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Alzheimer's Disease Detection: A Comparative Study of Machine Learning Models and Multilayer Perceptron

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Abstract **– The intersection of Artificial Intelligence (AI) and medical science has shown great promise in recent years for addressing complex medical challenges, including the early detection of Alzheimer's disease (AD). Alzheimer's disease presents a significant challenge in healthcare, and despite advancements in medical science, a cure has yet to be found. Early detection and accurate prediction of AD progression are crucial for improving patient outcomes. This study comprehensively evaluates four Machine Learning (ML) models and one Perceptron Model for early detection of AD using the Open Access Series of Imaging Studies (OASIS) dataset. The evaluated models include Logistic Regression, Random Forest, XGBoost, CatBoost, and a Multi-layer Perceptron (MLP). This study assesses the performance of each model, on metrics like accuracy, precision, recall, and AUC ROC. The MLP model emerges as the top performer, achieving an impressive accuracy of 95 %, highlighting its efficacy in accurately predicting AD status based on biomarker indicators. While other models, such as Logistic Regression (85 %), Random Forest (87 %), XGBoost (83 %), and CatBoost (89 %), demonstrate considerable accuracy, they are outperformed by the MLP model.**

Keywords **– Alzheimer's disease, biomarker indicators, machine learning, open access series of imaging studies.**

I. Introduction

Alzheimer's disease (AD) is a neurological disorder with detrimental impacts like cognitive decline, memory impairment, and changes in behaviour. It poses a significant public health challenge, due to the magnitude of its impact on individuals, families, and healthcare systems [1]. Early detection and accurate prediction of AD progression are crucial for timely intervention and targeted treatment of the patient [2]. This helps improve the quality of life of the patient and their families. Over the past years, the progress made in machine learning (ML) algorithms has shown promising outcomes, particularly in inter-domain research, such as medical science. The potential of ML can be utilised to study intricate medical data and leverage it for the early detection and prediction of diseases [3], [4]. In the case of AD leveraging ML algorithms on neuroimaging and clinical data offers the potential to identify subtle patterns and biomarkers indicative of disease progression, thus enabling proactive management and improved patient outcomes.

There are several open-source datasets available for studying Alzheimer's disease, including biomarkers, medical imaging, neuropsychological, genetic, and nonclinical data from the Alzheimer's Disease Neuroimaging Initiative (ADNI), Open Access Series of Imaging Studies (OASIS), and the National Alzheimer's Coordinating Centre amongst many others. For this study, the OASIS dataset [5] has been utilised. Algorithms for classification are commonly used to detect and categorise AD at an early stage. There is a variety of machine learning models available, including popular ones such as Logistic Regression, Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbours (KNN) [6]. These models can handle complex medical datasets, enabling them to detect linear and non-linear patterns in the data and make accurate predictions and classifications [7], [8]. In the field of Alzheimer's research, classification models are crucial for identifying patterns and features within data, which can help distinguish between different stages of the disease or pinpoint potential risk factors. This, in turn, facilitates the development of diagnostic tools and therapeutic interventions.

The flow of the paper is listed below. Section II reviews the previously undertaken research work. Section III contains the methodology, which details the dataset and the models utilised in the research. Section IV comparatively evaluates the performance of the proposed models. Section V contains the conclusion and future scope of the research.

II. Background Study

The section provides a comprehensive summary of the literature reviewed during this study. Morteza Amini et al. [9] proposed a machine learning-based framework for detecting the severity of AD using FMRI. The study utilised KNN, SVM, Decision Tree (DT), Linear Discriminant Analysis (LDA), and Random Forest (RF). The approach achieved an accuracy of 96.7 % using the QMFT pre-processing technique. In a similar

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study, AbdulAzeem et al. [10] in their study proposed a CNN-based framework for AD classification that achieved 99.8 % accuracy on binary classification and 97.5 % on multi-classification experiments. The study explored hyperparameter tuning and building suitable CNN-based architecture for AD detection. The proposed model achieved high accuracy with a lightweight architecture, giving insights into building similar CNN models for multi-class classification.

Baglat et al. [11] in their paper listed the importance of various data processes and dealt with missing values as there were several cases where the patient missed their appointment. Dealing with their missing values was essential for making accurate models. Mirzae et al. [12] in their paper discussed a range of federated learning methods that utilised both machine learning and computer vision pipelines to achieve advanced and accurate results for the early detection of AD.

Shahbaz et al. [13] applied six different machine learning algorithms on the ADNI dataset to classify the five stages of AD. The study revealed that the Generalized Linear Model (GLM) algorithm could classify the stages of AD with 88.24 % accuracy. In a similar study, Liu et al. [14] described how language disorders could be key symptoms of AD. AD causes difficulties in finding words, thus resulting in unclear speech and pauses. The study was based on language processing to explore the speech features of AD. Their study used IoT devices and collected 23 elderly persons' speech data and then utilised machine learning methods to identify AD and healthy control (HC) groups. In other words, AI technology was combined with the voice of subjects to detect the subtle changes that could be useful for early detection of AD.

Ezzati et al. [15] in their paper highlighted how hybrid models such as the SK-SVM and MK-SVM had far superior performance than regular ML algorithms. Another study by Ezzati et al. on ADNI included a total of 424 cognitively normal individuals, 656 with mild cognitive impairment, and 249 with AD. The authors presented six machine learning methods, which included DT, SVM, KNN, ensemble LDA, boosted DT, and RF. These machine-learning methods were used to classify participants with normal cognition from those with AD. Figure 1 indicates the machine learning and feature extraction approaches used by Afzal et al. in their paper [16].

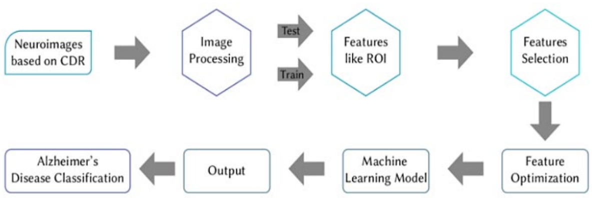

Fig. 1. The ML approach to the classification of AD depicting the algorithms, techniques, and methodologies.

Kundaram et al. [17] in their study proposed a new method for classifying AD using magnetic resonance imaging (MRI) scans. The method uses a DL hybrid technique to classify patients into three categories: AD, mild cognitive impairment (MCI), and normal control (NC). The method was tested on the ADNI dataset and achieved 98.57 % accuracy, higher than other studies. The new method could be extended to predict later stages of the disease. A similar study underlines a deep learning-based approach to identify mild cognitive impairment (MCI) patients at higher risk of converting to AD within three years [18]. Spasov et al. [19] affirmed the viability of employing multi-layered parametric learning on biomedical datasets of smaller scales to extract significant biomarkers.

Zhao et al. [20] presented an integrated framework that was developed to help predict cognitive scores in Alzheimer's patients. This framework incorporated anatomical prior knowledge and used a region-of-interest (ROI) mask and ROI loss. Results from experiments conducted on the longitudinal ADNI dataset showed that this framework was more effective than the independent regression model. Utilising the ROI loss for both cognitive score and MRI prediction could further enhance the framework performance. Saied et al. [21] in their study showed that the logistic regression model had the best accuracy of 98.97 % and efficiency in differentiating between four different stages of AD. It also demonstrated a transformative approach to clinics and monitoring systems where machine learning could be integrated with non-invasive microwave medical sensors and systems to intelligently predict the stage of AD in the brain.

III. Methodology

The section is primarily divided into four subsections: Dataset Description, Exploratory Data Analysis, and Model Exploration.

A. Dataset Description

The OASIS dataset is a valuable resource in the field of neuroimaging and clinical data analysis. It provides comprehensive data from individuals with varying degrees of cognitive impairment, including those diagnosed with AD. This dataset encompasses various parameters, including demographic information, cognitive assessments, and neuroimaging metrics, offering a multidimensional view of the disease progression. In this research paper, machine learning algorithms are utilised to predict AD progression using the OASIS dataset.

The input parameters of this dataset include age, years of education (EDUC), socioeconomic status (SES), Mini-Mental State Examination (MMSE) scores, Clinical Dementia Rating (CDR), estimated total intracranial volume (MTV), normalised whole brain volume (WV), and Atlas Scaling Factor (ASF), along with the target variable Group with class demented, non-demented and converted. Figure 2 shows a different input parameter of the dataset.

	Group	M/F	Age	EDUC	SES	MMSE	CDR	eTIV	nWBV	ASF
0	Nondemented	M	87	14	2.0	27.0	0.0	1987	0.696	0.883
1	Nondemented	M	88	14	2.0	30.0	0.0	2004	0.681	0.876
2	Demented	M	75	12	NaN	23.0	0.5	1678	0.736	1.046
3	Demented	M	76	12	NaN	28.0	0.5	1738	0.713	1.010
4	Demented	M	80	12	NaN	22.0	0.5	1698	0.701	1.034

Fig. 2. Input parameters of the OASIS dataset.

The demented class indicates the patients suffering from AD, while the non-demented represent those without the disease. The converted class indicated the patients who initially were healthy but later developed AD. This study involved pre-processing the dataset, exploratory data analysis, feature engineering techniques, and employing various machine learning algorithms for predictive modelling. By analysing the relationship between these parameters and the progression of AD, this study seeks to develop robust prediction models capable of identifying individuals at different stages of the disease and estimating their likelihood of future cognitive decline. The ability to identify at-risk individuals early on is crucial for effective treatment and disease management.

B. Exploratory Data Analysis

The univariate analysis indicates some interesting trends in the data distribution. The age distribution appears to follow a normal curve, indicating a balanced spread across different age groups. However, EDUC presents outliers with extreme values at 100, 80, and 75, while most data clusters lie below 40. SES distribution exhibits a distinct wavy pattern, suggesting variability across socioeconomic statuses. Meanwhile, MMSE distribution skews towards lower values, indicating a prevalence of lower Mini-Mental State Examination scores. The estimated total intracranial volume (eTIV) distribution leans slightly to the right, suggesting a tendency towards higher values. Conversely, the normalised whole brain volume (nWBV) distribution seems to mirror a normal distribution, indicating relative uniformity in normalised whole brain volumes. ASF distribution resembles a normal curve, reflecting a typical spread of values.

In contrast, categorical features offer insights into gender and diagnostic groups. Gender distribution, denoted by ‘M/F’, reveals intriguing patterns across different diagnostic groups. In the ‘Nondemented’ group, females dominate, whereas in the ‘Demented’ group, males outnumber females. In the ‘Converted’ group, females hold a slight majority over males. Furthermore, diagnostic group analysis unveils a hierarchical order of frequency, with ‘Nondemented’ being the most prevalent, followed by ‘Demented’, and finally ‘Converted’. These observations provide valuable insights into the data characteristics and potential trends within the studied population. The univariate analysis is depicted in Fig. 3.

The bivariate analysis depicted in Fig. 4 reveals important trends across different demographic and clinical groups for different diagnoses. The median age for ‘Nondemented’ and ‘Demented’ individuals is about 75, while for ‘Converted’ individuals, it is around 82. However, the ‘Converted’ group has a wider age range but to a lesser extent from minimum to maximum compared to the ‘Demented’ and ‘Nondemented’ groups.

Regarding education, ‘Nondemented’ and ‘Converted’ have similar median years at approximately 16.0, whereas for ‘Demented’, it is 12.5. The ‘Nondemented’ group has the widest educational range, while ‘Converted’ exhibits the lowest maximum and highest minimum values, and the ‘Demented’ group demonstrates the lowest minimum value.

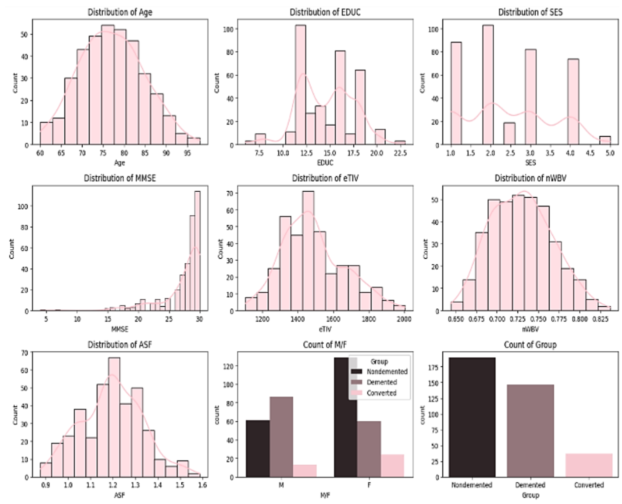

Fig. 3. Univariate analysis of the dataset.

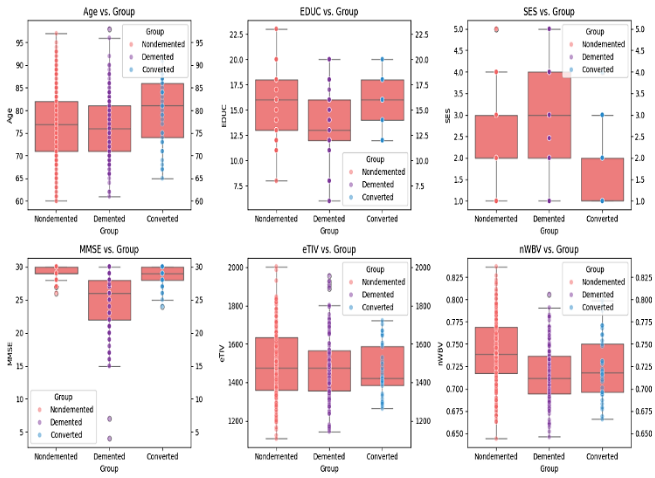

Fig. 4. Bivariate analysis of the dataset.

In socioeconomic status, both ‘Nondemented’ and ‘Demented’ groups have minimal outliers, with ‘Demented’ having the widest distribution and a median of around 3. ‘Converted’ lacks a lower whisker in the SES distribution. For the Mini-Mental State Examination, ‘Demented’ individuals have the widest distribution, with a median of 25, while the median for ‘Converted’ is slightly higher at 25.5, and ‘Nondemented’ lacks a clear median. Concerning estimated total intracranial volume, outliers are observed only in the ‘Demented’ group, while ‘Nondemented’ displays the widest box with a median of around 1500.

The nWBV distribution indicates minimal outliers for the ‘Demented’ group, with ‘Nondemented’ and ‘Converted’ having nearly identical distributions and median values between 0.7 to 0.75. Regarding the atlas scaling factor, no outliers are identified, and ‘Nondemented’ shows the widest box with median values ranging from 1.2 to 1.25. Finally, in terms of gender distribution, ‘Nondemented’ females outnumber males, while the opposite is observed in the ‘Demented’ group, and ‘Converted’ shows a slight female predominance as depicted in Fig. 5.

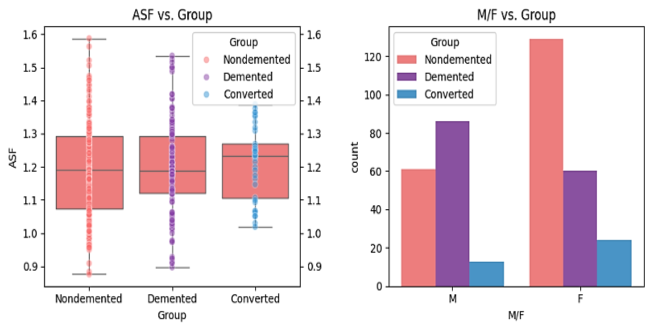

Fig. 5. Bivariate analysis for ASF and Gender vs. the Group.

C. Data Pre-processing

To pre-process the data, the initial step was to detect and delete duplicated values. Then, to capture the non-linear relations, the 'Age' variable was binned into categories such as 'Young', 'Middle-Aged', and 'Elderly'. Feature generation was also conducted to capture the joint effect on parameters like Social Economical Status (SES) and years of education (EDUC). Additionally, a ratio between nWBV and eTIV was also generated. Scaling is an important technique to ensure that all features contribute equally to the model. Therefore, feature scaling was performed using a standard scaler as many machine learning algorithms, including logistic regression, benefit from this procedure.

The class imbalance was handled by using oversampling. This technique involves generating synthetic samples for the minority class to balance the dataset. Multicollinearity is a condition where two or more features in the dataset are highly correlated. The parameters like eTIV and ASF showed the perfect negative correlation (−0.99) as depicted in Fig. 6. The multicollinearity was handled with Principal Component Analysis (PCA) to avoid instability issues in linear models like logistic regression. To evaluate model performance on unseen data, we divided the dataset into training and testing sets. 80 % of the data was the training data, while 20 % of the data was test data.

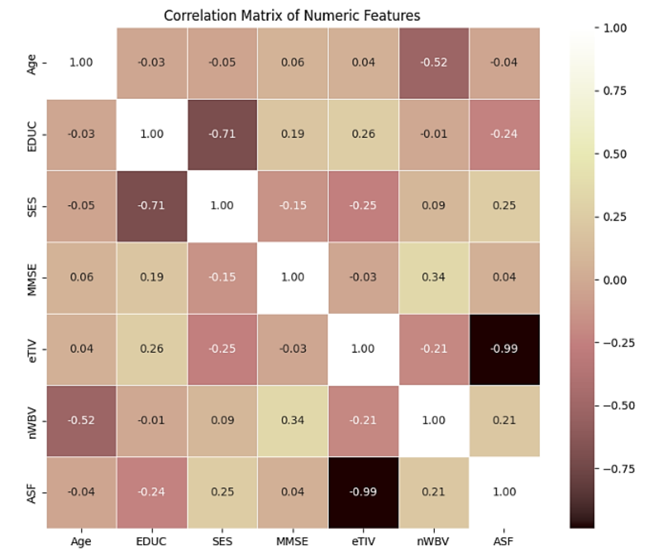

Fig. 6. Correlation matrix depicting the correlation between different parameters.

D. Model Exploration

The section focuses on the various classifiers that were explored in this study using the OASIS dataset. The study explored four machine learning models: Logistic Regression, Random Forest, XG Boost, Cat Boost, and deep learning multilayer perception model.

Initially, a simple Logistic Regression was used, which is a linear model that is helpful in classification problems. It estimates the probability of an instance belonging to a specific class. Hyperparameter tuning with Grid Search was used to determine the best value for the regularization parameter (*C*). This parameter controls the model complexity and prevents overfitting. Next, Random Forest was utilised, which is a popular multiclass classification algorithm. It is an ensemble method that combines multiple decision trees to improve prediction accuracy and reduce overfitting. Hyperparameter tuning was used to optimise several parameters, such as the number of decision trees in the forest, the maximum depth for each tree, and the number of samples at the leaf.

Another powerful classifier model, XGBoost, was also used. It is an ensemble method based on gradient boosting, known for achieving high accuracy. Hyperparameter tuning was used to optimise the number of boosting stages and the maximum depth allowed for each. CatBoost is another gradient-boosting classifier model that uses a decision tree method specifically designed to handle categorical features effectively. Hyperparameter tuning was used to optimise parameters such as the number of boosting stages (number of trees used) and the maximum depth allowed for each tree in the ensemble.

Finally, Multi-Layer Perceptron (MLP) was used, which is an artificial neural network architecture with multiple hidden layers that can learn complex, non-linear relationships within the data. It was trained on the dataset, and hyperparameter tuning was used to select the number of neurons in each hidden layer.

IV. Result and Discussion

The section highlights the results achieved in training the five models. Subsection A covers the evaluation parameters and Subsection B presents the comparison of the results.

A. Evaluation Parameters

The five models were trained on the OASIS dataset, with a standard test train split of 80–20 for fair comparison. The study used the standard evaluation to assess the performance of each model, including:

I. *Accuracy*: To measure the proportion of correctly classified samples.

$$\text{Accuracy} = \text{Correct classification/Total Images.} \tag{1}$$

II. *Precision*: To measure the model ability to minimise false positives (FP) in classifying AD Class.

$$\text{Precision} = \text{TP/(TP+FP).} \tag{2}$$

III. *Recall*: To measure the model ability to minimise false negatives (FN) in identifying AD Class.

$$\text{Recall} = \text{TP/TP+FN.} \tag{3}$$

All the models were written in Python using Sklearn, and hyperparameter tuning was performed using GridSearchCV. The models were trained on NVIDIA TESLA T4 GPU with 16 GB VRAM.

B. Result Comparison

The evaluation of various classifiers reveals distinct performance metrics across different algorithms. Among the models assessed – Logistic Regression, Random Forest, XGBoost, CatBoost, and MLP – it is evident that each possesses strengths and weaknesses in terms of accuracy, ROC AUC, precision, and recall for individual classes. The comparative result is discussed in Table I.

TABLE I

A COMPARATIVE RESULT OF THE FIVE MODELS ON VARIOUS PARAMETERS

Model	Accuracy	ROC AUC Class 1	ROC AUC Class 2	ROC AUC Class 3	Precision Class 1	Precision Class 2	Precision Class 3	Recall Class 1	Recall Class 2	Recall Class 3
Logistic Regression	85	85	99	93	67	94	91	55	94	97
Random Forest	87	87	98	96	75	91	86	55	91	94
XGBoost	83	81	98	95	62	88	81	45	88	91
CatBoost	89	80	98	95	86	94	86	55	91	1
MLP	95	93	99	97	86	91	91	55	1	94

Logistic Regression achieves an accuracy of 85 % and demonstrates notable precision in classifying Class 2 instances with a precision of 94 %. However, its precision and recall for Class 1 and Class 3 are comparatively lower. Random Forest exhibits a slightly higher accuracy of 87 % than Logistic Regression. It excels in precision for Class 1 with 75 % but falls short in recall for all classes compared to Logistic Regression. XGBoost, despite achieving an accuracy of 83 %, struggles with precision and recall across multiple classes. It notably achieves high precision for Class 2 with 88 %. CatBoost, with an accuracy of 89 %, highlights robust precision for Class 1 and Class 3 instances, with precisions of 86 % and 86 %, respectively. However, its recall for Class 1 is relatively low. MLP has an accuracy of 95 %. It demonstrates superior precision across all classes, particularly excelling in Class 2 with 91. Figure 7 depicts the comparison of the accuracy of different models.

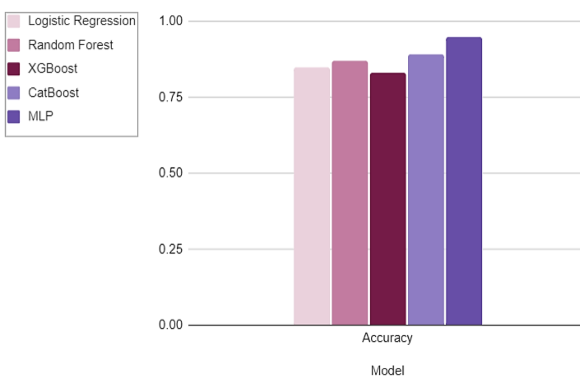

Fig. 7. Depicting a comparison of accuracy.

The Deep Learning MLP model is a top-performing model and highlights satisfactory results across all parameters. Figure 8 depicts the ROC curve of the MLP model.

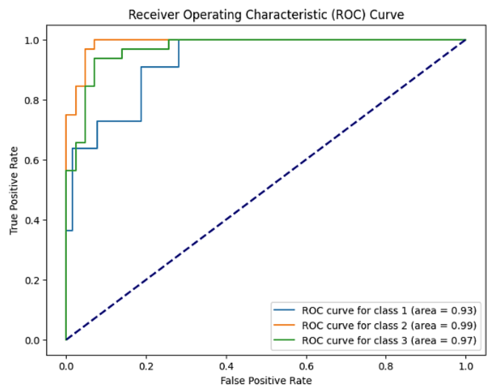

Fig. 8. ROC curve for the MLP model.

V. CONCLUSION AND FUTURE SCOPE

The study shows promising results in detecting AD using the OASIS dataset. The MLP model exhibits impressive performance across various evaluation metrics. With an accuracy of 95 %, it accurately predicts most instances in the dataset. It achieves a ROC AUC score of 93 % for Class 1, 99 % for Class 2, and 97 % for Class 3, indicating strong discriminative power in distinguishing between different classes. In terms of precision, the model demonstrates notable reliability with precision scores of 86 % for Class 1 (non-demented), and 91 % for both Class 2 (demented) and Class 3 (converted). However, regarding recall, the model performance varies across classes. While the model achieves perfect recall for Class 2 (demented), its recall for Class 1 (non-demented) is relatively lower at 55 %, suggesting it misses a significant portion of actual instances in this category. Despite this result, the model recall for Class 3 (converted) is relatively high at 94 %. In summary, the MLP model demonstrates strong overall performance, particularly in terms of accuracy, ROC AUC, and precision across all classes.

The findings of the study provide a strong foundation for further research and applications in the detection of AD. The results suggest several avenues for future exploration and improvement. One such avenue involves refining the MLP model to improve its recall, especially for Class 1 category that represents non-demented individuals. Advanced techniques like ensemble learning, feature engineering, or model optimisation could be investigated to potentially enhance the model ability to identify individuals in the early stages of AD accurately.

The robust performance of the MLP model suggests its potential integration into clinical practice as a diagnostic tool for AD. Future studies could explore the feasibility and efficacy of incorporating the model into healthcare settings, potentially aiding clinicians in early diagnosis and intervention strategies. It is crucial to validate the MLP model performance on diverse and larger datasets to ensure its generalisability across different populations and demographics. Conducting external validation studies on independent datasets would provide valuable insights into the model reliability and applicability in real-world scenarios.

Future research could also explore the integration of additional biomarkers or imaging modalities to enhance the MLP model predictive capabilities. Investigating biomarkers associated with Alzheimer's disease, such as genetic markers or neuroimaging features, could contribute to developing more accurate and comprehensive diagnostic models.

References

[1] A. Shukla, R. Tiwari, and S. Tiwari, "Review on Alzheimer disease detection methods: Automatic pipelines and machine learning techniques," *Sci*, vol. 5, no. 1, Mar. 2023, Art. no. 13. https://doi.org/10.3390/sci5010013

[2] C. Kavitha *et al.*, "Early-stage Alzheimer's disease prediction using machine learning models," *Frontiers in Public Health*, vol. 10, Mar. 2022, Art. no. 853294. https://doi.org/10.3389/fpubh.2022.853294

[3] S. A. Mahajan, G. Bangar, and N. Kulkarni, "Machine learning algorithms for classification of various stages of Alzheimer's disease: A review," *Machine Learning*, vol. 7, no. 8, pp. 817–824, Aug. 2020. https://www.researchgate.net/publication/344132855_IRJET_Machine_Learning_Algorithms_for_Classification_of_Various_Stages_of_Alzheimer's_Disease_A_review

[4] C. K. Fisher, A. M. Smith, and J. R. Walsh, "Machine learning for comprehensive forecasting of Alzheimer's disease progression," *Scientific Reports*, vol. 9, no. 1, Sep. 2019, Art. no. 13622. https://doi.org/10.1038/s41598-019-49656-2

[5] D. S. Marcus, A. F. Fotenos, J. G. Csernansky, J. C. Morris, and R. L. Buckner, "Open access series of imaging studies: Longitudinal MRI data in nondemented and demented older adults," *J. Cogn. Neurosci.*, vol. 22, no. 12, pp. 2677–2684, 2010. https://doi.org/10.1162/jocn.2009.21407

[6] D. Ebrahim, A. M. T. Ali-Eldin, H. E. Moustafa, and H. Arafat, "Alzheimer disease early detection using convolutional neural networks," in *2020 15th International Conference on Computer Engineering and Systems (ICCES)*, Cairo, Egypt, Dec. 2020, pp. 1–6. https://doi.org/10.1109/ICCES51560.2020.9334594

[7] T. Al-Shoukry, H. Rassem, and N. M. Makbol, "Alzheimer's diseases detection by using deep learning algorithms: A minireview," *IEEE Access*, vol. 8, pp. 77131–77141, Apr. 2020. https://doi.org/10.1109/ACCESS.2020.2989396

[8] M. Karnati, A. Seal, A. Yazidi, and O. Kreicar, "LieNet: A deep convolution neural network framework for detecting deception," *IEEE Transactions on Cognitive and Developmental Systems*, vol. 14, no. 3, pp. 971–984, Jun. 2021. https://doi.org/10.1109/TCDS.2021.3086011

[9] A. A. Yousry, W. M. Bahgat, and M. Badawy, "A CNN based framework for classification of Alzheimer's disease," *Neural Computing and Applications*, vol. 33, pp. 10415–10428, Mar. 2021. https://doi.org/10.1007/s00521-021-05799-w

[10] M. Amini, M. Mohsen, A. R. Moradi, and M. Ouchani, "Diagnosis of Alzheimer's disease severity with fMRI images using robust multitask feature extraction method and convolutional neural network (CNN)," *Computational and Mathematical Methods in Medicine*, pp. 1–15, Apr. 2021. https://doi.org/10.1155/2021/5514839

[11] P. Baglat, A. W. Salehi, A. Gupta, and G. Gupta, "Multiple machine learning models for detection of Alzheimer's disease using OASIS dataset," in *Re-imagining Diffusion and Adoption of Information Technology and Systems: A Continuing Conversation. TDIT 2020. IFIP Advances in Information and Communication Technology*, S.K. Sharma, Y.K. Dwivedi, B. Metri, and N.P. Rana, Eds., vol 617. Tiruchirappalli, India, Dec. 2020. Springer Cham. https://doi.org/10.1007/978-3-030-64849-7_54

[12] G. Mirzaei and H. Adeli, "Machine learning techniques for diagnosis of Alzheimer disease, mild cognitive disorder, and other types of dementia," *Biomedical Signal Processing and Control*, vol. 72, Feb. 2022, Art. no. 103293. https://doi.org/10.1016/j.bspc.2021.103293

[13] M. Shahbaz, A. Shahzad, A. Guergachi, A. Niazi, and A. Umer, "Classification of Alzheimer's disease using machine learning techniques," in *Proceedings of the 8th International Conference on Data Science, Technology and Applications DATA*, vol. 1, Prague, Czech Republic, 2019, pp. 296–303. https://doi.org/10.5220/0007949902960303

[14] L. Liu, S. Zhao, H. Chen, and A. Wang, "A new machine learning method for identifying Alzheimer's disease," *Simulation Modelling Practice and Theory*, vol. 99, Feb. 2020, Art. no. 102023. https://doi.org/10.1016/j.simpat.2019.102023

[15] A. Ezzati, A. R. Zammit, D. J. Harvey, C. Habeck, C. B. Hall, and R. B. Lipton, "Optimizing machine learning methods to improve predictive models of Alzheimer's disease," *Journal of Alzheimer's Disease*, vol. 71, no. 3, pp. 1027–1036, Oct. 2019. https://doi.org/10.3233/JAD-190262

[16] S. S. Kundaram and K. C. Pathak, "Deep learning-based Alzheimer disease detection," in *Proceedings of the Fourth International Conference on Microelectronics, Computing and Communication Systems: MCCS 2019*, *Lecture Notes in Electrical Engineering*, vol 673. Springer, Singapore, Sep. 2021. https://doi.org/10.1007/978-981-15-5546-6_50

[17] S. Afzal *et al.*, "Alzheimer disease detection techniques and methods: A review," *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 6, no. 7, pp. 26–38, Apr. 2021. https://doi.org/10.9781/ijimai.2021.04.005

[18] H. T. Gorji and N. Kaabouch, "Brain sciences: A deep learning approach for diagnosis of mild cognitive impairment based on MRI images," 2019.

[19] S. Spasov, L. Passamonti, A. Duggento, P. Liò, and N. Toschi, "A parameter-efficient deep learning approach to predict conversion from mild cognitive impairment to Alzheimer's disease," *Neuroimage*, vol. 189, pp. 276–287, Apr. 2019. https://doi.org/10.1016/j.neuroimage.2019.01.031

[20] Y. Zhao *et al.*, "Multi-view prediction of Alzheimer's disease progression with end-to-end integrated framework," *Journal of Biomedical Informatics*, vol. 125, Jan. 2022, Art. no. 103978. https://doi.org/10.1016/j.jbi.2021.103978

[21] I. M. Saied, T. Arslan, and S. Chandran, "Classification of Alzheimer's disease using RF signals and machine learning," *IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology*, vol. 6, no. 1, pp. 77–85, Mar. 2022. https://doi.org/10.1109/JERM.2021.3096172

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