Predicting Cognitive Test Performance from New Onset Behavioral and Personality Changes in Adults over 50 using Post-Selection Boosted Random Forest Classifier

Mervyn M.[a*], Welhenge A.[b], Creese B.[c]

[a]Dept of Computer Systems Engineering, University of Kelaniya, Sri Lanka
[b]EECMS, Curtin University, Perth, Australia
[c]Dept of Life Sciences, Brunel University of London, United Kingdom.

meesham@kln.ac.lk*, anuradhi.welhenge@curtin.edu.au, byron.creese@brunel.ac.uk.

ABSTRACT

Mild Behavioral Impairment (MBI) refers to neuropsychiatric symptoms of various severity levels that might not be discovered by conventional psychiatric nosology. These symptoms should persist for more than six (06) months. MBI is typically observed in adults of age 50 and above. This study investigates the prediction of cognitive test performance of cognitive and behavioral changes in adults over 50 years of age using a post-selection boosted Random Forest (RF) Classifier. The baseline cognitive aging data of the Simple Reaction Time (SRT) metric and Mild Behavioral Impairment Checklist (MBI-C) from the ongoing PROTECT study in the United Kingdom was used to classify the participants' cognitive ability into five classes. Using the post-selected boosted RF classifier, the study obtained an accuracy of 96.26% which was an improvement compared to the 95.52% accuracy obtained by the RF classifier. These findings suggest that machine learning-based prediction models can provide valuable insights into analyzing the cognitive decline of adults of a late age.

KEYWORDS: *Mbi, Cognitive Performance, Lasso Method, Deep Learning*

INTRODUCTION

Mild Behavioral Impairment (MBI) is a phrase generally used in a medical context to describe subtle but noticeable changes in a person's behavior and personality that indicate early signs of cognitive decline. This neuropsychiatric syndrome is more prominently observed in late ages, in people with higher cognitive impairment, with a percentage of frequency between 10% and 15%. The key symptoms observed in a person suspected are mood fluctuation, a noticeable lack of interest and motivation, signs of social withdrawal, and a sudden shift in personality. This study aims to find whether machine learning techniques can be used to predict simple reaction time (SRT) from MBI-C.

BACKGROUND

Mild Behavioral Impairment and its Association with Cognition

Mild Behavioral Impairment (MBI) describes a spectrum of late-life onset, sustained neuropsychiatric symptoms (NPS) that includes apathy, affect, impulse dyscontrol, social inappropriateness and abnormal thoughts and perception. MBI may be the first manifestation of an underlying neurodegenerative disease, or occur alongside, or after subjective cognitive impairment and Mild Cognitive Impairment (MCI) (Ismail et al., 2016). That MBI represents a risk state for dementia and is a symptom of underlying neurodegenerative disease is supported by observational cohort studies linking MBI to incident dementia, and AD biomarkers (Creese & Ismail, 2022).
Because of the epidemiological evidence linking MBI to incident dementia and cognitive decline, there is an increased research need to establish the methods that offer the most reliable prediction, which could in turn lead to early identification of dementia in those with MBI.
(Creese et al., 2019) conducted a study to find whether MBI was associated with neuropsychological performance in subjects without significant cognitive impairment. They measured attention, reasoning, executive function and

https://doi.org/10.54389/LGKX8150

working memory of the older adults participated in the study and MBI was recorded using the MBI- C. The study found that MBI could be an early marker of neurodegenerative disease compared to MCI.
The International Society to Advance Alzheimer's Research and Treatment - Alzheimer's Association (ISTAART-AA) has a research diagnostic criterion to measure MBI, Mild Behavioral Impairment Checklist (MBI-C) is specifically designed to assess MBI construct from the research criteria. This has 34 items, and the development process included the five domains of MBI which are 1. Decreased motivation; 2. Emotional Dysregulation; 3. Impulse dyscontrol; 4. Social inappropriateness; and 5. Abnormal perception or thought (Ismail et al., 2017). Studies were conducted to validate the Mild Behavioural Impairment Checklist (MBI-C) that aligned with the diagnostic criteria established by the ISTAART-AA. Findings indicate that nearly 25% of individuals attending Primary Care Centres with Subjective Cognitive Complaints (SCCs), who do not have a history of neuropsychiatric disorders, receive a diagnosis of MBI (Mallo et al., 2019).

Machine Learning and Deep Learning based Improvements

In the past few years, studies have shown that Mild Behavioral Impairment diagnosis can be enhanced using Machine Learning (ML) and Deep Learning (DL), focusing on detecting early signs of Alzheimer's disease. Studies conducted in recent years focused on developing ML and DL algorithms to determine the probability of a patient in later ages developing MBI which has a possibility of morphing into dementia or Alzheimer's disease. Combining ML techniques with expert diagnosis from medical professionals can significantly improve the accuracy level of the diagnosis. Anderson (Anderson, 2019) suggested that there is an urgent need for standardized cognitive tests in order to benefit from the recent discoveries in cognitive neuroscience, which can lead to the development of heightened sensitive measures of MCI.
ML techniques have shown promising results in predicting early signs of dementia. By using NPS to train the algorithms, it is possible to improve the accuracy of ML models (Gill et al., 2020). MBI being identified as a marker of pre-dementia is due to Neuropsychiatric symptoms (NPS) being commonly identified across multiple cognitive disorders. These symptoms are often overlooked due to their similarity with other commonly diagnosed cognitive disorders, especially observed in older adults. Gill S. concluded that baseline NPS categorized by domain and duration for MBI could predict diagnosis change using ML. The risk factor of MBI developing into dementia is significantly higher in individuals over the age of 50. They often exhibit several cross-over symptoms such as anxiety, depression, and apathy. An observational study used a multi-class emotional classifier with Random Forest classification to detect cross-over symptoms in adults of 70-75 years with diagnosed MCI (Zhou et al., 2023).
The ADNI dataset is used in several ML and DL centered studies conducted on cognitive decline. One study compared between two-class and three-class ML classification of cognitive features optimized for detecting early Alzheimer's stages. The two-class model performed better with a minimal assessment time compared to the three-class model (Kleiman et al., 2021).
A number of studies utilize deep learning techniques such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) to analyze structural MRI (Magnetic Resonance Imaging) data. Conventional Machine Learning approaches need a considerable portion of feature engineering in order to optimize the performance of the model. DL models show improved accuracy in differentiating between several psychiatric disorders by identifying patterns that may not be apparent using conventional ML models. A study which showed this fact was conducted in 2019, where Artificial Neural Networks was used to predict the efficiency of certain medications before they were prescribed to patients with depressive disorders in order to develop personalized treatment plans (Chang et al., 2019). Another such research developed an interpretative DL framework using CNN to classify the Alzheimer's Disease probability of patients. The study suggested the possibility of adopting the framework as a clinical strategy for generalized pathophysiological disease discovery (Qiu et al., 2020). Grouping some cognitive assessment features into classes which are optimized for detecting cognitive disorders can significantly improve routine screening. F. Yi et al. used the patient data from the ADNI database to develop an interpretable framework combining SHAP and XGBoost for multi-classification of normal cognition, MCI, and Alzheimer's disease (Yi et al., 2023).
Machine Learning and Deep learning applications in MCI have shown promising results in both prediction of cognitive decline as well as improving the accuracy of diagnosis. However, similar methods could be used to predict MBI using different parameters as inputs and this area has received limited attention in the literature. In this paper we are predicting the MBI-C by using SRT as an input parameter.

METHODOLOGY

Dataset

This study employs a cross-sectional analysis of data from the ongoing online PROTECT Study (www.protectstudy.org.uk), a longitudinal cohort study focusing on 14 201 non-demented individuals aged 50 and over in the United Kingdom. Launched in November 2015, the aim of this study is to investigate cognitive aging and identify risk factors for dementia within a large, UK-based population of >50 years. The study utilizes a digital platform to collect self-reported data on lifestyle, health, and cognitive performance, enabling large-scale participation and frequent data collection. Inclusion criteria required participants to be aged 40 years or older, reside in the UK, possess a good working understanding of English, and have the ability to use a computer with internet access. Individuals with an established diagnosis of dementia were excluded, as the study focuses on understanding cognitive changes in healthy aging and early risk factors for cognitive decline.

This research focuses on classifying the cognitive ability of the participants aged 50 and above using the Simple Reaction Time (SRT) metric into five (05) classes using the MBI-C.

Random Forest (RF) Classifier

In this research an RF Classifier was employed to predict SRT values against the baseline cognitive performance of the participants. The MBI-C values were used as input features, and the SRT values were predicted into five groups classified from low to high cognitive performance. The prediction was conducted class-wise rather than using exact values to improve prediction accuracy and reduce the training complexity of the model. The RF classifier was implemented on the dataset after finding the principal components from the Principal Component Analysis (PCA).

In ensemble learning samples and variables are sampled which is the basis of the popular RF algorithm (by Breiman) which groups multiple decision trees. During classification, the results were calculated based on the majority vote method. The RF implementation is as follows.

M – Training set, p - variables

1. Generating a sample set M* of size Q using bootstrap sampling from the training set M.
2. Generating a tree based on the sample set M* in RF, the following steps are repeated for each node. The process continues until a node reaches the predetermined size.
   - n variables were randomly selected from p variables.
   - Pick the best splitting variable and splitting point from r variables.
   - Split the current node into two child nodes according to the selected splitting variable and splitting point.
3. For a new observation z, the predicted value is calculated as

$$T(z) = majorityvoteT_v(z)1^V \qquad (1)$$

Post-Selection Boosted Random Forest (PBRF) Classifier

As the second part of this study post-selection boosting random forest algorithm (PBRF) was implemented. The Post-Selection Boosting Random Forest (PBRF) algorithm is an advanced ensemble learning technique that combines the strengths of Random Forest (RF) with the Lasso method to improve predictive performance while reducing model complexity. In this study, PBRF is implemented after applying Principal Component Analysis (PCA) to the dataset, further optimizing the model's performance (Wang & Wang, 2021). Principal components representing 90% of the variance have been used in this study.

The implementation of the PBRF algorithm was as follows.

1. Use Bootstrap Sampling to generate a dataset D* with sample size N from data set D
2. Construct a tree T* by randomly selecting r variables from all p variables for each node.
3. Do Lasso Regression to T*, which compress the weight coefficients of some trees to 0.
4. The final prediction is computed as a weighted average of the predictions from the selected trees.

$$y = \frac{1}{m}\sum_{n=1}^{m} \quad T_n(z) \qquad (2)$$

RESULTS

Random Forest (RF) Classifier

The RF classifier was used to analyze the impact of various feature splits on the outcome of the classification, with each split affecting a specific percentage of the selected sample. Figure 1, Figure 2 and Figure 3 depict the features, the percentage of the sample covered, and the accuracy predicted for each specific class.

The overall accuracy achieved by the RF classifier was 95.52%

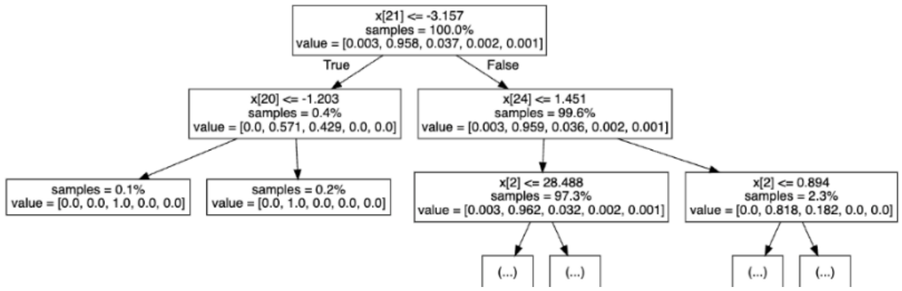

Figure 1: Split of the feature x[21]

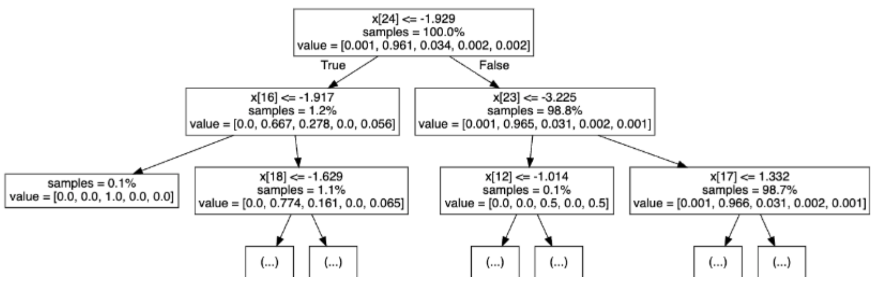

Figure 2: Split of the feature x[24]

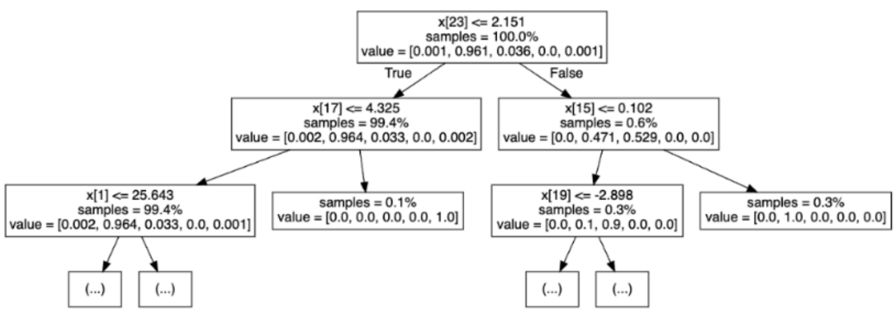

Figure 3: Split of the feature x[23]

Post-Selection Boosted Random Forest (PBRF) Classifier

The analysis conducted in this research was further expanded by using the PBRF classifier. Similar to the analysis conducted using the RF algorithm, the sample was split into nodes based on selected features to refine the classification, and the accuracy was predicted for the specific classes. Figure 4, Figure 5, and Figure 6 depict the selected features and their percentage of the sample size covered, along with the class accuracy predicted.

The overall accuracy obtained by the PBRF classifier was 96.26%.

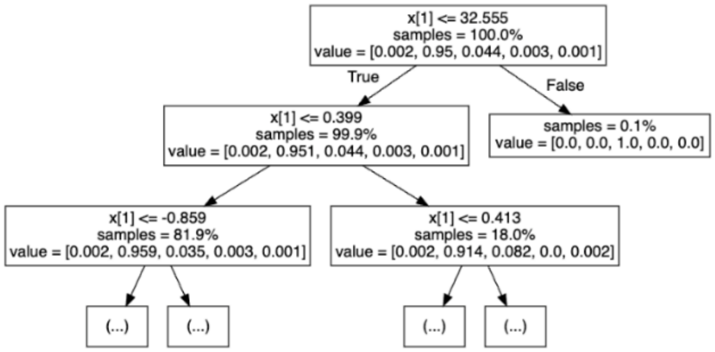

Figure 4: Split of the feature x[1]

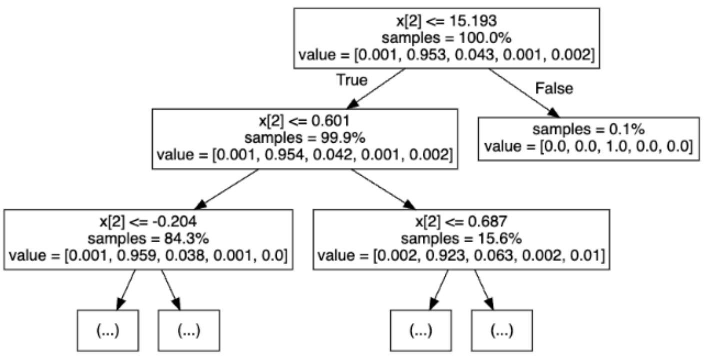

Figure 5: Split of the feature x[2]

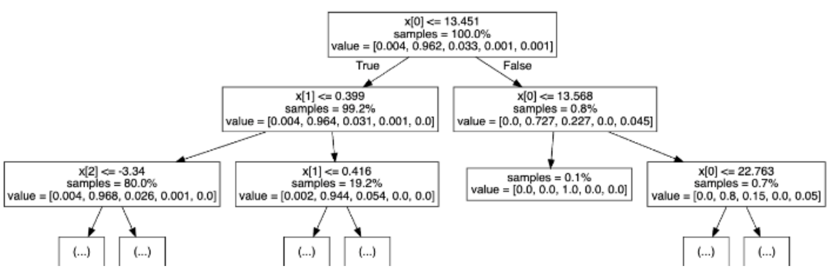

Figure 6: Split of the feature x[0]

Boosting helps the model separate classes better, making more accurate predictions. Overall, the model uses key features to classify data well, though some classes may be less balanced in certain areas. This result shows that PBRF performs better than the RF.

CONCLUSION AND DISCUSSION

Mild Behavioral Impairment (MBI) is a symptom of cognitive decline observed in adults over the age of 50. Using a cross-sectional analysis of the PROTECT dataset from the UK the baseline cognitive ageing was evaluated by using the Simple Reaction Time (SRT). The study used an improved Random Forest Classifier to predict the range of SRT values against the baseline of cognitive aging of the participants. The performance of the improved RF classifier was compared with the accuracy level obtained using a traditional RF algorithm, and it was observed that the improved RF classifier performed better exhibiting a higher accuracy of prediction. This research provides further evidence to support the claim that ML and DL methods will aid in the early detection of cognitive decline during late adulthood by predicting behavioral and personality changes in individuals.
Studies underscore the significance of utilizing standardized assessment tools like the MBI-C in clinical settings to

identify individuals at risk for cognitive decline and dementia. MBI research has gained traction in recent years, and it is recognized as a neurobehavioral syndrome associated with dementia and Alzheimer's. However, the underlying mechanisms linking MBI to cognitive decline are not fully understood. Understanding these mechanisms could significantly improve diagnosis of neurodegenerative disease.
The precise relationship between MBI and cognitive function is an area of ongoing research. Some studies have suggested that MBI is associated with poorer cognitive performance, particularly in the domains of executive function and memory (Petersen & Negash, 2008). However, the nature of this relationship is complex, and there is a need for more longitudinal studies to clarify the trajectories of cognitive and behavioural changes in individuals with MBI. To improve the knowledge of MBI, it will be essential to fill in these gaps through standardised tests, longitudinal studies, studies on a variety of populations, and integration with neuroimaging.

ACKNOWLEDGEMENTS

This PROTECT study was supported by the National Institute for Health and Care Research (NIHR) Exeter Biomedical Research Centre. The views expressed are those of the author(s) and not necessarily those of the NIHR or the Department of Health and Social Care. This research was also supported by the NIHR Collaboration for Leadership in Applied Health Research and Care Southwest Peninsula.

REFERENCES

1. Anderson, N. D. (2019). State of the science on mild cognitive impairment (MCI). *CNS Spectrums*, *24*(1), 78–87. https://doi.org/10.1017/S1092852918001347
2. Chang, B., Choi, Y., Jeon, M., Lee, J., Han, K.-M., Kim, A., Ham, B.-J., & Kang, J. (2019). ARPNet: Antidepressant Response Prediction Network for Major Depressive Disorder. *Genes*, *10*(11), 907. https://doi.org/10.3390/genes10110907
3. Creese, B., Brooker, H., Ismail, Z., Wesnes, K. A., Hampshire, A., Khan, Z., Megalogeni, M., Corbett, A., Aarsland, D., & Ballard, C. (2019). Mild Behavioral Impairment as a Marker of Cognitive Decline in Cognitively Normal Older Adults. *The American Journal of Geriatric Psychiatry: Official Journal of the American Association for Geriatric Psychiatry*, *27*(8), 823–834. https://doi.org/10.1016/j.jagp.2019.01.215
4. Creese, B., & Ismail, Z. (2022). Mild behavioral impairment: Measurement and clinical correlates of a novel marker of preclinical Alzheimer's disease. *Alzheimer's Research & Therapy*, *14*(1), 2. https://doi.org/10.1186/s13195-021-00949-7
5. Gill, S., Mouches, P., Hu, S., Rajashekar, D., for the Alzheimer's Disease Neuroimaging Initiative, MacMaster, F. P., Smith, E. E., Forkert, N. D., & Ismail, Z. (2020). Using Machine Learning to Predict Dementia from Neuropsychiatric Symptom and Neuroimaging Data. *Journal of Alzheimer's Disease*, *75*(1), 277–288. https://doi.org/10.3233/JAD-191169
6. Ismail, Z., Agüera-Ortiz, L., Brodaty, H., for the NPS Professional Interest Area of the International Society of to Advance Alzheimer's Research and Treatment (NPS-PIA of ISTAART), Cieslak, A., Cummings, J., Fischer, C. E., Gauthier, S., Geda, Y. E., Herrmann, N., Kanji, J., Lanctôt, K. L., Miller, D. S., Mortby, M. E., Onyike, C. U., Rosenberg, P. B., Smith, E. E., Smith, G. S., Sultzer, D. L., & Lyketsos, C. (2017). The Mild Behavioral Impairment Checklist (MBI-C): A Rating Scale for Neuropsychiatric Symptoms in Pre-Dementia Populations. *Journal of Alzheimer's Disease*, *56*(3), 929–938. https://doi.org/10.3233/JAD-160979
7. Ismail, Z., Smith, E. E., Geda, Y., Sultzer, D., Brodaty, H., Smith, G., Agüera-Ortiz, L., Sweet, R., Miller, D., Lyketsos, C. G., & ISTAART Neuropsychiatric Symptoms Professional Interest Area. (2016). Neuropsychiatric symptoms as early manifestations of emergent dementia: Provisional diagnostic criteria for mild behavioral impairment. *Alzheimer's & Dementia*, *12*(2), 195–202. https://doi.org/10.1016/j.jalz.2015.05.017
8. Kleiman, M. J., Barenholtz, E., Galvin, J. E., & for the Alzheimer's Disease Neuroimaging Initiative. (2021). Screening for Early-Stage Alzheimer's Disease Using Optimized Feature Sets and Machine Learning. *Journal of Alzheimer's Disease*, *81*(1), 355–366. https://doi.org/10.3233/JAD-201377
9. Mallo, S. C., Ismail, Z., Pereiro, A. X., Facal, D., Lojo-Seoane, C., Campos-Magdaleno, M., & Juncos-Rabadán, O. (2019). Assessing mild behavioral impairment with the mild behavioral impairment checklist in people with subjective cognitive decline. *International Psychogeriatrics*, *31*(2), 231–239. https://doi.org/10.1017/S1041610218000698

10. Petersen, R. C., & Negash, S. (2008). Mild Cognitive Impairment: *An Overview*. *CNS Spectrums*, *13*(1), 45–53. https://doi.org/10.1017/S1092852900016151
11. Qiu, S., Joshi, P. S., Miller, M. I., Xue, C., Zhou, X., Karjadi, C., Chang, G. H., Joshi, A. S., Dwyer, B., Zhu, S., Kaku, M., Zhou, Y., Alderazi, Y. J., Swaminathan, A., Kedar, S., Saint-Hilaire, M.-H., Auerbach, S. H., Yuan, J., Sartor, E. A., … Kolachalama, V. B. (2020). Development and validation of an interpretable deep learning framework for Alzheimer's disease classification. *Brain*, *143*(6), 1920–1933. https://doi.org/10.1093/brain/awaa137
12. Wang, H., & Wang, G. (2021). Improving random forest algorithm by Lasso method. *Journal of Statistical Computation and Simulation*, *91*(2), 353–367. https://doi.org/10.1080/00949655.2020.1814776
13. Yi, F., Yang, H., Chen, D., Qin, Y., Han, H., Cui, J., Bai, W., Ma, Y., Zhang, R., & Yu, H. (2023). XGBoost-SHAP-based interpretable diagnostic framework for alzheimer's disease. *BMC Medical Informatics and Decision Making*, *23*(1), 137. https://doi.org/10.1186/s12911-023-02238-9
14. Zhou, Y., Han, W., Yao, X., Xue, J., Li, Z., & Li, Y. (2023). Developing a machine learning model for detecting depression, anxiety, and apathy in older adults with mild cognitive impairment using speech and facial expressions: A cross-sectional observational study. *International Journal of Nursing Studies*, *146*, 104562. https://doi.org/10.1016/j.ijnurstu.2023.104562