance efficiency and improving learning capability of the framework. The results shows that the model achieves accuracy of 83% and precision of 82%, which indicates strong performance. The recall and F1-sore display a balance of 81 % across ford in a distinct phase in the progression of Alzheimer's disease multi class classification. This model will assist the clinicians and radiologist in early interpretation, detection, diagnosis and monitoring of Alzheimer's disease progression.

Keywords: Deep Learning (DL), Efficient Net, Dementia, Alzheimer's disease (AD), Neurodegenerative, Machine Learning (ML).

1. Introduction

Dementia is a neurological disorder identify by progressive cognitive decline which includes Alzheimer's disease. Frontotemporal, vascular, Lewy body and mixed dementia [9]. Dementia develops due to damage to brain cells, also occur due to reduced or blocked blood flow to the brain. This occurrence deprives the brain of essential oxygen and nutrients which can lead to the death of the brain tissue degeneration and impaired cognitive functioning. Dementia refers to a set of disorders that lead to cognitive functions like memory, reasoning, ability to execute daily activities and thinking. Alzheimer's disease is a neurodegenerative disorder categorized by gradual cognitive deterioration and memory impairment; this represents the most common type of dementia [2]. Artificial Intelligence (AI) is a transformative technology with profound implications across many domains, this achieved by developing a thinking machine that can imitate human intelligence initiated by researchers for more than six decades [6].

Algorithms based on machine learning particularly deep learning which is branch of Artificial Intelligence, have been used to detect Alzheimer's disease from MRI scans. Distinguishing between AD classification stages remains a challenge with traditional methods, However, Machine Learning have significantly improved automated Alzheimer's detections [10]. Scientists focus their efforts on developing a model for detecting Alzheimer's disease in its early stages before symptoms become apparent. Early detection of AD has facilitated the detection of Alzheimer's disease symptoms prior to high-risk stages. The effect of the AD in the central brain can be illustrated in figure 1 which shows comparison between the healthy brain (left) and a brain suffering from AD (right) [3].

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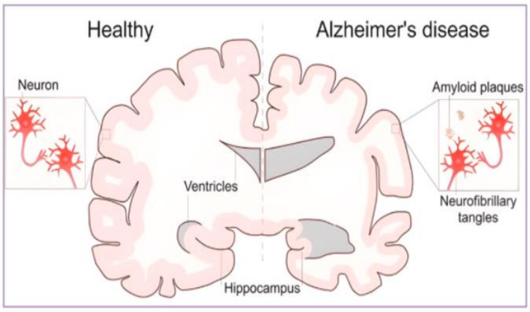

Figure 1: Healthy Brain vs Alzheimer's disease brain (Eqtidar et al, [3])

1.1 Covolutional Neural Networks

Convolutional Neural Network (CNNs) architectures are different neural network designs to enhance how features are learned, recused, example of these architectures is EfficientNet, SE-ResNet and DenseNet. EfficientNet is one of the CNN architectures designed to achieve high accuracy with fewer parameters and computations. Also, SE-ResNet (Sequence-and-Excitation ResNet) which is improve version of ResNet that enhancing feature representation, Residual Network learn to recognize mapping effectively, enabling the training of deep network. DenseNet connects is an enhanced version of ResNet that improving feature representation, Residual Network learn identity mapping effectively, enabling the training of deep network. DenseNet promotes feature reuse and enhancing gradient flow with high performance by connecting each layer to every other layer.

1.2 Magnetic Resonance Imaging

MRI is an advanced technique employed to capture detailed images of the body's internal structures for diagnostic purpose. MRI scans have provided a detailed image of the brain enabling the studying of the brain pattern and region including hippocampus which is a critical region of Alzheimer's disease progression [8]. Manual interpretation of the scanned image with MRI is more challenging and it consume more time and not efficient. Automated approach with Artificial intelligence techniques, notably deep learning has been adopted for diagnosis of Alzheimer's disease (AD) which addressed the shortcomings of traditional approaches of diagnosis.

Consequently, there is a need for an automated scalable computational framework for diagnosing and detecting Alzheimer's disease directly from MRI imaging; to address this gap, this study proposes the development of a deep learning model based on MRI analysis develop to accelerate multi class classification for better capture the complexity of AD thereby improving diagnosis and enable fast caregiving to the patients.

2. Related Works

In a related development, Rubab et al., [7] presents the use of deep learning for early detection of Alzheimer's disease which offer a detail survey of categorization, segmentation and feature extraction techniques. The research solved the challenge by analyzing three-dimensional (3D) cross-section brain MRI images. During data preprocessing, the data classified into different types of brain tissue including gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF). The author acquired data from OASIS, IBSR, FBIRN, ADNI and Kaggle's dataset includes 10,432 scan images designated for testing AD progression.

As illustrated in figure 2, the categorization technique separates the input data into Alzheimer's disease (AD) and non-AD classifications based on the datasets. The result of the findings shows that machine learning enhances prediction accuracy and achieving rates between 80% and 98% when using convolutional neural networks (CNNs) and three-dimensional CNN framework. Although several methods still require further refinement, the result is promising and the solution is considered a valuable technique for supporting radiologists and other healthcare professionals

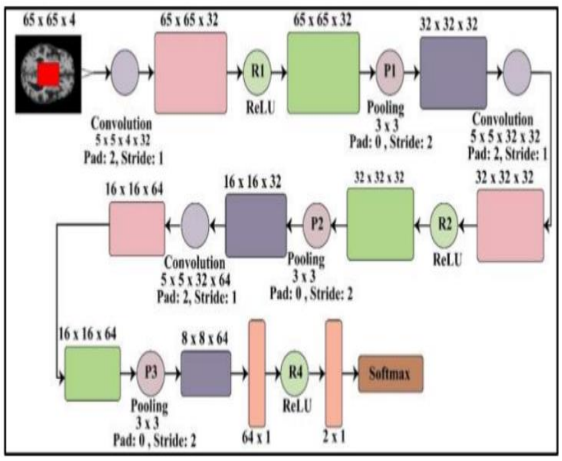

Figure 2: Alzheimer's disease categorization with MRI scans (Rubab et al., [7])

Furthermore, Babatunde et al.,[1] proposes early diagnosis of (AD) for early diagnosis and care. The research examines the use of deep learning which is a subset of artificial intelligence for early prediction and categorization of Alzheimer's disease using magnetic resonance imaging (MRI). Datasets of approximately 44,000 brain MRI scan was collected, categorized into four diagnosis classes (very severe dementia, severe, moderate and mild). These were used to train the framework using a convolutional neural network (CNN).

The framework was validated and tested using multiple deep learning approaches including a CNN, a Spatial-Channel Convolutional Attention Network (SCCAN) and a pre-trained VGG16 (Visual Geometry Group) framework utilizing transfer learning. The researcher's method involves comprehensive data preprocessing, augmentation, normalization and splitting into training, validation and test to ensure strong model performance.

The result displays the effectiveness of deep learning in accuracy categorizing the early stages of Alzheimer's disease, highlighting its potential for integration into clinical diagnostic tools. The author inferred some limitations including dataset diversity, class imbalance and the generalizability of the framework across different populations. The study also demonstrates that deep learning offers reliable, scalable, effectiveness and interpretable solutions for early diagnosis of Alzheimer's disease enabling prompt preventive measures the clients.

Muhammad *et al*, [5] proposes detection and classification of Alzheimer's disease using deep and machine learning. proposes detection and classification of Alzheimer's disease using Deep and Machine Learning. Alzheimer's disease is very difficult to detect in the early stage which can cause delay in timely diagnoses and prevent quick management caregiving. The author offers a realistic approach that combined clinical symptoms with brain imaging to detect and stages of Alzheimer disease progression.

The approach presents a dual-modal framework including four ML classifiers model: K-Nearest Neighbors (KNN), Support vector Machine (SVM), Random Forest (RF) and Decision Tree (DT). These were used to trained on demographic datasets and clinical features. In addition, five DL methods was used for stage wise classification, which includes CNNs, EfficientNetB3, DenseNet-121, ResNet-50 and MobileNetV2 applied with MRI datasets as well.

For stage wise classification, five DL models was used which are CNN, EfficientNetB3, DenseNet-121, ResNet-50, and MobileNetV2 were applied to MRI scans. SHAP and Grad-CAM visualization was incorporated for interpretability The structural markers and amyloid from amyloid PET and MRI are examined using qualitative measurements. The relatively low amyloid burden demonstrates the complex and still unresolved relationship between amyloid PET findings. The brain image techniques strengthened by efficient AI algorithms have showed research pillar in cognitive disorders, with the support of advances in diagnosis, prevention and drug discovery.

The findings demonstrates that the random forest (RF) framework achieves the highest accuracy of 97% on clinical datasets and CNN delivers the strongest overall performance with 94% in MRI-based staging. SHAP and Grad-CAM were applied to find the clinically significant characteristics and brain regions such as hippocampal atrophy and ventricular enlargement.

Another contributor to the problem domain is Lorna and Ismael [4], the author proposes a multi-class Alzheimer's disease categorization from MRI with a ResNet-SE method with improved interpretability. The research solves the critical problem of categorizing Alzheimer's disease (AD) across four different stages of progression refers to as moderate demented, mild, very mild and non-demoted. Magnetic resonance images (MRI) datasets were also used for the analysis and the work is difficult because of class imbalance with the moderate dementia class representing only 1% of the 6,400 images in the dataset.

The approach used is depth Convolutional Neural Network (CNNs) enhanced with LeNet's 5 layers to ResNets hundreds of layers which enables by residual connections that prevent vanishing gradients. ResNet display shortcut connections to implement recognizes mappings expressed as y=f(x) + xy = f(x) + xy= f(x) + x, which allow network to train and learn residual functions and successfully train with over 100 layers. The advancement in the framework architecture has resolved degradation issue in deep plain networks and achieves best performance on ImageNet.

The result of the findings shows that the framework's strong performance with an accuracy of 78.89% a macro F1-score of 82.56% and a weighted F1-score of 79.08%. The recall is 100% for the rare moderate demented class and generate 72.21% for the very mild demented

3. Methodology

The section presents the development of the framework analyzing Magnetic Resonance Imaging (MRI) scans applying the machine learning pipeline on a CNN deep learning model enhanced by Efficient Net, SE-ResNet and DenseNet classifiers. Improvement of datasets was done using feature extractions, transformations and loading from multiple sources. Figure 5 is the architectural framework of the proposed model.

3.1 MRI Datasets and Attributes

The datasets were obtained from the ADNI Repository. This study utilized longitudinal 3D MRI data as the primary data source as illustrated in the figure 3. MRI images from 16, 611 patients aged 60 to 96 were included, each patient scanned at least once during the study, 3, 583 patients were classified as having cognitive Normal (CN); 4,257 of the patients were classified as Moderate Cognitive Impairment (MCI) and 8,761 of the patients were classified as having Alzheimer's disease (AD). Table 1 shows the description of MRI data.

3.2 Data Preprocessing

Addressing quality issues in the MRI scan datasets is necessary in data processing, Real-word data quality issues include duplicate records, invalid data, missing values and outliers. Data preprocessing affects the results of the DL models, the data pre-processing includes normalization, resizing, Noise reduction and data augmentation

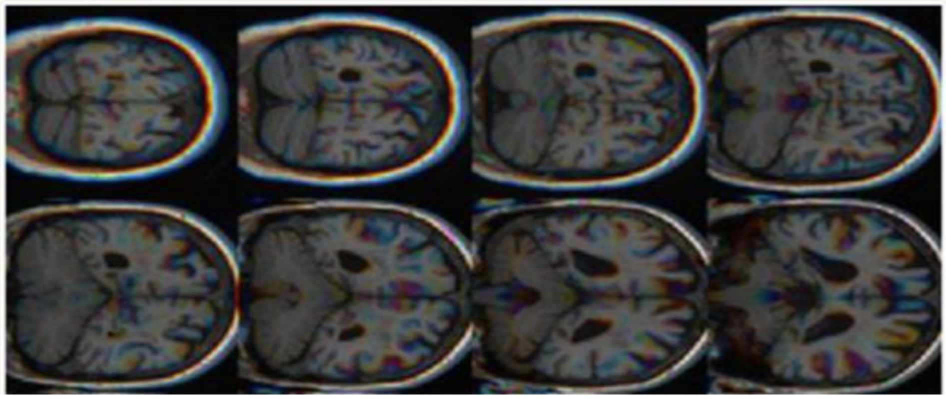

Figure 3: Sample images of the ADNI datasets

Table 1: Demographics Image of the MRI Datasets

CLASS	IMAGE COUNT	MALE	FEMALE
AD	**8,761**	**4,576**	**4,185**
MCI	**4,267**	**2,100**	**2,167**
CN	**3,583**	**1,085**	**2,498**
TOTAL	**16,611**	**7,761**	**8,850**

Multi-Sliced 3D MRI Images Data-Processing

During the preprocessing of 3D magnetic resonance imaging (MRI) scan for Alzheimer's disease (AD) analysis and implementation, brain can be categorized into three orthogonal anatomical perspective includes Axial, coronal and sagittal. Each of the perspective categories are important for precise disease classification as show in Figure 4.

Integrating sagittal, coronal and axial views during 3D MRI data processing strengthens Alzheimer's disease (AD) categorization by capturing complementary spatial and anatomical information. This multi-view method allows deep learning models to extract richer representations for disease related structural alterations. The different three perspectives improves both detection and diagnosis accuracy and clinical of Alzheimer's disease.

3.3 Feature Extraction,

Feature extraction (FE) of AD biomarkers on 3D MRI is the process of measuring anatomical, texture, shape and intensity characteristics of the brain that help detect and diagnosis the AD

3D CNNs Method for extracting hidden patterns from 3D MRI Scans

Extraction of hidden patterns from 3D MRI data for AD analysis is executed on a layer by layer following a structural data processing flow of the dataset.

a. Input Layer: 3D MRI Volume

A 3D MRI scan of the brain is represented as a volumetric tensor:

$$X \in R^{H \times W \times D \times C} \quad \text{...........} \quad (1)$$

Where:

H, W, D = height, width, and depth (number of slices)

- C = number of channels (typically 1 for grayscale MRI)

Sample: A 3D MRI of size 128×128×128 voxels. This volume is fed into the CNN as the input. Each voxel encodes the intensity of a particular tissue type.

b. Convolutional Layer: Local Feature Extraction

The convolutional layer uses **3D kernels to** scan the input volume and extract local features such as edges, textures, or anatomical structures.

Operation:

$$Y^{f}_{I,j,k} = \sum_{u=0}^{k-1} \sum_{v=0}^{k-1} \sum_{w=0}^{k-1} \sum_{v=0}^{k-1} X_{I+u,J+v,K+W} \cdot W_{u,v,w} + b^{f} \quad \text{.............} \quad (2)$$

w^{f} = 3D Kernel for filter f

b^{f} = bias

y^{f} = feature map corresponding to filter f

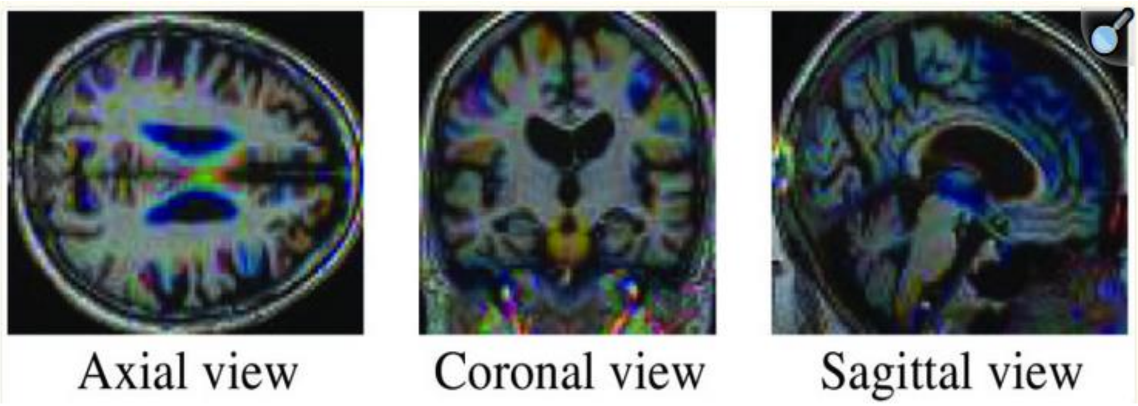

Figure 4: Multi-Slice Brain Images

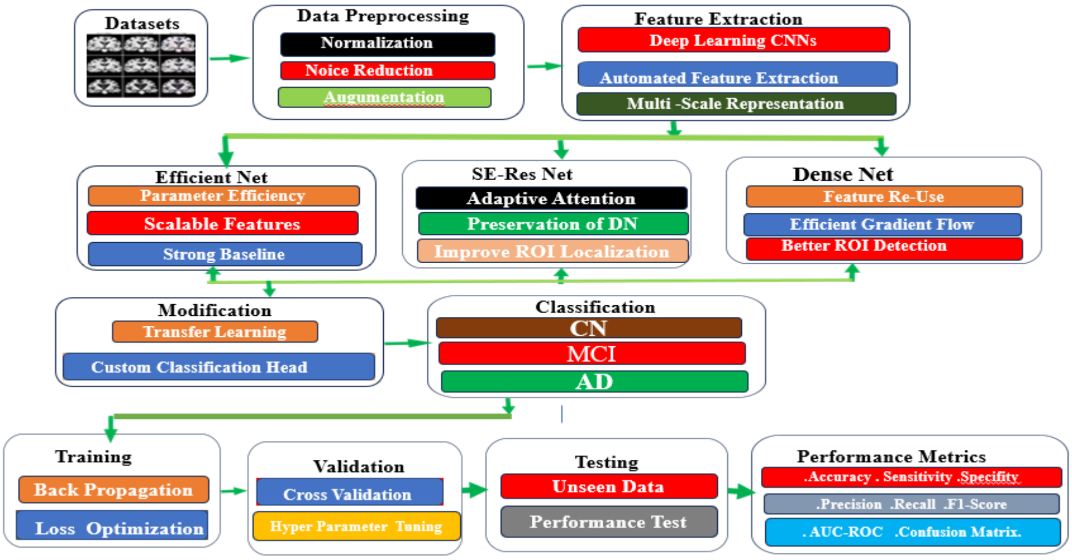

Fig 5: A CNN Architectural Framework for AD Classification Using MRI Images

C. Pooling Layer: Spatial Down sampling
Pooling layers reduces spatial dimensions while retaining dominant features

Operation (Max Pooling):

$$y_{l,j,k} = \sum_{(u,v,w)} \in \text{pool window}^{max} X_{1+U,J+V,K+W} \text{ ....} \textbf{(3)}$$

d. Fully Connected (FC) Layer: Feature Integration
After several convolutional and pooling layers, 3D feature maps are flattened into an ID vector and inputted into fully connected layers.

Operation:

$$y_l = f(\sum_j p_{l,j} x)_j + b^j \text{ .... (4)}$$

Where:
X_j = flattened feature from convolution layer
$W_{i,j}$ $b_{i =}$ weights and biases

F = activation function (e.g, ReLu, sigmoid)

iv. Deep Learning Modified / Advanced CNN Architectures
Modifying a single deep learning model refers to improving the internal structure, learning behavior, or training strategy of one architecture such, EfficientNet, SE-ResNet and DenseNet without combining it with other models. The goal is to enhance performance, generalization, and efficiency while keeping deployment and inference simple. Modifying algorithm implies changing the layers Depth, width and kernel size.

Model-Specific Architecture Modifications with 3D MRI Images (CNNs
Standard CNNs are optimized by increasing the number of convolutional layers, incorporating batch normalization to regularize training and applying dropout to reduce overfitting.

i. EfficientNet (3D adaptation)
EfficientNet models benefit from fine-tuning higher blocks while freezing early layers to preserve generic feature extraction. Additionally, adjusting compound scaling parameters (e.g., B0 to B4) allows the model to achieve high accuracy, fewer parameters. with controlled computational cost.

The scaled EfficientNet model is:

$$N(_{\varnothing}) = \text{Scale}\ (N_0;\ \acute{\alpha}^{\varnothing}{}_{.,}\ \beta^{\varnothing}{}_{.,}\ \ddot{Y}^{\varnothing}{}_{.}) \text{ .... (5)}$$

This equation formally represents the model-specific modification introduced by EfficientNet.

a. Benefits for 3D MRI in AD with Efficient Net architectures

Better parameter efficiency

- Captures volumetric features in 3D MRI with fewer parameters than vanilla CNNs.
- Less prone to overfitting on limited AD datasets.

ii. SE-ResNet (Squeeze-and-Excitation Residual Network) in 3D adaption

SE-ResNet architectures can be optimized by adjusting the SE ratio, which governs channel reduction in SE blocks. Furthermore, inserting SE blocks selectively in deeper layers enhances high-level feature representation while minimizing computational overhead.

a. SE-ResNet Residual Learning

Residual mapping:

$Y = X + F(\mathrm{X}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$

with SE attention applied to F(x)

b. Benefits for 3D MRI in AD with SE-ResNet architectures

Adaptive attention to important features

Channels corresponding to regions affected by AD (e.g., hippocampus, entorhinal cortex) are amplified automatically.

iii. DenseNet (Dense connectivity, 3D adaptation)

In DenseNet architectures, modifying growth rate controls the new feature maps added per layer. Reducing dense block size and growth rate can significantly lower memory consumption and overfitting without substantial performance degradation.

a. DenseNet Growth Rate

Feature map concatenation:

$X_l = H_l([\,X_l, X_l \ldots\ldots\ldots . X_{l-1}\,]), \ldots\ldots\ldots\ldots (7)$

where the growth rate k determines the number of new feature maps added per layer. Modifying a single model through architecture level changes offers a practical balance between performance improvement and computational efficiency.

b. Benefits of 3D MRI in AD with DenseNet architectures

Feature reuse across la Squeeze-and-Excitation Residual Network.

- Small but critical structures (like hippocampal atrophy) are preserved and propagated through the network.

Deep Learning (CNNs) Multiclass Classification of AD

Deep learning model through Convolutional Neural Network (CNNs) has displayed a powerful ability to automatically extract hidden pattern features from magnetic resonance image volumes. To enhance detection and diagnosis accuracy and interoperability feature extraction or selection of (ROIs) which is typically performed before categorization. The model categorized the disease into Cognitive Normal (CN), Mild Cognitive Impairment (MCI), and Alzheimer's disease as illustrated in the figure 6.

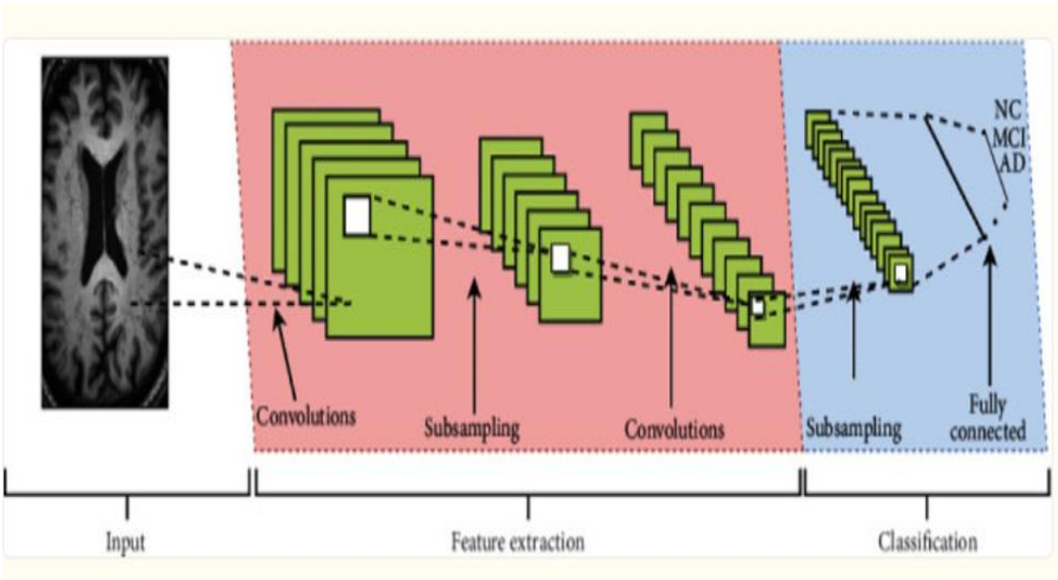

Figure 6: Deep learning (CNNs) Multiclass Classification of AD

Multiclass Classification

The aggregated feature vector is passed to a classification head composed of:

a. Fully connected (dense) layers

The fully connected (FC) layers act as high-level feature interpreters. Each neuron receive input from all neurons in the previous layer. is connected to all neurons in the existing layer and they combine and transform extracted CNN features into a form suitable for classification.

Function:

$Z = \mathrm{Wx} + \mathrm{b}$……………………….………. (8)

Where:

- X is the consociated feature vector
- W and b are trainable weights and biases

b. ReLU activation functions

Each dense layer is followed by execution of the ReLU activation function

ReLU (Z) = max (0, z)…………………(9)

c. Dropout for regularization

After dense layers. Dropout is used to reduce overfitting, temporarily disabling some neurons in the training to aid the network develop strong distributed feature representations

Mathematical intuition:

$\vec{Z} = \{^{0,} \frac{Zj}{1-p} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (10)$

with probability P otherwise

d. SoftMax Output Layer

The output layer contains three neurons representing CN, MCI and AD.

A SoftMax function converts raw outputs into class probabilities:

$\mathbf{P(y = i)} = \frac{e^{zi}}{\sum_{j=1}^{3} e^{z\,j}}$……………. ….(11)

The classifier outputs probabilities for three classes datasets are:

- Cognitively Normal (CN)
- Mild Cognitive Impairment (MCI)
- Alzheimer's disease (AD)

v. Training, Validating, Testing on AD MRI Datasets

Splitting a dataset before training, validating, and testing is the fundamental practice of dividing data into distinct, non-overlapping subsets to ensure a machine learning model generalizes well to new, unseen data, rather than just memorizing the training data. The standard dataset splitting ratios in AD 3D MRI used in this study is 70%, 20%, 10%. This implies:

Description of Each Dataset Split

i. Training Set: Is used to learn model weights. It can also be used to:

- compute gradients,
- update network weights,

ii. Validation set: Model performance accuracy is examined on the validation set as parameters including learning rate and layer quality are fine-tuned.

This is used **during training** for:

- Selecting learning rate
- Early stopping
- Dropout rate tuning

A comprehensive 10-ford cross validation was performed to validate the framework effectiveness and performance across different partitions

iii. Test set: To measure the framework's robustness post-training, the test set is untied exclusively and is not part of the taring or validation stages. This subset is used only once, after training is finished. Table 2 is an illustration description of datasets after splitting.

Table 2: Description of Datasets after splitting

Class Label	Number of MRI-scans	Total slices after data augmentation	Slices in training split	Slices in validation split	Slices in test split
AD	8,761	8,761	6,133	1,314	1,314
MCI	4,267	4,267	2,987	640	640
CN	3,583	3,583	2,508	537	537
TOTAL	16,611	16,611	11,628	2,492	2492

vi. Performance Evaluation Metrics
Performance metrics are utilized to test 3D CNN deep learning algorithms on Alzheimer's disease (AD) 0n 3D MRI datasets. Thus, multiple evaluation metrics are required not only accuracy.

1. Accuracy: Accuracy shows the proportion of correctly predicted MRI scans

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad \text{....……..} \quad (12)$$

2. Precision: Precision measures how many MRIs predicted as a certain class truly.

$$\text{Precision} = \frac{TP}{TP+FP} \quad \ldots\ldots\ldots\ldots\ldots\ldots. \quad (13)$$

3. (Sensitivity) Recall:

$$\text{Recall} = \frac{TP}{TP+FN} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots..\ldots.. \quad (14)$$

4. F1-Score: The F1-score measures the balance in precision and recall through harmonic mean.

$$\text{F1} - \text{score} = \frac{2 - \ Precision - Recall}{Precision + Recall} \quad \ldots\ldots \quad (15)$$

It delivers a single value that harmonizes recall and precision with The F1-score defined as their harmonic average.

4. Results and Discussion

4.1 Infrastructure
Infrastructure for the model development includes:

i. CPU
- Multi-core CPU (6-18 cores, e.g., Intel i7/i9)
- High clock speed (3.5 GHz)

ii. RAM - 64 GB+
- 1-2 TB SSD

iii. Operating System
- Windows works, CUDA and python environment setup

iv. Python Environment
- Python 3.10 or 3.11

Packages:
- PyTorch (preferred for CNNs)
- TensorFlow / Keras (EfficientNet pretrained)
- Torchvision for datsets & models
- Scikit-learn, numpy, pandas for data analysis

4.2. Model
A deep learning framework based on CNNs was implemented and augmented using advanced CNN architecture such as Efficient Net, SE-ResNet and DenseNet

4.3. Evaluation Performance Metrics

Table 3: Evaluation Performance Metrics

5-Fold	Accuracy	Precision	Recall	F1-Score
1	0.82	0.81	0.80	0.80
2	0.85	0.84	0.83	0.83
3	0.83	0.82	0.82	0.82
4	0.84	0.83	0.83	0.83
5	0.81	0.80	0.80	0.80
Average	0.826667	0.816667	0.813333	0.813333

4.4. Confusion Matrix (Test Set)

Table 4: Confusion or Misclassification Test set

	Pred CN	Pred MCI	Pred AD
True CN	28	3	1
True MCI	4	25	3
True AD	0	2	29

4.3. Result Analysis
The result of the proposed model is analyzed and presented in the Table 5 which is illustrated in figure 7.

Table 5: Classification Report per Class Metrics

Class	Accuracy	Precision	Recall	F1-Score
CN	88	88	87	87
MCI	79	79	78	78
AD	90	90	94	92
Micro Avg.	90	86	86	86
Weighted Ave.	86	85	84	84

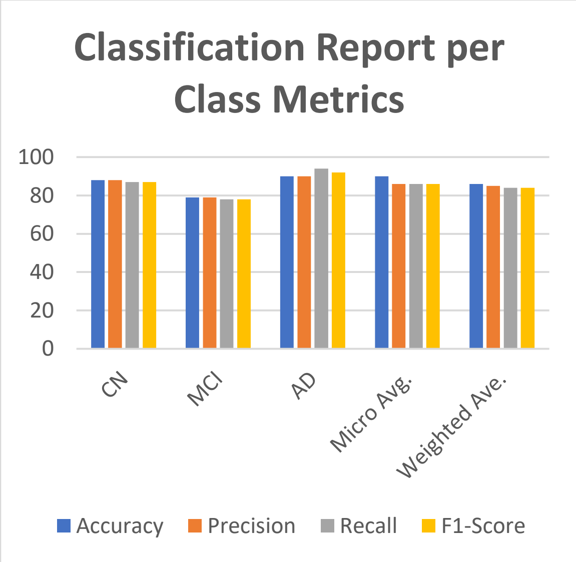

Figure 7: Classification Report per Class Metrics

4.5 Interpretation of Results

As indicated in Table 3, the model displayed stable performance across all folds, with minimal variation that is due to the low standard deviation. The precision and recall closely aligned which shows that the model predict accurately without favoring one class over others. The little differences between folds demonstrates the models's is stable and effective for classifying three target classes (CN, MCI and AD). Summary is illustated in Table 5.

Table 5 demonstrates that the model classified AD most accurately, but display slightly more confusion or misclassification between CN and MCI which is common in MRI datasets. Table 5 illustrates that the model achieves its hignest oucomefor AD diagnosis and detection with precision at (90%) and recall (94%) which suggesting very few misclassified. CN is classified accurately (F1-score 87%), showing relaible recognition of normal brains. MCI display some difficulties as (F1-score 78%), reflecting subtle structural disparities that lead to misclassifications. The model performed robustly over all with AD and CN but MCI detection may require additional image datasets to improve performance.

4.6 Result Discussion

A Convolutional Neural Network (CNN) was developed to perform multiclassification of Alzheimer's diseasewith 3D magnetic resonance imaging (MRI) scans. The model was enhanced by advance CNNs architectures includes Efficient net, SE-ResNet and Dense Net. The results indicate that the framework performs best in diagnosing Alzheimer's disease (AD) achieving a precision of (90%) and a recall of (94) which shows few cases are misclassified. CN is classified accurately (F1-score 87%), showing relaible recognition of normal brains.

Structured Comparison of the Develeoped Model with exixting Model

The proposed 3D CNN framework indicates strong performnce achieving an average accuracy of 82.67% and macro F1-score of 81.33%, compared to the previous models by the authors Lorna & Ismael [4] of 78.89% accuracy and Macro F1-score.

The existing model attains perfect recall (100%) for the rare Moderate Demented class, its performance drops to 71.21% for the very mild class. This is an indication to show variability across categories. Conversely, the proposed model demonstrates consistent performance across folds, with stable effectiveness, accuracy, and overall performance range.

Additionally, the proposed model shows consistent performance across folds with consistent accuracy, effectiveness and performance range from 0.81 to 0.85. It indiactes robust generalization across all classes. The weighted F1-score shows the consistency of the proposed framework displaying its ability to balance performance across both common and rare classes. In general, the model generate a more oustanding and accurate multi calss categorization of Alzheimer's disease in MRI scans

5. Conclusion

The experimental results show that the proposed CNN-based deep learning model for categorization of Alzheimer's disease using MRI data is robust, scalable, effective and reliable for diagnosis. The proposed "AD Neuroimaging-Based Classification System" Classification model displays strong classification capability for AD, reasonable accuracy for CN and moderate performance for MCI. The future research could be an improvement in MCI classification refinement by incorporating more MRI scans multimodal biomarkers or features.

Limitations

Class Imbalance

Classes like CN, MCI and AD may be imbalanced in the MRI data which can lead to data error of the model toward the majority classes and affect sensitivity of the minority classes.

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