Prediction of Cognitive Impairment in Middle-aged and Elderly People: A Method Based on Granger Causality

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Abstract

Cognitive impairment is a common disease among middle-aged and elderly people, which seriously affects health outcomes and quality of life, and carries a risk of progressing to severe stages such as dementia. Early identification is beneficial for timely intervention and treatment. This study proposes a new model for predicting cognitive impairment that integrates static and dynamic data, including medical, demographic, and social relationship features. It combines Granger causality with deep learning and uses multiple metrics to evaluate model performance. The performance comparison results between our model and the baseline model demonstrate that our model's predictions have a certain level of accuracy. In addition, causal features derived from Granger causality analysis are used to identify cognitive impairments. Statistical analysis shows that the selected features have statistical significance, further verifying the robustness of our model and its potential for predicting cognitive impairment.

Keywords: Artificial Intelligence; Causal reasoning; Cognition of Time; Dynamic Systems Modeling

Introduction

The global elderly population is constantly expanding. Cognitive impairment, as a major factor leading to poor health among middle-aged and elderly people, has made related health problems increasingly prominent, placing a heavy burden on the public health system(Duan et al., 2020). The prevalence of cognitive impairment is notably high, with a global median prevalence rate of 19.0%(Pais, Ruano, P. Carvalho, & Barros, 2020). Studies show that cognitive impairment may develop into dementia, treatment will become difficult, and patients will also have difficulty recovering(Buratti et al., 2015). Not only that, it is a prognostic factor for mortality in the elderly(Perna et al., 2015). Therefore, early detection and intervention of cognitive impairment are essential.

Traditional models for predicting cognitive impairment typically rely on electronic health record (EHR) data, which often lacks important information about daily functioning, such as physical abilities and social relationships. This limitation may lead to biased predictions. Moreover, most existing models use cross-sectional data, which cannot effectively capture the process of cognitive decline over time(Graham et al., 2020). Furthermore, high-dimensional data is usually used for prediction, but this approach lacks generalizability because it is difficult to obtain all the information of other patients for prediction. In recent years, some researchers have attempted to incorporate causal inference into machine learning frameworks for cognitive health prediction, aiming to improve both interpretability and prediction accuracy(Wang et al., 2024).

To address these challenges, we propose a cognitive impairment prediction model that combines Granger causality(Granger, 1969) analysis and deep learning models. Our contributions are as follows. Firstly, our model uses the China Health and Retirement Longitudinal Study (CHARLS)

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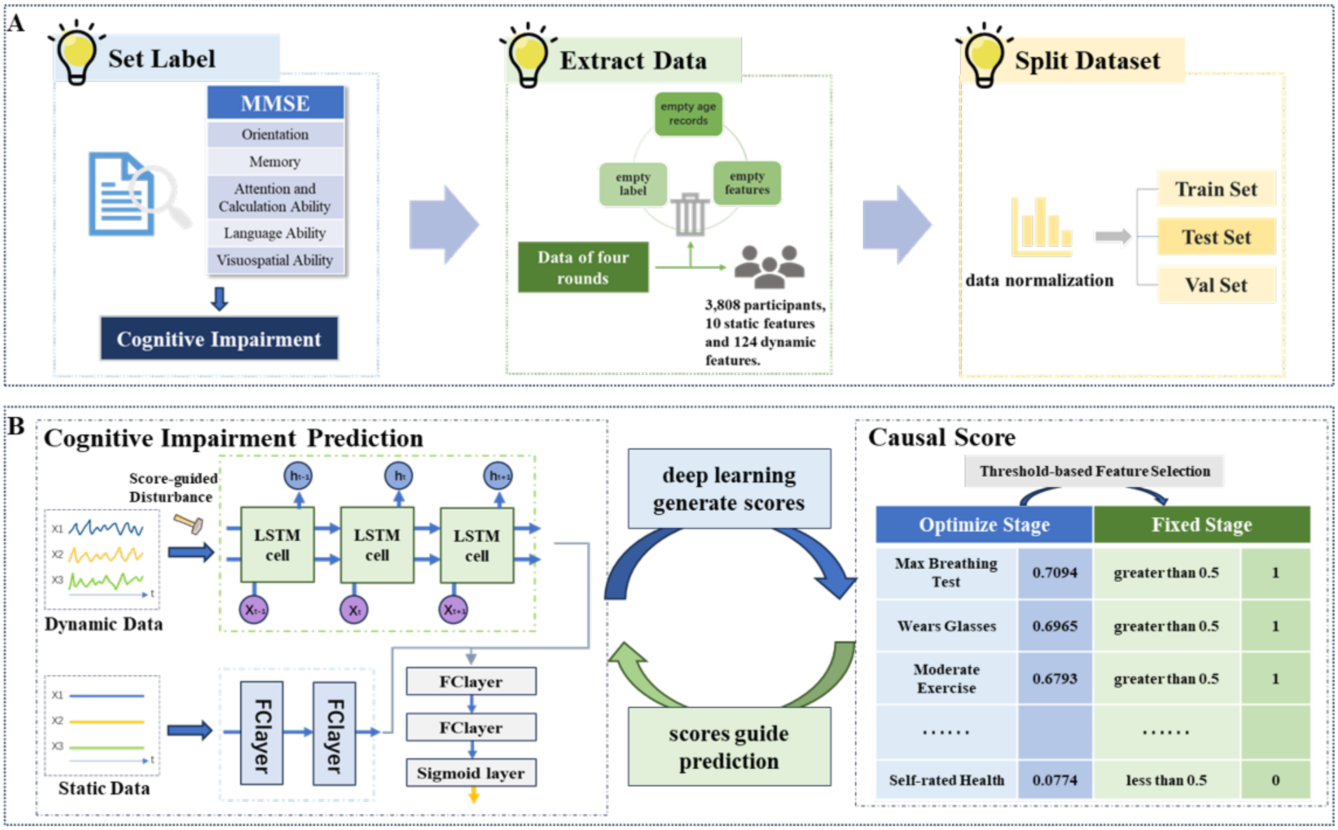


Figure 1: A model for predicting cognitive impairment using the CHARLS dataset. (a)Show the data processing section, which includes label setting, data extraction, normalization, and dataset partitioning. (b)Show the prediction section, including the prediction of cognitive impairment and the acquisition of causal scores.

dataset(Zhao, Hu, Smith, Strauss, & Yang, 2014) for prediction, which not only utilizes health data but also incorporates other information such as social relationship information and daily activity information, providing more complex and complete data for the model's predictions. Secondly, our model includes not only cross-sectional data but also longitudinal temporal data, which can explore the correlation between features and labels in both temporal and static dimensions. Finally, our model introduces a causal scoring method based on Granger causality and integrates the results into a deep learning model. Using only a small number of features in the final prediction allows the model to focus on the most important variables, improving the accuracy and generalizability of predicting cognitive impairment in middle-aged and elderly people.

Materials and Methods

Participants and Data Sources

Data used in this study were obtained from the China Health and Retirement Longitudinal Study (CHARLS), a nationally representative longitudinal survey aimed at middle-aged and older adults in China. The survey collects comprehensive data on social, economic and health circumstances through computer-assisted face-to-face personal interviews (CAPI), conducted every two years. In this study, we used four rounds of data: data from 2011, 2013, 2015, and 2018. After excluding participants with missing values in label calculation, empty age records, and missing feature data in 4 rounds of data, a total of 3808 participants were included in the analysis.

Cognitive Impairment Labeling

The Mini Mental State Examination (MMSE) score is used to assess cognitive impairment. The MMSE is a brief neuropsychological test that provides an overview of cognitive function, often supplemented by more specialized tests to evaluate other areas such as language, praxis, and executive function in patients with mild cognitive impairment (MCI)(Arevalo-Rodriguez et al., 2015). The MMSE score ranges from 0 to 30, with lower scores indicating more severe cognitive impairment.

We use the MMSE score in the model to determine cognitive impairment. The classification task is treated as a binary classification problem, where a label of 1 represents cognitive impairment (individuals with illiteracy and a score less than or equal to 17, primary school education and a score less than or equal to 20, and secondary school or above with a

Table 1: The Ten Static Features Used to Improve the Model's Predictive Performance. These variables represent an individual's highest level of education. For example, "High School" represents the highest level of education achieved by receiving a high school diploma.

Illiterate	Did Not Finish Primary School but can Read	Elementary School	Middle School	Vocational School
High School	Private Tutoring	2/3-year college	College Grad	Post-graduate degree

score less than or equal to 24 are classified as having cognitive impairment), and 0 represents no cognitive impairment. We evaluate the patient's cognitive status during the fourth round of data as the label for our final prediction.

Granger Causality based Learning

Causal deep learning. Although traditional machine learning models excel at prediction, they typically only capture correlations rather than actual reasons. Causal deep learning(Ali, Zuo, Ali, Zuo, & Rahman, 2021) combines causal relationships with deep learning models to capture potential causal relationships between variables and improve the interpretability and predictive accuracy of the model(Moraffah, Karami, Guo, Raglin, & Liu, 2020).

Causal relationships have been applied in many fields, especially in healthcare. It enables algorithms to estimate treatment outcomes and extract actionable information from observed patient data to make intervention decisions, surpassing traditional supervised learning methods(Sanchez et al., 2022). For example, the CARE-30 model integrates causal reasoning into multi-modal learning for ICU readmission prediction(Wang et al., 2023). Therefore, we apply it to the field of cognitive impairment in middle-aged and elderly people, using causal relationships to identify features that are truly related to cognitive impairment and use them for prediction.

Granger Causality. Granger causality analysis was proposed by Clive Granger in 1969, aiming to explore causal relationships between time-series data. Granger causality analysis is based on the following hypothesis: If the past values of one time series improve the prediction accuracy of another time series, the former is said to "granger cause" the latter. Let X_t and Y_t represent two time series. The causal relationship is determined by testing the following regression model:

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{i=1}^{p} \gamma_i X_{t-i} + \varepsilon_t$$

Where α is the constant term, β_i and γ_i are the coefficients, and ε_t is the error term. If γ_i is significantly different from zero, it indicates that the past values of X have a significant predictive power for the future values of Y, suggesting that X Granger causes Y.

In recent years, Granger causality analysis has been widely applied in deep learning. For example, Granger causality has been integrated with autoregressive multilayer perceptrons (MLP) and recurrent neural networks (RNN), helping researchers discover causal relationships in time-series data(Shojaie & Fox, 2022). In the context of our model, we integrate it with a predictive framework. Specifically, we consider the data from the preceding four rounds as historical information. We then place a primary emphasis on discerning the causal influence that historical data exert on labels of cognitive impairment.

Static variable processing based on cognitive reserve theory. The Cognitive Reserve Theory states that the reserve capacity formed by an individual's accumulated experience through education and other means can delay symptom presentation or enhance the brain's compensatory ability when cognitive function is impaired(Stern, 2002). Taking inspiration from this, we incorporated static variables related to education level (such as primary school, secondary school, university, and graduate education experience) into the model to improve predictive performance. Table 1 shows the selected variables. Due to the emphasis on temporal structure in the Granger causality method, we did not apply causal score intervention to static features, but instead participated in modeling as static background information.

Model Integration. Our model integrates dynamic and static data through Long Short-Term Memory (LSTM) networks and Multi-Layer Perceptrons (MLP) to predict cognitive impairment. Dynamic variables such as age and blood data are modeled using LSTM, which is suitable for capturing temporal dependencies in time series data. Static features are processed using MLP, which can capture complex non-linear relationships between static variables and cognitive impairment. After processing dynamic and static data separately, the output results are fused and passed through two fully connected layers and one Sigmoid layer to obtain the final prediction of cognitive impairment. The schematic diagram of the model is shown in Figure 1.

We maintain and optimize the causal scores derived from Granger causality analysis. These scores quantify the impact of features on cognitive impairment. We weight these causal scores with the input dynamic data, which has the effect of modifying the historical data and guides the model to pay more attention to variables that have a stronger causal relationship with cognitive impairment. Throughout the process, we alternately update the causal scores and model parameters to gradually improve the model's understanding of the relationship between features and labels, as well as the model's performance.

After completing the iterative training process, dynamic variables with a causal score greater than 0.5 are retained. These variables are assumed to exhibit stronger causal rel-

Table 2: Top Eight Dynamic Features with the Highest Causality Scores Obtained by Granger Causality. IADL_Phone Calls represents the ability to make phone calls on ones' own. Card_Activities refers to whether or not one has participated in chess and card activities. Household Registration includes rural registered residence and urban registered residence. Activities_friends represents the frequency of participating in social activities with friends.

IADL_Phone Calls	Max Breathing Test	Card_Activities	Sarcopenia
Wears Glasses	Household Registration	Moderate Exercise	Activities_Friends

Table 3: Comparison of Model Performance for Cognitive Impairment Prediction Using the Top 8 Dynamic Features and 10 Static Features. Baseline models include XGBoost, logistic regression (LR), random forest (RF), and Ensemble models combining these methods.

	AUROC	AUPRC	Accuracy	F1-score	Recall	Precision
XGBoost	0.8402	0.6205	0.7780	0.5968	0.6861	0.5281
LR	0.8481	0.6237	0.7797	0.5909	0.6642	0.5322
RF	0.8379	0.6241	0.7885	0.6084	0.6861	0.5465
Ensemble	0.8449	0.6053	0.7830	0.5867	0.6875	0.5116
Ours	**0.8640**	**0.6779**	**0.8077**	**0.6452**	**0.7246**	**0.5814**

evance to cognitive impairment. The original values of the selected dynamic variables, together with static background features, are then used for the final prediction.

We use Binary Cross-Entropy (BCE) loss to optimize the model, which is a common loss function for binary classification tasks. The BCE loss measures the discrepancy between the predicted probabilities and the true binary labels, helping to guide the model's learning process towards better classification performance. The BCE loss is computed as:

$$\text{BCE Loss} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)\right]$$

where y_i is the true label (0 or 1), $\hat{y}_i$ is the predicted probability, and N is the number of samples. The loss function penalizes the model more heavily when the predicted probability deviates significantly from the actual label, driving the model to improve its accuracy over time.

Results

Performance of Predictive Model

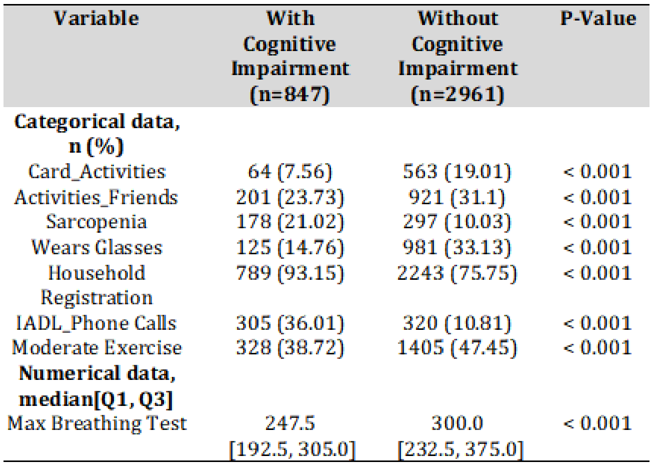
In this study, several machine learning models were used as baseline models, including XGBoost, logistic regression (LR), random forest (RF), and Ensemble models combining these methods. Use the ten static features (as shown in Table 1) and the top eight dynamic features ranked by causal score (as shown in Table 2) to predict cognitive impairment, and evaluate the model using various performance indicators, including area under the receiver operating characteristic curve (AUROC), area under the precision recall curve (AUPRC), Accuracy, Precision, Recall, and F1-score. The results are shown in Table 3.

Our model has shown good performance on various evaluation metrics. The AUROC score for cognitive label prediction is 0.8640, indicating that our model has good ability to distinguish between patients with cognitive impairment and those without cognitive impairment, and can effectively balance the proportion of true positives and false positives. The AUPRC value is 0.6779, highlighting that the model can more accurately identify true cognitive impairment patients while reducing misjudgments. The accuracy of the model is 0.8077, reflecting its overall correct classification rate. The F1-score is 0.6452. The recall rate is 0.7246. This indicates that ours model performs well in identifying patients with cognitive impairments, capturing the majority of actual patients. The precision is 0.5814. These results indicate that the model can predict cognitive impairments more accurately and reliably, providing valuable references for practical applications.

Statistical Significance of Causal Features

The top eight dynamic features with the highest causal relationship scores can be divided into three thematic categories. Personal information includes the type of household registration. Physical health-related characteristics include maximum breathing test results, the presence of sarcopenia, and the wearing of glasses. Daily and social activity variables include the ability to make independent phone calls, participate in card activities, socialize with friends, and have moderate exercise habits.

To evaluate the effectiveness of these features, statistical methods are used for analysis and testing. We use Chi-Square test and Mann-Whitney U test for categorical data and numerical data separately to calculate the p-value of each feature. The results indicate that the top eight features related to cognitive impairment that we selected have statistical significance, with p-values less than 0.001, as shown in Table 4. This confirms that the causal scoring method can successfully identify the variables that have the greatest predictive impact on cognitive impairment.



Variable	With Cognitive Impairment (n=847)	Without Cognitive Impairment (n=2961)	P-Value
Categorical data, n (%)			
Card_Activities	64 (7.56)	563 (19.01)	< 0.001
Activities_Friends	201 (23.73)	921 (31.1)	< 0.001
Sarcopenia	178 (21.02)	297 (10.03)	< 0.001
Wears Glasses	125 (14.76)	981 (33.13)	< 0.001
Household Registration	789 (93.15)	2243 (75.75)	< 0.001
IADL_Phone Calls	305 (36.01)	320 (10.81)	< 0.001
Moderate Exercise	328 (38.72)	1405 (47.45)	< 0.001
Numerical data, median[Q1, Q3]			
Max Breathing Test	247.5 [192.5, 305.0]	300.0 [232.5, 375.0]	< 0.001

Table 4: Using statistical methods to analyze various dynamic features. We calculated p-values for each feature using the Chi-Square test for categorical data and the Mann-Whitney U test for numerical data. Card_Activities, Activities_Friends, Sarcopenia, Wears Glasses, and Moderate Exercise represent whether one participates in chess and card activities, socializes with friends, suffers from sarcopenia, wears glasses, and engages in moderate exercise. Household Registration indicates whether it is a rural registered residence. IADL_Phone Calls indicate inability to make phone calls on ones' own.

Discussion

Our model combines static and dynamic data and applies Granger causality to deep learning. The comparison with the baseline model shows that our model performs well in predicting cognitive impairment. In addition to evaluating the performance of the model, we further investigated the credibility of causal features determined through Granger causality. By using statistical methods to calculate p-values, we have demonstrated that these features are predictive factors for cognitive impairment, further validating the robustness and feasibility of our model in predicting cognitive impairment.

In addition, the eight top dynamic features related to cognitive impairment in middle-aged and elderly people that we have identified have also been extensively studied. For example, patients with mild cognitive impairment (MCI) already face difficulties performing everyday tasks that require higher-level executive functions, such as using the telephone(Ahn et al., 2009). And studies have shown that the elderly's active participation in leisure and entertainment activities, especially intellectual activities like playing cards, can improve cognitive reserve, protect cognitive function, and reduce the risk of dementia(Yates, Ziser, Spector, & Orrell, 2016). Similarly, increasing the frequency of contact with friends can reduce the risk of cognitive impairment(Tan et al., 2019).

Furthermore, the max breathing test, which measures lung function, has shown that poor lung function is associated with poor cognitive outcomes. This relationship may be explained by either lung dysfunction that acts as a risk factor for cognitive decline or, conversely, cognitive impairment and dementia that lead to reduced lung function(Singh-Manoux et al., 2011).

Moderate intensity aerobic exercise has also been found to improve cognitive function by improving symptoms of depression, sleep quality, and other factors(Song & Doris, 2019). Furthermore, sarcopenia and cognitive impairment may be interconnected through similar biological mechanisms. Research has revealed that individuals with sarcopenia are at approximately twice the risk of developing mild cognitive impairment and dementia compared to those without sarcopenia(Peng, Chen, Wu, Chang, & Kao, 2020).

Additionally, wearing glasses is related to visual and economic conditions. Loss of sensory function may lead to increased cognitive load, changes in brain structure and function, as well as decreased emotional and social well-being, all of which may increase the risk of cognitive impairment(Nagarajan et al., 2022). In terms of registered residence, the prevalence of mild cognitive impairment in rural areas is twice that in urban areas(Liu et al., 2021).

Overall, the eight most important dynamic features we identified have a certain causal relationship with cognitive impairment. And it can predict cognitive impairment well when combined with ten static background features. In the future, it is hoped that this model can provide strong support for early prediction and intervention of cognitive disorders, which will help improve the cognitive health of the middle-aged and elderly population.

Limitations. One limitation of our model is that the sample size is relatively small and the span between longitudinal data is large, which may affect the generalizability of the results. The second limitation is that although we used a robust set of features to predict cognitive impairment, there may still be data that we did not observe. The third limitation is that some image data can also help predict cognitive impairment, but we did not include it. Future research can address these limitations and improve the predictive ability of models by integrating larger and more diverse datasets, considering more features and broader longitudinal information.

Broader Impacts. Improving cognitive impairment prediction can support early interventions and enhance diagnostic accuracy. The integration of causal deep learning also offers insights into disease mechanisms, while contributing to public health by identifying at-risk individuals earlier and potentially reducing dementia-related healthcare costs.

Disciplinary Diversity & Integration. In this study, we combined knowledge from neuroscience, machine learning, healthcare, and epidemiology to develop a predictive model for cognitive impairment. The interdisciplinary nature of this study allows us to integrate different perspectives and expertise, from understanding the biological mechanisms of cognitive decline to applying advanced computing technologies for prediction.

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