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EADDA: Towards Novel and Explainable Deep Learning for Early Alzheimer's Disease Diagnosis Using Autoencoders

Mohammed Raza Syed[1], Neel Kothari[2], Yash Joshi[3], Dr. Aruna Gawade[4]

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Abstract: According to the WHO, Alzheimer's disease (AD) is the seventh most common cause of death worldwide as of 2023. The early identification of AD is difficult, and there are currently no known preventative procedures. It is crucial to develop an accurate computer-aided system for the early detection of AD to help AD patients. One of the most promising areas for the early identification of Alzheimer's disease is neuroimaging, and early diagnosis is crucial for determining the creation and efficacy of treatment alternatives. To do so, the authors propose a novel architecture which is a Deep-learning centric, computationally efficient and is an integrated Early Alzheimer's Disease detection system. A joint autoencoder-latent vector-based classification system is proposed. Specifically, a convolutional autoencoder is used to generate a latent vector. This latent vector is further passed through a Latent Classifier module (LCM) to be classified using the Deep Parallel Ensemble (DPE), consisting of 5 base classification models: SVM, Random Forest (RF), Extra-Trees Classifier (ETC), XGBoost (XGB), and Multi-Layer Perceptron (MLP). The system is trained and tested on a 5-class Alzheimer's dataset consisting of high-resolution MRI images. The proposed system "EADDA" gives a testing accuracy of 86.57%, being the only work exploring and experimenting with the ADNI 5-class dataset.

Keywords: *Early Alzheimer's disease (AD), ADNI 5-class, Deep Learning, Autoencoders, Classification, Neuroimaging*

I. Introduction

The human brain is a complicated organ with millions of neurons that convey information using various electrical and chemical signals. This communication is disrupted by Alzheimer's disease (AD), an incurable neurological condition that causes progressive cell death. The cerebral cortex, which is responsible for reasoning, social behaviour, problem-solving, coordination and language, is initially impacted, followed by the hippocampus, which oversees memory [1]. The AD sufferer will gradually lose his independence at work. Although the precise origin is unknown, environmental, behavioural, and genetic factors may be involved. With approximately 55 million humans afflicted by the disease in 2023 [2], Alzheimer's ranks as the seventh most common cause of death in the world [3]. By 2050, it is anticipated that there will be three times as many Alzheimer's patients worldwide. The cost of care is expected to exceed $1.1 trillion by 2050, having a huge influence on both the economy and society[4].

In general, Alzheimer's disease cognitive and memory tests assess a person's capacity for memory, information recall, and task performance. A common examination is the Mini-Mental State Examination (MMSE) [5] as well as the Alzheimer's Disease examination Scale-Cognitive Subscale (ADAS-cog) [6]. The most popular imaging tests for AD are Magnetic Resonance Images (MRIs) and Positive Emitron Topography (PET) scans (AD). High-resolution images of the brain are provided by MRI scans, which can be used to spot AD-related structural alterations such as brain shrinkage. PET scans can produce precise images of the brain's activity and can reveal regions with diminished blood flow that might be connected to the condition. The amounts of certain proteins, such beta-amyloid and tau, which are linked to AD, are measured by blood and spinal fluid testing. The disease's distinguishing feature is an abnormal buildup of these proteins in the brain. It is possible but challenging to identify Alzheimer's in its early stages using biomarker testing [7] in conjunction with cognitive and behavioural evaluations.

There is currently no known treatment or prevention for the disease. It has been established that the early stages of AD might start up to 20 years before clinical symptoms or outward behavioural changes appear. Therefore, rather than using the conventional methods of diagnosis, biological indicators are greatly needed to assist in forecasting the start of AD. This work explicitly aims to provide a solution for the early detection of Alzheimer's Disease.

Convolutional Neural Network (CNN), the most popular deep learning design, has drawn a lot of interest in medical image analysis due to its success in picture analysis and classification [8]. Pre-trained models like ResNet, DenseNet, Xception, VGG16 and VGG19 have already

[1] *Dept. of Computer Engineering, Dwarkadas J. Sanghvi College of Engineering, Mumbai, India. ORCID ID: 0000-0003-4761-669X*
[2] *Dept. of Computer Engineering, Dwarkadas J. Sanghvi College of Engineering, Mumbai, India. ORCID ID: 0000-0001-8336-4800*
[3] *Dept. of Computer Engineering, Dwarkadas J. Sanghvi College of Engineering, Mumbai, India. ORCID ID: 0009-0004-6174-270X*
[4] *Dept. of Computer Engineering, Dwarkadas J. Sanghvi College of Engineering, Mumbai, India. ORCID ID: 0000-0001-8941-5381*
[1]*mohdraza.syed@gmail.com* [2]*neelkothariak@gmail.com*
[3]*joshiyash05@gmail.com* [4]*aruna.gawade@djsce.ac.in*

been trained on a huge dataset and can be tailored for certain tasks, like identifying Alzheimer's disease in brain scans. Using pre-trained CNN models has the benefit of utilizing basic picture properties such as edges and forms, which are crucial for seeing patterns in brain scans. This expedites the detection process and lowers the amount of training needed to produce reliable results. Additionally, these models are trained on huge datasets, enhancing the robustness of the outcomes and enabling good generalization to fresh data. Pretrained CNN models also have the advantage of being integrated with other methods, such as transfer learning, to enhance the output even more.

However, with the rise of quality-rich and intricate data (MRI images in the case of AD), it becomes essential to work with tools that can find the perfect trade-off between comprehensiveness and detail and computation costs. This work exploits Autoencoders, which is an evolving deep-learning algorithm, as an attempt to find that balance.

The following are the three research contributions:

1) In this study, we investigate the application of autoencoders for data denoising and dimensionality reduction of high-dimensional brain MRI images from the ADNI 5-class dataset.

2) The autoencoders aid in the identification of only the most crucial characteristics in the image, lowering the costs associated with computing extraneous features from the image.

3) The unique model that has been developed classifies these "most important" properties using a variety of cutting-edge classification techniques.

Following is the breakdown of the remaining sections of the study:

Section II talks about the literature review, and Section III talks about the proposed system. The methodology and results of the experiment are covered in Section IV of the publication. The conclusion and potential lines of inquiry are covered in Section V.

II. Review of Literature

Deep learning methods have been used in the medical industry to diagnose Alzheimer's illness, among other things. Image analysis is one method for using deep learning to find Alzheimer's. Convolutional Neural Networks (CNNs) can be trained using MRI or PET images of the brain to find patterns connected to Alzheimer's disease. CNNs may be trained to recognize minor alterations in the brain's structure that signal sickness, including a decrease in brain volume. This method can be used to identify Alzheimer's in its earliest stages while therapies are still accessible, and the disease's development can be delayed. Speech analysis is a different method for using deep learning to find Alzheimer's. On voice samples, recurrent neural networks (RNNs) or transformers can be trained to recognize changes in speech patterns connected to Alzheimer's disease. For instance, persons with Alzheimer's may have trouble finding words and speaking spontaneously, which may be identified by listening to speech patterns. This technology can offer a non-invasive way to identify Alzheimer's disease and is simple to use in clinical settings.

In recent years, several methods for neuroimaging classification have been put out to enhance classification performance. Gokce UYSAL et al. [9] extract 16 characteristics from the MRI data and use different classifiers for the classification task, including K-Nearest Neighbors (KNN), Logistic Regression (LR), and SVM. However, most of the recent research has focused on employing ensemble approaches and deep learning for the classification job. The study that follows looks at a few deep learning classification structures used in neuroimaging, as well as convolutional neural network methods (described in section 2.1), ensemble learning methods (discussed in section 2.1), and ensemble learning methods (mentioned in section 2.2).

1. CNN Methods For Neuroimaging:

For the objective of early Alzheimer's disease diagnosis, numerous machine learning-based algorithms have recently been applied to binary and multi-class classification. The vast potential of deep learning has been shown in the field of medical picture diagnostics, where it was initially applied to region segmentation or feature extraction before being replaced by more conventional machine learning techniques like SVM and boosting.

K A N N P Gunawardena at al. [10] explore the application of Convolutional Neural Networks for Pre-detection of Alzheimer’s Disease from Structural MRI data. They explore the usage of SVM classifiers as well as a CNN using image segmentation. Currently, the study only focuses on the coronal view of an MRI, but future work could also include using the axial and sagittal views to identify the landmarks of the disease. Another potential improvement would be to use an autoencoder to extract features from the input image.

Amir Ebrahim and Suhuai Luo try various deep-learning methods, including 2D CNN’s, 2D CNN+LSTM and 3D CNN’s utilizing transfer learning. Sreeja Sasidharan Rajeswari et al. [11] propose a Transfer Learning Approach for Predicting Alzheimer’s Disease.VGG-19, VGG-16, Resnet-50, Xception models were used for transfer learning for the prediction of Alzheimer's disease in a less laborious manner. Helcy D. Alon et al. [12] also propose a Transfer Learning Approach but for Dementia Detection and Classification from Neuroimaging by utilizing a YoloV3

CNN model on MRI images. Jyoti Islam et al. [13] explores using a custom-built CNN model upon multiple layers of framework on MRI OASIS dataset to get highly specific and sensitive results. P C Muhammed Raees and Vinu Thomas [14] and Amir Ebrahim and Suhuai Luo [15] also employ transfer learning along with custom tuning of hyperparameters to obtain the highest accuracy using the VGG19 and ResNet-18 model respectively.

Chaihtra DH et al. [16] and Muntasir Mamun et al. [17] jointly explore the DenseNet 121 CNN for Alzheimer's Disease Detection Using Brain MRI Images. The authors also explore DenseNet121, MobileNet, InceptionV3 and Xception neural networks along with applying a convolution neural network for further analysis; however, the scope of the methodology is limited to certain datasets and would need rectification to expand their scope. Muntasir Mamun at al. [17] Used Alzheimer's Dataset of 6219 images on 3 different Pretrained models, Resnet101, DenseNet121 and VGG16.Another Custom CNN model was built, and it outperformed with the highest accuracy of 97.6%. In a similar study, A. Hadeer et al. [18] apply transfer learning to a pre-trained VGG-19 model on a custom augmented ADNI 4-class dataset to achieve promising results.

Using whole brain MRI, Fazal ur Rehman Faisal et al. [19] developed an automated approach to identify Alzheimer's disease and moderate cognitive impairment. They recommend using an end-to-end deep CNN custom-layered architecture using the entire picture volume as input for the multi-label AD biomarker identification process. The authors suggested a straightforward but efficient convolutional technique that simultaneously runs normal convolution, depth wise convolution, and point-wise convolution to extract multi-level features from brain MRI data. A further technique is a skip convolution layer. However, the suggested CNN for 3D whole-brain image processing does not yet incorporate patient history data.

Sergey Korolev at al. [20] investigate the usage of VoxCNN, Resnet models to understand the Normal Cohort, Late and Early Mild Cognitive Impairment.

Zheng-Lin Tong et al. [21] propose a three-layer Stacked Denoising Auto Encoder (SDAE) for feature extraction of the ADNI. This SDAE was combined with a tuned SVM123 classifier with 10 cross-fold validation to classify the AD.

Esra Çankaya Polat et al. [22] use the PET patient images from the ADNI dataset. Authors adopt a method where a new image is compared with all the PET images and an image similarity score is generated on the basis of Mutual Information. The accuracy score was determined using the AUC, which was 0.85. However, there is no use of pre-filtering techniques, which can potentially enhance the prediction accuracy.

2. Ensemble Methods for Neuroimaging:

M. Tanveer et al. [23] and Aya Gamal et al. [24] investigate the classification of Alzheimer's Disease using an ensemble of Deep Neural Networks trained through transfer learning. M. Tanveer et al. [23] explore training multiple deep neural networks on a large dataset of brain imaging data and then combining the output of these networks to improve the accuracy of the classification. The authors report that their ensemble approach outperforms traditional machine learning methods and other deep learning approaches for Alzheimer's disease classification. However, the current DTE (Deep Ensemble with Temporal Embeddings) method for improving the generalization of deep models in Alzheimer's disease prediction lacks an optimal strategy for selecting models for the ensemble and assigning appropriate weights to each individual model. Whereas 3D augmentation of 3D MRI images was first carried out by Aya Gamal et al. [24]. The top 3 classification models, 3D CNN, DenseNet201+CBAM, and modified DenseNet201, were then employed in an ensemble learning technique.

Using NMF-TDNet Features from a 3D brain MRI image, Huan Lao and Xuejun Zhang [25] examine the regression and classification of Alzheimer's disease diagnosis. They introduce the NMF-TDNet, a data independent nonnegative matrix factorization tensor decomposition network, to produce multi-level filter banks for sample learning.

After an extensive survey of the literature, it was found that no research work had been conducted on the 5-class ADNI dataset, which, unlike the well-explored ADNI 4-class dataset, is a dataset having high-quality MRI images of the brain corresponding to 5 different types of Alzheimer disease groups. Secondly, the possibility of utilizing the strength of autoencoders in order to mine the most relevant features from high-quality MRI images of the brain was yet to be explored. Autoencoders can specifically be more effective in identifying accurate and relevant features for classification than generic transfer learning methods since they can be trained specifically for the task at hand, unlike model which are pre-trained on a fixed set of classes.

III. Proposed System

The low-level workflow diagram for the proposed Alzheimer's disease detection system pipeline -EADDA is shown by Figure 1, while the consequent sections describe each component of the workflow.

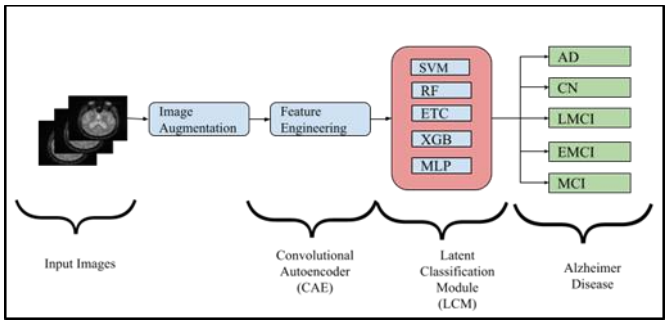

Fig. 1. Workflow Diagram.

Class	Before Augmentation	After Augmentation
AD	171	630
CN	580	705
EMCI	240	675
LMCI	72	497
MCI	233	651

1. Dataset Description:

The Alzheimer's Dataset for this proposed study has been obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI) repository (adni.loni.usc.edu). The dataset utilised consists of 1296 MRI Images altogether. Following this, the information is split into five categories: Cognitive Normal (CN), Alzheimer's Disease (AD), Early Mild Cognitive Impairment (EMCI), Late Mild Cognitive Impairment (LMCI), and Mild Cognitive Impairment (MCI).

EMCI, LMCI, MCI: Although these patients can attempt to carry out their usual tasks, they do have noticeable cognitive deficits that affect their daily lives. These patients range from 24 to 30 on the MMSE [26]score with Clinical Dementia Rating [27]of 0.5 MCI that changes into AD is referred to as pMCI, and MCI that remains the same is referred to as sMCI.

AD: these patients struggle to maintain independence due to memory, language, judgment, and problem-solving difficulties. These patients have an MMSE score between 20 and 26 and a Clinical Dementia Rating between 0.5 and 1.

CN: Individuals with cognitively normal brains have normal memory, language, attention, and other abilities. Studies have been done to better understand the causes of cognitive decline and to pinpoint possible risk factors or protective factors. These patients have MMSE scores varying from 24 to 30 and the Clinical Dementia Rating 0.

Figure 2 depicts single samples from each of the above classes of the dataset.

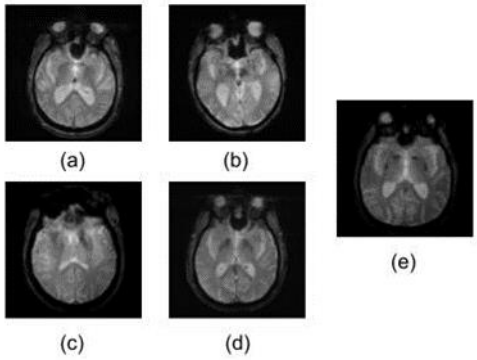

Fig. 2. Example of different MRI brain images

(a) AD (b) CN (c) EMCI (d) LMCI (e) MCI

2. Data Augmentation

To create new training data for image processing tasks, different transformations are applied to the current dataset as part of the data augmentation technique. This method is especially helpful for picture classification problems because it increases the amount and diversity of the training dataset, which is crucial for enhancing the accuracy and robustness of deep learning models. By introducing variations such as rotation, scaling, shearing, flipping, and other transformations, data augmentation allowed the proposed model to learn from a wider range of visual inputs, making it more capable of recognizing patterns and features in new images.

On initial experimentation, it was found that the proposed system failed to achieve desirable accuracies for Alzheimer's Disease Detection. On closer research and experimentation, it was found that this could mainly be attributed to the evident data imbalance in the dataset, as shown in the Before Augmentation column in Table 1. Thus, data augmentation is performed on the existing dataset to increase the number of samples for better learning by machine-learning classifiers.

The Image Data Generator object of Keras library is used to perform varied transformations to fulfill augmentation. The various parameters and their values are mentioned in Table 2.

Table 1 shows the number of samples for each class before and after the augmentation process.

Table 1. Augmentation Statistics

Table 2 also shows the number of images in each class of the dataset before and after image augmentation.

Table 2. Augmentation parameters

Parameters Tuned	Value
Rotation Range	0.25
Width Shift Range	0.3
Height Shift Range	0.40
Shear Range	0.15
Zoom Range	0.5
Horizontal Flip	True
Fill Mode	nearest

3. Process flow of the Proposed System:

After image augmentation, the input image is initially passed through the autoencoder block for feature reduction and to form a latent vector to be fed into the Deep parallel ensemble for classification. The embeddings (latent vector) obtained from the bottleneck layer are mined by passing through the Deep parallel ensemble of the Latent Classification Module (LCM) and the best-performing classifier is chosen and used in order to finally classify the input image into any 1 of the 5 output classes. Figure 3 represents the overview of the proposed system.

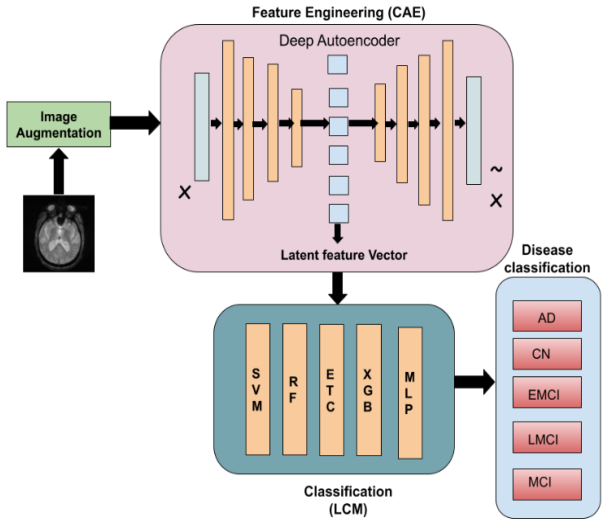

Fig. 3. EDDA System Overview

3.1. Autoencoder Block:

Following data augmentation, the Convolutional Autoencoder (CAE), which is made up of encoder and decoder modules, as shown in Figure 4, generates features using the data. The CAE's encoder and decoder modules each have four hidden layers built into them, and an extra bottleneck layer that introduces feature compression is also included. The layers are dense layers with a combination of "relu" and "sigmoid" activation functions. The CAE automatically extracts features from the input photos, which are then scaled down at the bottleneck layer. The image is rebuilt by the decoder. The Mean Squared Error (MSE) was used to calculate the reconstruction error. According to Eq. (1), it was measured between the input and the reconstructed picture.

$$MSE = \frac{1}{n}\Sigma(x_i - y_i)2 \qquad (1)$$

When n denotes the number of data points, y_i denotes the expected values, and x_i denotes the observed values.

The decoder block of the CAE separated after successfully reconstructing the input features, and the latent vector was mined from the bottleneck layer of the CAE.

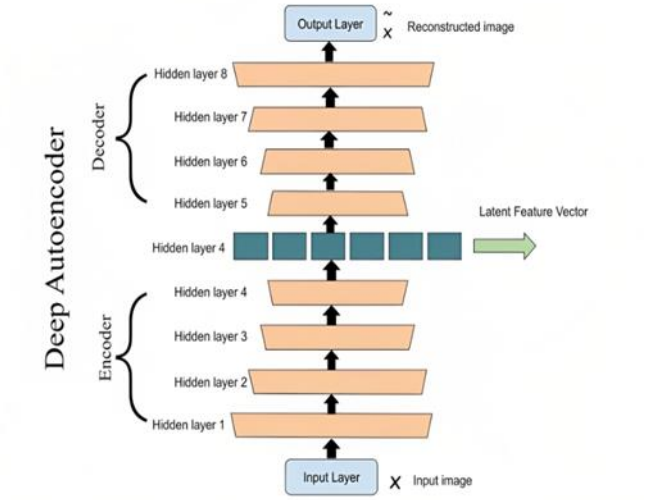

Fig. 4. Convolutional Autoencoder (CAE) Block

3.2. Proposed Deep Parallel Ensemble:

The suggested deep parallel ensemble is a classification ensemble, which consists of the convolutional autoencoder, sand a group of traditional machine learning classification models built in a parallel architecture under the name Latent Classifier Module (LCM), as shown in Figure 5.

The latent feature vector, extracted from the CAE, is used to train the LCM. The LCM is created by placing the basic learners parallel to one another. The basic learners in the LCM are all executed at once and are not dependent on one another. The best-performing classifier out of all the classifiers is used to provide the final classification result. Due to the fact that many machine learning models were used as the foundation learners, the DPE is a heterogeneous deep parallel ensemble.

3.3. Architecture of Latent Classification Module:

High-level features are produced by the convolutional autoencoder which are used to train the LCM.

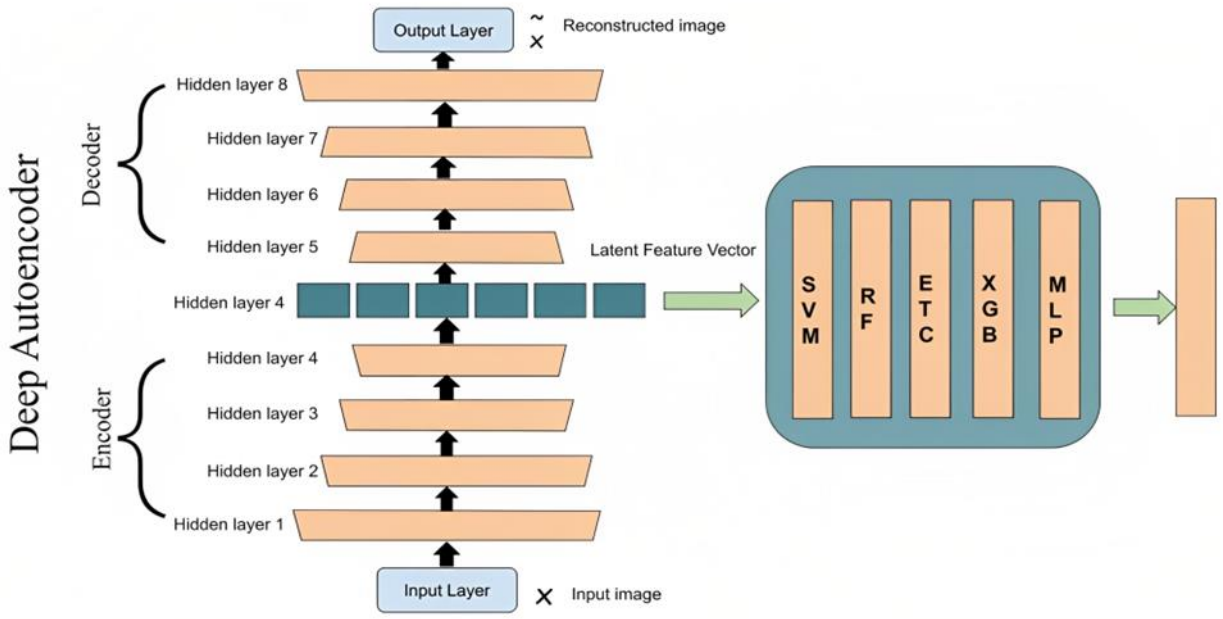

Fig. 5. Deep Parallel Ensemble

The following machine learning base learners are used to construct the LCM in the proposed DSE framework: SVM, Random Forest, Extra-Trees Classifier, XGBoost, and Multi-Layer Perceptron. To enhance the model's capability to categorize unknown input, several classifiers have been carefully included in the Latent Classifier Module.

IV. Experiments Details and Results

1. Performance Evaluation:

This study's usage of a variety of metrics made it possible to evaluate the models' effectiveness in depth. This is significant because deep learning models' complexity cannot be accurately captured by a single metric. The researchers might get a better understanding of the model's strengths and weaknesses by taking into account a variety of measures.

This study illustrates the value of several measures for evaluating model performance and emphasizes the significance of performance evaluation in deep learning. By using these methods, researchers can create models that are more useful for classifying MRI scans and other types of medical imaging data.

2. Comparison with baseline models:

The 5-Class ADNI Dataset is used to assess how well the suggested system performs. Despite requiring less training time and processing computation, as demonstrated in Table 3, the suggested Deep Parallel Ensemble approach surpasses all other pre-trained models utilized on the same dataset.

On the MRI dataset, many pre-trained models, including MobileNet [28], EfficientNet B4, EfficientNet B7 [29], ResNet50 [30], DenseNet121 [31], and VGG19 [32] were trained. Using the metrics such as Accuracy, Precision, Recall, and F1-Score, it was discovered that ResNet50 provided the best accuracy, which was no higher than 79.77%, and Efficient B7 provided the lowest accuracy, which was no less than 48.39%. With a maximum accuracy of 86.57%, precision of 79.19%, recall of 77.47%, and F1-score of 78.32%, the proposed methodology outperformed all pre-trained models.

Table 3. Evaluation metrics for the models used for transfer learning.

CNN Models Without Transfer Learning	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
MobileNet	69.662	46.03	44.62	45.31
EfficientNet B4	47.01	34.03	37.22	35.55
ResNet50	79.77	49.32	40.91	44.72
DenseNet121	55.20	47.06	43.96	45.46
VGG19	76.21	36.11	24.62	29.28
EfficientNet B7	48.39	42.28	33.17	37.18
EADDA	**86.57**	**79.19**	**77.47**	**78.32**

Table 3 depicts the various score metrics and their values for the aforementioned models while Figure 6 is a multi-bar graph representation of the same for each model with the proposed model of this research. Figure 7 is a combined multi-bar representation for comparing the transfer learning models with the proposed EADDA.

3. Comparing with other existing methods:

The categorization outcomes of the suggested methods have been contrasted with those from numerous earlier publications using the ADNI Dataset. Starting with Chaihtra DH et al. [16], the authors recommended using a variety of transfer learning models, including DenseNet121, MobileNet, and InceptionV3, on the ADNI (4-Class) Dataset, with DenseNet121 being the most accurate at 91%. [10] used the proposed CNN architecture and the ADNI (3-Class) Dataset in his work, which produced an accuracy of 96%. In their research, Muntasir Mamun et al. [17] suggested a unique CNN architecture on the ADNI (4-Class) Dataset that outperformed Resnet101, DenseNet121, and VGG16 and provided

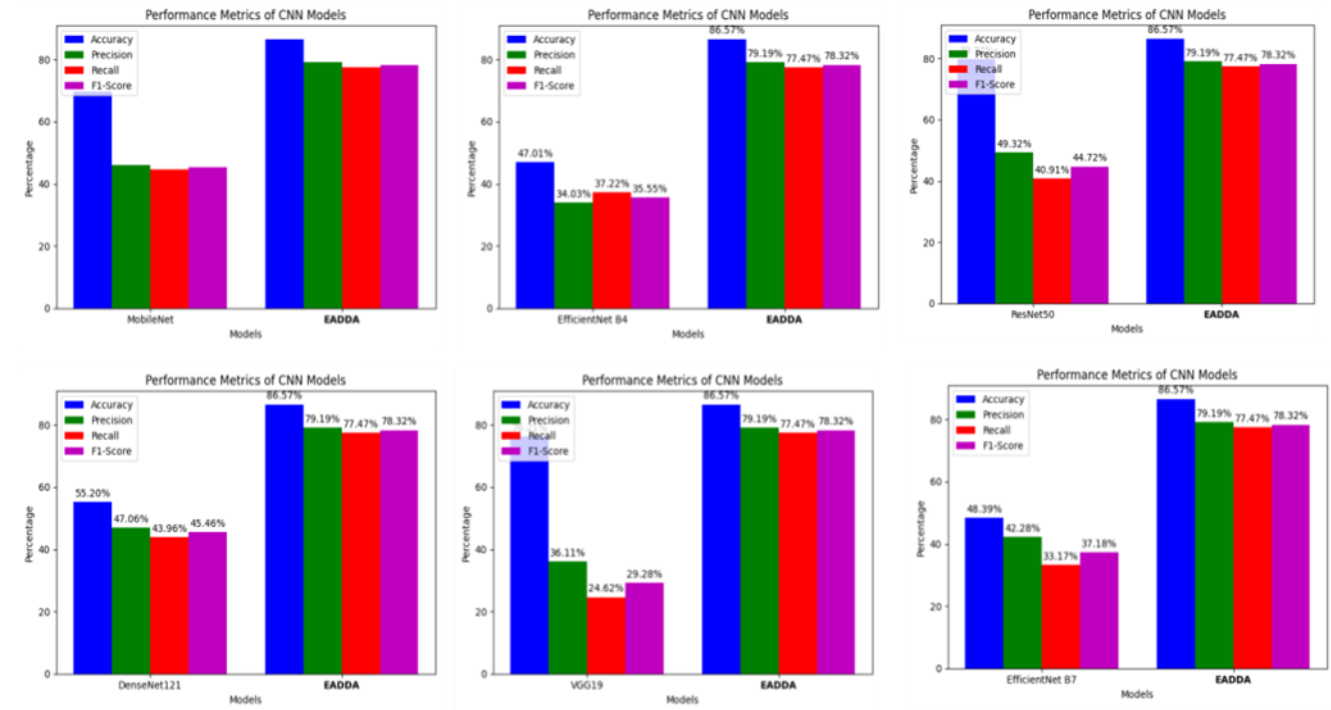

Fig. 6. Performance of transfer learning model vs EADDA

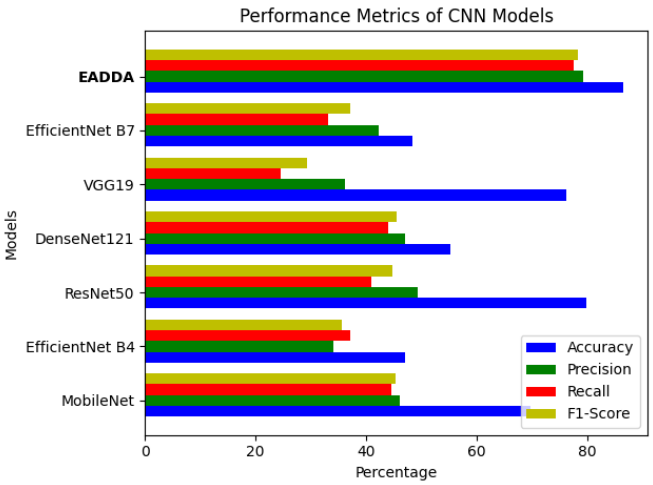

Fig. 7. Combined Multi bar-graph representation of comparison of models

an accuracy of 97.6%. In their proposed research works, authors P C Muhammed Raees and Vinu Thomas [14] and A. Hadeer et al. [18] used the ADNI (3-Class) Dataset and ADNI (4-Class) Dataset, respectively, on the transfer learning model of VGG19, which provided them with an accuracy of 90.02% and 97%, respectively.

With a regression approach and SVM classifier on the ADNI-1 (3-Class), ADNI-2 (4-Class), and OASIS Dataset, Huan Lao and Xuejun Zhang [25] proposed an original, innovative approach and achieved an accuracy of 89.16%. In their suggested work, Amir Ebrahim and Suhuai Luo [15] used 2D-CNNs combined with an LSTM model and 3D-CNNs combined with a transfer learning ResNet-18 model, which provided an accuracy of 96.88% on the ADNI (4-Class) Dataset. A tabular representation of the methodologies and accuracies is given by Table 4 with a visual representation of their comparison in Figure 8.

Table 4. Comparative study of related works

Author	**Dataset Utilized**	**Models Used**	**Results of Proposed Model**
Chaihtra DH [16]	Kaggle Brain MRI Dataset (4-Class)	**DenseNet121 (Proposed),** MobileNet, InceptionV3	Accuracy:91%
K A N N P Gunawardena [10]	ADNI Dataset (3-Class)	**CNN (Proposed),** SVM	Accuracy:96%
Muntasir Mamun [17]	Kaggle Brain MRI Dataset (4-Class)	**Custom CNN (Proposed),** Resnet101, DenseNet121, VGG16	Accuracy:97.6 %
P C Muhammed Raees and Vinu Thomas [14]	ADNI Dataset (3-Class)	**VGG19 (Proposed),** AlexNet, VGG16, GoogLeNet	Accuracy:90.02 %
Huan Lao and Xuejun Zhang [25]	ADNI-1 (3-Class), ADNI-2 (3-Class), OASIS (2-Class)	**(NMF-TDNet) input to SVM (proposed)**	Accuracy:89.16 %
A. Hadeer [18]	ADNI Dataset (4-Class)	VGG19 **(Proposed),** CNN	Accuracy:97%
Amir Ebrahim Suhuai Luo [15]	ADNI Dataset (4-Class)	**3D CNNs (ResNet-18) (Proposed),** 2D CNNs, 2D CNNs + LSTM	Accuracy:96.88 %
Lin et al. [33]	ADNI Dataset (4-class)	**CNN**	Accuracy:88.79 %

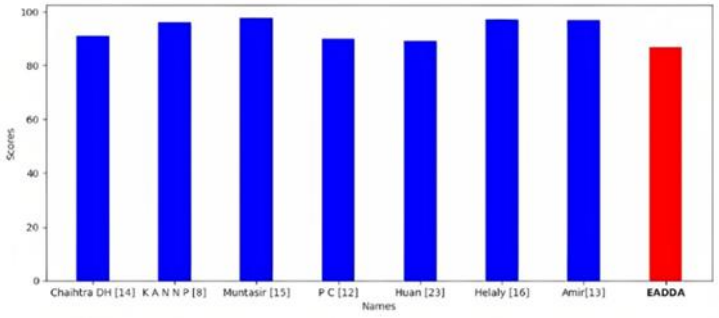

Fig. 8. Performance of previous works vs EADDA

A point to consider regarding the accuracies in Figure 8 is that transfer learning methods have been applied on the ADNI-3,4 class datasets in the other methodologies unlike EADDA which is a custom autoencoder based model applied on the ADNI-5 class.

4. Performance of Latent Classifiers Module

We implemented 5 different classifiers, including Support Vector Machines (SVM) [34], Random Forest [35], Extra Trees Classifier [36], XGBoost [37], and Multi-layer Perceptron[38], for the classification of the 5-Class ADNI dataset. Extra Trees Classifier provided the best accuracy of 86.57%, surpassing all other classifiers, as shown in evaluation metric Table 5, out of these 5 classifiers in the Latent Classifier Model (LCM) of the proposed Deep Parallel Ensemble Architecture. Figure 9 illustrates the comparison of different classifiers using score metrics, including Precision, Recall, and F1-Scores, visualized as bar graphs. Figure 10 shows the combined multi-bar representation of a comparison of the classification models.

Table 5. Evaluation metrics for classifiers in the DPE

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Support Vector Machine	68.36	63.25	60.14	61.66
Random Forest	74.79	66.74	63.55	65.11
Extra-Tree Classifier	**86.57**	**79.19**	**77.47**	**78.32**
XGboost	71.04	64.31	61.24	62.74
Multi-Layer Perceptron	65.62	59.65	56.11	57.83

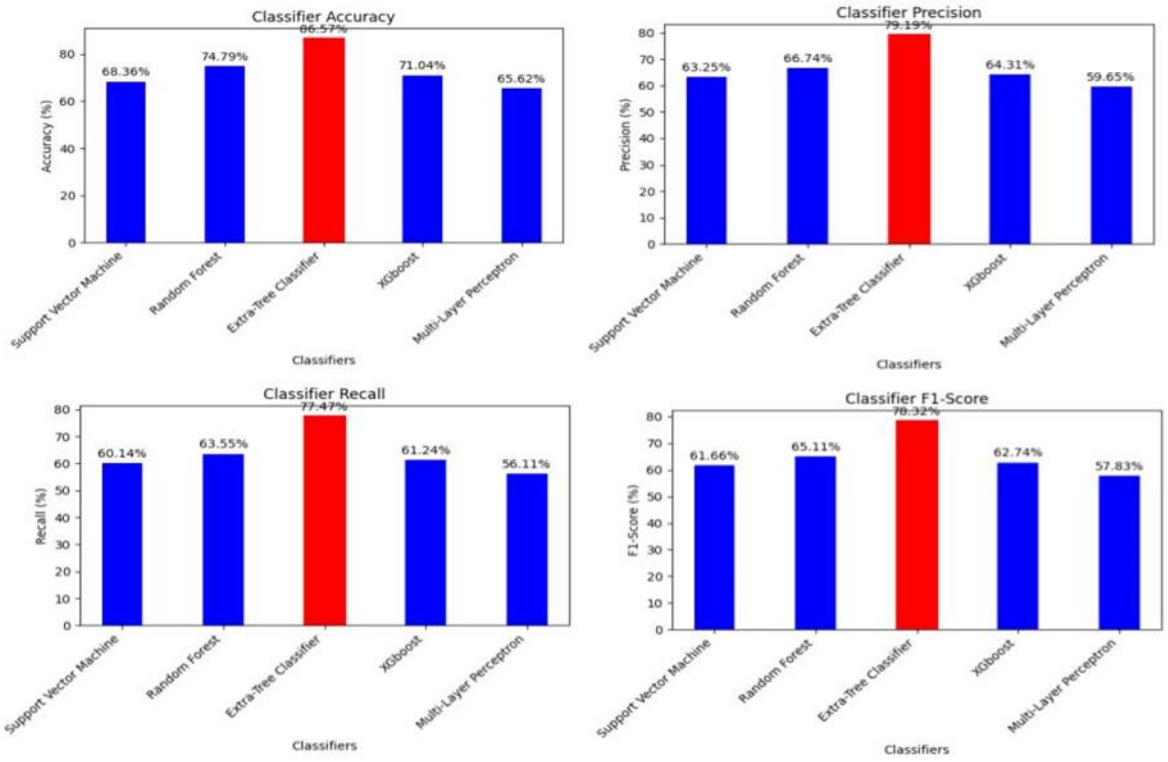

Fig. 9. Score metrics for classifiers in the DPE

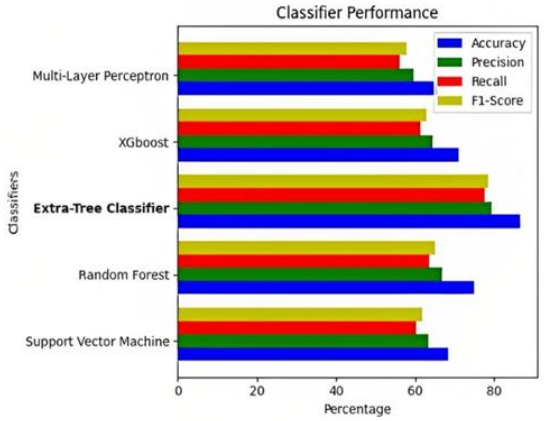

Fig. 10. Combined multi-bar representation of a comparison of the classification models.

5. Performance of Latent Classifiers Module

For the proposed Deep Parallel Ensemble Architecture, a variety of trial-and-error methods has been used to determine the optimal and most accurate number of encoding layers and decoding layers. The accuracy of 4 Encoding Layers and 4 Decoding Layers, as shown in Table 6, was found to be the greatest and best, at 86.57%, as compared to 2 Encoding & 2 Decoding Layers and 6 Encoding & 6 Decoding Layers, whose accuracy was found to be 76.31% and 81.98% respectively.

Table 6. Evaluation metrics at different layers

Auto Encoding Architecture	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
2 encoding layers and 2 Decoding Layers + Parallel Ensemble	76.31	64.39	62.34	63.35
4 Encoding + 4 Decoding Layers + Deep Parallel Ensemble	**86.57**	**79.19**	**77.47**	**78.32**
6 Encoding + 6 Decoding Layers + Deep Parallel Ensemble	81.98	74.11	72.32	73.20

Additionally, Accuracy Precision, Recall, and F1-Score were calculated and compared for each of the many layers that have been examined at, and the results are shown in a graph in Figure 11.

V. Conclusion

In conclusion, millions of individuals throughout the world are impacted by the tragic affliction known as Alzheimer's disease. Effective illness management and symptom control depend on early disease identification. The early diagnosis of Alzheimer's disease using MRI scans that can distinguish between AD, LMCI, EMCI, MCI, and CN has been described in this work. When it comes to the early identification of Alzheimer's disease, the suggested system's cascaded Autoencoder and ensemble of classification algorithm architecture provide promising results. Modern cutting-edge systems fared better than the stated strategy. The proposed approach has the potential to identify significant patterns in data, support previous expert judgements, support diagnostic hypotheses, and ultimately uncover patterns for diseases other than Alzheimer's. The overall accuracy of the suggested system is 86.57%. The results of this study indicate that deep learning has the potential to improve Alzheimer's disease detection's accuracy and dependability.

Future research can focus on refining this architecture and investigating its applicability in larger and more diverse datasets.

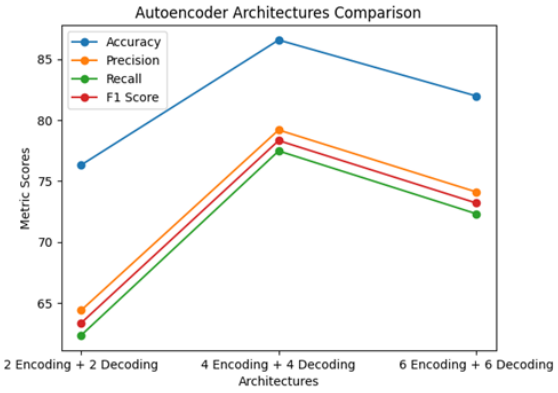

Fig. 11. Graphical representation of Evaluation metrics at different layers

Another direction could be to investigate the use of more complex and sophisticated neural networks architectures, such as deep neural networks or hybrid models, to improve the accuracy of the model. Additionally, it could be useful to explore the combination of other types of data sources, such as brain imaging data or longitudinal clinical data, with the input data to enhance the performance of the model. Another area for future research could be to evaluate the model's ability to predict disease progression and monitor treatment efficacy.

Conflicts of interest

The authors declare no conflicts of interest.

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