Explanation-driven HCI Model to Examine the Mini-Mental State for Alzheimer's Disease

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Directing research on Alzheimer's towards only early prediction and accuracy cannot be considered a feasible approach towards tackling a ubiquitous degenerative disease today. Applying deep learning (DL), Explainable artificial intelligence(XAI) and advancing towards the human-computer interface(HCI) model can be a leap forward in medical research. This research aims to propose a robust explainable HCI model using shapley additive explanation (SHAP), local interpretable model-agnostic explanations (LIME) and DL algorithms. The use of DL algorithms: logistic regression(80.87%), support vector machine (85.8%), k-nearest neighbour(87.24%), multilayer perceptron(91.94%), decision tree(100%) and explainability can help exploring untapped avenues for research in medical sciences that can mould the future of HCI models. The outcomes of the proposed model depict higher prediction accuracy bringing efficient computer interface in decision making, and suggests a high level of relevance in the field of medical and clinical research.

CCS Concepts: • **Explainable AI → Human Computer Interface**.

Additional Key Words and Phrases: Human Computer Interface, Explainable AI, Deep Learning, Machine Learning, Alzheimer's Prediction, SHAP, LIME

1 INTRODUCTION

The genesis of Alzheimer's disease is due to the accumulation of unusual proteins such as 'Amyloid' and 'Tau', which form deposits of plague and tangles within the brain cells. As per the world Alzheimer's Disease Report 2019, 80% of the general population are perturbed with the thought of developing dementia, and an estimate of one out of four people believe it is impossible to prevent dementia. Alzheimer's is usually prevalent in people above the age of 65 years. In an estimate, about one in eight people above the age of 65 suffer from this disease. Infrequent

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times, the condition has also started to affect people below 60 years of age. The symptoms of Alzheimer's in patients usually develop slowly but severely affect their daily cognitive capabilities over time. The current treatment for Alzheimer's has not been able to find a cure. Hence early detection through effective prediction becomes a vital factor in such cases. With an ever-growing population, there is a considerable upsurge in the number of Alzheimer's patients. Therefore it is crucial to group the patients into categories depending on the stages of the disease. In an estimate from multiple global reports about Alzheimer's, 95% of the people believe they will develop dementia at some point in their lifetime. Globally, the presence of dementia is estimated to be 3.9% among 60 or more than 60 years.

New technological advancements have brought in better technologies that can help find a cure and gradually slow the progress of dementia. HCI has paved a new way for researchers and medical specialists to reinvent techniques adapted for research. It is used to create a novelty to examine the Mini-Mental or emotional [11] State or Folstein test. DL has given researchers great tools at their disposal that helps them optimize and have time-efficient results on a multitude of data. Models created can either be predictive, which means making a future prediction, or descriptive, which means extracting meaningful knowledge and information from the input data. Some models can be developed to possess both predictive and descriptive statistics. As DL becomes more and more integrated with our everyday lives, it also opens up avenues for AI's growing application in the medical sector, be it for research, detection, or advanced monitoring of patients' health.

With the healthcare and medical field moving towards a more data-driven approach towards problem identification and solving, it is highly likely to develop an immerse environment using DL. Healthcare and DL have shared a well-integrated past, with today's researchers upping the tempo towards more analytical and complete models. The paper has used classification algorithms of ML to segregate the patients into broader groups of demented and non-demented patients. Recent studies have shown some improvement in helping clinical procedures. Still, they lack an edge due to specific reasons such as

(i) Dependence on single modality
(ii) Diagnosis and prediction are studied as different variables for research
(iii) Most research only focuses on optimizing the accuracy of machine learning algorithms and leaving out Explainable AI's untapped concepts.

Through the medium of this research, XAI means LIME and SHAP; LIME and SHAP are surrogate models when an outcome cannot be directly measured so that the engineer may develop a model out of the creation itself. The following are our contributions in this study:

(i) We aimed to create an explanation driven HCI model.
(ii) We have achieved high accuracy for different algorithms
(iii) Our proposed model is compared with the other popular DL state-of-the-art.
(iv) We have used SHAP and LIME explanation algorithm to elaborate the blackbox DL Models.

2 RELATED WORK

Various researches and papers with specialization in ML and DL focusing on healthcare projects have been referred to, for the purpose of this research.

2.1 Deep Learning and Machine Learning

DL and ML algorithms have paved the way for medical research to help develop novel models with high predictional accuracy and predictability[9, 12, 21, 30–32, 34, 36, 42]. Several such models and papers have been referred to for this research. Mandiliotis, Dimitris and Toumpas's research [22] published in International Conference on Universal Access in Human-Computer Interaction focuses on using DL algorithms like neural network and ensemble techniques on TCM database to obtain predictive models for early detection of Alzheimer's [3]. The

DL algorithms gave an R squared value of 92.7% on training and 86.2% on the test set. Random forest gave an F squared value of 86.9% on the training set and 89% on the test set.

Janghel, RR and Rathore [14] aimed at creating a highly accurate prediction model for Alzheimer's detection on an ADNI dataset while using CNN. The dataset has been pre-processed using ML classification algorithms such as SVM, Logistic regression, Decision Tree. The final model created after pre-processing and implementation of CNN has proved to be highly accurate and a better performer than similar approaches.
Ahmad, Irfan and Pothuganti [1] have aimed to compare different approaches of ML for early prediction of Alzheimer's. Various classification algorithms such as SVM, Fast RCNN, to create prediction models. The resulting model portrayed Fast RCNN to perform the classification and prediction activity with the best performance.

Xiao, Ruyi and Cui [41] have focused on the implementation of Sparse Logistic Regression to counter the high dimensional small sample characteristics of Alzheimer's patient data. The experimentation results showed that the newly adopted method of classification presented a classification accuracy of 96.1%. It is further indicated that Sparse aided logistic regression methods help capture the brain areas that have a high impact on the disease. Kuang, Jie, and Zhang [19] aimed to develop a Logistic Regression Model, a Decision Tree Model and an Artificial Neural Network Model to predict the progression of cognitive impairment accurately. The research seeks to compare the accuracy from the three models and project the best suitable model for predicting Alzheimer's. Mofrad, Rosha Babapour and Schoonenboom's [24] research are aimed to develop a clinically viable decision tree model for biomarker fluid that helps significantly in the diagnosis of Alzheimer's. The model was created using classification and Regression Tree analysis and was successfully able to identify two cerebrospinal fluids, and the decision tree model was performed with an accuracy of 86%. Jin, Mingwu and Deng, Weishu's paper talk about [15] early prediction of different stages of the disease using magnetic resonance imaging (MRI). It has been done using the ensemble decision tree model and neighborhood component analysis (NCA). The experiment results showed the NCA was the best prediction model, and the boosting tree could achieve an accuracy of 56.25%.

2.2 Explainable AI

Essemlali, Achraf and St-Onge researched on understanding the structure of the disease using XAI [5, 33]. The research focuses on applying DL algorithms while using a modified version of BrainNet CNN. The experiment claims to have made substantially accurate predictions on the used dataset and claims to have been the first research in the field of XAI.

Kamal, Md Sarwar, and Northcote published [16] and approached to classify the disease using ML algorithms. In the first stage of the experiment, SpinNet and CNN were used to classify the MRI. Then, the researchers moved on to KNN and SVM to organise the data. In the final stages of the research, XAI is introduced in the form of LIME for simple understanding. The accuracy of the resultant model was 97.6% which was 10.96% higher than the SpinNet approach.

Wang, Ning and Chen [40] have proposed three different models of DL architectures to automatically Alzheimer's in the Dementia Bank dataset by identifying discrepancies in speech patterns. Experiment results show that the model outperforms other models with an accuracy of 92.2% and an F1 score of 95.2%.

Holzinger, Andreas and Malle [7] aim to use Graphical Neural Networks for the process of early prediction of Alzheimer'. The paper voices its concerns to the AI community to push for research in XAI in the healthcare sector as it may have substantial results. Hossain et al. [13] have talked about the immense scope of untapped growth in the use of XAI for research and treatment of Covid-19 patients [35]. The healthcare sector can grow at a drastic rate with the proper application of these techniques. The paper also focuses on the importance of results from similar research that can strengthen the claim for such research.

Gabriel R and Martinez-Monterrub [39] have focused on the implementation of ML algorithms for classification such as SVM and Random Forest. Further, the paper applies case-based reasoning techniques for chronic kidney disease. The final model of Neural Network presented an accuracy of 95%.

Liu, Lin and Zhao, Shenghui and Chen, Haibao and Wang, Aiguo [20], have proposed a new method focusing on the use of spectrogram features extracted from the speech pattern of the patients to help in the early prediction of Alzheimer's. The speech data collected from the elderly was run through ML algorithms. The collected data was tested against speech data made available through Dem Care project for comparison. The best performing algorithm, in this case, was a logistic regression with an F1 score of 86.9%.

Kautzky, Alexander and Seiger, Rene and Hahn [17] had researched intending to create a more accurate prediction model which would be able to identify symptoms even before they occur. The resultant model achieved an accuracy of 62% from the decoding set and 61% from the validation set. Higher accuracy of 77% was achieved when the presence or absence of neuropathological change was studied. The conclusions derived from the research were that machine learning aided detection of neuropathological hallmarks for the disease would enable risk mitigation through early detection.

2.3 Human Computer Interaction

With the emergence of HCI in the medical field, research has evolved multifold [2, 10, 25]. The research [22] by Mandiliotis, Dimitris and Toumpas focus on focuses on aspiring to the innovative approaches to tackle AD as directed by the vision of WHO and AD International Association, to develop a novel HCI environment, named 'Symbiosis'. This approach aims to create a novel model to incorporate the whole Alzheimer's community's needs: the patients, caregivers, and doctors. The outcomes of this model claim to act as potent facilitators for the Alzheimer's Disease Community.

Gao, Ying [6] aims to use the concept of HCI design to study the cognitive disfunction among Alzheimer's patients. The study aims to use puzzle games to identify cognitive dysfunction in the patients, hoping to prompt mental ability recovery and delay the progress of dementia. The HCI environment was created using virtual reality to immerse the patients in a three-dimensional space. This paper proposes the plan of intuitive items for Alzheimer's patients by concentrating on the qualities of Alzheimer's illness patients, the social attributes of Alzheimer's patients and the conduct of utilizing items.

Carrasco, Eduardo, and Epelde published [4] on a characteristic human-computer collaboration worldview are proposed for people with intellectual debilitations like Alzheimer's Disease. The worldview comprises utilizing a practical virtual person, delivered on a typical TV, to assume the part of an individual virtual aide that shows updates, notices and performs short discoursed with the patient. The test results showed that with both dialogues, all users engaged naturally with the avatar. All of the users understood the information conveyed by the avatar and answered successfully utilizing the TV remote control.

Authors in [29] focus on evaluating Alzheimer's assistance systems using an HCI environment. The framework considers a standard like bringing down medical care costs, learning capacity, ease of use, constancy, meaningfulness, and work with computerizing. The ultimate result of the paper delineates utilizing outlines and tables to show the effect of applying HCI when planning an interface to accomplish easy to use, intuitive interfaces, and higher convenience of the frameworks.

2.4 Alzheimer's Disease

The emergence of research and immense development in the healthcare industry has helped in promoting to reduce the strenuous efforts in the medical field [26]. This has largely been focused on increasing life expectancy and providing better medical services to patients monitoring [8]. With the integration of research and innovation, new approaches and have been proposed by Sukriti Srivastava, Razi Ahmad, Sunil Kumar Khare [38] for the

adoption of steam cell theory and Nanoparticle drug delivery to be an appropriate approach for facilitating Alzheimer's therapeutics.

The study by Mehta, R.I. and Schneider, J.A [23] states Alzheimer's to be a biologically and pathologically multilayered disease. It aims to emphasize on the fact that advancement in research for the study of relativity of dementia with subject to age indicates the neuropathologic criteria which needs refinement. In the paper [28], further extensive research towards prediction of Alzheimer's using plasma photo therapy has been emphasized to proved greater accurate results. With the combination of cognitive tests, medical professionals can help improve diagnostic prediction and facilitate the recruitment for trials.

Mukhopadhyay and Banerjee [27] talk about the approval of the first antibody for the treatment of Alzheimer's. The proposed antibody is subjected to medical qualities that help in reducing the deposit of Amolyid in the brain. The researchers have focused on stimulating thought provoking ideas, keeping the efficacy of the newly developed drug as a test of time, but this research as a testament to the endless depth of possibilities for a cure.

3 METHODOLOGY

3.1 Datasets

3.1.1 Description. The Dementia dataset [18] used in this study is a longitudinal collection of 150 people aged 60 to 96 years old. The dataset holds categorical data holding multiple attributes with a wide range of age factors for both genders.Each subject was scanned on two or more occasions, separated by at least one year for a total of 373 imaging sessions. Each patient received three or four different T1-weighted MRI images obtained in separate scan sessions. Both male and female patients under consideration were right-handed. Seventy-two of the patients were categorized as non-mentally ill throughout the study. At their initial visits, 64 of the participants, including 51 persons with mild to severe Alzheimer's disease, were categorized as demented and remained such for subsequent scans. Another 14 people were diagnosed as non-dementia during their first assessment before being reclassified as demented at a later session. The attributes used in datasets are Gender (M/F), Hand, Age, Years of education (EDUC), Socioeconomic status (SES), Mini-Mental State Examination (MMSE), Clinical Dementia (CDR), Estimated total intracranial volume (eTIV), Normalized whole-brain volume (nWBV) and Atlas scaling factor (ASF).

3.1.2 Data Pre-processing. To make the knowledge discovery process more accessible and qualified, incomplete, noisy, or inconsistent datasets are preprocessed before using categorization algorithms. Categorical fields like Gender(M/F), hand are converted into numerical data. After that, the correlation between attributes is calculated. As some of the dataset parameters like MMSE and SES have missing values, the missing values are replaced with the median for that particular parameter. Finally, the data is divided into train and test set in a 4:1 ratio.

3.2 Proposed Framework

The abstract architecture of the model used is displayed in Fig. 1 composed of data preprocessing, different algorithms for the HCI Model, statistical performance measures and explanation extraction frameworks.

For better accuracy, categorical data of demanted and non demanted samples with different attributes are converted into numeric pattern. After calculating correlation and median, individual algorithms like logistic regression, support vector machine, multilayer perceptron and decision tree are used in the HCI model and used for statistical accuracy measurement and XAI. One can choose any of the algorithm for HCI model. For LIME explanations, lime tabular explainer is calculated, whereas, for SHAP, kernel explainer is used. Both LIME and SHAP show the top features based on their feature importance for the predictions.

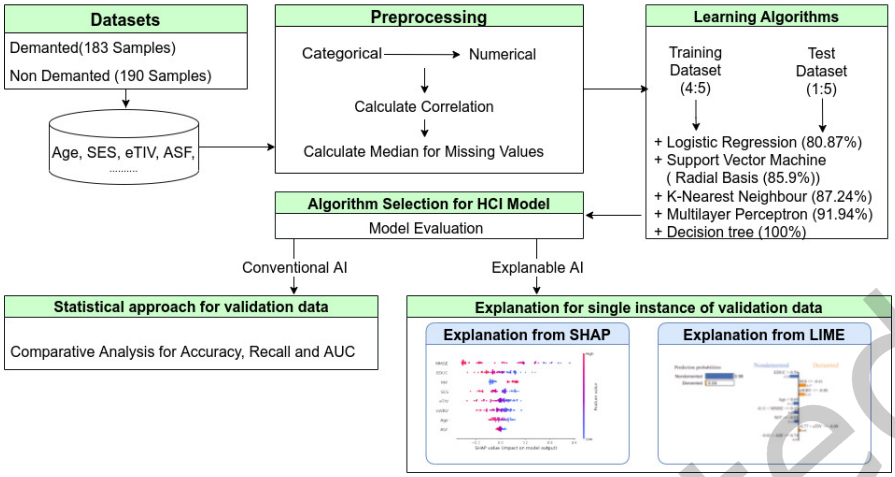

Fig. 1. Methodology

4 EXPERIMENT AND ANALYSIS

4.1 Results

As the dataset is converted into numerical, they are fed to every classification algorithms used. All the algorithms considered from the sklearn python library and performed classification are based on two categories: Nondemented and Demented. The final model developed is used as an HCI tool to classify the results individually with the help of LIME and SHAP. The evaluation metrics used is training accuracy, recall and area under the curve(AUC), and the results are shown in Table 1.

Table 1. Evaluation Metrics for different HCI Models

Algorithm	Training Accuracy	Recall	AUC
Logistic Regression	80.87%	69.76	0.76
SVM radial basis kernel	85.9%	62.79	0.79
KNN	87.27%	60.46	0.72
MLP	91.94%	67.44	0.77
Decision Tree	100%	79.06	0.75

To test the model statistically, each model undertook the McNemar test[37]. Table 2 shows the chi-squared and p-value of the models. We can reject the null-hypothesis for every models as test set and predicted set performed equally well, since the p-value is smaller than $\alpha = 0.005$.

4.1.1 Logistic Regression. With 80.87% of training accuracy, an HCI model is developed for Logistic Regression is imposed to LIME and SHAP. Fig. 2 interprets that the features nWBV(20%), SES(15%), eTIV(2%) have the highest weights for contributing to the overall demented prediction probability. Interestingly, the prediction probability for the dementation is reduced by the features EDUC(17%), Age(13%), MMSE(12%) and M/F(10%).
Examining the logistic regression model from Fig. 3 and Fig. 4, MMSE, M/F and EDUC are the top 3 important features. The SHAP values suggest that ASF does not have any impact on the model's output.
Fig. 5 shows the confusion matrix to evaluate the results from LR.

Table 2. McNemar test results

Algorithm	chi-squared	p-value
Logistic Regression	17.05	3.63 x e^{-05}
SVM radial basis kernel	15.05	0.00010
KNN	20.04	7.5 x e^{-06}
MLP	13.06	0.0003
Decision Tree	14.0625	0.0001

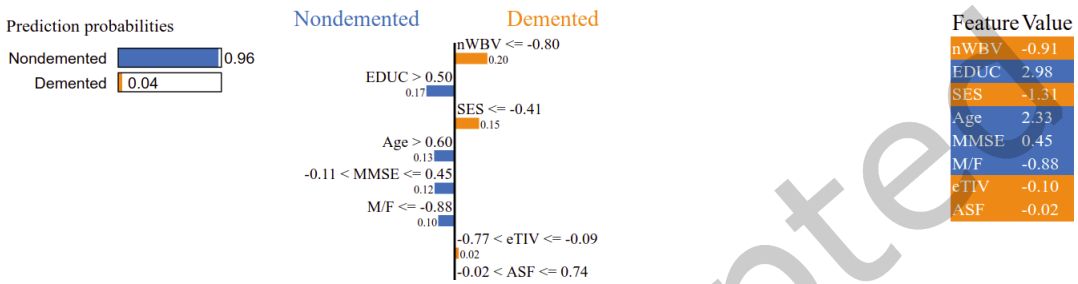

Fig. 2. LIME explanation with Logistic Regression

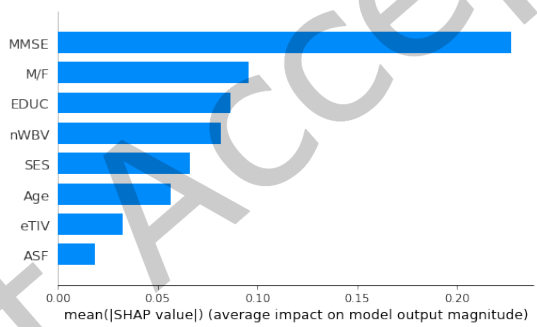

Fig. 3. SHAP explanation with Logistic Regression

4.1.2 SVM with Radial basis kernel. An HCI model for SVM with a Radial basis kernel is applied on LIME and SHAP with a training accuracy of 85.90%. The characteristics nWBV (18%), SES (11%), Age (3%), eTIV (3%) and ASF(2%) have the highest weights for contributing to the total demented prediction probability, as shown in Fig. 6. The characteristics M/F (12%), MMSE(11%) and EDUC(9%) lower the demented prediction probability for the prediction (10%).
The top three essential characteristics of the SVM model shown in Fig. 7 and Fig. 8 are MMSE, M/F, and EDUC. According to the SHAP values, Age has no effect on the model's output.
Fig. 9 shows the confusion matrix to evalute the results from SVM.

4.1.3 K Nearest Neighbour. The model with an K Nearest Neighbour(KNN) classifier gave the highest accuracy of 87.24%, and when interpreted using LIME, displays the results as in Fig. 10. nWBV (18%) and eTIV(3%) act as major determinants towards a Demented +ve case, while M/F (20%) and MMSE (16%) occupy higher shares of

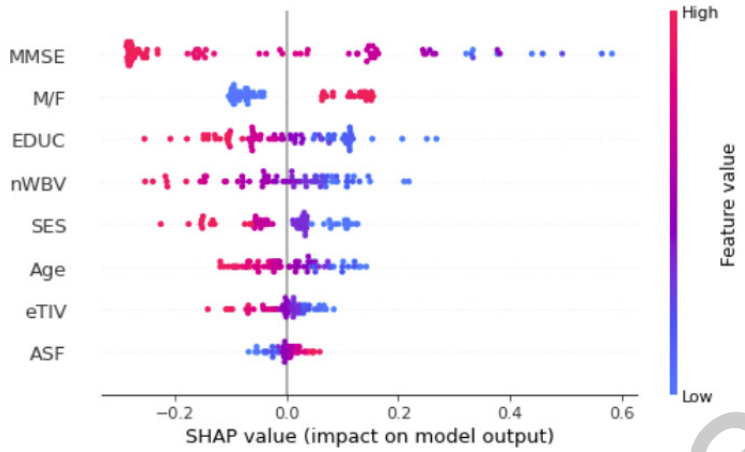

Fig. 4. SHAP explanation with Logistic Regression

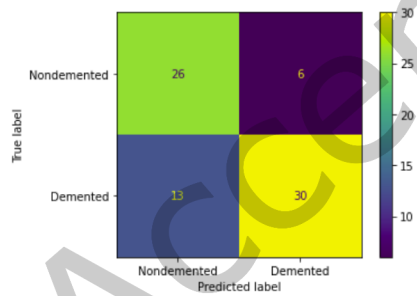

Fig. 5. Confusion Matrix for Logistic Regression

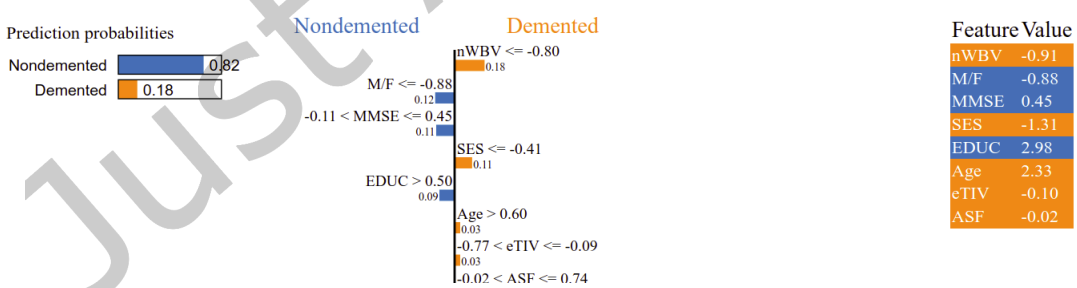

Fig. 6. LIME explanation with SVM

contribution for a Demented -ve case.
Fig. 11 and Fig. 12 displays similar results with the SHAP explanatory model. It demonstrates the top parameters that influence either of the results.
Fig. 13 shows the confusion matrix to evalute the results from KNN.

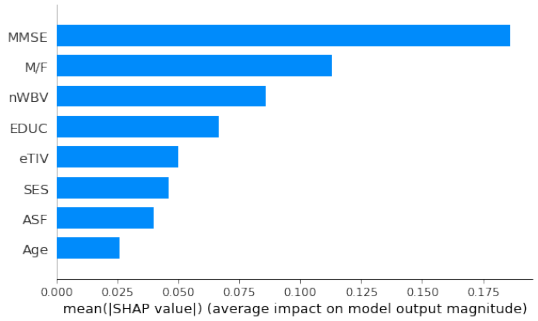

Fig. 7. SHAP explanation with SVM

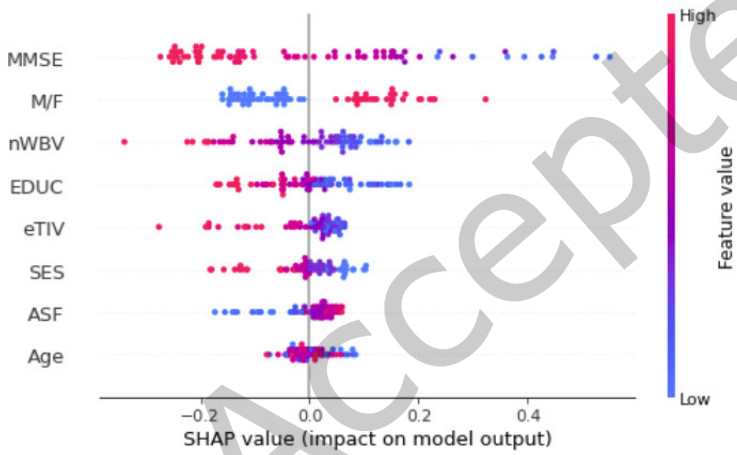

Fig. 8. SHAP explanation with SVM

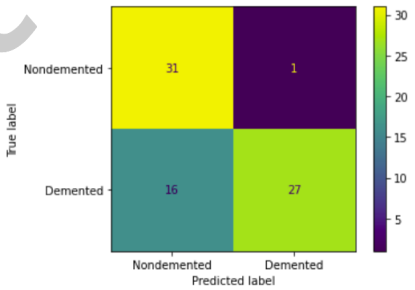

Fig. 9. Confusion Matrix for Support Vector Machine

4.1.4 Multilayer Perceptron. For multilayer perceptron (MLP) with learning rate of 0.001 and hidden layer of size (5,2), features eTIV(8%), SES(8%) and nWBV(8%) hold the highest weights for dementation prediction where as EDUC, MMSE, M/F, ASF hold the higested weight for non-demenation prediction as shown in Fig. 14. The

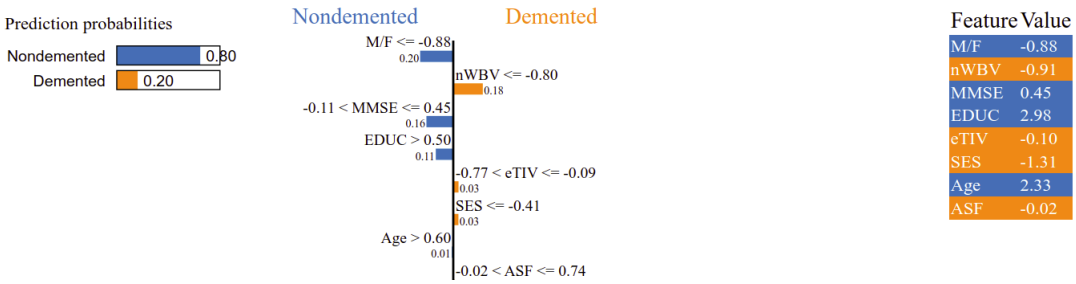

Fig. 10. LIME explanation with KNN

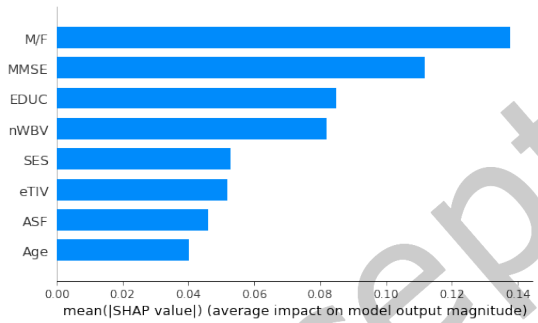

Fig. 11. SHAP explanation with KNN

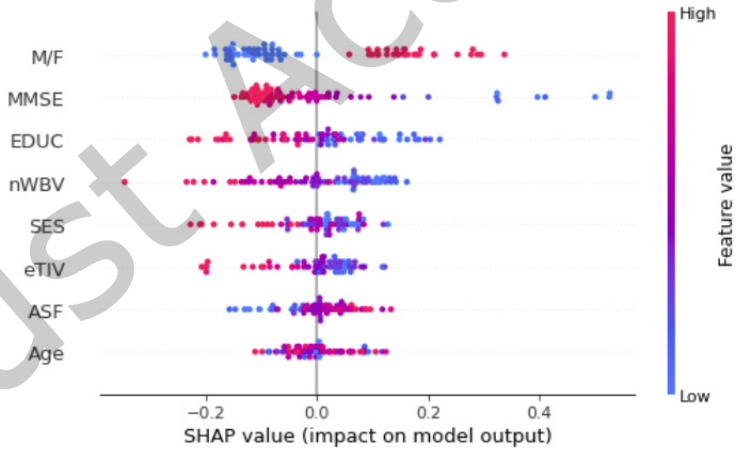

Fig. 12. SHAP explanation with KNN

model achieved 91.94% training accuracy.
The tree explainer diagram of SHAP in Fig.15 and Fig.16 shows that MMSF, eTIV and EDUC hold major contribution for the examination where as Age has low impact.
Fig. 9 shows the confusion matrix to evalute the results from MLP.

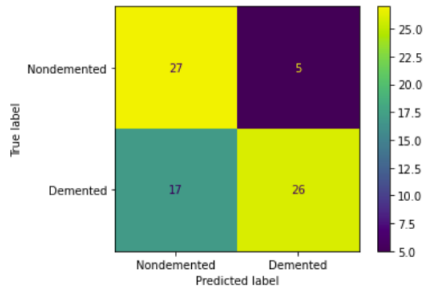

Fig. 13. Confusion Matrix for K Nearest Neighbour

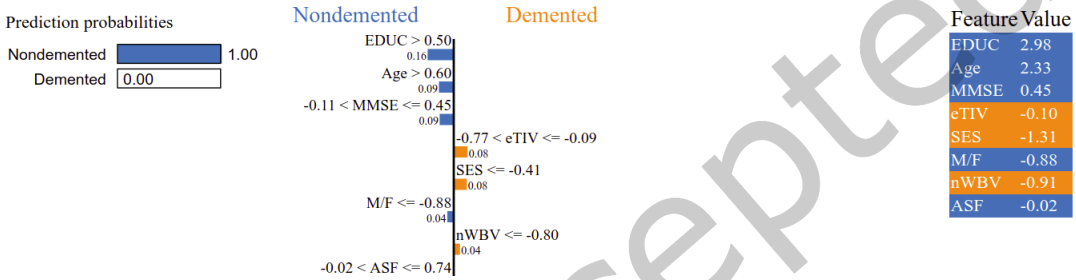

Fig. 14. LIME explanation with MLP

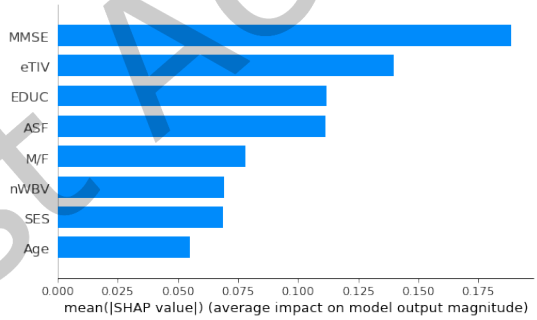

Fig. 15. SHAP explanation with MLP

4.1.5 Decision Tree. The features like nWBV(13%), ASF(6%), and SES(2%) have the greatest weights for dementia prediction, whereas MMSE(23%), EDUC(22%), M/F(14%), eTIV(4%) and ASF(2%) have the highest weights for non-dementia prediction. The model has a training accuracy of 100% as shown in Fig.18.

The tree explanation diagram of SHAP in Fig.19 and Fig.20 demonstrates that MMSF, EDUC, and nWBV all contribute significantly to the examination, but eTIV has a minor influence.
Fig. 9 shows the confusion matrix to evalute the results from Decision Tree.

Fig. 16. SHAP explanation with MLP

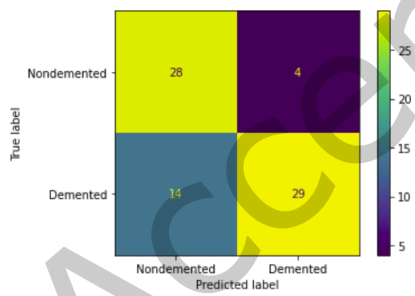

Fig. 17. Confusion Matrix for Multilayer Perceptron

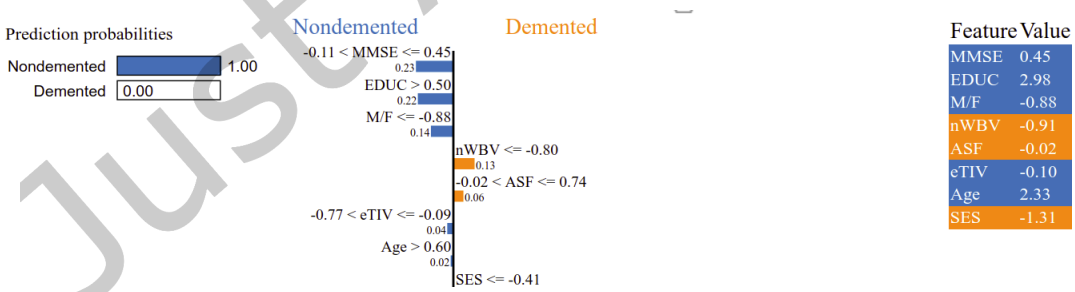

Fig. 18. LIME explanation with Decision Tree

5 DISCUSSION

Although various researches are conducted to examine Alzheimer disease, their primary focus is on the accuracy of benchmark ML algorithms. Conversely, we focus on the interpretability and developing the different HCI Models and comparing the performance in a widely used longitudinal data sets[18].

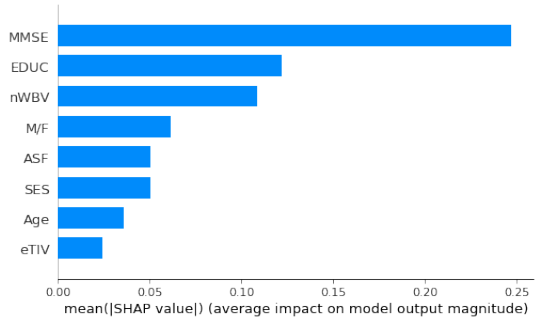

Fig. 19. SHAP explanation with Decision Tree

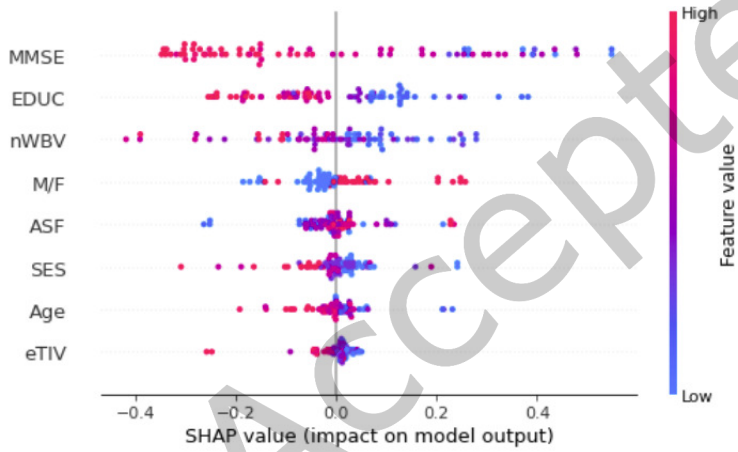

Fig. 20. SHAP explanation with Decision Tree

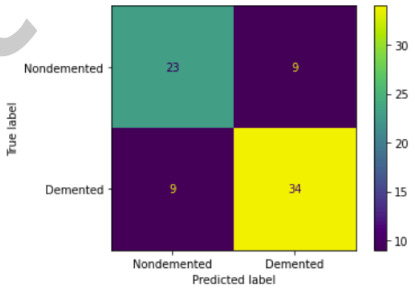

Fig. 21. Confusion Matrix for Decision Tree

Though there will be some practical challenges like running LIME and SHAP, getting probabilities from algorithms, the proposed HCI model will increase the trust in DL. The more the public's confidence in DL, the more medical professionals, will use it, allowing them to encourage innovation and accelerate the adoption of next-generation

capabilities. Furthermore, despite shifting confidence, the most significant characteristics remained constant. SHAP values, in particular, are reliable and effectively express the relevance of each feature in terms of the model prediction. However, its exponential run time might take an incredibly long time to obtain these values for numerous characteristics. On the other hand, LIME has certain limits when it comes to model objects and the sorts of models it can describe (probabilistic models only).

6 CONCLUSION AND FUTURE DIRECTIONS

The notable differences between the LIME and SHAP explainer can be observed in terms of the contribution of features in examining Alzheimer disease. MMSE hold a significant contribution in Shapely values, whereas nWBV dominates the LIME features. Among the different HCI models, the model from the decision tree has the highest accuracy. Still, on an individual basis, our findings show that both LIME and SHAP give coherent explanations. More classification algorithms can be integrated into future work with the dataset from the industry so that the authentic influence of algorithm performance can be considered. Furthermore, the speed of learning for the Decision Tree and Random Forest algorithms may be considered in terms of the number of characteristics and occurrences.

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