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ALZHEIMER'S DISEASE PREDICTION BY USING DEEP STACKED ENSEMBLE MODEL ENHANCED WITH SQUEEZE-AND-EXCITATION ATTENTION MECHANISM

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ABSTRACT

Context. Alzheimer's disease (AD) is a progressive, neurological degenerative disease causing memory loss, impaired cognition, and dementia. Timely identification of AD is crucial for the provision of effective treatment and intervention. Magnetic Resonance Imaging (MRI) has also become a critical tool in understanding the structural changes in the brain that occur during Alzheimer's development. Nonetheless, the manual processing of MRI scans is time-consuming, subjective, and susceptible to human error. As such, there is increasing demand for automated and precise diagnostic technology that can support clinicians in the earlier detection and staging of Alzheimer's disease based on medical imaging data.

Objective. The present study focuses on developing and evaluating a deep learning-based stacked ensemble model for the classification and staging of Alzheimer's disease brain MRI scans. The primary objective is to improve the diagnosis accuracy and reliability through a combination of the strengths of several pre-trained convolutional neural network (CNN) architectures, combined with sophisticated attention mechanisms and meta-learning techniques.

Method. The proposed approach utilizes a deep stacked ensemble learning framework composed of three well-performing CNN architectures: MobileNetV2, ResNet50, and DenseNet121. These models are pre-trained on the ImageNet dataset, benefiting from robust feature extraction capabilities. To further improve their performance, each CNN model is enhanced with a Squeeze-and-Excitation (SE) attention module, which adaptively recalibrates channel-wise feature responses, emphasizing important features while suppressing irrelevant ones. The extracted high-level features from all three SE-augmented CNNs are then concatenated and fed into a meta-learner consisting of fully connected layers. This meta-classifier incorporates dropout and batch normalization techniques to prevent overfitting and improve generalization. The overall architecture is trained and validated on a dataset of brain MRI images categorized into different stages of Alzheimer's disease, including normal control, mild cognitive impairment, and various stages of dementia.

Results. The experimental evaluation demonstrated exceptional performance, achieving an Accuracy of 99%, a Precision of 99%, a Recall of 98%, and an F1-score of 99%. These metrics indicate the model's strong predictive capability and reliability in distinguishing between different stages of Alzheimer's disease.

Conclusions. The experimental outcomes highlight the effectiveness and robustness of the proposed deep stacked ensemble model in the automated diagnosis and staging of Alzheimer's disease using MRI scans. The integration of multiple CNNs with attention mechanisms and meta-learning significantly enhances classification performance. These findings suggest that the model can serve as a reliable decision-support system for neurologists, aiding in early diagnosis, timely intervention, and improved patient outcomes in clinical settings.

KEYWORDS: Convolution Neural Networks, Deep Learning, Alzheimer's disease, Squeeze-and-Excitation, Deep Stacked Ensemble.

ABBREVIATIONS

AD is an Alzheimer's disease;
CNN is a Convolutional Neural Network;
SE is a Squeeze-and-Excitation;
ROC is a Receiver Operating Characteristic;
MRI is a Magnetic Resonance Imaging;
AUC is an Area Under the Curve.

NOMENCLATURE

X is a set of input variables;
f is a Classification function;
Y is a set of output labels;
H is a hypothesis space of deep learning models;
TP is a True Positive;
TN is a True Negative;
FP is a False Positive;
FN is a False Negative;
d is a dimension of feature vectors;
n is a number of samples;
r is a reduction ratio;
C is a channel in SE block;
W is a width in SE block;
s, z, e are intermediate variables in SE block;
σ is a sigmoid activation function.

INTRODUCTION

Alzheimer's disease is a neurological health problem that gradually impairs memory, thinking, and behavior, especially in older people [1–9]. AD needs to be detected early for timely treatment. According to the report, the predicted growth of U.S populations living with AD will increase from 6.5 million to 13.8 million by 2060 under the present state of affairs of medical treatment (Alzheimer Association 2023), and globally, approximately 55 million people are affected by

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dementia, with over 60% of the cases in the countries described as middle and low-income countries.

In recent years, there has been some success in the automatic detection and classification of AD using neuroimaging data (such as magnetic resonance imaging scans) with the advance of deep learning models, especially Convolutional Neural Networks (CNN) [10,11]. However, there are still considerable gaps in the current models that should be filled to achieve more precise and accurate diagnoses. CNN-based models are widely used in AD detection by leveraging their ability to extract spatial features from neuroimaging data. Various studies have proposed novel CNN architectures, including 3D CNN architectures with multi-level features [12], adaptive hybrid attention networks [13], and deep feature fusion networks [14], to achieve better AD classification accuracy. However, despite technological advancements, CNN-based models are still heavily challenged in their ability to capture long-range dependencies and global context information from MRI scans. These pieces of information are key considerations in the diagnosis, particularly in the early stages of AD.

The object of study is the application of a deep stacked ensemble model with a Squeeze-and-Excitation (SE) attention mechanism for classifying and staging Alzheimer's disease (AD) using brain magnetic resonance imaging (MRI) scans.

The subject of the study focuses on applying deep learning to MRI images to enhance the reliable and easily understood multiclass classification of Alzheimer's disease, facilitating early recognition and informing medical decisions.

The purpose of the study is to develop a Deep Stacked ensemble model that integrates three strong CNN architectures (MobileNetV2, ResNet50, and DenseNet121) to augment feature extraction from MRI images for classifying Alzheimer's disease as well as introduces Squeeze-and-Excitation (SE) Attention Mechanism into every CNN to recalibrate the channel-wise feature maps, enabling the network to enhance meaningful features and reduce irrelevant features, thereby increasing diagnostic accuracy.

1 PROBLEM STATEMENT

Let $X=\{x1, x2,...,xn\}$ be the set of input variables, where each $xi \in Rd$ represents the feature vector extracted from an MRI scan of the brain. The problem of Alzheimer's disease classification and staging is to learn a function f: $X \rightarrow Y$ where $Y=\{y1,y2,...,yn\}$ and each $yi \in \{0,1,2,3\}$ corresponds to one of the four Alzheimer's stages: 0 for NonDemented, 1 for VeryMildDemented, 2 for MildDemented, and 3 for ModerateDemented. The classification function $\boldsymbol{f}$ must be trained to minimize the categorical cross-entropy loss while satisfying constraints related to limited data availability, imbalanced class distribution, and computational efficiency. The model is expected to achieve high classification performance, as measured by accuracy, Precision, Recall, and F1-score.

2 REVIEW OF THE LITERATURE

Alzheimer's disease is a progressive neurodegenerative disorder that has an adverse influence on cognitive abilities, thus necessitating early and precise diagnostic criteria to support optimal management of the disease. The implementation of recent advancements in deep learning has demonstrated promising results for the automated classification and staging of Alzheimer's disease (AD) using brain MRI scans. This literature review examines recent studies that explore various deep-learning models for detecting and classifying Alzheimer's disease.

El-Latif, Chelloug, Alabdulhafith, and Hammad [12] introduce a lightweight Convolutional Neural Network (CNN) to achieve exact Alzheimer's Disease (AD) identification from MRI image data. The proposed model reached 99.22% accuracy for binary class identification and 95.93% for multi-classification, surpassing existing models in achievement. Furthermore, Sethuraman, Malaiyappan, Ramalingam, Basheer, Rashid, and Ahmad [13] apply Alexnet to identify different stages of AD from real-time ADNI datasets. The proposed model achieved an accuracy of 96.61% in binary class identification. Hazarika, Kandar, and Maji [14] developed a lightweight hybrid model that combines LeNet and AlexNet. The ensemble model achieved an accuracy of 93.58% in multiclass identification. Tuvshinjargal and Hwang [15] developed the VGG-C Transform model, achieving the best results with normalization added to VGG-C, resulting in a test accuracy of approximately 77.46%. Jraba, Elleuch, Ltifi, and Kherallah [16] utilized convolutional neural network (CNN) models to automatically identify relevant Alzheimer's disease from brain MR images. The cutting-edge performance of CNN models enables the identification of the four Alzheimer's disease stages from mild dementia through moderate dementia and their non-dementia manifestations. The study investigates three modern architectures – ResNet-152, VGG16, and Inception-V3 – to reveal complex image patterns in brain images. Hasan, Hossain, and Ullah [17] presented a weighted ensemble deep transfer learning framework that utilized two pre-trained CNN architectures, including ResNet152V2 and DenseNet201. The proposed framework's performance has been evaluated using two different MRI datasets to assess its generalization potential across diverse input data. Researchers perform an in-depth analysis of the framework's performance across various case studies. Experimental outcomes demonstrate that the weighted ensemble architecture outperforms the base models. Raza, Naseer, Tamoor, and Zafar [18] utilized a CNN-based deep learning model as the reference model. The performance of the proposed model was tested on different epochs, including 10, 25, and 50. The proposed model achieved an accuracy of 97.84%. Ramzan, Khan, Rehmat, Iqbal, Saba, Rehman, and Mehmood [19] utilize deep Residual Neural Networks (RNNs), including a transfer learning approach, for classifying the 6 AD stages. While, Alsubaie, Luo, and Shaukat [20] proposed Convolutional Neural

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Networks (CNNs), Recurrent Neural Networks (RNNs), and Generative models to detect Alzheimer's Disease. Mirzaei and Adeli [21] used a Support Vector Machine, Random Forest, Convolutional Neural Network, and K-means in the detection and classification of AD with an emphasis on neuroimaging. Huang, Liu, Zhang, and Li [22] investigated the alterations in cerebral grey matter in patients with the early stage of MCI using voxel-based morphometry to diagnose the early stage of Alzheimer's disease. Jung, Luna, and Park [23] designed a new cGAN for generating high-quality 3D MR images at various stages of AD, incorporating an additional module for 3D spatial interpolation. In particular, the cGAN architecture comprises an attentional 2D generator, a 2D discriminator, and a 3D discriminator that generates ongoing 2D images along the axial view to create high-quality 3D MR volumes. Mohammed, Fakhrudeen, and Alani [24] focus on the datasets used to develop Deep Learning techniques. The study also breaks down the stages of AD diagnosis and focuses on pre-processing techniques. Reddy, Rangarajan , Shuaib, Jeribi, and Alam [25] perform a comparative analysis of VGG16, VGG19, and Alexnet models to classify Alzheimer's disease. The VGG16 and VGG19 achieved 100% accuracy, while AlexNet achieved 98.20%. Mahmud, Rahman, Fattah, Subrina, Khan, Alshamrani, and Alqahtani [26] introduce a novel viewpoint to diagnosing Alzheimer's disease by combining deep transfer learning and explainable artificial intelligence (XAI) approaches. The extensive experimentation conducted on popular pre-trained convolutional neural networks (CNNs) revealed the effectiveness of the ensembles, specifically Ensemble-1 (VGG16 and VGG19) and Ensemble-2 (DenseNet169 and DenseNet201), in terms of superior diagnostic performance, achieving up to 95% Accuracy, Precision, Recall, and F1 score. The author [27] presents a framework combining 3D Convolutional Neural Network (3D-CNN) and Recurrent Neural Network (RNN) techniques to identify Alzheimer's disease. Mehmood Khan [28] proposed a Siamese 4D-AlzNet model, achieving a remarkable 95.05% accuracy. Nehar, Bellaouar, Benyoub, and Aissa [29] employ VGG16 and VGG19 models to classify MRI images based on Alzheimer's Disease and achieved remarkable accuracy (98.14% to 99.59%). The authors [30] employ the ResNet-101 transfer learning technique to classify Alzheimer's disease. The proposed model achieves 98.21% and 97.45% accuracy on the ADNI and OASIS datasets. Khaleel and Lakizadeh [31] employ the FSBILSTM model on the OASIS dataset, achieving an accuracy of 99.6%.

In summary, the available studies indicate that deep learning models are successful in reliably identifying Alzheimer's disease from brain MRI scans. Although some models achieve higher performance through architectural innovations, others emphasize the importance of transfer learning, normalization, and data augmentation in enhancing diagnostic performance. Nevertheless, this still leaves the need for stronger, more understandable models to generalize across different datasets and clinical situations. Incorporating attention mechanisms, such as Squeeze-and-Excitation (SE), offers excellent potential for enhancing feature extraction and model interpretability in the AD classification task.

Table 1 – Summary of related work

Serial No	Reference & Year	Model	Dataset	Classification Method (Accuracy)
1	[12] 2023	Lightweight CNN	OrDs	Binary: 99.22% & Multiclass: 95.93%
2	[13] 2023	AlexNet	ADNI	Binary: 96.61%
3	[14] 2023	Ensemble model (LetNet+ AlexNet)	ADNI	Multiclass: 93.58%
4	[15] 2022	VGG-C Transform model	Kaggle	Multiclass: 77.46%
5	[16] 2024	ResNet-152, VGG16, and Inception-V3	Images collected from different resources	Multi classifier: 98% for ResNet 152, 96% for Inception-v3, 80% for VGG 16
6	[17] 2024	Ensemble model (ResNet152V2 and DenseNet201)	(Alzheimers-dataset-4-class-of-images) (12800 images) Kaggle Dataset (40384)	Multiclass: 89.95% for 12800 images 98% accuracy for 40384 images
7	[18] 2023	CNN	ADNI	97.84%
8	[25] 2024	VGG16 VGG19 Alex Net	Healthy Aging Data in the U.S. (250,000 Samples)	VGG16: 99.9 VGG19: 98.8 Alex Net:99.9
9	[27] 2024	Hybrid model (3D CNN and RNN)	ADNI	Hybrid Model: 99.5%
10	[30] 2024	Resnet-101	ADNI and OASIS datasets	ADNI: 98.21% OASIS: 97.45%
11	[32] 2024	DenseNet-201 EfficientNet-B0 GoogleNet Inception-v3 ResNet50 MobileNet-v2	(Alzheimers-dataset-4-class-of-images)	DenseNet-201: 93.33 EfficientNet-B0: 90.32% GoogleNet: 92.57 % Inception-v3: 84.84% ResNet50: 88.95% MobileNet-v2: 91.02%
12	[31] 2025	FSBILSTM	OASIS	OASIS: 99.6%

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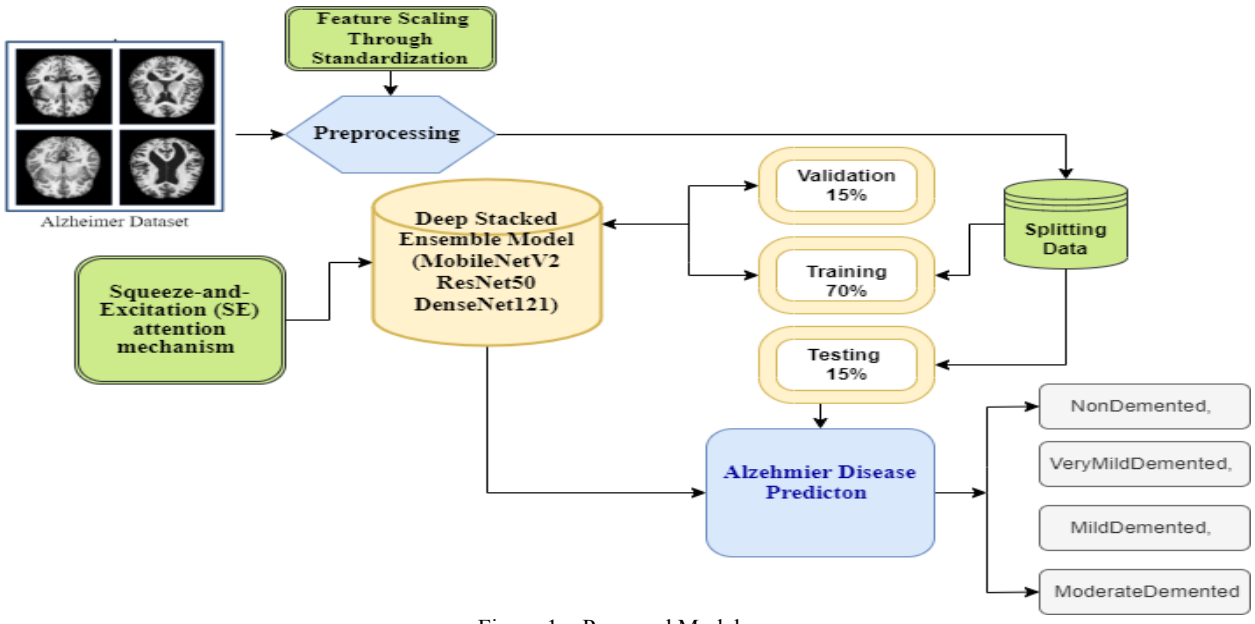

Figure 1 – Proposed Model

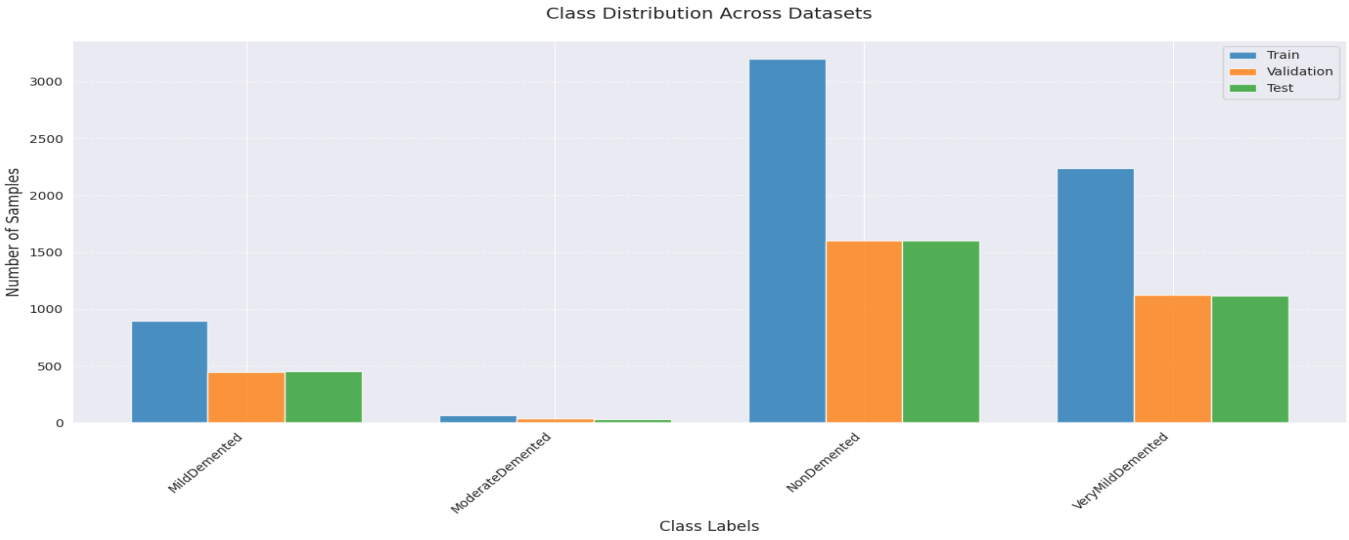

Figure 2 – Class Distribution

3 MATERIALS AND METHODS

The method developed in this research focused on designing and implementing an accurate and generalizable deep learning architecture for classifying and staging Alzheimer's disease based on brain MRI images. The overall process of the proposed model is shown in Figure 1.

The dataset used in this research is named "alzheimers-dataset-4-class-of-images". It includes four categories of brain MRI scans: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The overall distribution of the dataset is shown in Figure 2. To achieve fair training and evaluation, the dataset was divided into three parts: 8.960 (70%) for training, 1.920 (15%) for testing, and 1.920 (15%) for validation.

The study proposed a deep-stacked ensemble framework that combines well-known CNN backbones, including MobileNetV2, ResNet-50, and DenseNet-121, with feature extraction capabilities to train the classification model. Each base model was trained in advance using ImageNet to leverage transfer learning. To enhance attention to disease-relevant features in the MRI scans at the model level, each CNN is coupled with a Squeeze-and-Excitation (SE) attention block. This attention mechanism helps detect subtle variations in anatomic features that occur between different stages of AD.

After extracting the SE-enhanced features, the outputs from all three branches of the CNN are concatenated to create a single feature vector. The following steps are performed to train the data. The first step is to define the input shape. Let the shape of the input images be:

$$img\_shape \leftarrow (224,224,3).$$

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The second step is to determine the number of output classes.

The third step is to define the Squeeze-and-Excitation (SE) Block. Let $X \in R^{H \times W \times C}$ be the input tensor.

Define the SE block as follows: Compute global average pooling over spatial dimensions:

$$s \leftarrow \frac{1}{H.W} \sum_{i=1}^{H} \sum_{j=1}^{W} Xi, j.$$

Pass through a bottleneck fully connected layer:

$$z \leftarrow \text{relu}(W1 \bullet s + b1), W1 \in R^{C/r*C}.$$

Expand back to the original channel size using sigmoid activation:

$$e \leftarrow \sigma(W2.z + b2), W2 \in R^{c*c/r}.$$

Reshape e to match X's channel dimension and scale:

$$\text{Output} \leftarrow X \bullet \text{re.shape}(e).$$

Here, r is the reduction ratio.

The fourth step is to define the base model construction function. For any pre-trained architecture, define Global Average Pooling, Batch Normalization, a fully connected layer with 256 units, ReLU activation, and Dropout with probability 0.45.

The fifth step involves constructing three branches using different pre-trained models: MobileNetV2, ResNet-50, and DenseNet-121.

The last step is to apply shared input and concatenate Features. Finally, compile the final model with the details of the optimizer (Adamax) and the loss function (Categorical Crossentropy).

Evaluating the suggested deep stacked ensemble model for classifying Alzheimer's disease, the study employs various evaluation metrics to assess the model's performance at different stages of the disease, as determined by examining brain MRI scans. These metrics are accuracy, Precision, Recall, and F1-score.

Accuracy refers to the proportion of correct predictions in the overall model, calculated by counting the percentage of true positives and true negatives among all predictions. Mathematically, accuracy is represented as

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

Precision is the ratio of correctly predicted positive cases to the total predicted positives. Mathematically, Precision is represented as

$$\text{precision} = \frac{TP}{TP + FP}. \quad (2)$$

Recall (also known as sensitivity) is the percentage of true positives that the model correctly records. It is essential to reduce false negatives in medical use. Mathematically, Recall is represented as

$$\text{recall} = \frac{TP}{TP + FN}. \quad (3)$$

F1-Score is the harmonic average of Precision and Recall, yielding an aggregated number without compromising anyone. Mathematically, the F1 score is represented as

$$f1 - \text{Score} = \frac{(2 * (\text{precision} * \text{recall}))}{(\text{precision} * \text{recall})}. \quad (4)$$

4 EXPERIMENTS

The proposed deep stacked ensemble model has been tested on the "alzheimers-dataset-4-class-of-images" dataset, which contains 12800 brain MRI scans categorized into four classes: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. Each category of the class is represented in Figure 3. All images were made compatible with standard deep learning models and processed uniformly by resizing them to 224 × 224 pixels and scaling their pixel values to the range of 0 to 1. In total, 8.960 images were used for training, while 15% (1.920 images) were included in the validation set and another 15% (1.920 images) in the testing set. Before training, specific pre-processing steps were applied to the images to enhance image quality and facilitate better model generalization. After that, the proposed deep stacked ensemble model combined the capabilities of MobileNetV2, ResNet50, and DenseNet121, which were pre-trained on the ImageNet dataset, to help accelerate the process of identifying useful features.

With every pre-trained model, the Squeeze-and-Excitation (SE) attention module was added to ensure it could adaptively control the importance of features in the layers, retaining the most important and discarding the least important ones. The Classification performance of the proposed model was qualitatively evaluated using standard evaluation criteria, including Precision, Recall, F1-score, and overall Accuracy.

5 RESULTS

The model's overall classification accuracy was impressive, amounting to 99%, and class-wise metrics are summarized in Table 2.

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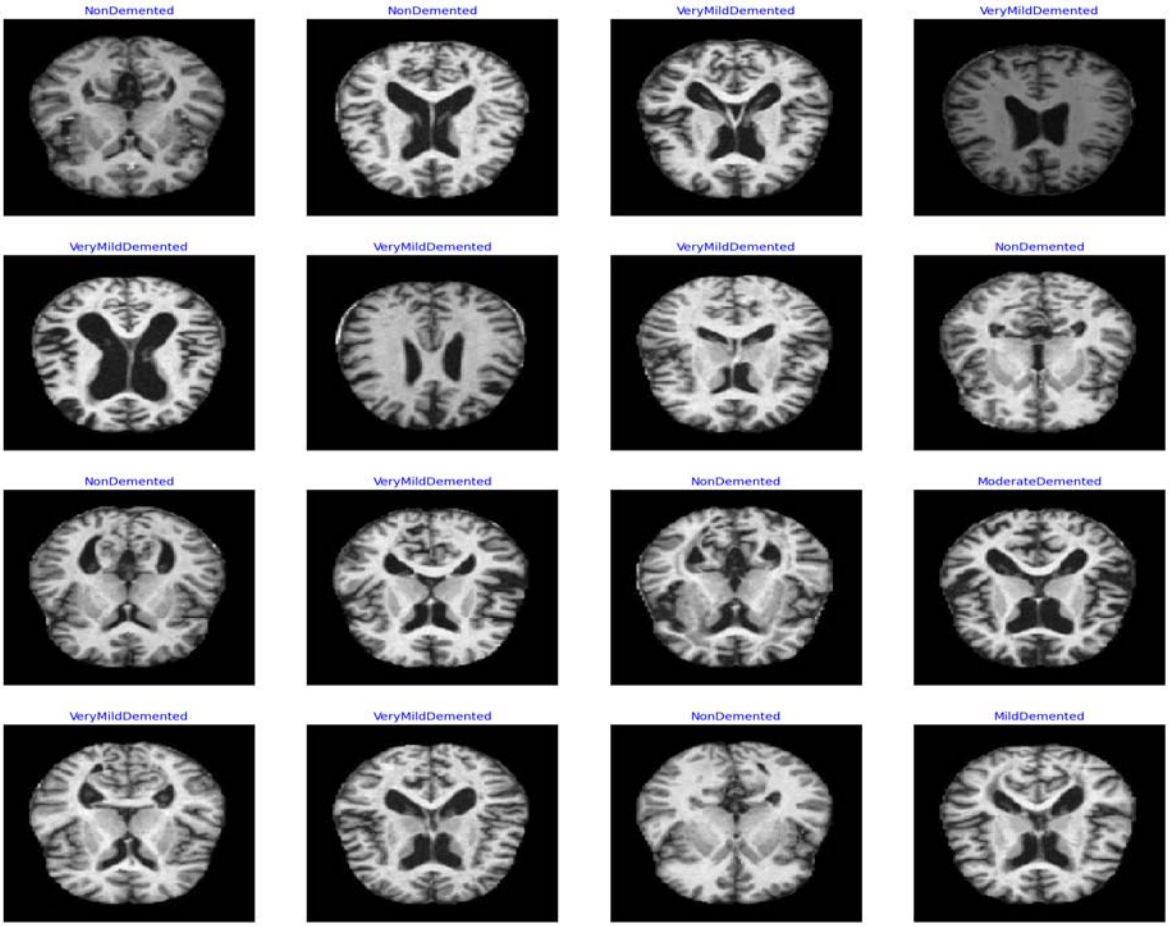

Figure 3 – Alzheimer's Disease Class Images

Table 2 – Classification Report of the Proposed Model

Class	Precision	Recall	F1-Score	Support
MildDemented	1.00	0.96	0.98	278
ModerateDemented	1.00	1.00	1.00	20
NonDemented	0.98	1.00	0.99	959
VeryMildDemented	1.00	0.98	0.99	663
Average	0.99	0.98	0.99	1920
Accuracy	99 %			

The training and validation accuracy, as well as the loss of the proposed model, are represented in Figures 4 and 5.

Figure 4 presents a visual representation of the training and validation results for the proposed deep-stacked ensemble model, showing the accuracy and loss trends over the epochs. The amounts of training and validation accuracy from the accuracy graph can improve significantly during the first few epochs, only stabilizing at 99% towards the end of the 10th epoch, demonstrating the model's learning and generalization capabilities. At the same time, the loss curve shows significant early improvements in the errors of both training and validation sets, which drop to nearly zero as the model converges. Furthermore, the confusion matrix of the proposed model is represented in Figure 6.

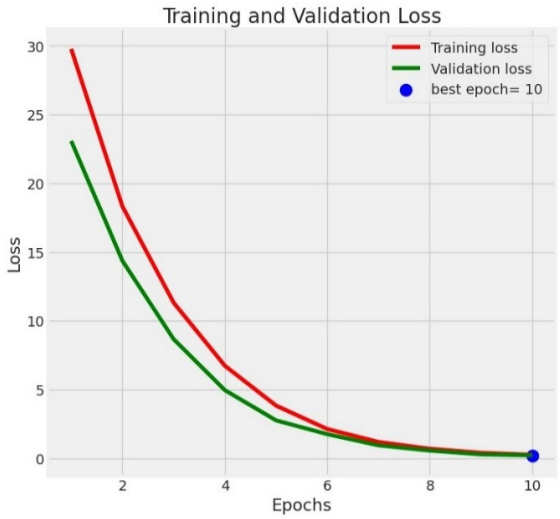

Figure 4 – Training and validation Loss

Figure 6 illustrates the confusion matrix for the proposed deep-stacked ensemble model in classifying Alzheimer's disease stages using brain MRI scans. A confusion matrix summarizes the performance of a classification algorithm by giving the counts of true positives, false positives, true negatives, and false negatives for each class. This matrix indicates the extent to which our model has succeeded in distinguishing the

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four classes of Alzheimer's disease: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The diagonal elements of the confusion matrix indicate the correlation classes for each category and demonstrate the model's efficiency, as these counts should be close to the sample sizes for each class. The ROC curve of the proposed model is represented in Figure 7.

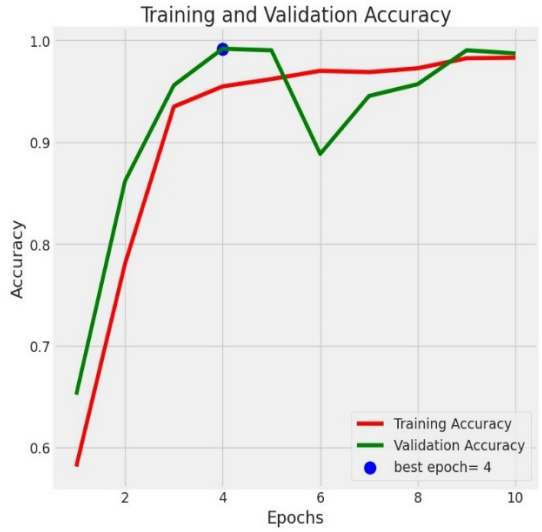

Figure 5 – Training and Validation Accuracy

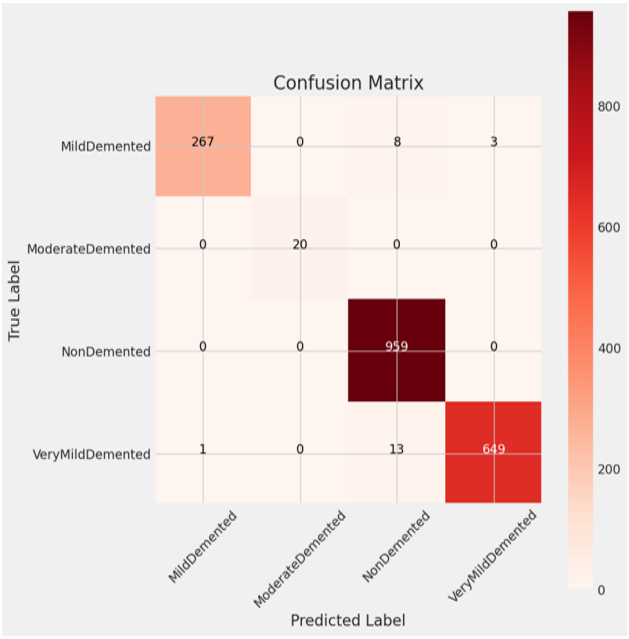

Figure 6 – Confusion Matrix of Proposed Model

Figure 7 shows the results of the ROC curve analysis for the proposed deep stacked ensemble approach, which describes the relation between the true positive rate (sensitivity) and the false positive rate (1-specificity) for different threshold settings. Figure 6 presents a plot comparing the ROC curves for the NonDemented, VeryMildDemented, MildDemented, and ModerateDemented classes, allowing for an intuitive assessment of how well the model distinguishes between stages.

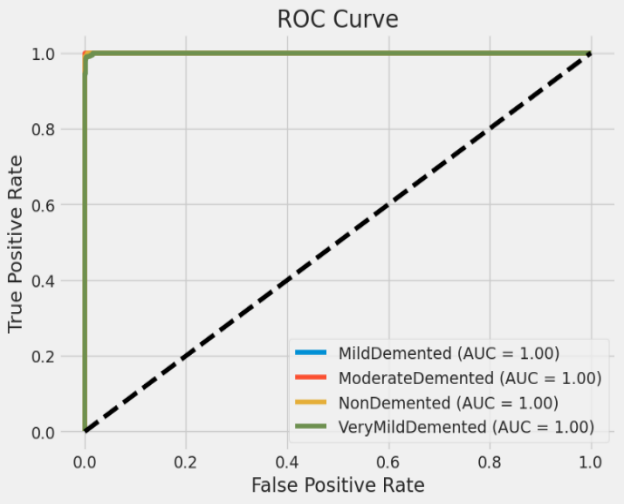

Figure 7 – ROC Curve

One key observation that results from the analysis of the ROC curve is that the AUC (1.0 for each class), which is derived from the reported accuracy, Precision, Recall, and F1-score of 99%, 99%, 98%, and 99% correspondingly, indicates that the model performance is overall excellent.

6 DISCUSSION

A comparison to the state-of-the-art models was carried out to ensure the performance of the proposed approach. The proposed deep-stacked ensemble model outperforms existing models in terms of accuracy. A comparative analysis is presented in Table 3.

Table 3 – Comparison of Proposed Model with Similar Studies

Model	Accuracy	Reference
DenseNet-201 EfficientNet-B0: GoogleNet Inception-v3 ResNet50 MobileNet-v2	93.33% 90.32% 92.57 % 84.84% 88.95% 91.02%	[32]
Ensemble model (ResNet152V2 and DenseNet201)	89%	[17]
Proposed Model **Deep Stacked Ensemble Modle** (MobileNetV2, ResNet50 , DenseNet121) With SE mechanism	**99%**	

The proposed model achieved 99% accuracy, surpassing previous research and demonstrating strong generalization and discriminative ability. The study also demonstrates that the SE block is crucial in recalibrating feature importance, resulting in significant gains in sensitivity levels and a reduction in false negatives –a vital step in producing accurate medical diagnoses. Therefore, the deep stacked ensemble framework establishes new ground in AD classification, achieving significant accuracy, Precision, Recall, and F1-score.

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CONCLUSIONS

The present work proposes and evaluates a deep stacked ensemble model for both staging and classifying Alzheimer's disease using brain MRI images. To optimize the model, three CNN frameworks were employed: MobileNetV2, ResNet-50, and DenseNet-121. These frameworks included the Squeeze-and-Excitation (SE) attention mechanism, which enabled the model to focus on features important to the task. This design successfully addressed the issues associated with redundant features and improved classification accuracy across all four AD stages. The developed model demonstrated remarkable generalization and robustness, with an overall accuracy of 99%, impressive Precision, Recall, and F1-score, and superior performance compared to most current state-of-the-art methods. Moreover, the ROC curve also verified the model's outstanding discriminative power across all stages of Alzheimer's disease, with an AUC that approached 1.0. This highlights the practical utility of the method in clinical settings where AD detection is early and highly accurate.

Despite its promising results, some of the most critical aspects of this research remain to be addressed. One significant limitation is that the work is based on a single readily accessible dataset. However, it is diverse; it likely fails to capture the entire field of real-world clinical heterogeneity. Extending the model's robustness and generalizability is possible through an evaluation of the model against more highly representative multi-center datasets that include chronologically updated patient records. The incorporation of additional modality features, such as PET scans or clinical records, into a combined approach for deep learning has the potential to provide a more comprehensive overview of the patient's overall situation. Additionally, the use of XAI strategies may enhance clinical confidence by making the model's predictions more easily interpretable for neurologists. By optimizing the model for real-time execution at edge devices, it could be deployed readily in any resource-constrained healthcare setting, which could significantly enhance its contribution to AD in early diagnosis.

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ПРОГНОЗУВАННЯ ХВОРОБИ АЛЬЦГЕЙМЕРА ЗА ДОПОМОГОЮ ГЛИБОКО СКЛАДОВАНОЇ АНСАМБЛЕВОЇ МОДЕЛІ, ПОСИЛЕНОЇ МЕХАНІЗМОМ УВАГИ СТИСНЕННЯ ТА ЗБУДЖЕННЯ

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АНОТАЦІЯ

Актуальність. Хвороба Альцгеймера (ХА) – це прогресуюче неврологічне дегенеративне захворювання, що спричиняє втрату пам'яті, порушення когнітивних функцій та деменцію. Своєчасне виявлення ХА має вирішальне значення для забезпечення ефективного лікування та втручання. Магнітно-резонансна томографія (МРТ) також стала критично важливим інструментом для розуміння структурних змін у мозку, що відбуваються під час розвитку хвороби Альцгеймера. Тим не менш, ручна обробка МРТ-сканів є трудомісткою, суб'єктивною та схильною до людських помилок. Як наслідок, зростає попит на автоматизовані та точні діагностичні технології, які можуть допомогти клініцистам у ранньому виявленні та стадіювання хвороби Альцгеймера на основі даних медичної візуалізації.

Мета. Це дослідження зосереджено на розробці та оцінці багатошарової ансамблевої моделі на основі глибокого навчання для класифікації та стадіювання МРТ-сканувань головного мозку при хворобі Альцгеймера. Основною метою є підвищення точності та надійності діагностики шляхом поєднання сильних сторін кількох попередньо навчених архітектур згорткових нейронних мереж (CNN) у поєднанні зі складними механізмами уваги та методами метанавчання.

Метод. Запропонований підхід використовує структуру глибокого багатошарового ансамблю навчання, що складається з трьох високопродуктивних архітектур CNN: MobileNetV2, ResNet50 та DenseNet121. Ці моделі попередньо навчені на наборі даних ImageNet, використовуючи потужні можливості витягу ознак. Для подальшого покращення їхньої продуктивності кожна модель CNN покращена модулем уваги стискання та збудження (SE), який адаптивно перекалібрує реакції на ознаки по каналах, підкреслюючи важливі ознаки, водночас пригнічуючи нерелевантні. Виділені високорівневі ознаки з усіх трьох SE-доповнених CNN потім об'єднуються та подаються в мета-навчальну систему, що складається з повністю зв'язаних шарів. Цей мета-класифікатор включає методи відсіву та пакетної нормалізації, щоб запобігти перенавчанню та покращити узагальнення. Загальна архітектура навчається та перевіряється на наборі даних зображень МРТ мозку, класифікованих за різними стадіями хвороби Альцгеймера, включаючи нормальний контроль, легкі когнітивні порушення та різні стадії деменції.

Результати. Експериментальна оцінка продемонструвала виняткову продуктивність, досягнувши точності 99%, прецизійності 99%, повноти 98% та F1-оцінки 99%. Ці показники вказують на високу прогностичну здатність та надійність моделі у розрізненні різних стадій хвороби Альцгеймера.

Висновки. Експериментальні результати підкреслюють ефективність та надійність запропонованої моделі глибоко укладеного ансамблю в автоматизованій діагностиці та стадіюванні хвороби Альцгеймера за допомогою МРТ-сканувань. Інтеграція кількох згорткових нейронних мереж (CNN) з механізмами уваги та метанавчанням значно покращує ефективність класифікації. Ці результати свідчать про те, що модель може служити надійною системою підтримки рішень для неврологів, допомагаючи у ранній діагностиці, своєчасному втручанні та покращенні результатів лікування пацієнтів у клінічних умовах.

КЛЮЧОВІ СЛОВА: згорткові нейронні мережі, глибоке навчання, хвороба Альцгеймера, стиснення та збудження, глибоко укладений ансамбль.

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