Medicon Engineering Themes
Volume 3 Issue 1 July 2022
Review Article

ReSmart-15: A Soft Information Gain Based Questionnaire for Early Dementia Detection

Hyeseong Park[1], Myung Won Raymond Jung[1], Ji-Hye Kim[2] and Uran Oh[3]*

[1]AKA Cognitive Corp., South Korea

[2]Department of Family Medicine, Yonsei University College of Medicine, South Korea

[3]Department of Computer Science and Engineering, Ewha Womans University, South Korea

***Corresponding Author:** Uran Oh, Department of Computer Science and Engineering, Ewha Womans University, South Korea.

Received: June 27, 2022; **Published:** July 01, 2022

DOI: 10.55162/MCET.03.060

Abstract

As the number of people affected by dementia increases, there is a need for diagnosing potential symptoms of early dementia, and questionnaires such as the mini-mental state examination (MMSE) are widely used for early dementia detection. To build a more effective questionnaire, we propose ReSmart-15, a dementia detection questionnaire that includes daily behavior-based questions in five categories (i.e., attention, spatial ability, spatiotemporal ability, memory, and thinking ability). To evaluate the effectiveness of each question in detecting early dementia, information gain can be used to rank their contributions. However, the current information gain-based method requires hard classification results such as whether the patient had been diagnosed with early dementia or not. In this paper, we propose a "soft information gain" based ranking system where each patient is diagnosed with an early dementia probability (from 0 to 1), not with a hard decision of early dementia (0 or 1). We conducted an experiment to test the effectiveness of ReSmart-15 compared to MMSE and found that the top 2 questions were from ReSmart-15, and 60 percent of the ReSmart-15 questions were in the top 10.

Keywords: Early demantia; Questionnaire; Soft information gain

Introduction

Alzheimer's Disease (AD) is the most common neurodegenerative disorder associated with advanced progressive dementia [1, 2]. The symptoms of AD include changes in mood and behavior, sleep problems, and cognitive decline [3, 4]. With an increasing life expectancy, the number of people affected by dementia is rising [3], and there is a need for clinical means to detect the potential symptoms, which could require clinical treatments. However, existing screening tools for dementia are limited. For instance, the Mini-Mental State Examination (MMSE) [5], one of the most widely used tests for measuring the clinical dementia rating scale (CDR) [6] and the most commonly administered psychometric screening assessment for cognitive functioning, is insensitive to detecting the early stages of dementia [7]. The utility of cognitive assessment (i.e., MMSE) decreases when the patient has mild cognitive decline [8-10].

A lack of self-awareness of cognitive decline is a symptom of dementia [11, 12]. It is known that the difficulties with the MMSE in detecting early dementia have been caused by low specificity [10, 13, 14]. Using screening tests with low specificity could lead to a misdiagnosis of dementia in elderly individuals and the misdiagnosis could cause unnecessary anxiety in the users. Maki et. al [15] introduced SED-11Q informant-based assessments as a preferable assessment for detecting early dementia. It was used to make the questionnaire more informative, aiming to investigate the state of daily activities performed in various contexts that include questions about social interactions and personality.

Inspired by the SED-11Q [15], we propose a questionnaire named *ReSmart-15*, which is an informant-based survey to distinguish reliably differentiated nondemented individuals from demented individuals. It modifies the existing MMSE questionnaire for better detection of early dementia, gathering more information about daily activities. The questionnaire consists of daily behavior-based questions in five categories (i.e., attention (3Q), spatial ability (3Q), spatiotemporal ability (3Q), memory (3Q), and thinking ability (3Q)), which are explained by CogniFit, a company that designs cognitive assessment through monitoring the patient's cognitive rehabilitation process [16].

While building an informant-based questionnaire to detect early dementia, we need to improve the diagnostic accuracy and extend appropriate populations with different types and stages of dementia. In this regard, there is a demand to develop a new validated screening alternative. With feature-selection methods based on machine learning (ML), it is possible to determine the importance of the test's features and discard the insignificant ones, which can reduce the complexity of the screening task. Inspired by NMD-12 [17-19], the effectiveness of the ReSmart-15 questionnaire can be validated by information gain (IG), which ranks the importance of all its features. Each question in the questionnaire was treated as a feature that has different importance in the prediction of a dementia diagnosis.

Although the previous IG-based method is helpful for scoring the importance of each feature, it requires labeled results for all patients that show whether they were diagnosed with early dementia or not. For simplicity, we can diagnose a patient with early dementia when the number of negative answers is more than half of the total number of questions. However, such a hard decision regarding early dementia can reduce the reliability of the labels [20]. In this regard, we propose using a soft information gain (SIG) where the diagnosis results show the early dementia probability (from 0 to 1), not the hard decision of early dementia (0 or 1). In this way, labeled results for early dementia are not required, and the reliability of the results can be enhanced. A detailed explanation of SIG will be described in the next section.

Method

Information Gain for each Question

In this section, we demonstrate how to determine the effectiveness of each question using information gain. Let $E(U)$ be an entropy, and $E_q(U)$ be the amount of information to make an exact classification based on the partition by questions q, where U is the user data sample in the training set. Then, $E(U)$ and $E_q(U)$ can be calculated as follows:

$$E(U) = -\frac{|U \backslash D|}{|U|}\log_2\frac{|U \backslash D|}{|U|} - \left(1-\frac{|U \backslash D|}{|U|}\right)\log_2\left(1-\frac{|U \backslash D|}{|U|}\right), \tag{1}$$

$$E_q(U) = \sum_{j=1}^{l_q}\frac{|U_{q,j}|}{|U|}\times E(U_{q,j}), \tag{2}$$

Where $D \subset U$ is the set of users diagnosed with early dementia, $U_{q,j}$ is the set of users who answered j to question q, and l_q is the number of distinct values in q, i.e., the number of answers in the question q. For example, questions answered by either yes or no make $l_q = 2$ [20]. The IG of each question q can be calculated by the difference between $E(U)$ and $E_q(U)$. The questions with higher IG values are considered more important than those with lower IG. In this regard, the importance of all questions can be ranked based on the IG values [21, 22].

Soft Information Gain for Each Question

Previous IG-based method requires the results of whether the user is diagnosed with early dementia or not, which is used to make the set D. In the simplest way, we can diagnose early dementia when the number of negative answers is more than half the number of total questions, but such a hard decision of early dementia can reduce the reliability. Instead, we propose using soft information gain (SIG) where the diagnosis results show the early dementia probability (from 0 to 1), not the hard decision of early dementia (0 or 1). Let $P_{u,q}$ be an early dementia degree for user u measured by question q, where the value is from 0 to 1. For example, questions answered by either yes or no make $P_{u,q}$ = 1 when the answer is yes (negative) and $P_{u,q}$ = 0 when the answer is no (positive). Then, the early dementia probability for user u, denoted by P_u, can be calculated as the expectation of all early dementia degrees, i.e., $P_u = \mathbb{E}_q [P_{u,q}]$. Then, $E(U)$ and $E_q(U)$ can be calculated as follows:

$$E(U) = \mathbb{E}_{u \in U} [P_u] \log_2 \mathbb{E}_{u \in U} [P_u] - (1 - \mathbb{E}_{u \in U} [P_u]) \log_2 (1 - \mathbb{E}_{u \in U} [P_u]), \qquad (3)$$

$$E_q(U) = \sum_{j=1}^{l_q} \frac{|U_{q,j}|}{|U|} \times E(U_{q,j}). \qquad (4)$$

SIG of each question q can be calculated by the difference between $E(U)$ and $E_q(U)$. Figure 1 shows an example of how early dementia probability is calculated.

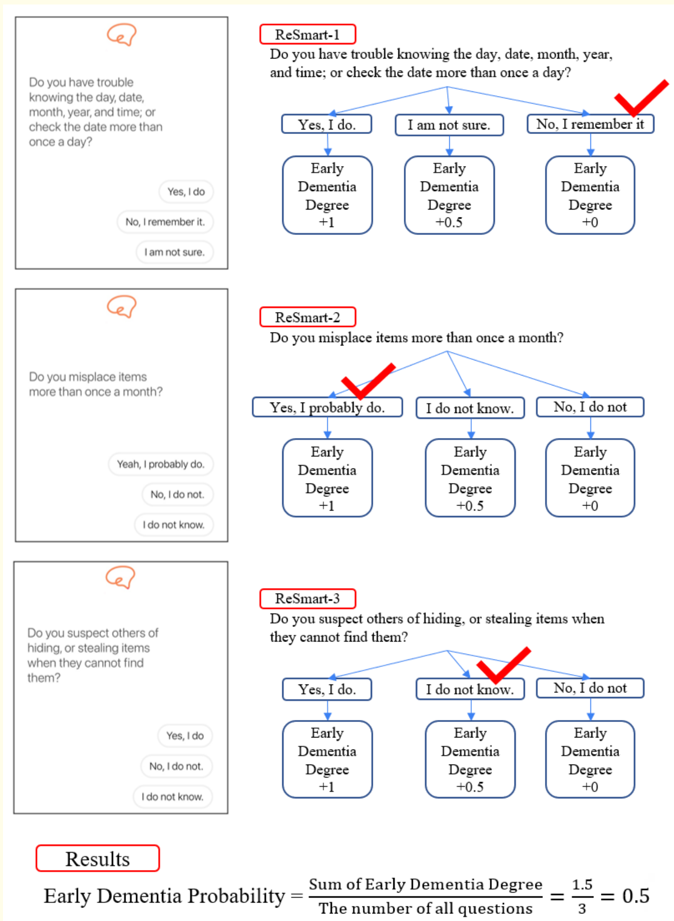

Figure 1: Early Dementia Probability Calculation.

Results

We collected audiences from SurveyMonkey to recruit 155 participants (92 female). Their average age was 36.31 (*SD*=11.70, range=18-65). To show the effectiveness of ReSmart-15 compared to another existing screening questionnaire for early dementia detection, we conducted a user study where participants were asked to submit their responses to 35 different questions: 15 questions from ReSmart-15 and 20 questions from MMSE.

As shown in Table 1, our experiment found that the top 2 questions were from ReSmart-15, and 60 percent of the ReSmart-15 questions were in the top 10. This suggests that ReSmart-15 was composed of influential questions filtered by information gain, which may increase the accuracy of the early diagnosis of dementia. Furthermore, information gain can be used to remove redundant or unnecessary features with low importance (i.e., ReSmart-13 and ReSmart-6), and can simplify the procedure of diagnosis.

Rank	*SIG*	*Questionnaire*	*Questions*
1	0.060	ReSmart-9	Are you having a hard time remembering where things are usually kept?
2	0.052	ReSmart-12	Do you often forget the points that you want to talk about?
3	0.051	MMSE-11	I am going to name three objects. When I am finished, I want you to repeat them. Remember what they are because I am going to ask you to name them again in a few minutes. Apple, Penny, Table. Score 1 point for each word correctly repeated. Order of words does not matter.
4	0.046	ReSmart-3	Do you suspect others of hiding, or stealing items when they cannot find them?
5	0.044	MMSE-17	Take a plain piece paper in your hand, fold it in half, and put it on the floor. Score 1 point if they take the paper. Score 2 points if they take it and fold it. Score 3 points if they take it, fold it and put it on the floor. Score 0 points if they follow none of these commands.
6	0.041	MMSE-13	Remember the 3 words I mentioned to you a few minutes ago; please repeat them now. The correct answer is: Apple, Penny, Table. Score 1 point for each word correctly repeated. The order is not important.
7	0.040	MMSE-12	An example of counting backwards by 5 is (100, 95, 90, 85). Starting at 100, count backwards by 7. You can stop after 5 subtractions. The correct answers are 93, 86, 79, 72, 65. Score 1 point for each correct answer. If they do not understand the question, score 0.
8	0.038	ReSmart-10	Do you repeat questions or statements or stories in the same day?
9	0.037	ReSmart-11	Are you getting lost in familiar surroundings such as their own neighborhood?
10	0.036	ReSmart-1	Do you have trouble knowing the day, date, month, year, and time; or check the date more than once a day?
11	0.036	ReSmart-15	Do you confuse names of family members or friends?
12	0.036	ReSmart-5	Do you often forget appointments?
13	0.034	ReSmart-4	Do you have trouble handling money, such as when giving tips or calculating change?
14	0.034	MMSE-9	Whose home is this? (a picture is given)
15	0.031	ReSmart-8	Do you have trouble concentrating more than an hour?
16	0.030	MMSE-16	Repeat the following phrase: “No if, ands, or buts” Score as correct only for an exact repetition of the words in the correct order.
17	0.030	ReSmart-2	Do you misplace items more than once a month?
18	0.030	MMSE-4	What day of the week is it today?
19	0.028	MMSE-19	Write any complete sentence on this piece of paper. Score as correct only if the sentence contains a subject and verb and makes sense. Ignore spelling errors.
20	0.027	MMSE-2	What month is it? Score as correct if their answer is right or off by a month only if it is the first or last day of the adjacent month (ex. If it is June 1 and they say May 31, that is acceptable).

21	0.027	MMSE-6	What country are we in?
22	0.026	ReSmart-7	Do you become disoriented in unfamiliar places?
23	0.024	ReSmart-14	Do you feel that learning a new stuff takes longer than before?
24	0.024	MMSE-8	What city (or town) are we in?
25	0.023	MMSE-14	Ask the user to name the object that appears on the screen. (a picture of watch is given) Score as correct for "wristwatch", "watch", or "timepiece". Score as incorrect for "clock", "time" or any other answers.
26	0.021	MMSE-5	What season is it?
27	0.020	MMSE-10	What room are we in?
28	0.019	MMSE-7	What state (or province) are we in?
29	0.015	MMSE-15	Ask the user to name the object that appears on the screen. (a picture of pencil is given) Score as correct for the word "pencil" only.
30	0.015	MMSE-20	Ask the user to copy the design on the screen with a pencil and paper. Score as correct only if their drawing has 2 shapes that both have 5 sides and the 2 shapes overlap to form a 4-sided figure.
31	0.013	ReSmart-13	Do you have to drink coffee to wake yourself up?
32	0.012	MMSE-1	What is today's date? Score as correct if their answer is right or only off by one day (ex. for May 12, May 11 or May 13 are acceptable answers). Do not accept a day of the week.
33	0.011	MMSE-3	What year is it?
34	0.005	ReSmart-6	Do you remain energetic in everyday life?
35	0.005	MMSE-18	Read the words on the screen and then do what it says. (The screen shows the phase "Close your eyes") Score as correct only if they close their eyes.

Table 1: The Questions ranks through soft information gain.

Conclusion

In this paper, we build an effective questionnaire named ReSmart-15 which is a dementia detection questionnaire that includes daily behavior-based questions in five categories (i.e., attention, spatial ability, spatiotemporal ability, memory, and thinking ability). As the current information gain-based method requires hard classification results such as whether the patient had been diagnosed with early dementia or not, we propose a "soft information gain" based ranking where each patient is diagnosed with early dementia probability (from 0 to 1), not with a hard decision of early dementia (0 or 1). The experiment shows the effectiveness of ReSmart-15 compared to MMSE and found that the top 2 questions were from ReSmart-15, and 60 percent of the ReSmart-15 questions were in the top 10. The effectiveness of the ReSmart-15 questionnaire is shown in this work, but reducing dementia symptoms is also important as well as diagnosing early dementia. The method for reducing dementia symptoms will be proven in future work by developing a mobile app that will be helpful for the users.

References

1. Escudero J, Zajicek JP and Ifeachor E. "Early detection and characterization of Alzheimer's disease in clinical scenarios using Bioprofile concepts and K-means". Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE (2011): 6470-6473.
2. Prince MJ., et al. World Alzheimer Report 2015-The Global Impact of Dementia: An analysis of prevalence, incidence, cost and trends (2015).

3. Hohenfeld C., et al. "Changes in brain activation related to visuo-spatial memory after real-time fMRI neurofeedback training in healthy elderly and Alzheimer's disease". Behavioural brain research 381 (2020): 112435.
4. Liu Ys, Wang Ym and Zha Dj. "Brain Functional and Structural Changes in Alzheimer's Disease with Sleep Disorders: A Systematic Review". Frontiers in Psychiatry 12 (2021): 772068.
5. Cockrell JR and Folstein MF. "Mini-mental state examination". Principles and practice of geriatric psychiatry (2002): 140-141.
6. Morris JC. "The clinical dementia rating (CDR): Current version and scoring rules. Neurology 43.1 (1993): 2412-4.
7. dLawrence J., et al. "A pilot program of improved methods for community-based screening for dementia". The American Journal of Geriatric Psychiatry 9.3 (2001): 205-211.
8. Benedict RH and Brandt J. "Limitation of the Mini-Mental State Examination for the detection of amnesia". Topics in geriatrics 5.4 (1992): 233-237.
9. Nys G., et al. "Restrictions of the Mini-Mental State Examination in acute stroke". Archives of clinical neuropsychology 20 (2005): 623-629.
10. Tombaugh TN and McIntyre NJ. "The mini-mental state examination: a comprehensive review". Journal of the American Geriatrics Society 40 (1992): 922-935.
11. Mograbi DC, Brown RG and Morris RG. "Anosognosia in Alzheimer's disease–the petrified self". Consciousness and cognition 18 (2009): 989-1003.
12. Maki Y., et al. "patients' distress and self-awareness of deficits in Alzheimer's disease". American Journal of Alzheimer's Disease & Other Dementias® 27 (2012): 339-345.
13. Ihl R., et al. "Differential validity of psychometric tests in dementia of the Alzheimer type". Psychiatry research 44 (1992): 93-106.
14. Wind AW., et al. "Limitations of the Mini-Mental State Examination in diagnosing dementia in general practice". International journal of geriatric psychiatry 12 (1997): 101-108.
15. Maki Y, Yamaguchi T and Yamaguchi H. "Symptoms of Early Dementia-11 Questionnaire (SED-11Q): a brief informant-operated screening for dementia". Dementia and Geriatric Cognitive Disorders Extra 3 (2013): 131-142.
16. Jung R., et al. "ReSmart: Brain Training Games for Enhancing Cognitive Health". Advances in Computer Vision and Computational Biology; Springer (2021): 331-337.
17. Chiu PY., et al. "NMD-12: A new machine-learning derived screening instrument to detect mild cognitive impairment and dementia". PloS one 14 (2019): e0213430.
18. Chang Chun-Hung., et al. "Plasma d-glutamate levels for detecting mild cognitive impairment and Alzheimer's disease: Machine learning approaches". Journal of Psychopharmacology 35.3 (2021): 265-272.
19. Bougea Anastasia., et al. "A novel machine learning algorithm predicts dementia with lewy bodies versus Parkinson's disease dementia based on clinical and neuropsychological scores". Journal of Geriatric Psychiatry and Neurology 35.3 (2022): 317-320.
20. Park H., et al. "ReSmart-15: An Information Gain based Questionnaire for Early Dementia Detection". HEALTHY 2022 in 27th annual conference on intelligent user interfaces.
21. Faouri S, M AlBashayreh and M Azzeh. "Examining stability of machine learning methods for predicting dementia at early phases of the disease". Decision Science Letters 11.3 (2022): 333-346.
22. Rajab Mohammed D., et al. "Assessment of Alzheimer-related Pathologies of Dementia Using Machine Learning Feature Selection". medRxiv (2022).

Volume 3 Issue 1 July 2022