Alzheimer's Detection using XAI in Capsule Network & Post Detection Management with Portable Solution

A.H.M Sakif Shale[1*], Sabikun Naher Monisha[1†], Barnita Barai Sithee[1†], Shamim Kaiser[1†]

[1*]Institute of Information Technology, Jahangirnagar University, Savar, Dhaka, 1342, Bangladesh.

*Corresponding author(s). E-mail(s): sakifdhrubo1997@gmail.com; Contributing authors: sabikunmonisha01@gmail.com; barnitabaraisithee@gmail.com; mskaiser@juniv.edu;
†These authors contributed equally to this work.

Abstract

Alzheimer's Disease **AD** is a neurodegenerative disease that gets bad with time and it has no known cure. The research focuses on early detection, individualized caregiving, and an all-encompassing approach to healthcare. We present a comprehensive approach to early AD detection through the development and implementation of a Convnet model, which is enhanced by using transfer learning techniques including (Dense121, Restnet, and InceptionV3). The proposed model performs four-class image classification to distinguish between Mild, Moderate, Very Mild, and Non-Demented states.
Capsule Networks (CapsNet) architecture integrated, which accelerates in preserving spatial sequential hierarchy in image data Explainable AI (XAI) techniques have been incorporated, particularly, LIME and LRP are used to influence how neural networks make decisions, ensuring that classifications are transparently and comprehensibly justified. This makes it easier to integrate neural networks into clinical practice.

Keywords: AD Detection, Transfer Learning, CapsNet, Explainable AI, AD Management.

1 Introduction

Image-based data is interpreted via DL. It can categorize patterns, assisting in multiclass image classification. AD is an incurable neurological disease that only gets bad over time. The most dependable detection method is MRI-based image classification, allowing identified patient management to slow the progression of the illness and accelerate treatment.

Around 26.6 million people worldwide have AD and it is projected to increase to 106.2 million by 2050. The majority of AD cases in 2006 were in Asia (48%), with this proportion expected to increase to 59% by 2050.[1] It is not a disease on its own but rather a type of Dementia. It mainly affects the normal human brain workflow. The human affected by AD face difficulties in completing simple tasks. AD interrupts brain regions regarding control of memory, actions, cognitive thinking, and languages. Patients gradually lose their ability to recognize, quickly respond, or continue conversation. The "Memory 3 S," aims to raise awareness that a new Alzheimer's disease patient emerges approximately every 3 seconds globally.

Alzheimer's Disease in Bangladesh is an increasingly serious problem, especially among people over 65. According to experts, there will be more than 2 million Alzheimer's patients in Bangladesh by 2050; 1 case for every 50 people. According to 2017 data from the WHO, in Bangladesh 9,917 deaths were due to dementia, accounting for 1.26 percent of all fatalities.[2] A meta-analysis says the average annual cost per Alzheimer's patient is $20,461, with costs going up with disease severity. $14,675 for mild, $19,975 for moderate, $29,708 for severe (MMSE).[3] This is a big challenge for Bangladesh since our economic condition is pretty poor compared to other developed countries like the USA. As stated earlier, Alzheimer's disease is ever-increasing. By 2030, the total AD patients will be more than 7 billion people. Alzheimer's patients need continuous monitoring and aid by caregivers. If this increases to a large number, getting adequate caregiving personnel will be increasingly difficult.[4]

Since AD is known to be incurable, there is currently no cure available for this problem. However, AD may still be under control if we can identify it early. To detect AD using the existing dataset are trained using CNN, RestNet50, and Densenet121 models. The testing accuracy is as follows 99.73%, 74.0%, and 94.3%.

We proposed a nobel approach to develop a more accurate detection technique and identify the afflicted area from a 2D MRI image employing XAI. It identifies the impacted region and also uses the metadata to compute the feature contribution. We also proposed a management system with features such as a notepad, time-to-time notification, mind games, and location to control the condition of AD patients. We created a portable device software to manage AD patients and create a better life for them.

In literature study related works are given including explanations for the most important terms used in this thesis-basic concept and architecture of DL models have been discussed through this chapter. Then the model is introduced, analyzed, model description, architectural view, and proposed mobile application. It explains the results of the implemented model and discussion about that. Lastly, in future work, and conclusion are mentioned.

2 Related Work

Ammarah Farooq et al conducted this study to examine the application of DL techniques in conjunction with MRI data to analyze cases of Alzheimer's disease. This involves dividing subjects into classes based on MRI volumes as well as sex plus age groups. First, the reliability and quality levels were tested in MRI data due to the preprocessing step and later it was modeled through DL algorithms. This research attempts to enhance diagnostic aids for finding Alzheimer's disease so that they can eventually become.[5]

Junhao Wen et al presented this research study which makes a specialty of using convolutional neural networks (CNN) together with MRI scans to investigate AD. Among the CNNs underneath observed are 2D slice-stage, 3D patch-level, ROI-based totally, and 3D situation-level CNNs. Disparities in situation choice, photo pre-processing, and validation strategies make it tough to distinguish between investigations. Numerous studies' findings show how overall performance is considerably hampered by information leaking.[6]

Haijing Sun et al used a ResNet model combining STN, Mish activation function, and non-local attention mechanism to detect early AD. Spatial information of MRI images is transformed using STN. The classification accuracy is almost 97.1%, high precision is 95.5% and 95.3% recall, and 95.4% F1 value is attained with their proposed model. ResNet helps to extract the features more precisely thus preserving diagnostic accuracy.[7]

E. Ranguelova, E. Pauwels, and J. Berkhout set the goal of the paper to analyze the Layer-Wise Relevance Propagation (LRP) approach and suggest improvements to the claims made about how well LRP heatmaps correlate with interpretable image attributes It is reported that there is a substantial correlation between interpretable picture features and layer-wise relevance propagation heatmaps performed on benchmark datasets.[8]

Mahmud et al point out that the application of XAI in DL models potentially improves interpretability, while Mahmud 2024 reached an accuracy of 96% by developing a model through saliency maps and grad-CAM techniques. Using deep transfer gaining knowledge of AD analysis with an accuracy of 95% using an ensemble model. Vimbi 2023 offers a systematic evaluation of XAI in AD detection and discusses exclusive approaches and frameworks of XAI used, in conjunction with their capability for scientific analysis. All those studies underline the fact that the potential of XAI usually lies in making AI fashions for AD diagnosis more obvious and interpretable.[9]

G Vasukidevi et al investigated the application of capsule networks in predicting AD. Nagashbayev (2020) and Nisha (2023) each devised customized capsule network architectures for AD diagnosis, with Nisha's model exhibiting notable levels of accuracy, sensitivity, and specificity. Introducing a new approach, Basheer (2021) introduced a pioneering algorithm for forecasting dementia through the utilization of a capsule network, achieving an impressive accuracy rate of 92.39%. Expanding on this work, Bhatele (2022) broadened the scope of capsule networks to encompass a completely automated early detection system for various neurodegenerative conditions, such as AD, boasting high levels of accuracy. Collectively, these investigations underscore the promise of capsule networks in predicting AD and underscore the necessity for further investigation in this domain.[10]

Manan Binth Taj Noor et al in this research paper used DL methodologies for the identification and diagnosis of neurological disorders (NLD) including Alzheimer's disease (AD), Parkinson's disease (PD), and schizophrenia (SZ) from MRI data. The study emphasizes that CNN is the most popular DL architecture in this regard with more emphasis on AD than PD and SZ. The pre-processing methods such as, linear regression, modulation, segmentation, voxel based morphometry, cortical reconstruction, de-noising and data augmentation have been explained in the paper in order to improve MRI scan analysis towards detection of NLD. The paper is structured into sections focusing on different aspects: The kind of DL architectures applied to MRI analysis, essential pre-processing steps for data, and comprehensive descriptions of AD, PD, and SZ identification. Collectively, the research paper offers first-hand information as to the developments in DL models that can be applied for identifying NLD from MRI data, as well as the prospects of these technologies in enhancing diagnostics validity and patients' treatment results.[11]

Al-Farabi et al introduced a DL model of capsule network based classification for the classification of AD vs NC using MRI images from the ADNI dataset. The research is focused on empowering the classification of AD by using capsule networks on structural magnetic resonance imaging. These frameworks have been modified and reduced to a significant number of trainable parameters, enabling them to be used on lower-powered computers with GPUs but still achieving results that match current methods. As the results from independent and dependent subject studies have demonstrated, it is possible to achieve good performance when there are fewer parameters and fewer MRI images in the AD and NC classes using the proposed framework.[12]

R.C. Suganthe et al made the paper's purpose to detect AD from MRI scans, incorporating superior technologies such as deep convolutional neural networks. Previous research has shown the effectiveness of deep gaining knowledge of fashions in accomplishing high accuracy in Alzheimer's ailment analysis. The proposed model can categorize people into distinct tiers of Alzheimer's sickness with an accuracy of 79.12%, showing enhancements over existing methods. DL techniques, especially CNN, which is important in enhancing the precision and performance of Alzheimer's ailment detection via MRI imaging. By integrating advanced methodologies with MRI scans, the research provides a promising technique for early detection of AD and control of its sickness, marking it a huge development in the discipline.[13]

Sobhana Jahan et al detected AD risk factors and the prevention using different modalities of clinical, psychological, and MRI segmentation data with the help of Explainable AI is the focus of the study. It attains a high accuracy of 98%. 5 class classification (Alzheimer's disease, cognitively normal, non-Alzheimer's dementia, uncertain dementia, others) accuracy achieved 81%, using a Random Forest (RF) classifier. Using the SHAP explainer, the study improves predictability by giving out features such as Judgment, Memory, Homehobb, Orient, and Sumbox. Finally, the paper presents a new model to address managing and monitoring patients with Alzheimer's, though its efficiency needs confirmation in a real-world setting. The accuracy is significantly higher for the multimodal option compared to dealing with the multiple datasets separately pointing to the importance of the multiple modalities for the exact prediction of Alzheimer's disease.[14]

Zhenyu Cui et al made the paper to implement or propose the diagnostic framework for Alzheimer's ailment where a superior Inception(V3) neural network was used in diagnosing the disease from brain MRI pictures; the paper emphasizes the importance of early detection since the ailment is documented to be untreatable and hard to detect early signs and symptoms. To enhance the recognition accuracy, it incorporates three enhanced forms of Inception blocks and efficient statistics pre-processing; thus, it has a score of 85.7%. The greater network is more expert in analyzing MR pix to develop grade getting-to-know processing for fashion that might serve in early and right detection of Alzheimer's ailment and mild cognitive impairment. The examination showed all and sundry signs that deep getting to know combined with sophisticated picture processing increases the accuracy of Alzheimer's disorder detection.[15]

Yuqi Guo et al confirmed they have a look at evaluated 14 cell apps designed for utilization through aged grownup shoppers who've Alzheimer's disorder and associated dementias (AD/RD). Most of them touched on basic needs in areas such as schooling and social relations, but they did not have full function to phenomenologically encompass the conditions of those situations. Priority areas to enhance include actual-time interaction with healthcare structures, as well as cultural appropriateness. The advanced and so-modern apps are often too costly, which limits readily availability for AD/RD victims with speech disability. There had also been the lack of culturally touchy capabilities intelligibly, doubtlessly exacerbating health disparities. In general, the investigation emphasizes the severity of the issue and the necessity to develop new and improved apps to increase the support of AD-affected patients.[16]

Juan Ruiz et al focused their research paper on investigating the effectiveness of the ensembling method in classification analysis and proving the ability to improve the classification result through the combination of several classifier models. The study assessed each classifier and concluded that 28 can bring the best performance in the 4-class problem from the DenseNet implementation. The comparison of DenseNet-121 and ResNet-18 showed that DenseNet-121 learned faster and provided higher accuracy than ResNet-18 which can be explained by the distinction in the number of parameters in DenseNet-121.[17]

Waleed Salehi et al wanted to show how wearable computing such as smartwatches and fitness trackers have changed virtual fitness since they are altering the truths control indicator and improving documentation of records between patients, caregivers, and health providers. It promotes a more accessible health system; while IoT can facilitate continuous AI-based WE and treatments for Alzheimer's disease. Wearable devices help in the collection of shared data, which facilitates personalized targeted healthcare services and preventive actions. Remote monitoring, tracking, telehealth care, and patient engagement are promoted by harmonization with digital health systems. However, these perceptions are personal even when they are required to be used as design guidelines to achieve optimal representation.[18]

Tanjim Mahmud et al to prevent overfitting, a dropout layer of 0. 5 and data augmentation with the help of ImageDataGenerator were used. The performance of the proposed model was tested for MRI scans on the OASIS dataset using deep learning with the Adam algorithm and categorical cross-entropy loss. The process of annealing brought into effect the learning rate (LR) on the move, by applying the 'ReduceLROn-Plateau' method that halves the LR if the validation loss fails to decrease further in the succeeding five iterations. Accuracy, Precision, Recall, and F1 score finally yielded good results for the pre-trained model of VGG19, VGG16, ResNet50, And Xception model. Section 5 is the conclusion section that gives the summary of findings and contribution of the paper.[19]

3 Methods

3.1 Dataset Acquisition and Preparation

In this research, two labeled datasets are utilized: Oasis_longitudinal_data[1] and Alzheimer 4 Classification instead of Oasis_cross_sectional_data[2] which was used in the previous analysis. All these datasets are picked from Open Access Series of Imaging Studies abbreviated as OASIS. Dataset 1 includes 150 patients' MRI images acquired longitudinally with the age range of 60 to 96 years. The second dataset includes 3D MRI radiological images classified into four categories: These are the categories: Mild, Moderate, Non-Demented, and Very Mild.

3.2 Data Preprocessing

Thus, to clean the data and ignore NaN and categorical values; these are included in the Oasis_longitudinal_data dataset. Quantitative data is presented as 0.002% missing, which informed the authors to remove these entries. The dataset includes three columns with categorical values: Group: Some of the values are Demented and Non-Demented; M/F: 'Male' of 'Female' displays the value of the categorical variable. Regarding the feature, it is crucial to mention that the presented dataset is limited only to right-handed people. In regards to the categorical features, the LabelEncoder from Scikit-Learn is applied for their transformation. LabelEncoder assigns different integer values to different categories since they cannot be ordered in the way, there is no numeric relationship between category 1 and category 2. In the case of the Alzheimer 4 Classification dataset, which is used in this work,Figure **??** the training set was further divided into training and validation subsets, with a split ratio of **80:20**.

3.3 Data Augmentation and SMOTE analysis

Data augmentation methods were employed to reduce the overfitting tendency. However, even by increasing the data set, class disparities continued to linger in this set of features. Imbalances in the training data distribution caused the above issues, so SMOTE (Synthetic Minority Over-sampling Technique) analysis was conducted. Figure **??** After performing data augmentation and SMOTE analysis, a dataset was obtained with 6,400 instances across 4 classes.

[1]https://www.kaggle.com/datasets/sabikunmonisha/oasis-longitudinal
[2]https://sites.wustl.edu/oasisbrains/home/oasis-2/

3.4 Deep Learning Models

CNN is used as the base architecture for image classification.[6].**Transfer Learning** is an approach of using pretrained-model parameters like weights and bias and is implemented on a small dataset.[5] **Dense121** architecture is made of dense blocks. Each dense block is again made of convolution layers, a dense block, and a transition layer. 1×1 Conv followed by 2×2 average pooling are used as the transition layers between two contiguous denseblocks[20].**RestNet-50** a variant of the Residual Network architecture utilized in AD detection due to its deep layers and residual connections help to mitigate the vanishing gradient problem during training.[7].**Capsnet** Capsule Networks address the limitations of (CNNs) known as Translation Invariance caused techniques such as data augmentation.**InceptionV3** necessitates downloading along with Hyperparameter Tuning. The parameters entail various aspects such as input shape (224,224,1), adjusting the dimensions and color channels of the image, and weights that signify the dataset employed for model-pretraining.[15]

3.5 Explainable AI

XAI paves a way to increase the transparency and comprehensibility of AI models' decision-making processes for humans. Describe the particular methods for improving the explainability of selected models. Possible techniques encompass LIME , SHAP,LRP-0.[8]

3.5.1 SHAP

Shapley Adaptive Explanation has been employed to calculate the contribution of meta-feature data (specifically Oasis_longitudinal-force plot) to classify the image. Figure 2

$$\phi_i(N, v) = \sum_{S \subseteq N \setminus i} \frac{|S|! \cdot (|N| - |S| - 1)!}{|N|!} \left(v(S \cup i) - v(S)\right)$$

3.5.2 LIME

LIME is a surrogate model that is created as an explainer to explain the prediction focus on the local proximity to the model prediction.

$$\text{Explanation} = \arg\min_{g \in G} \left[L(f, g, \Pi_{x_+}) + \Omega(g) \right]$$

3.5.3 LRP-0

LRP-0 explains the output of the complex Neural Net highlighting input feature to make the decision.

$$R_i^{(l-1)} = \sum_j \frac{z_i^{(l)}}{z_j^{(l)}} R_j^{(l)}$$

Uniform LRP-0 accepts so many local artifacts thus creating noise. As a result, the focus on the object is not properly executed,shown in Figure 2

$$R_j = \sum_k \frac{a_j w_{jk}}{\sum_{0,j} a_j w_{jk}} R_k$$

3.6 Management

For better patient management, we created an extensive mobile app that possesses complex features. The app will solely focus on Alzheimer's patients and it aims to drastically better their everyday lives. The app helps with quick recall of important information and includes interactive exercises to engage patients in cognitive function-supporting activities. This has a two-fold function; it practices core knowledge and, at the same time, provides game scores to track how the patient is doing cognitively. Their novel solution allows both to be improved upon for a better life, whilst also providing the opportunity to monitor the advancement of mental health with quantitative data. The current version of the application link is provided for further development.[3]

[3]https://github.com/Sakif8004/Alzheimer-s-App

4 System Model

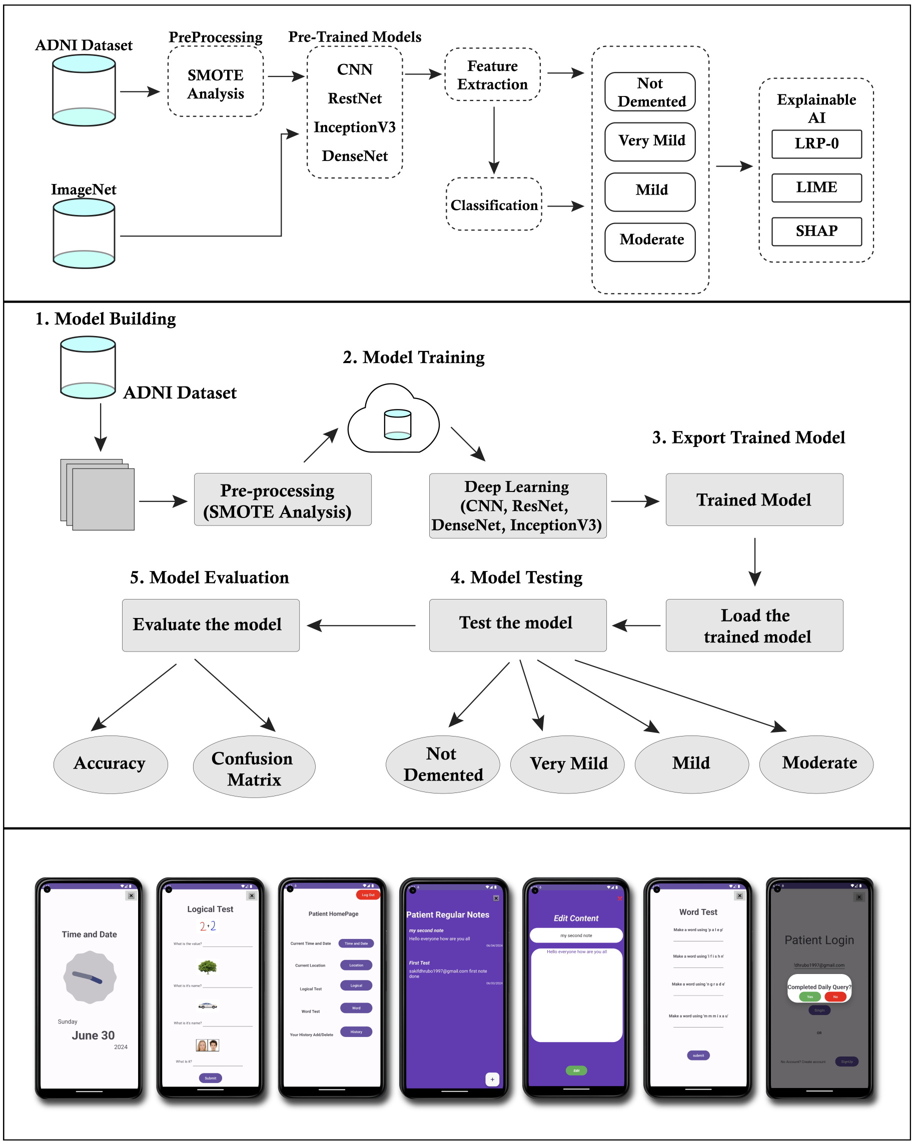

Fig. 1 Workflow of research, illustrating the integration of DL techniques and Explainable AI (XAI) for Early AD Detection and Further Management.

5 Results and Discussion

Table 1 Validation, and Testing Accuracy of base architecture of CNN and pretrained-models

Model	Validation Accuracy	Test Accuracy
CNN	89.6%	99.73%
Restnet50	75.8%	74.0%
Dense121	96.0%	95.3%
InceptionV3	92.7%	92.3%

Table 2 Validation, and Testing Loss of base-architecture of CNN and pretrained-models

Model	Validation Loss	Test loss
CNN	0.319%	0.321%
Restnet50	6.06%	6.54%
Dense121	13.20%	16.3%
Inceptionv3	18.49%	18.92%

Our study illustrates how augmented MRI images can vary in classifying data, aiming to prioritize early detection of elderly patients for subsequent neurocognitive screening using pre-trained DL models. In (Table 1). validation and testing accuracies for the base architecture CNN and pre-trained models presented. The table compares the performance metrics of different models based on their validation and testing accuracies. The base architecture CNN achieved a validation accuracy of 89.6% and a notably high test accuracy of 99.73%. This shows that the CNN model generalized well to unseen data, showcasing robust performance. The consequences of ResNet50 demonstrated a lower validation accuracy of 75.8% and a similar test accuracy of 74.0%, indicating overfitting. Moving to DenseNet121, achieved a high validation accuracy of 96.0% and a slightly lower test accuracy of 95.3% indicating strong performance in both training and generalization. It highlights DenseNet121 as a reliable choice for this classification task. Inceptionv3 also performed well with a validation accuracy of 92.7% and a test accuracy of 92.3%, consistent performance across validation and test.

The (Table 2) compares the validation and testing losses for the mentioned model. The base architecture CNN achieved a validation loss of 0.319% and a test loss of 0.321%, indicating minimal deviation between predicted and actual values ResNet50 showed higher losses with a validation loss of 6.06% and a slightly higher test loss of 6.54%. DenseNet121 gained a validation loss of 13.20% and a higher test loss of 16.3%. This indicates that DenseNet121 accounts for larger errors in making predictions on unseen data and having issues with feature extraction. Inceptionv3 also demonstrated significant losses with a validation loss of 18.49% and a test loss of 18.92%.

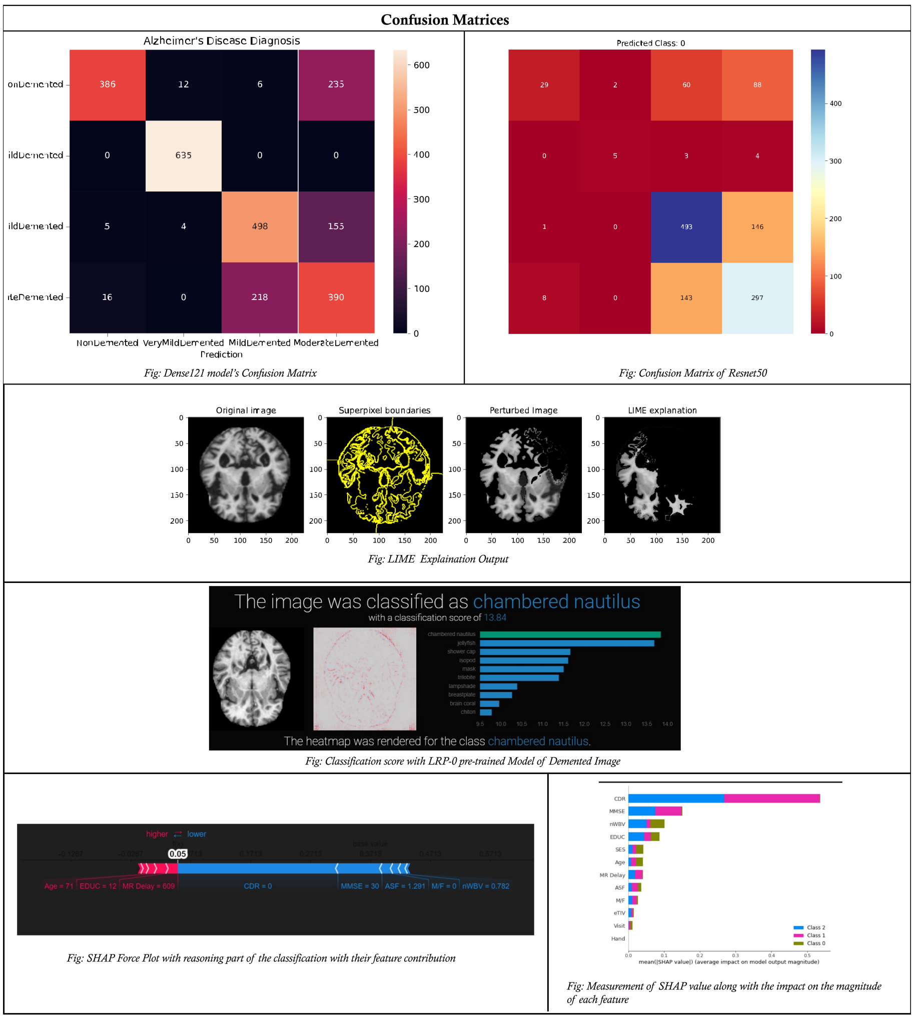

Fig. 2 Illustrating the output of pre-trained models and Explainable AI (XAI) for Early AD Detection and Further Management.

On the sequence, key challenges include inadequate training, lack of resources, and limited time for thorough early dementia detection. Our forthcoming endeavors may include the improvement of XAI, showcasing its ability to offer more accurate insights into the early identification of Alzheimer's disease through MRI data, particularly in pinpointing the affected regions; Figure 2 the confusion-matrix illustrates that Dense121 exhibits superior performance compared to Restnet50 when dealing with unfamiliar data. The Lime-explanation sheds light on the impacted boundaries within the brain. The LRP-0, a pre-existing model, computes the classification score. Lastly, the SHAP value presents the contribution of each feature in the analysis, aiding in expediting the detection process through a thorough examination of the individual factors influencing each patient.

6 Conclusion

To sum up, this paper has investigated the applicability of machine learning approaches to the screening of AD at an early stage. The analysis emphasizes the necessity to comprehend the model's actions to achieve accurate and interpretable results. In this study, three kinds of Explainable AI (XAI),[14]including model-based and post hoc have been used to reveal model performance and decision-making. More notably, SHAP, LIME, and LRP-0 have made it possible to dissect contributions and relationships of features better.

Also, the paper has explored the area of managing the already detected AD patients and provided a sample portable device software for the betterment of the patients[3]. The software's primary objective is to help the patients by providing notifications after a certain amount of time. This area has a huge opportunity to grow in future .

In the end, the some challenges and future opportunity have been discussed.[11] Like the proposed Mobile Application can potentially undergo some updates to cater to various aspects, enhancing its acceptance. Meta-data integration of patients will allow the identification of the underlying cause of individuals and offer precise preventive suggestions. More data acquisition of additional is essential. The application can be further set to feature an advanced guidance system designed to assist patients in navigating their way back home[4]. With Generative AI (GEN AI), the application can incorporate a speech-to-text or text-to-speech function and also ensure direct clinical suggestions,[21] and allow individuals with reading or typing difficulties to listen to written content and simultaneously convert their spoken words into written form.

References

[1] Brookmeyer, R., Johnson, E., Ziegler-Graham, K., Arrighi, H.M.: Forecasting the global burden of alzheimer's disease. Alzheimer's & dementia **3**(3), 186–191 (2007)

[2] Roy, N., Hassan, A.-M., Alom, R., Rajib, M.H.R., Mamun, K.: The situation of alzheimer's disease in bangladesh: facilities, expertise, and awareness among general people. Journal of Neurological Disorders **8**(7), 1–7 (2020)

[3] Marešová, P., Dolejs, J., Mohelska, H., Bryan, L.K.: Cost of treatment and care for people with alzheimer's disease: a meta-analysis. Current Alzheimer Research **16**(14), 1245–1253 (2019)

[4] Volicer, L.: Management of severe alzheimer's disease and end-of-life issues. Clinics in geriatric medicine **17**(2), 377–391 (2001)

[5] Farooq, A., Anwar, S., Awais, M., Rehman, S.: A deep cnn based multi-class classification of alzheimer's disease using mri. In: 2017 IEEE International Conference on Imaging Systems and Techniques (IST), pp. 1–6 (2017). IEEE

[6] Wen, J., Thibeau-Sutre, E., Diaz-Melo, M., Samper-González, J., Routier, A., Bottani, S., Dormont, D., Durrleman, S., Burgos, N., Colliot, O., *et al.*: Convolutional neural networks for classification of alzheimer's disease: Overview and reproducible evaluation. Medical image analysis **63**, 101694 (2020)

[7] Sun, H., Wang, A., Wang, W., Liu, C.: An improved deep residual network prediction model for the early diagnosis of alzheimer's disease. Sensors **21**(12), 4182 (2021)

[8] Ranguelova, E., Pauwels, E.J., Berkhout, J.: Evaluating layer-wise relevance propagation explainability maps for artificial neural networks. In: 2018 IEEE 14th International Conference on e-Science (e-Science), pp. 377–378 (2018). IEEE

[9] Mahmud, T., Barua, K., Habiba, S.U., Sharmen, N., Hossain, M.S., Andersson, K.: An explainable ai paradigm for alzheimer's diagnosis using deep transfer learning. Diagnostics **14**(3), 345 (2024)

[10] Vasukidevi, G., Ushasukhanya, S., Mahalakshmi, P.: Efficient image classification for alzheimer's disease prediction using capsule network. Annals of the Romanian Society for Cell Biology, 806–815 (2021)

[11] Noor, M.B.T., Zenia, N.Z., Kaiser, M.S., Mamun, S.A., Mahmud, M.: Application of deep learning in detecting neurological disorders from magnetic resonance images: a survey on the detection of alzheimer's disease, parkinson's disease and schizophrenia. Brain informatics **7**, 1–21 (2020)

[12] Nagashbayev, A.-F., Fatih Demirci, M.: Alzheimer's disease classification using capsule networks on structural mri. In: Proceedings of the 2020 5th International Conference on Biomedical Imaging, Signal Processing, pp. 7–11 (2020)

[13] Suganthe, R., Geetha, M., Sreekanth, G., Gowtham, K., Deepakkumar, S., Elango, R.: Multiclass classification of alzheimer's disease using hybrid deep convolutional neural network. NVEO-NATURAL VOLATILES & ESSENTIAL OILS Journal— NVEO, 145–153 (2021)

[14] Jahan, S., Abu Taher, K., Kaiser, M.S., Mahmud, M., Rahman, M.S., Hosen, A.S., Ra, I.-H.: Explainable ai-based alzheimer's prediction and management using multimodal data. Plos one **18**(11), 0294253 (2023)

[15] Cui, Z., Gao, Z., Leng, J., Zhang, T., Quan, P., Zhao, W.: Alzheimer's disease diagnosis using enhanced inception network based on brain magnetic resonance image. In: 2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), pp. 2324–2330 (2019). IEEE

[16] Guo, Y., Yang, F., Hu, F., Li, W., Ruggiano, N., Lee, H.Y., *et al.*: Existing mobile phone apps for self-care management of people with alzheimer disease and related dementias: systematic analysis. JMIR aging **3**(1), 15290 (2020)

[17] Ruiz, J., Mahmud, M., Modasshir, M., Shamim Kaiser, M., Alzheimer's Disease Neuroimaging Initiative, f.t.: 3d densenet ensemble in 4-way classification of alzheimer's disease. In: Brain Informatics: 13th International Conference, BI 2020, Padua, Italy, September 19, 2020, Proceedings 13, pp. 85–96 (2020). Springer

[18] Salehi, W., Gupta, G., Bhatia, S., Koundal, D., Mashat, A., Belay, A.: Iot-based wearable devices for patients suffering from alzheimer disease. Contrast Media & Molecular Imaging **2022**(1), 3224939 (2022)

[19] Mahmud, T., Barua, K., Barua, A., Das, S., Basnin, N., Hossain, M.S., Andersson, K., Kaiser, M.S., Sharmen, N.: Exploring deep transfer learning ensemble for improved diagnosis and classification of alzheimer's disease. In: International Conference on Brain Informatics, pp. 109–120 (2023). Springer

[20] Lombardi, A., Diacono, D., Amoroso, N., Biecek, P., Monaco, A., Bellantuono, L., Pantaleo, E., Logroscino, G., De Blasi, R., Tangaro, S., *et al.*: A robust framework to investigate the reliability and stability of explainable artificial intelligence markers of mild cognitive impairment and alzheimer's disease. Brain informatics **9**(1), 17 (2022)

[21] Xue, C., Kowshik, S.S., Lteif, D., Puducheri, S., Jasodanand, V.H., Zhou, O.T., Walia, A.S., Guney, O.B., Zhang, J.D., Pham, S.T., et al.: Ai-based differential diagnosis of dementia etiologies on multimodal data. Nature Medicine, 1–13 (2024)