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Research Article

Comparison of Machine Learning Model with Explainable AI: Applicable to Dementia

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A B S T R A C T

Introduction: In the healthcare domain, clinical practice needs effective models with flourishing interpretability to address any issues. Cases like dementia, in which diagnosis needs a proper explanation for such urgent problems, need an accurate model with effective interpretability. In medical practice, the implementation of Machine Learning (ML) models presents difficulties because of a lack of clarity on how particular results are derived, even though their outcomes are accurate.

Objective: Traditional ML models with Explainable Artificial Intelligence (XAI) and without XAI by using OASIS dementia datasets are used to find out which has more interpretability to show the comparative analysis.

Methods: SHAP of XAI are used to provide explanations, whereas metrics like accuracy, recall, precision, F1-score, and AUC are used to evaluate the base model, whose results are then compared with other metrics to find the importance of interpretability in the model to overcome the gap between ML models and their implementation in clinical practice.

Results: The traditional ML model provides good anticipating accuracy with an Area Under Curve (AUC) up to 0.94, but incorporating ML with the XAI model together gives better clinical results and enables medical professionals to build trust in predictions made by models.

Conclusion: This clarifies the decision-making capabilities of ML models, eliminating risk factors. Thus, this study describes the need for an effective way to diagnose diseases, not only through good models with high accuracy but also with models providing interpretability and clarity on prediction.

Keywords: Machine Learning, Explainable Artificial Intelligence, Dementia, Predicting Models, Interpretability Comparison

Introduction

Explainable Artificial Intelligence (XAI) usage in the medical field has tremendously increased over the years, providing medical professionals with more clarification that they might need to make decisions while diagnosing and treating patients. However, this is not provided by traditional ML models, making it strenuous for healthcare specialists to trust AI system predictions. Complex diseases need models with effective interpretability to improve diagnosis outcomes. Diseases like dementia, which are not only in one form but of various forms, affect the cognitive abilities.[1] Thus, to classify and predict diseases like dementia, an AI system built of ML models with XAI, a system that could be implemented in the real world to treat people affected with dementia, allowing everyone to understand the outcomes, enhancing the chances of survival.[2]

Although this group of disorders has no cure, the treatment of disorders like neurodegenerative disorders is challenging; its treatment depends on the diagnosis.[3] Also, the increase in complex learning approaches has made ML models more accurate but harder to explain.[4] Therefore, XAI algorithms are methodologies that understand black-box models, exposing and eliminating wrong predictions while classifying categories.[5] People contemplate explanations for any decisions that have been made, leading to the same expectation in decision support systems to have built trust in the decisions of medical professionals.[6]

Therefore, even after massive improvements, problems such as transferability, ethical challenges, and real-world applicability still exist. These challenges thus present the need for changes and advancements in modern technologies that are being put into use in clinical systems for better diagnosis and treatment.

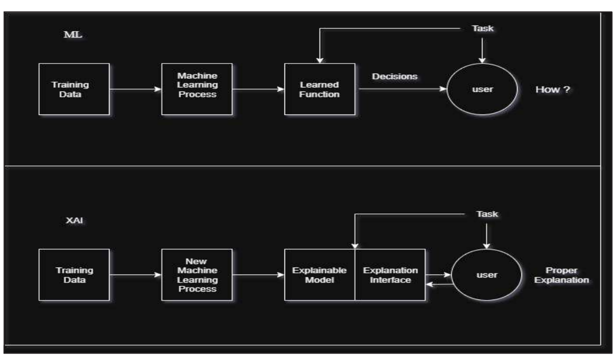

Figure 1.Comparison between ML model vs ML with XAI model

The following representation depicts the difference between the results generated using ML models and ML using XAI models [Figure 1]. An ML model uses training data to train a model, which in turn provides the outcome telling the decision needed for a particular task. However, users demand a genuine understanding of the process leading to a specific decision, which is clearly lacking in these models, reducing user trust and lucidity in the model. Whereas, in the second part of the figure, the ML model is incorporated with XAI, which results in an explanation of the prediction apart from the decision only. Therefore, bridging the gap in prediction by making it effective by enhancing interpretability for the medical professionals or for any users of that decision-making system.

Although ML models can predict complex diseases like dementia, a lack of interpretability prevents their implementation in the real clinical world, which could be challenging for practical use. However, XAI approaches like SHAP and Local Interpretable Model-agnostic Explanations (LIME) bridge this limitation by providing accurate interpretability.

Contribution

Analysed various papers related to why ML models with XAI are important, making AI decision-making systems applicable in clinical practice. The analysis based on the comparison between traditional models and models with XAI methods also presented the gaps between the building of models for advancement in diagnosis, prognosis, and treatment of patients, and the actual implementation of those models in the healthcare world. In addition, even though the accuracy of prediction is the same through the comparison of the metrics of performance of two models, it is necessary to present the need for the explanation of models, which is shown using the OASIS dataset to predict dementia, and explain why basic ML models appear unclear, and XAI interpretability is more acceptable.

The paper has the following contributions:

- ML models used with XAI and ML models without XAI implementation are compared to show the lack of understanding.
- Working on a real-world problem of dementia using the OASIS dataset by implementing an algorithm in both ways with and without XAI models.
- Addressing gaps in the research demonstrating the lack of interpretability in practical applications in the medical domain.
- Models with effective explainability, lucidity, and clarity have more advantages, which are described in this study.
- Performance metrics are used to prove the need for effective interpretability in models.

Related Work

Nagajyothi, D., & Reddy, C.V.R., researchers analyse various models and propose an ensemble stacking classifier to enhance the reliability and accuracy of the model to detect dementia early for better treatment of patients before it's

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too late and also describe the need for interpretability in models for predicting complicated neurological-related diseases like dementia.[1] Therefore, there is a need for a greater rise in advanced diagnostic systems for dementia, with a rise in the number of dementia cases over the past years. Thus, Tyler Morris et al. developed a convolutional neural network with an XAI algorithm to allow everyone to understand decisions made by the system.[2]

Enea Parimbelli et al. presented that black-box models need advancement to enable interpretability with accurate prediction, as with an increase in the number of complex models, presenting difficulties in interpreting the models' outcomes.[4] With the rise in usage of XAI algorithms, however, certain issues also appear over time. For example, some data scientists could easily misinterpret the outcomes; thus, Mohamed Karim Belaid et al. propose a compare-xAI benchmark model to tackle the issue by mitigating errors by providing various solutions to overcome this limitation.[5]

Fariha Jahan et al. describe how early detection of dementia in patients can help them reduce the progression of dementia, as it has no cure so far. They used six ML models to get accurate predictions up to 98% and incorporated them with XAI approaches like SHAP and LIME to improve the interpretability.[8]

Most comparisons have focused on explanation, reliability, and interpretability of outcomes related to neurological diseases in these studies and comparisons of ML models with ML model + XAI approaches in general. The following diagram demonstrates a similar comparison of models with and without XAI [Figure 2].

Figure 2 illustrates a brief comparison of traditional ML models, such as RF, with XAI approaches like SHAP and describes how black-box models have low interpretability even though the prediction accuracy is good. Models incorporated with XAI have high interpretability while maintaining the accuracy of the prediction of models.

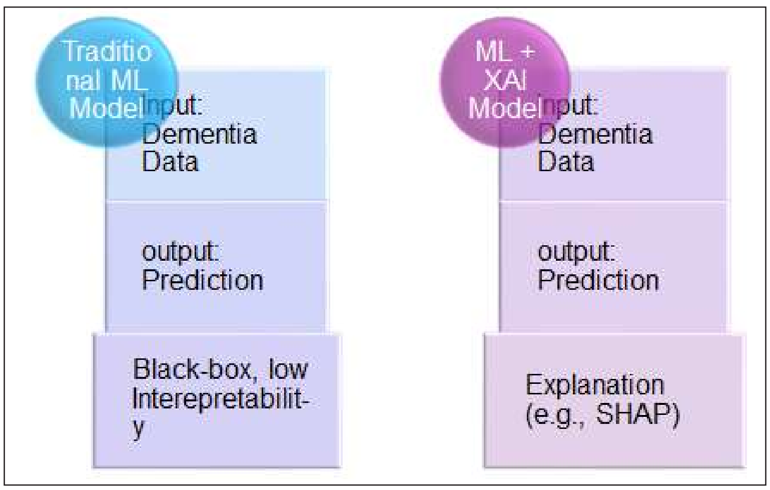

Figure 2.Comparison of the interpretability of models

Table 1.Presents a summary of Related papers

Reference	Dataset	Models	Descriptions
7	Alzheimer's Disease Neuroimaging Initiative (ADNI)/ Open Access Series of Imaging Studies (OASIS) Clinical	RF, SVM, DT, Multi-Layer Perceptron (MLP), SHAP	Interpretable Multimodal prediction of dementia
8	Dementia Patient Health, Prescriptions ML	DT, RF, KNN, SHAP, LIME	Identification of dementia in patients with an explanation
9	Ageing survey data	Logistic Regression (LR), Decision Tree Classifier, RF, SVM, SHAP	An interpretable healthy ageing scale model to build trust
10	ADNI	SVM, SHAP, LIME	Alzheimer's classification prediction using XAI

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11	ADNI magnetic resonance imaging (MRI)	Multimodal Quantification of Brain whIte matter bio-mArkers (MUQUBIA), SHAP	Classification of dementia with cost-effective clinical and MRI information
12	The Telco Customer Churn, a re-al-world	DT, LR, Naïve Bayes (NB), Gradient Boosted Tree, SHAP, LIME	Transparency becomes more efficient in ML applications using SHAP and LIME
13	University of California, Irvine (UCI) datasets	Deep Learning (DL), DT, Linear Regression (LR), NB, SHAP, LIME	Analysis of the accuracy of ex-plainable ML
14	review paper – no dataset	ML, XAI	Review of the interpretability of ML models in diagnosing dementia
15	Survey paper – no dataset	XAI	Survey of XAI approaches in real-world applications
16	PHM08-CMAPSS dataset	Support Vector Regression (SVR), LIME, SHAP	Prediction of historical data using SHAP

Table 1 describes the papers related to dementia diseases and how XAI incorporated with ML models provides effective interpretability with accurate prediction and the need for more focus on the implementation of XAI with ML models in the clinical domain for better results with proper explanations. Nana Nyarko Brenya Appiah Kubi and Sajid Nazir[7] demonstrated how effective ML models, along with XAI approaches, can be used to strategise treatment for patient care after diagnosis and prognosis of dementia. Silvia De Francesco et al.[11] researchers made use of MUQUBIA and SHAP algorithms to classify dementia cost-effectively with effective performance. Sophie A. Martin et al.[14] state that general applicability and interpretability are lacking across various datasets used by the model to predict results.

Therefore, to summarise, the major focus of all these studies is to provide clinical practice with AI systems that not only give accurate predictions but also provide effective interpretability to enable medical professionals to build their trust in these decision-making systems and who, in turn, can provide patients with proper explanations on the outcomes of their diseases.

Research gap

The use of AI systems in the medical field today has become important in significantly enhancing diagnosis, prognosis, and treatment of different clinical applications in early prediction of multiple diseases to avoid a worst-case outcome, such as dementia. However, their focal point is to build a model using ML algorithms with more accurate performance and ignore interpretability, leading to difficulty for doctors, medical professionals to trust the outcomes [Figure 3]. Implementing algorithms with and without XAI to evaluate the performance and bridge the outcomes that are made by models without XAI and with XAI is demonstrated using the OASIS clinical dataset.

Figure 3.Representation of Research Gap

The following are some of the major gaps:

- Many studies explain the need to shift the focus from accuracy to explainability because of the lack of importance given interpretable ability of the model.
- Difficulty in implementing the decision-making system in real-world clinical practice because of a lack of explanation and clarity on the outcome made by the model.
- Direct comparison between frameworks to justify the result of models, whether it's correct or not, is absent or limited.
- Building clinical Trust is a major issue for the implementation of the model, even if the model's performance is accurate, due to a lack of understanding of the decisions made by the model.
- The healthcare domain needs evaluating metrics able to measure both explainability and the efficiency of the model's outcome.

Methodology

Methodology Overview

The procedure of methodology applied and shown in this study is conditional on a properly sustained group of actions, which assists in constructing a competent and interpretable model. The relevant data is gathered and collected from Kaggle, which is the OASIS clinical dataset consisting of 436 rows and 12 columns. Figure 4 demonstrates the framework and workflow of the methodology performed.

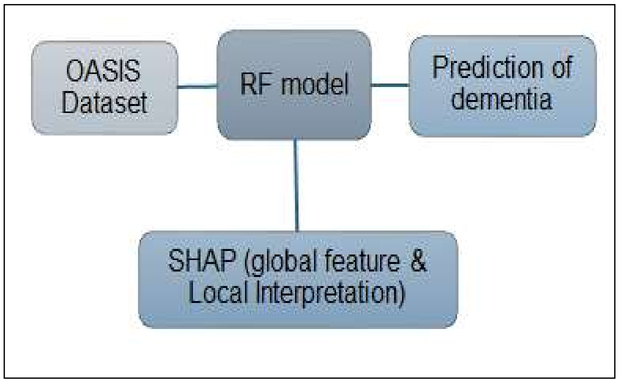

Figure 4.Flowchart of Methodology Framework

After gathering the right dataset, pre-processing is performed on the dataset to improve the accuracy and overall performance of the model.

The pre-processing is an important process to format the dataset according to the needs of the model. The pre-processing steps performed on these OASIS data sets are as follows: firstly, the relevant columns which are needed are selected, which are the following columns: M/F (Male/Female), Hand, Age, Educ (Education), SES (Socioeconomic status), MMSE (Mini-Mental State examination score), CDR (Clinical Dementia Rating), eTIV (Estimated total volume), nWBV (Normalised whole brain volume), and ASF (Atlas Scaling Factor). Next, certain values of columns are converted to numerical values, and the median and mode functions of the Python library are used to fill missing values. Then, categorical variables are encoded, and features are standardised. In the following step, which is the model development step, the base model is trained and tested using different matrices such as AUC, recall, F1-score, etc., and finally the SHAP method is incorporated for proper interpretation of the prediction.

Dataset Description

The dataset used for model training is the OASIS clinical dataset, which is taken from the source called Kaggle. The dataset includes 436 rows and 12 columns. The dataset is used to train the model to identify whether a person seems healthy or is diagnosed with dementia, and to understand the outcomes using XAI with an ML model.

Models

There are two models used to show comparison,

- Base Model, namely, RF
- XAI Model, namely, SHAP incorporated with RF

Evaluating Metrics

Evaluating the performance of the model needs quantitative measures to assess the model's effectiveness. Therefore, provides a means to measure the effective performance of the model.

The following metrics are used to measure the performance of the models.

- **Accuracy:** This metric measures the accuracy of the model, whether the model is making predictions well or not.

$$Accurracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision:** Precision metric measures actual positive predictions given by the model from all other positive predictions. An important metric in medicine, where knowing the correct and actual results is crucial.

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

- **Recall:** Recall is the metric used to measure the actual positive predictions of the model by dividing it by the Actual positive and False negative predictions.

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

- **F1 Score:** F1-score is used to measure accuracy or the effectiveness of both precision and recall metrics, as it finds the average of the precision and the recall. It is used to tell whether the performance is effective or not.

$$F1\text{-}score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

The Area Under the Receiver Operating Characteristic Curve (AUC-ROC Curve): It is a plot of the actual correct predictions against the ones that are false positive rate of predictions. The higher the ROC curve better the performance.

Performance Metrics

Base Model Results

The base model is trained using the OASIS dataset, which is later evaluated using a performance metric describing the overall efficiency of the model and whether the outcomes are accurate.

Base model performance metrics

Figure 5 demonstrates the base model classification report, providing numbers that show the accuracy this model has achieved. These performance metrics present that diagnosing whether people have dementia has higher accuracy than depicting the traits for dementia, as shown in the figure, with 0.91 values of precision, recall, and F1-score, which indicate the model is more reliable in diagnosing healthy people than predicting dementia, for which the model accuracy is 0.70 for precision and recall. F1-score. The overall accuracy of the model indicates that the model has effective performance with an accuracy of 0.86.

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==Base Model Metrics ==

	precision	recall	f1-score	support
0	0.91	0.91	0.91	68
1	0.70	0.70	0.70	20
accuracy			0.86	88
macro avg	0.81	0.81	0.81	88
weighted avg	0.86	0.86	0.86	88

AUC: 0.9404411764705882

Figure 5.Base model metrics

The values of macro avg (0.81) and weighted average (0.86) indicate the overall performance of the classes, weighted and non-weighted. The model thus performs well in differentiating dementia with no dementia, which is supported by the overall accuracy value of the model, that is, AUC is 0.94, but the model still needs more interpretability as it lacks explanation, which is a much-needed thing in the medical industry.

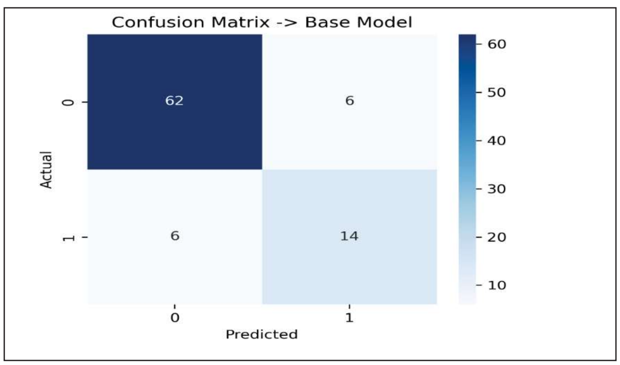

Figure 6.Confusion matrix of the base model

Confusion Matrix

A confusion matrix is represented, which provides the values like true positive (TP = 62), true negative (TN = 14), false positive (FP = 6), and false negative (FN = 6) to evaluate the model performance, and it also helps to measure values for other metrics like precision, recall, accuracy, and F1-score.

In the following Figure 6, it is clearly visible that true positive and true negative predictions of dementia for class 0 and class 1, which have high value as compared to false positive and false negative, thus present models differentiating capability are effective. Furthermore, there are still some false predictions that could lead to the risk of wrong prediction, thus depicting the need for interpretability in the base model.

AUC-ROC curve

The ROC curve of the base model illustrates the curve, depicting the model's ability to differentiate the classes. The AUC-ROC curve is a plot of True positive rate against false positive rate using a threshold value. The more area under the AUC-ROC curve, the higher the performance accuracy of the model.

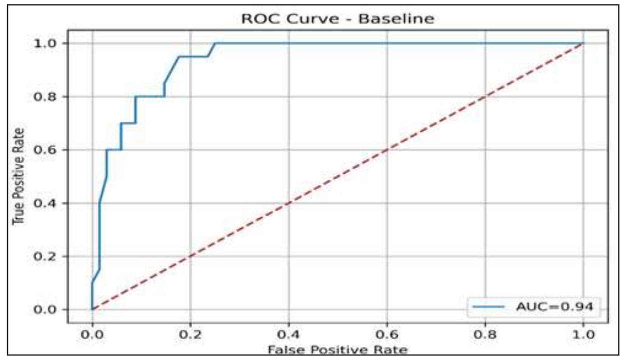

Figure 7.AUC – ROC Curve

AUC is 0.94 as shown in Figure 7, i.e., the overall model has a high separating ability. The high number up to 0.94, ranging from 0 to 1, depicts that even after randomly selecting data values model still provides an effective prediction. Therefore, it helps to improve the predictive capacity of the model.

XAI Implementation.

After analysing the base model, there seems to be a lack of explanation on why a particular prediction is made by the model. To overcome this problem, SHAP is used with an RF model to improve the interpretability, as it provides global and local interpretability.

Global Interpretability

Global interpretability is one of the SHAP methods that provides a complete understanding of how models work and what the important features in the dataset are for accurate model prediction. Beyond predictive accuracy, predictability was further introduced as SHAP. Therefore, the graph [Figure 8] depicts the important feature from low to high that helps influence the model in predicting whether the person has dementia or not, which increases the clarity and explainability of the model.

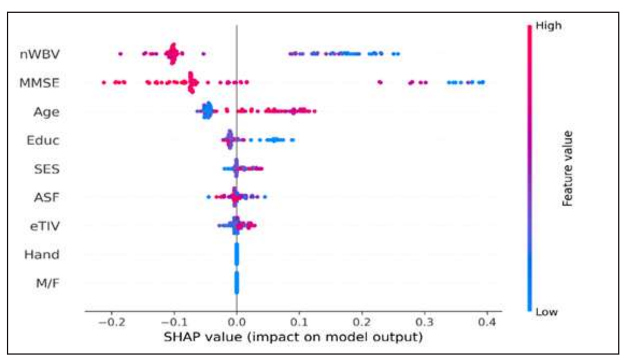

Figure 8.SHAP summary plot

From the SHAP summary plot, we concluded that nWBV and MMSE are the features widely used to predict the outcomes for dementia. Thus, global interpretability helps in building trust of medical professionals in the decision made by the model, as it provides a proper explanation of the model's prediction.

Local Interpretability

Local interpretability, on the other hand, explains why a particular prediction is made. The local explainer explains how the model reached the specific outcome. Figure 9 demonstrates how features like MMSE and nWBV contributed to the prediction of the result with an influence of 0.39 on the model, whereas M/F and Hand have no influence on model predictions.

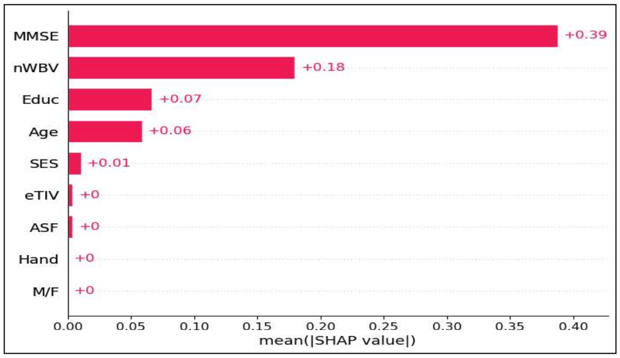

Figure 9.SHAP Bar Plot

To summarise, local and global interpretable models enhance the overall explainability of the model while maintaining the accuracy, providing all the explanations needed to bridge the gap between ML models and their implementation in clinical practice.

Result

Evaluating performance metrics clarifies that even though there isn't any big difference in the accuracy of the model, interpretability was still an issue. Therefore, implementing SHAP provides an explanation that acts as a building block for medical professionals to trust models' predictions. Comparative analysis [Table 2] is presented in the form of a table showing the results of both methods. From the results, it's clear that the explainability of the model with SHAP is high as compared to the base model, leading to more clinical usability of models with effective interpretability.

Explainability of the RF Model when implemented with SHAP by approximately 35%, providing features impacting the interpretability outcome of the model.

Table 2.Comparison Analysis Between Models

Comparison based on	ML Model (RF)	ML + XAI (SHAP)
Accuracy	0.86	0.86
AUC	0.94	0.94
Interpretability	Low	High
Clinical Use	Limited	Strong

Table 3.Interpretability Score quantitative comparison

Feature	Interpretability Score	Impact
MMSE	0.39	Highest
nWBV	0.18	High
Educ	0.07	Moderate
Age	0.06	Moderate
Others	≤ 0.01	Low

Discussion

This paper discusses the importance of incorporating an effective interpretable model that maintains accuracy and provides a proper explanation. Proper explanation of outcomes bridges the gap between model working and its implementation in the healthcare industry, where clinical officials can trust the decision. Therefore, various performance metrics have been used to provide comparative analysis of models' predictions with and without XAI, and the results demonstrate that ML models with XAI provide effective interpretability while maintaining the accuracy of predictions.

To evaluate the model performance, accuracy, precision, recall, and F1-score metrics were put into use, and their results reveal that the model has good accuracy, i.e., 0.86. A 0.94 value of AUC indicates that the model's separation capacity is reliable. Whereas the global and local methods specify why the model gave this particular outcome and how it reached that result, providing all the explanation that, in turn, gives clinical practitioners all the transparency they need to trust the outcome.

The SHAP summary plot and SHAP bare plot illustrate what the important features (like MMSE and nWBV) are, the ones that play a major role in predicting the outcome, and explain how the overall results are derived using the global and local interpretability methods of SHAP. Therefore,

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incorporating these methods in models enhances overall confidence in the decision-making systems.

Ethical and data privacy implications of XAI in dementia prediction provide transparency, lucidity, and security in the handling of patient data to prevent misuse; also, federated learning can be used to protect data. Ensuring explainable models uphold these principles builds integrity and accountability in clinical AI decision-making systems. Explainability affects trust, accountability, and adoption in real-world medical settings, as it builds trust of patients in the outcome of AI systems and makes AI systems more accountable for their decisions, which indeed helps in the implementation of systems in clinical practice.

Conclusion

To conclude, the results obtained from the comparative analysis of models demonstrate that a system with interpretability has higher clinical usability than one without explanation. The evaluation metrics help to robustify the quantitative results of the model, whereas global and local explanations robustify the qualitative outcomes of the model, enabling the fulfilment of requirements needed to integrate the system into the healthcare industry, which is significantly discussed in this study.

Therefore, this study systematically demonstrates related work. From those works, we concluded various gaps, hence providing a comparative analysis bridging the gap between the computation of the model and its integration in clinical practice. The analysis between ML models and ML models with XAI is depicted using the OASIS clinical dataset to predict dementia.

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References

1. Nagajyothi, D., & Reddy, C.V.R. (2025). Optimizing dementia prediction: A comparative performance study of ML and DL. Journal of Theoretical and Applied Information Technology, 103(11), 74–82. www.jatit.org
2. Morris, T., Liu, Z., Liu, L., & Zhao, X. (2024). Using a convolutional neural network and explainable AI to diagnose dementia based on MRI scans. NIH Research Report, https://doi.org/10.48550/arXiv.2406.18555
3. Poonam, K.M., Guha, R., & Chakrabarti, P.P. (2023). Frontotemporal dementia detection model based on an explainable machine learning approach. In Computational Intelligence in Data Science (IFIP Advances in Information and Communication Technology, Vol. 630, pp. 230–242). Springer, Cham. https://doi.org/10.1007/978-3-031-38296-3_18
4. Parimbelli, E., Buonocore, T.M., Nicora, G., Michalowski, W., Wilk, S., & Bellazzi, R. (2023). Why did AI get this one wrong? —Tree-based explanations of machine learning model predictions. Artificial Intelligence in Medicine, 134, 102471. https://doi.org/10.1016/j.artmed.2022.102471
5. Belaid, M.K., Rabus, M., Hüllermeier, E., & Krestel, R. (2022). Compare-XAI: Toward unifying functional testing methods for post-hoc XAI algorithms into an interactive and multi-dimensional benchmark. arXiv preprint arXiv:2207.14160. https://arxiv.org/abs/2207.14160
6. van der Waa, J., Nieuwburg, E., Cremers, A., & Neerincx, M. (2021). Evaluating XAI: A comparison of rule-based and example-based explanations. Artificial Intelligence, 291, 103404. https://doi.org/10.1016/j.artint.2020.103404
7. Brenya Appiah Kubi, N.N., & Nazir, S. (2024). Dementia prediction with multimodal clinical and imaging data. Journal of Ambient Intelligence and Humanized Computing. https://doi.org/10.1007/s41870-024-02326-7
8. Jahan, F., Shifat, S.M., Anannya, F.Z., & Hasan, M.M. (2024). Short paper: Dementia patient health, prescriptions ML dataset: LightGBM classification of XAI-based LIME and SHAP for dementia detection. Proceedings of the 2024 International Conference on Artificial Intelligence. https://doi.org/10.1145/3704522.3704550
9. Gašperlin Stepančič, K., Ramovš, A., Ramovš, J., & Košir, A. (2024). A novel explainable machine learning-based healthy ageing scale. BMC Medical Informatics and Decision Making, 24, 2714. https://doi.org/10.1186/s12911-024-02714-w
10. Alatrany, A.S., Khan, W., Hussain, A., Kolivand, H., & Al Jumeily, D. (2024). An explainable machine learning approach for Alzheimer's disease classification. Scientific Reports, 14, 13211. https://doi.org/10.1038/s41598-024-51985-w
11. De Francesco, M.S., Crema, C., Archetti, D., Muscio, C., Reid, R.I., Nigri, A., Bruzzone, M.G., Tagliavini, F., Lodi, R., D'Angelo, E., Boeve, B., Kantarci, K., Firbank, M., Taylor, J.P., Tiraboschi, P., & Redolfi, A. (2023). Differential diagnosis of neurodegenerative dementias with the explainable MRI-based machine learning algorithm

MUQUBIA. Scientific Reports, 13, 18745. https://doi.org/10.1038/s41598-023-43706-6
12. Hasan, M.M. (2023). Understanding model predictions: A comparative analysis of SHAP and LIME on various ML algorithms. Journal of Science, Technology and Research, 5(1), 17–26. https://doi.org/10.59738/jstr.v5i1.23(17-26).eaqr5800
13. Yildirim, M., Yildirim Okay, F., & Özdemir, S. (2023). A comparative analysis of the reliability of interpretable machine learning. Pamukkale University Journal of Engineering Sciences, 29(6), 1125–1135. https://doi.org/10.5505/pajes.2023.49473
14. Martin, S.A., Cole, J.H., & Townend, F.J. (2022). Interpretable machine learning for dementia: A systematic review. Alzheimer's & Dementia, 18(12), 2471–2489. https://doi.org/10.1002/alz.12948
15. Islam, S.R., Eberle, W., Ghafoor, S.K., & Ahmed, M. (2021). Explainable artificial intelligence approaches: A survey. arXiv preprint arXiv:2101.09429. https://arxiv.org/abs/2101.09429
16. Jalali, A., Schindler, A., Haslhofer, B., & Rauber, A. (2020). Machine learning interpretability techniques for outage prediction: A comparative study. Journal of Ambient Intelligence and Humanized Computing. https://doi.org/10.36001/phme.2020.v5i1.1244