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A Novel Deep Learning Framework for MRI Based Classification of Alzheimer's Disease

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Abstract

Alzheimer's is one of the most common type of dementia that affects old-age people. It occurs due to the the damage of brain cells in a patient. This damage affects the capability of brain cells to communicate with each other effectively. Since Alzheimer's is a progressive disease, various other medical conditions may arise over time. There are several research studies that suggest severe concerns in regards to the disease prevalence in the US population. A careful consideration in the context of these studies asserts that it would affect more than 14 million people by the year 2060 in the US region. Therefore it is critically important to diagnose Alzheimer's at early stages to save the patient's life. In recent era, it is a very problematic task for the researcher to diagnose the disease before it becomes fatal. Many recent works have explored the use of deep learning model

for diagnosis of Alzheimer stages but most of the state-of-the-art deep learning models are computationally expensive and suffer from over-fitting and vanishing gradient problem. Also, some of techniques are weak in accurately diagnosing the early stages and utilize imbalance dataset and small dataset.while existing models require high computational resources yet they do not work well with all datasets .The study proposes a lightweight deep learning model for accurate multistage Alzheimer diagnosis. This study we propose a light weight Xception Attention Network(XAtten-Net) model with only 1.2 million parameters which uses separable convolutions instead of standard convolution to reduce the parameter count. The proposed model consists of two datasets i.e. Oasis and Kaggle.The first dataset acheived 95% accuracy, 96% recall, 92% precison and 0.99 F1-Score on the OASIS dataset, while Kaggle attained 91.63% accuracy, 91.63% recall, 87% precision and 0.98 F1-score.

Keywords: Alzheimer's disease, deep learning, multiclass classification, Lightweight Model

1 Introduction

Alzheimer's disease (AD) is classified as one of the most prevalent types of dementia among the various dementia subtypes. Physical changes in brain tissue cause abnormal protein buildups, such as amyloid plaques and tau tangles, which are toxic to neurons responsible for transmitting messages [1]. Neurons are responsible for transmitting signals between different parts of the brain, as well as from the brain to muscles and other organs throughout the body, however, this toxic buildup causes neurons to die gradually. The disorder develops over many years, with damage to brain cells often beginning a decade or more before symptoms even start to appear. Memory loss is the most common and easily recognizable symptom of AD. The affected person loses the capability even to perform daily life activities which is clinically the significant sign of disease severity. As disorder progresses, the damage extends beyond the brain and further impacts the ability to communicate effectively such as finding it difficult to use which words in particular situations. Reading and writing abnormalities also begin to appear as cognitive decline progresses. It is commonly diagnosed in older adults aged above 65 but cases of patients aged between 40 to 50 years are also often reported. Age remains one of the strongest known risk factor even though it's not the sole cause of disorder.Despite the decades of research, scientists could not isolate the single cause of this disorder. Alzheimer's Disease ranks among the top 10 leading causes of mortality worldwide[2]. In 2020 alone, it affected 5.8 million peoples[3] and the number is predicted to reach 14 million by the year 2060. It is commonly diagnosed in older adults aged above 65 but cases of patients aged between 40 to 50 years are also often reported. Age remains one of the strongest known risk factors even though it's not the sole cause of disorder.Despite the decades of research, scientists could not isolate the single cause of this disorder. Alzheimer's Disease ranks among the top 10 leading causes of mortality worldwide[2]. In 2020 alone, it affected 5.8 million people[3] and the number is predicted to reach 14 million by the year 2060.

In the United States alone, the Alzheimer's Association estimates that the affected population will climb to 13.8 million by 2050. Diagnosing remain challenging due to the complex brain structure and fluctuating nature of early signs, which are easily mistaken for normal aging.[4, 5]. As neuron damage continues, patients stuggle to recognize the close family and friends, word finding problem.[6]. In 2017, AD was responsible for 121,404 deaths, making it the fifth leading cause of death in the United States [7] .Early diagnosis of AD and timely medical intervention has shown to significantly improve patient outcome and save life.[8]. In the disease's terminal stages, patients often experience severe behavioral changes alongside respiratory and cardiac complications, which are usually the cause of death [9]. Although early symptoms may appear mild, the deaths of neurons and toxic protein buildups ultimately results in substantial cognitive decline [10]. Over the past decade, the field of medical image analysis has seen rapid advancements, which are largely driven by breakthroughs in the field of Artificial Intelligence, and more specifically in deep learning. Deep artificial neural networks have consistently outperformed traditional machine learning models across a multitude of complex benchmarks. This transformation has deeply affected medical imaging where DL algorithms are capable of learning hierarchical feature representations directly from raw pixel data. The comprehensive utility of deep learning spans the entire MRI processing chain. From initial image acquisition and hardware reconstruction to complex downstream tasks like segmentation and disease prediction, Deep Learning(DL) has fundamentally changed how medical data is handled and interpreted today. To address the diagnostic challenges associated with AD, the research community has developed a range of computer-aided diagnosis (CAD) systems capable of distinguishing between disease stages [11].Recent approaches utilize the advance machine learning and deep learning framework for extracting important features from mri scans and time diagnosis of AD.[12], However, a major portion of existing methods remain limited to binary classification tasks, distinguishing only between healthy controls and AD patients, or propose highly complex, computationally costly deep learning frameworks which cannot be deployed in clinical environments as they have limited computational power.

This study utilized two datasets of Alzheimer disease which are commonly used and publicly available and accessible.The first dataset we selected for our study is oasis-1 which contains 434 3D MRI scans of 416 subjects aged between 18-96. All subjects are right handed and included data from both male and female patients, which makes it gender balanced. The other dataset which we used is Kaggle-6400 dataset, which is also commonly used dataset for validation and assessing generalization capabilities of deep learning models. we propose a lightweight and computationally efficient lightweight model for 4-stage diagnosis of Alzheimer disease called Xception Attention Network(XAtten-Net), which uses separable convolutions instead of standard convolutions to reduce the computational cost.

2 Literature Review

AI's swift growth has revolutionised medical imaging analysis. Deep Learning (DL) stands out as a more successful method because of its ability to automatically extract

feature representations from high-dimensional data, such as MRI and PET scans. Machine learning approaches have been thoroughly studied for the diagnosis of brain related conditions. In particular, architectures like CNN, VGG-16, DenseNet, and VGG-19 have only achieved great accuracy in the diagnosis of cognitive impairment. The literature study that follows examines many deep learning techniques that have recently been used to improve Alzheimer's detection sensitivity and accuracy.

Battineni et al [21] proposed a deep convolutional neural network(ConvNet) based framework for multiclass classification of early stage Alzheimer Disease(AD). They used 2D MRI scans from OASIS-3 dataset comprising of 2168 MRI images of patients at different stages of AD. Their proposed CNN acheived an accuracy of 83.3% and classified AD at four stages. In another study, EL-Geneedy et al. [22] employed a OASIS dataset and sliced mri scans with 6400 images belonging to four classes. They proposed a shallow 2D CNN model. Their proposed model acheived an accuracy of 99.68% and sensitivity of 99.68%.

In the study [24] employed OASIS-3 and kaggle-6400 alzheimer datasets. Their work uses Vision Transformer(ViT) with unique preprocessing strategy that included saggittal plane slicing. PCA is used for dimensionality reduction and watershed segementation is employed to enhance the region wise interpretability. The trained different ViT models on 2D sliced images from above datasets. Best performing ViT acheived an 81.25% accuracy on oasis-3 dataset and 97.34% accuracy on kaggle-6400 dataset. Despite the impressive performance, the model is computationally expensive as it has 86.6 Million parameters.

[25] The study collected 300 instances of gait data and focused on classifying two stages: healthy and Alzheimer's disease (AD). They used a hybrid deep learning model combining CNN and RNN, achieving 93% accuracy and an AUC-ROC of 95%. [26]They collected 798 MRI subjects from ADNI. Diagnosis two stages are AD and CN. They deployed a deep learning architecture,3DCBAM,and 92.92% accuracy, 95.41%sensitivity, 89.88%specificity and 0.9660% AUC. [27]Performed an experiment on 102 MRI subjects collected from ADNI. Diagnoses of different types of Alzheimer's stages are CN, EMCI, and LMCI. They used different deep learning architectures, MobileNetV2 and EfficientNetV2B0; it attained 86.5% and 88%accuracy.

[28]Collected 1300 subject from ADNI. Diagnoses two stages of CN and AD. Deployed different deep learning strategy DenseNet, CNN (Baseline), ResNet-18, Resnet-18(transfer learning) and HST. It attained accuracy of 92%, 81.33%, 80.67%, 95.33% and 92.67%.

[29] This study was proposed two hybrid models and collected a dataset from NACC and ADNI publicly available databases and achieved results in the form of accuracy 99.82% and 96.19%.

[30]Performed experiment on 591 patients.The dataset was collected from public databases and local hospitals of different stages of Alzheimer's AD, FTD and CN achieved accuracy 89% using VGG-16 3D techniques of deep learning.

[31]Performed experiment on 1098 MRI and PET subjects collected from OASIS3. Diagnosis healthy and AD. They used deep learning architecture Fusion. it attained 95% accuracy, 93.33% sensitivity, 96.66%specificity and 93%AUC.

[32]Experiment on two types of imaging modalities, MRI and PET. Those images are collected from ADNI I and categorized into three types: NC, AD, and MCI. The deployed ViT-TST result achieved 99.048% accuracy in the binary classification and 99.014% accuracy in multi-classification.

[33]Gather 2248 subjects from the ADNI. Those subjects are divided into three types of diseases: 118 are AD, 401 are MCI, and 229 are NC. They employed VECNN model has attained 92.14% accuracy, Precision 86.84%, 89.95% sensitivity and 93.27% specificity.

[34]This study experiment was conducted on two stages of Alzheimer's CN and AD. Data was collected from three different public databases: ADNI, OASIS and AIBL. Applied MIMD-3DVT attains 97.14% accuracy. [35]Two methodologies were employed:CNN and VGG-16 with transfer learning, achieving accuracy of 99.99% and 97.44%. MRI images were collected from kaggle and classified as Non-Demented and Mild Demented.

[36]Gathered 1045 MRIs and PETs from ADNI. Performed two experiments: the first is diagnosis between AD, MCI, and CN, and the results are 92.22% sensitivity, 96.07% specificity, 92.17% precision, and 92.26% F1-Score; the second experiment is performed between EMCI and LMCI, and the results are 81.63% sensitivity, 85.19% specificity, 83.33% precision, and 92.268247% F1-Score.

[37]This study deployed the Inception-ResNet wrapper technique and gathered a dataset from OASIS and performed experiments between various stages: HC and MCI, MCI and AD, and HC, achieving results in the form of accuracies of 95.3%, 94.1%, and 95.9%.

[38]The experiment was conducted and collected 412 MRI and 412 PET images from the ADNI. In this study, a distinction was made between EMCI and LMCI, and the methodology implemented was ResNet-18 with 3-channel inputs, and the performance was 73.09% accuracy.

[39]In this study the experiment was conducted on multiple stages of Alzheimer's disease. MRI images were gathered from Kaggle, and a CNN-based lightweight model was deployed for classifying, and overall performance achieved 95.93% accuracy.

[40] Two methodologies were employed: DenseNet-169 and ResNet-50 achieved accuracy at 7.36% and 85.8%. MRI images were collected from kaggle and classified into multiple stages of disease.

[41]In this study ADD-Net methodology was proposed. The dataset was collected from kaggle and classify multiple stages of Alzheimer's. The first experiment was conducted on imbalanced MRI images, and then model performance degraded.The second experiment was conducted on balance dataset then model achieved better results: 98.63% accuracy,99.76%AUC,98.61% F1-score,98.63%precision, 98.58% recall and 0.0549% loss.

[42]In this study two Experiment were conducted. The first dataset was contained 6400 MRI images of four classes of Alzheimer's, and the second dataset was contained 6330 MRI images of three classes. This study proposed model was used VGG-16 and result was achieved are first experiment are 90.4%, 0.905% , 0.904%, 0.969,and 0.904 and second experiment are 71.1%, 0.71%,0.711%, 0.85% , 0.71% accuracy, precision, recall, AUC and F1-score.

Table 1: Research Gaps in Existing Literature

Ref	Year	Stages	Model	Results	Dataset	Limitation
[24]	2025	VMD, MD, MoD, ND	ViT	97.34%/81.25% Acc	Kaggle, OASIS	Complex preprocessing; high cost; high params
[25]	2025	Healthy vs AD	CNN+RNN Hybrid	93% Acc, 95% AUC	300 gait samples	Binary only; small dataset
[26]	2025	AD vs CN	3D-CBAM	92.92% Acc; 95.41% Sens; 89.88% Spec	ADNI-1/2/3/GO	Only two stages diagnosed
[27]	2025	CN, EMCI, LMCI	MobileNetV2, EfficientNetV2B0	86.5/88% Acc	ADNI	High compute cost; poor result
[28]	2025	AD vs CN	DenseNet, CNN (Baseline), ResNet-18, ResNet-18 (TL), HST	92%, 81.33%, 80.67%, 95.33%, 92.67%,; Acc	ADNI	High compute cost; binary only
[29]	2025	I-n-MCI, AD, CN, MCI	Hybrid Model((LSTM+FNN), (ResNet-50+MobileNetV2) ,HST	99.82%,96.91%; Acc	NACC,ADNI	Redundancy is existing when feature learning due to training process is very challenging.
[30]	2024	AD FTD, CN	VGG-16(3D)	89.82% Acc;	ADNI, ULille, FTLDNI	All classes of subject cannot available in every domain comes different domain due to imbalance issue occur.
[31]	2024	AD vs Healthy	Fusion model	95% Acc; 93.33% Sens; 96.6%Spec;93%AUC	OASIS-3	Used multimodality of images but computation power is high and only diagnosis of two stages.
[32]	2024	AD,MCI, NC	ViT-TST	95% Acc; 93.33% Sens; 96.6%Spec;93%AUC	ADNIT1	Computation cost is high.
[33]	2024	AD,HC and MCI	VECNN	92.14% Acc; 86.84% Prec; 93.27%Sens;89.95%Spec;	ADNI	Computational complexity is high and also overfitting issue occur.
[34]	2024	NC and AD	MIMD-3DVT	97.14% Acc;	OASIS,ADNI, AIBL	Dataset are collected from different domain and dataset is very small. Training process is very challenging.
[35]	2024	Mild-Dementedvs Non-Demented	CNN, VGG-16	97.99%, 97.44% Acc;	Kaggle	Trainable parameter is high and also overfitting issue faces and just diagnosis also two stages.
[36]	2023	AD,MCI and CN, LMCI vs EMCI	BLADNET	92.22% , 96.07%, 92.17%, 92.26% , 81.63% , 85.19% , 83.33% , 82.47%, Sens; Spec;, Prec;, F1-Score Acc;	ADNI1,ADNI 2/GO	Model complexity is high because its structure is hybrid and this model perform not well in real patient data because real data has its own features.
[37]	2023	AD vs HC MCI vs AD, HC vs MCI	I-RNWCNN	95.9%, 94.1%, 95.3% Acc;	OASIS	Focus binary classification and use hybrid structure of mode parameter is high .
[38]	2023	EMCI vs LMCI	Resnet-18(3 channel)	73.09% Acc;	ADNI	Resulting performance is poor .
[39]	2023	Mild Demented, Moderate Demented, Non-Demented, Very Mild Demented	Light weight CNN	95.93% Acc;	Kaggle	Required high computational resources.
[40]	2023	MID, MOD, ND, VMD	DenseNet-169, Resnet-50	87.36% 85.8% Acc;	Kaggle	Trainable parameter is high and also overfitting issue faces .

NC: Normal Control, **AD**: Alzheimer's Disease, **MCI**: Mild Cognitive Impairment, **VMD/MD/MoD/ND**: Very Mild/Mild/Moderate/Non Demented, **EMCI/LMCI**: Early/Late MCI, **pMCI/sMCI**: progressive/stable MCI, **CN**: Cognitively Normal, **TL**: Transfer Learning, **Acc**: Accuracy, **Sens**: Sensitivity, **Spec**: Specificity

[43]Gather 855 subjects of PET images from the ADNI website publicly available. Those subjects are dividing into two types of diseases: 635 are normal brain subjects and 220 are AD. The CNN model employed has attained 96% accuracy, 96% sensitivity and 94% specificity.

[44]Experiment were conducted on two datasets, ADNI and MIRIAD. The first dataset is divided into two categories, 427NC and 314AD, while the second dataset contained 23 Normal and 46 AD patient. In this study,the ResNet-50 architecture was proposed in different ways on both datasets. The proposed model was used with Softmax, SVM, and RF, and result are attained in the form of accuracy: The best result for the first dataset is 99% and for the second dataset, 96%.

[45]In this experiment, dataset was collected from kaggle. These datasets were divided into four stages of Alzheimer's: non-dementia, mild-dementia, very mild dementia and moderate dementia. Employed two CNN architecture based technique Res-Net 50 and DenseNet-169. The performance achieved by both techniques is 0.8192% and 0.8382% accuracy.

[46]In this study, experiments were conducted on two dataset dataset1 and dataset2. The first dataset contain 6400 and second 6330 MRI images.Both data set are available on kaggle. Both experiments use VGG16. The results are 90.4%,0.905%,0.904%,0.969% and 0.904% and 71.1%,0.71,0%.711,0%.85% and 0.71%

[47]In this study, three strategies were employed: CNN, VGG16, and VGG19. These models classify different stages of Alzheimer's disease, and the performance achieved is 0.7102%, 0.7806%, 0.5004%, 0.5004%, 0.7704%, 0.8122%, 0.4617%, 0.5708%, and 0.3878% accuracy, AUC, F1-score, precision, and recall; and 0.7766%, 0.8155%, 0.4505%, 0.5848%, and 0.3667% accuracy, AUC, F1-score, precision, and recall, respectively. The dataset was collected from Kaggle for experiment purposes.

[48]The experiment was conducted with 6000 MRI images collected from Kaggle and divided into four categories: mildly, moderately, very mildly, and non-demented. In this study two experiments were conducted: the first experiment used VGG19 and the second used DenseNet169. Results are attained in the form of accuracy 88% and 78%.

3 Materials and Methods

This study uses a processed version of the OASIS MRI dataset [49], which was created as part of the OASIS-1 cross-sectional neuroimaging project and is publically accessible at Kaggle [50]. MRI images from 461 patients make up the whole OASIS collection. The resulting data set consists of about 86,188 MRI slices which are spread over four diagnostic categories. With roughly 13.7K photos for very mild dementia, 67K for non-dementia, 488 for moderate dementia, and 5K for mild dementia, the dataset's class distribution is unbalanced. Later on in the training process, class weights were employed to address imbalance. This study used another Alzheimer's disease dataset from Kaggle [51] to assess generalisation.It has 6,400 scans that fall into the same four categories as the OASIS dataset: 2,240 for Very Mild Demented, 3,200 for Non-Demented, 64 for Moderate Demented, and 896 samples for Mild Demented. The majority class had 2,560 samples in the training set after the data was split (for example, using an 80/20 train-test split). In order to oversample the minority classes, we rigidly applied SMOTE to the training set, producing a balanced distribution of 2,560 samples per class.

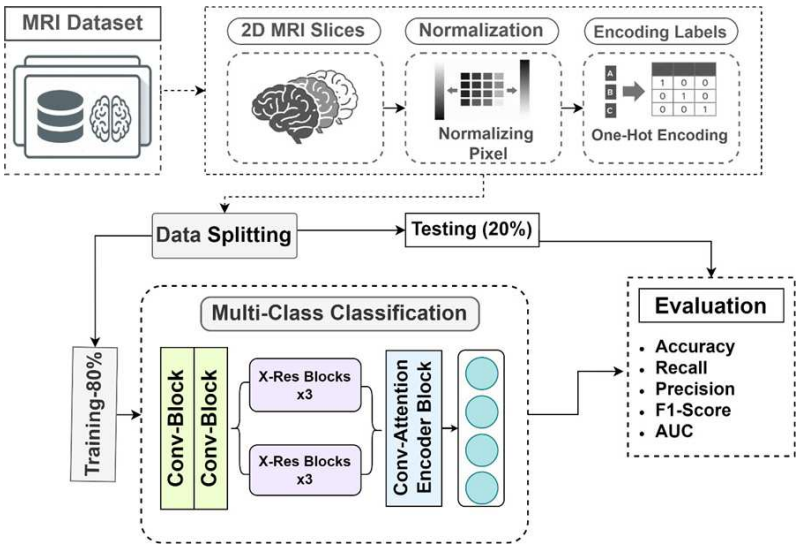


Fig. 1: System Model of Proposed Study

The data is highly appropriate for staging categorisation issues of Alzheimer's disease since it is stratified according to the Clinical Dementia Rating (CDR), which specifically divides the participants into three classes: non-demented, very mild dementia, mild dementia, and moderate dementia. In order to speed up the learning of convolutional neural network-based models, the images were scaled to 110x110 pixels and normalised pixel by pixel. All of the JPG files used in this study were indexed and given names that matched the class folders. Twenty percent of the data utilised in this study were used for testing, while the remaining eighty percent were used for training. A full system architecture of the proposed methodology is displayed in Figure-1.

To reduce the possibility of data leaking, this partitioning was carried out on a patient-by-patient basis. When using 2D slices instead of full 3D volumetric studies, the processing overhead is much smaller. Thus, while maintaining the anatomical characteristics linked to the various stages of cognitive decline, the processed OASIS dataset offers a strong foundation for the training and evaluation of neural network models to detect Alzheimer's disease. Each class's samples from the Kaggle-6400 dataset are displayed in Figure-2.

3.1 Xception-Attention Network

The proposed model is a lightweight Xception-Attention Network (XAtten-Net) classifier which is designed for multiclass alzheimer diagnosis. It has four blocks which are initial feature extraction, parallel feature extraction, conv-attention block and classification head. The architecture of proposed XAtten-Net is presented in 3. It has total of 1.2 million parameters and has small memory footprint. Three key features of the architecture are novel: (1) the use of parallel residual branches to enhance the feature information representation; (2) the incorporation of a convolutional attention encoder

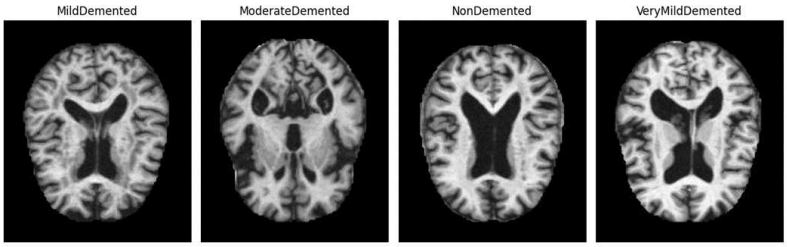


Fig. 2: Sample from each class

that uses locally extracted convolution features and self-attention mechanism for the global context extraction; and (3) a lightweight architecture that reduces the problem of parameter count without sacrificing the high classification performance. Because of this, such a model is particularly well-suited for medical imaging applications where it is crucial to find tiny patterns and there is a moderate amount of data. designed for the multi-class detection of Alzheimer's disease using an MRI scan. The initial feature extraction blocks uses two convolution sub-blocks, each block has convolution layer followed by Batch Normalization which keeps the training process stable and ensures efficient gradient flow during training. Then a Rectified Linear Unit(ReLU) is used as activation function to introduce non-linearity, followed by MaxPooling2D block to downsample the feature space.

After initial feature extraction block, we have parallel extraction block, which has two branches comprising each of three xception blocks. Xception blocks keeps the parameter count small by using depthwise separable convolutions. Each Xception block uses a Separable Convolution(SC) layer, followed by Batch Normalization, then a ReLU activation, then again SC layer followed by Batch Normalization again. It also has residual path which preserves the extracted information and uses Conv2D layer to keep the shape of both branches in Xception block similar, at the end of each Xception block, results are merged and passed onto next xception block for further processing. These two Branches: Branch A and Branch B uses three xception blocks and outputs from both are merged at the end and feature map is fed into Conv-Attention Encoder block.

Convolution-Attention Encoder block uses combination of convolution layer and multihead attention mechanism.This block first uses a convolution layer to extract the local spatial features, then prepares the feature map for attention layer. Multi-Head attention mechanism enables the model to focus on important regions in MRI and capture the relationship between relevant parts of it which is important for alzheimer diagnosis. Layer Normalization is then used to normalize the output of attention layer and then feature map is fed into Feed forward network(ffn), then global average pooling is used to aggregate the extracted features and aggregated feature vector is fed into Fully connected dense layer. Finally we have a classification head, which uses two fully connected layer. The first FC layer uses a ReLU activation, followed by dropout regularization to prevent model from overfitting. Then we have a final fully connected layer with softmax activation and 4 neuron to perform the final classification.

Table-2 shows the parameter configuration at each layer of proposed model.

Table 2: Parameter Configuration of Proposed Model

Layer	Parameters	Act.
Input	Shape: (H, W, 3)	–
Conv Block 1	32 filters, 3×3, MaxPool 2×2	ReLU
Conv Block 2	64 filters, 3×3, MaxPool 2×2	ReLU
Parallel Branches	2 paths × 3 ResBlocks, filters [64,128,128]	ReLU
Concatenate	Merges A & B (256 filters)	–
Encoder Conv	256 filters, 3 × 3	ReLU
MHA	4 heads, key dim 64	Softmax
Encoder FFN	Dense 256 → 256	ReLU
Latent Proj.	GAP → Dense 128	–
Classifier	Dense 256 (Dropout 0.3)	ReLU
Output	Dense 4	Softmax
Total Parameters: 1.2M		

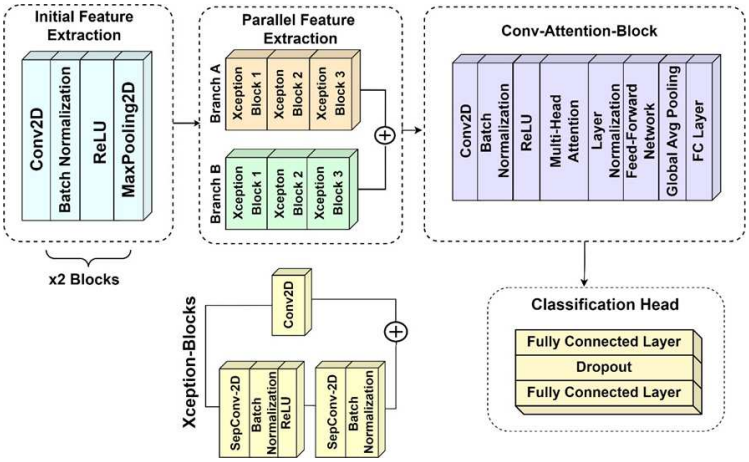


Fig. 3: Proposed Model Architecture

4 Evaluation and Results

Accuracy is a measure of how well the model correctly classifies images, defined in the equation:

$$Accuracy = \frac{TP + TN}{Total} \tag{1}$$

In our case, the dataset is imbalanced, so accuracy alone is not enough. Recall is considered the most important metric in the medical field because it is safer to overdiagnose someone (False Positive) than to misclassify a sick patient as healthy

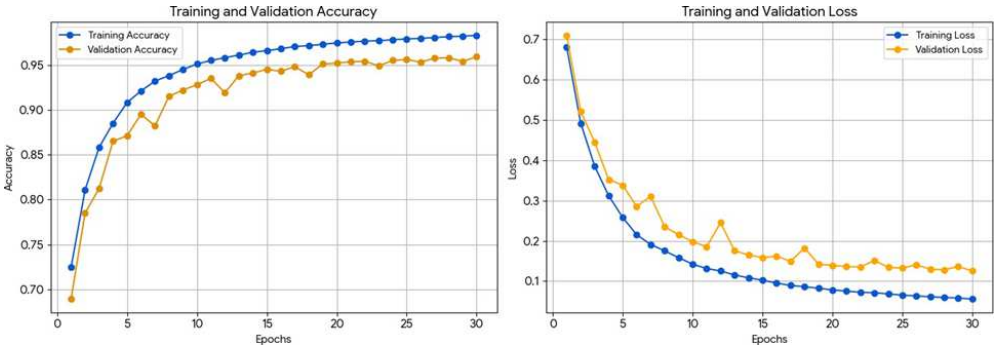


Fig. 4: Training Curves for Oasis Dataset

(False Negative). Recall is the percentage of actual positives values that were correctly calssified by you classifier.

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

Precision is an important evaluation metric we used. It indicates reliability and tells how often the model is correct when it predicts a positive result. It can be calculated as

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

F1-Score is the harmonics means of Recall and precision. Unlike accuracy, which can be artificially high if the model just predicts the majority class, a high F1-Score ensures that the model is performing well on the minority class (the sick patients) as well. It can be calculated:

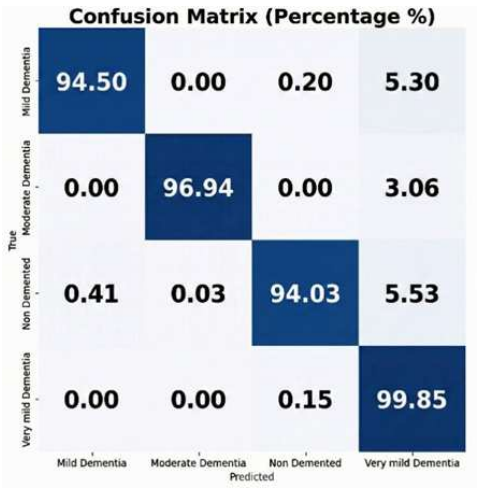
$$F1\text{-}Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

4.1 Oasis Dataset

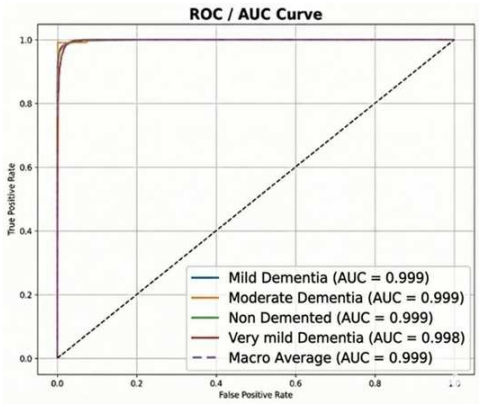
The model was trained for 30 epochs using a batch size of 32. The Figure 4 shows training accuracy vs. validation accuracy curves, and training loss vs. validation loss curves. The model achieved a training accuracy of 97% and a validation accuracy of 95.3%, while the loss was at 0.05 and validation loss at 0.12.

Figure 5a shows the confusion matrix on test model on oasis dataset, the values of confusion matrix are in percentages. Figure 5b shows the ROC-AUC curve of the model. Area under curve (AUC) tells the class separability of model, a score of 1 is considered perfect. Our model achieved AUC score of 0.99 for all classes.

Figure 6 shows the comparison of the different metrics for all classes and their Micro-Averages.



(a) Confusion Matrix on Test Set of Oasis Dataset



(b) ROC/AUC Curve Oasis Dataset

Fig. 5: Performance evaluation on the Oasis dataset.

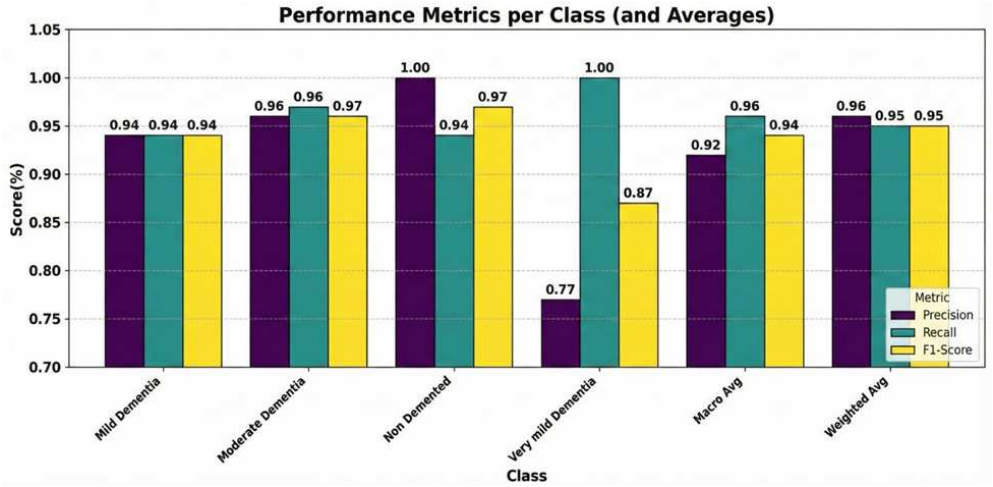


Fig. 6: Performance Metrics Comparison for Oasis Dataset

4.2 Kaggle-6400 Dataset

The proposed model was trained with same training configuration as above on kaggle-6400 dataset, Figure 7 below shows the training curves of model. It achieved training accuracy of 0.99 while val accuracy was at 0.92, the gap of 8% is because test set is of small size and imbalanced.

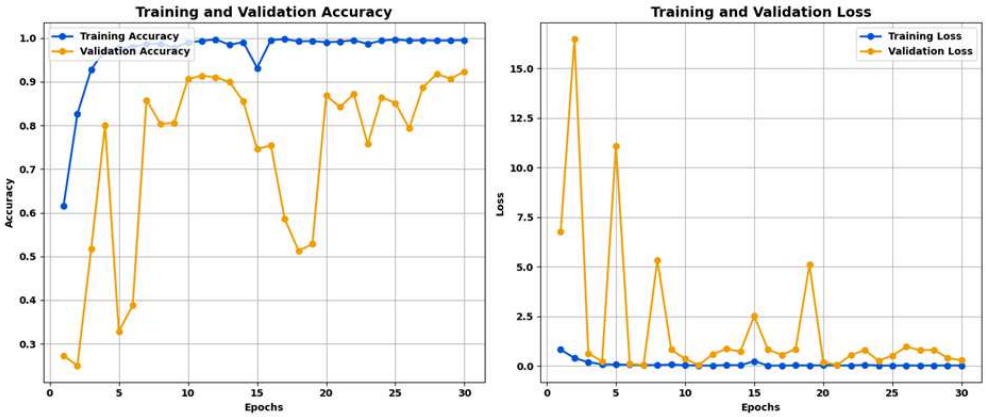
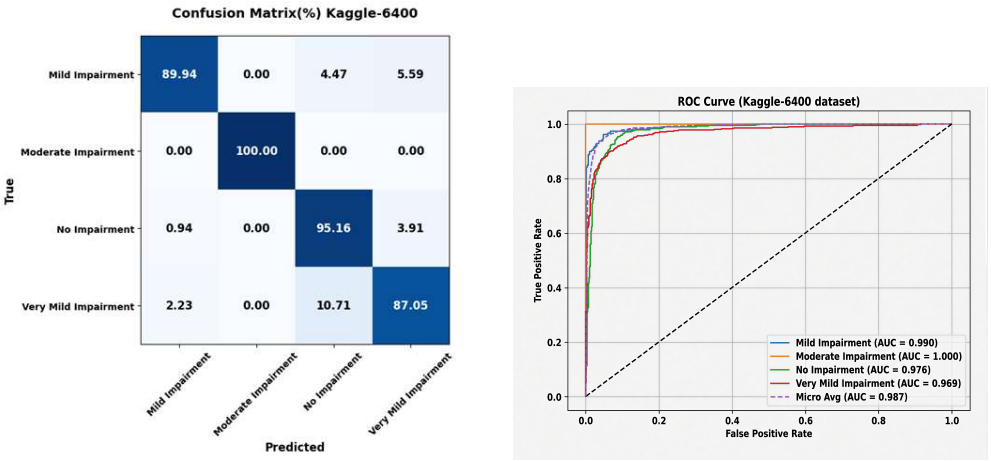


Fig. 7: Training Curve for kaggle-6400 dataset

Figure 8a shows the confusion matrix on test set for proposed model on oasis dataset, the values of confusion matrix are in percentages. Figure 8b shows the ROC-AUC curve of the model. Area under curve (AUC) tells the class separability of model, a score of 1 is considered perfect. Our model achieved AUC score of 0.99 for all classes.



(a) Confusion Matrix (b) ROC-AUC Curve

Fig. 8: Performance evaluation on the Kaggle-6400 dataset.

Figure 9 shows the comparison of the different metrics for all classes and their Micro-Averages.

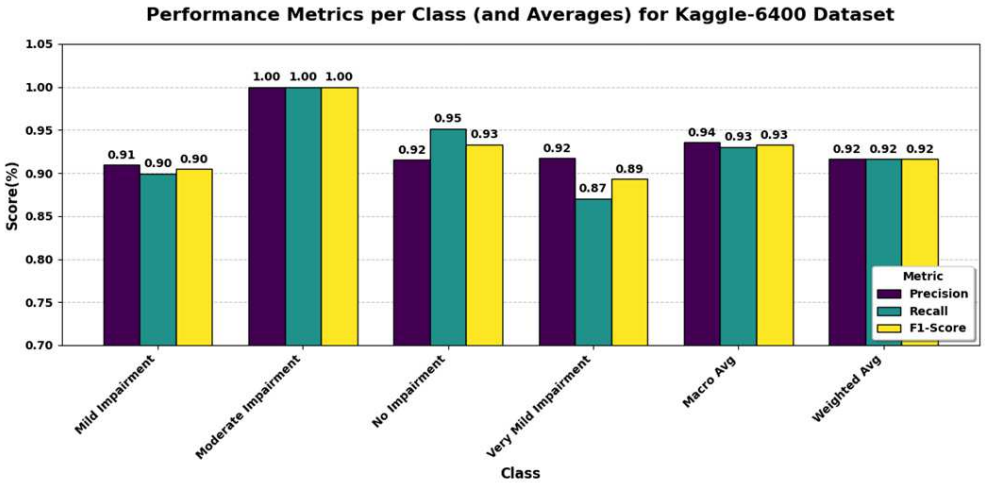


Fig. 9: Performance matrices comparison (micro-average) across all classes

Table 3: Comparison with Previous Studies

Model	Data	Ref.	Param.	Acc.	Rec.	Prec.	F1
CNN	–	[21]	–	83.30%	91.00%	–	–
CNN	OASIS	[22]	4.6M	99.68%	100.00%	–	–
CNN	Kaggle	[39]	6.5M	95.93%	95.88%	95.94%	95.90%
ViT-B/16	OASIS-3	[24]	∼86.6M	81.25%	68.33%	87.46%	68.73%
ViT-B/16	Kaggle	[24]	∼86.6M	97.66%	97.32%	98.02%	97.65%
Proposed	OASIS	–	1.2M	95.00%	96.00%	92.00%	99.00%
Proposed	Kaggle	–	1.2M	91.63%	91.63%	87.00%	98.00%

5 Comparative Analysis

Table 3 gives the comparison of our proposed model against recent studies. While Study [22] proved to be a strong competitor with 99% accuracy, the Proposed Model is much lightweight compared to parameter count. Furthermore, Study [24] struggled significantly with Recall (68%) likely due to poor performance on minority classes whereas the Proposed Model maintains high performance across all categories, resulting in a balanced F1-Score of 94%.

6 Conclusion

The diagnosis of Alzheimer's disease in early stages is very challenging task for doctors. patients are increasing day by day in the world. therefore efficient methods are required to diagnose the early stages of Alzheimer's and start the proper treatment of patients to save their precious lives. Computer scientists and machine learners have worked to provide some measures but they do have some limitations that are very

common in the existing techniques such as high computational power, over fitting, vanishing gradient and some of the techniques perform well with one dataset but cannot do well with others. in this study we have addressed and proposed a solution for all the stated deficiencies in the previously existing techniques and introduced Xception-Attention Network(XAtten-Net) model for accurate and early diagnosis of Alzheimer's stages. our model handles efficiently over fitting and vanishing gradient problem. furthermore, training process is not lengthy and can be traned in no time and It maintaines low computation power. experimental result are acheived 95% accuracy, 96% recall, 92% precison and 0.99 F1-Score on the OASIS dataset. while attiend 91.63%accuracy, 91.63%recall, 87%precision and 0.98F1-score on the kaggle datasets. in future this model will be extended for other type of imaging modalities likes PET, CT and US images and can also be used for diagnosis of other type of diseaes.

The proposed research introduces an Xception Attention Network(XAtten-Net), which achieves the highest performance across all evaluation metrics, including accuracy, recall, F1-score, and AUC, while remaining computationally efficient. The model was evaluated using the OASIS and Kaggle datasets. In the future we will apply the proposed model apply to other type of Alzheimer's datasets, as well as expand it to other type of imaging modalities such as PET, CT and US along with demographics data. Furthermore the model will be extended to diagnoses other type of diseases.

Declarations

Funding

The authors received no specific funding for this work.

Competing Interests

The authors declare no competing interests.

Ethics Approval

Not applicable. This study involved the computational analysis of existing MRI datasets and did not involve the recruitment of new human participants.

Consent to Participate

Not applicable.

Consent for Publication

Not applicable.

Data availability

The datasets analyzed during the current study are publicly available on Kaggle. The OASIS brain MRI dataset can be accessed at https://www.kaggle.com/datasets/

ninadaithal/imagesoasis, and the Augmented Alzheimer MRI Dataset is available at https://www.kaggle.com/datasets/uraninjo/augmented-alzheimer-mri-dataset.

Code Availability

The code used in this study is available from the corresponding author upon reasonable request.

Author Contributions

All authors contributed to the study conception and design. All authors reviewed and approved the final manuscript.

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