Journal of Artificial Intelligence and Computing Applications (2025) 3(1): 13–23

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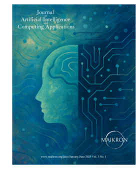
Journal
of
Artificial Intelligence
and
Computing Applications



Research article

Appraising cognitive status in dementia via touch-based reaction time: a preliminary machine learning study

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ABSTRACT

People with dementia (PwD) perform cognitive-based therapeutic activities. Literature reports a variety of studies exploring relationships between the cognitive status of PwD as determined by the Mini-Mental State Examination (MMSE) and their reaction times from a myriad of stimuli incorporated into cognitive activities. Nevertheless, these technology-supported activities usually include distracting elements, complex instructions, and unfamiliar devices for older adults, introducing bias into reaction times. The objective of this work is to appraise the cognitive status of people with dementia using reaction times from touch interaction tasks. For this purpose, a relatively simple cognitive activity (involving the intuitive tap gesture) and a 32-inch wide touchscreen were designed and implemented. Afterward, 21 PwD from a day center located in Sonora, Mexico were recruited. The participants were instructed to carry out a cognitive activity consisting of five consecutive taps and their reaction times were recorded. The collected data was analyzed using (i) a correlation analysis, (ii) a bootstrap evaluation of machine learning classification models, and (iii) a logistic regression analysis. From the empirical results, it can be concluded that there is a negative relationship between the MMSE score of PwD and the reaction times from taps. In addition, the bootstrapped mean accuracy results of the classifiers suggest that it may be feasible to automatically classify PwD.

Keywords: dementia, cognitive tasks, machine learning

1. Introduction

Dementia is a general term for a group of progressive symptoms that affect cognitive functions such as memory, thinking, orientation, comprehension, calculations, learning capacity, language, and judgment [1, 2]. According to the World Health Organization, it is projected that there will be 78 million people suffering from dementia by 2030 and 139 million by 2050 [3]. One of the most common risk factors for developing dementia is longevity. Most people who develop dementia are 65 years of age or older [2].

The cognitive function of people with dementia (PwD) deteriorates affecting their quality of life and requiring assistance from caregivers to carry out daily activities [4]. In this regard, there are two types of caregivers: *informal* and *formal*. The former refers to a role commonly played by PwD's family members who do not have caregiving experience [5], whereas the latter refers to professionals formally trained to assist PwD in day centers [4].

In day centers, PwD perform cognitive activities that help improve their cognitive functions and emotional state [6]. The cognitive activities carried out by

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https://doi.org/10.5281/zenodo.16860215

PwD are selected based on their current cognitive status (which is formally assessed using neurocognitive tests such as the Mini-Mental State Examination (MMSE) [1]) and based on formal caregivers' subjective observations about the previous performance of PwD on cognitive activities [7].

Technology-supported cognitive activities provide the opportunity to automatically collect data from PwD, including reaction times [8], attained overall scores [9], or the number of activities completed [10]. For this reason, previous studies have designed and implemented cognitive activities using devices such as tablets [11, 12], computers [13, 14], and tangible devices [1, 8]. Then, the data collected are analyzed to assess the cognitive status of PwD.

The *reaction time*, defined as the time between a stimulus and the motor response to that stimulus [13], has been investigated to determine the cognitive status of PwD [11, 1, 13, 8, 12, 14, 15]. Those studies measure the reaction time of PwD while performing relatively complex cognitive activities on a screen including distractors such as butterflies or moles with hats [16]. In addition, in order to carry out cognitive activities, PwD frequently had to follow elaborate instructions that may have been difficult to understand, e.g., pressing a left or right button according to a green, red or blue light with no apparent clues [8, 11] or even use unfamiliar devices for older people, e.g., a relatively small keyboard [14]. However, it is known that traditional input devices such as keyboards can be an adoption barrier for the elderly [17]; moreover, detailed and complex instructions may be inappropriate for PwD [18]; and creative design features may distract PwD from a given cognitive activity and therefore increase their reaction times [19, 20]. Thus, due to the aforementioned challenges, some research efforts exploring potential relationships between the cognitive status of PwD and their reaction times may be biased by possible difficulties experienced by PwD while performing relatively complex cognitive activities. Furthermore, some research efforts have used supervised machine learning techniques such as support vector machines [14] and random forest [12, 15] to classify the cognitive status of PwD based on their reaction times. For example, random forest models have been trained to screen individuals for cognitive impairment [12], while other approaches have built machine learning models for automated cognitive assessment [8].

The objective of this work is to appraise the cognitive status of people with dementia using reaction times from touch interaction tasks. For this purpose, a relatively simple cognitive activity (involving the intuitive tap gesture) and a 32-inch wide touchscreen were designed and implemented. Afterward, 21 PwD from day center *Dorita de Ojeda* (located in Sonora, Mexico) were recruited. The participants were instructed to carry out a cognitive activity consisting of five consecutive taps and their reaction times were recorded. The data collected was analyzed using (i) a correlation analysis, (ii) a bootstrap evaluation of machine learning classification models, and (iii) a logistic regression analysis.

This work contributes by providing empirical evidence of a negative relationship between the MMSE score of PwD and the reaction times from taps. In addition, bootstrapped mean accuracy results of machine learning models suggest that it may be feasible to automatically classify PwD as individuals having a relatively *low* or *high* MMSE score based on reaction times from taps.

The rest of this article is as follows. Section 2 presents related work; Section 3 describes the participants, instruments, and methods used to explore relationships between the MMSE score of PwD and the reaction time from touch interaction tasks; Sections 4 and 5 present and discuss results, respectively; and Section 6 presents concluding remarks.

2. Related work

Literature reports a variety of studies exploring the potential relationship between the cognitive status of PwD (as determined by the MMSE) and their reaction times from a myriad of stimuli incorporated into cognitive activities, which are carried out on technological devices such as tablets, computers, and tangible devices, see Table 1.

In the context of dementia, cognitive activities (designed to measure and collect reaction times) often involve relatively complex instructions, a large number of stimuli, and multiple difficulty levels, see [8, 11, 1, 12, 14]. However, such characteristics may complicate cognitive activities unnecessarily. In addition, cognitive activities are frequently implemented on devices that can be overwhelming for older adults.

In this vein, the study presented in [8], instructed participants to press one out of two buttons depending on a color displayed on a screen while ignoring distractors, e.g., a multicolor LED. The authors collected and analyzed the reaction time from pressing the correct button. In a more elaborate scenario, the authors of [11] implemented a serious game in which participants had to place their hands in a particular position to free their index fingers in order to tap and hold objects for 15 seconds. Similarly, the authors of [1] implemented the traditional Whack-a-Mole game and instructed participants to locate and tap a mole as soon as it appeared on the screen, recording their reaction times. Likewise, in [12], participants were instructed to tap an object that appeared at a random location within a circular area divided into four sections. In [14], the authors evaluated a relatively more complex cognitive activity, in which participants had to press a key on the computer in response to a stimulus displayed on a screen. Unlike the aforementioned studies, this present work makes use of a relatively simple cognitive activity (based on the intuitive tap gesture) involving simple stimulus and using a wide touchscreen.

It should be mentioned that other studies have explored the feasibility of building machine learning models to screen individuals for (mild) cognitive impairment based on their reaction times. For example, random forest and support vector machine models were built in [12, 15] and [14], respectively. In this regard, this present work explores the feasibility of automatically classifying PwD as individuals having a relatively low or high MMSE score based on reaction times from taps using three machine learning algorithms: logistic regressions, decision trees, and support vector machines.

3. Material and methods

This section describes the participants involved in the study (Section 3.1), the instruments used (Section 3.2), and the procedure to appraise the cognitive status of PwD using reaction times from touch interaction tasks (Section 3.3).

3.1 Participants

Twenty-one individuals formally diagnosed with dementia were recruited from day center *Dorita de Ojeda* to participate in the present study. All participants have an MMSE score of 24 or less (indicating cognitive impairment) with a mean of 14.04 and a standard deviation of 7.36. The age of the participants ranged from 57 to 91 years with a mean of 78.28 and a standard deviation of 7.64.

3.2 Instruments

A 32-inch screen with an infrared detection frame was used to enable touch interaction functionalities (see Figure 1 for details). The participants' interactions were recorded using a 150-degree wide-angle camera with a focal distance of 2.1 mm, which was perpendicular to the screen base.

An activity was designed to collect the reaction time of participants from taps. The activity involved a patient tapping five circles that appear one after the other at random locations on a touchscreen. The activity begins once an instructor presses a software-integrated button on the touchscreen. As a result, the first circle appears at a random location, and if and only if the patient taps on the circle, the circle disappears and another one appears at another random location on the touchscreen (see Figure 2). Upon completion, the system displays a flashing visual cue indicating the end of the activity. The activity was implemented using pygame (a Python library). In addition, the design of the graphical user interface was based on best design practices for PwD [21].

3.3 Procedure

The study took place at day center *Dorita de Ojeda*. Formal caregivers (working at the day center) recommended conducting the study in several sessions due to the number of participants. They also recommended conducting the study at 11 am, since that is the time PwD normally carry out cognitive activities. The participants and formal caregivers were informed about the objective of the study and their participation was voluntarily. In addition, they were informed that they were free to leave the activity at any time for any reason. Participants performed the activity individually (see Figure 3). It should be mentioned that participants' ages and MMSE scores were requested from the day center's staff.

Before officially beginning the activity, each participant was given a test round to guarantee that the participant understood the instructions. The activity started when the instructor asked the participant to begin. Once the participant completed the activity, a message indicating the end of the activity was displayed at the center of the touchscreen. The activity was recorded using a wide-angle camera and OpenCV in Python.

The reaction time from each tap was computed via video analysis using LINCE PLUS [22], a software for qualitative video analysis. LINCE PLUS allows for video annotations to identify meaningful events, in this case, reaction times from taps. Reaction times were stored in a file with a total of twenty-one (n=21) records each consisting of 9 fields: identifier, MMSE score, MMSE category, five reaction times, and total time (i.e., the sum of reaction times). The MMSE category was set to *low* if the MMSE score was less than 16; otherwise, it was set *high*. This cut-off value was defined to achieve a relatively balanced number of patients in each category: 10 participants categorized as *low* and 11 participants categorized as *high*.

Table 2 reports the dataset, Figure 4 presents histograms and pairwise relationships of reaction times and MMSE scores, and Figure 5 presents box plots highlighting outliers for reaction times for each tap.

The data analysis was guided by the objective of this present study, which is to appraise the cognitive status of PwD using reaction times from touch interaction tasks. The analysis involved three methods: (i) a correlation analysis, (ii) a bootstrap evaluation of machine learning classification models, and (iii) a logistic regression analysis.

The correlation analysis was conducted to explore relationships between the MMSE score of PwD and the reaction times from taps. Due to the relatively small sample and the presence of outliers (Figure 5), Spearman's rank correlation coefficient was used.

To explore the feasibility of machine learning models for classifying PwD as having a *low* or *high* MMSE score based on reaction times, three commonly used machine learning algorithms were used: decision trees, support vector machines, and logistic regression. Using the *MMSE category* as the target variable, models were built for two feature sets, one set including all reaction times from tap 1 to tap 5 in addition to the total time, and another set including only the reaction time from tap 1 (under the hypothesis that the initial reaction time may be the most informative). Due to the small number of instances available for training and evaluating the models, a bootstrap evaluation of machine learning models was used, see Algorithm 1. Bootstrapping is a statistical method for estimating the distribution of an estimator, which, in this article, corresponds to a machine learning model. For each feature set and each

Table 1. Related work comparison

Research effort	Participant type	Activity type	Delivery tool	Machine learning models
[8]	Mild cognitive impairment	A choice task	A tangible device	Not specified
[11]	Mild cognitive impairment & Alzheimer's	A serious game	A tablet	No
[12]	Healthy & Mild cognitive impairment	A tap-based task	A tablet	Random forest
[1]	Healthy & Mild cognitive impairment	A serious game	A tangible device	No
[14]	Healthy & PwD	A tap-based task	A computer	Support vector machine
Authors' present work	PwD	A tap-based task	A wide touchscreen	Decision trees, logistic regressions, and support vector machines

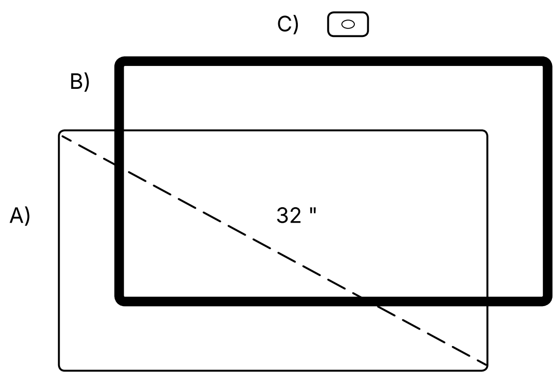


Figure 1. Hardware for touch interaction: A) a 32-inch wide touchscreen, B) an infrared detection frame, and C) a wide-angle camera

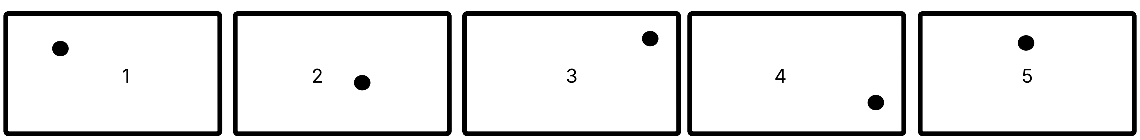


Figure 2. Touch activity designed for this study (numbers represent the sequence of events on the screen)

Figure 3. A patient from day center *Dorita de Ojeda* performing the activity

Table 2. Dataset of 21 People with dementia including reaction times from taps and MMSE scores

ID	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**	**P11**	**P12**	**P13**	**P14**	**P15**	**P16**	**P17**	**P18**	**P19**	**P20**	**P21**
MMSE score	23	23	17	17	22	19	21	21	15	16	16	10	15	5	9	8	15	3	20	0	0
MMSE category	H	H	H	H	H	H	H	H	L	H	H	L	L	L	L	L	L	L	H	L	L
Tap 1	2	4	7	4	2	5	2	2	10	4	8	5	7	6	31	11	5	8	3	3	4
Tap 2	2	1	7	4	9	5	5	6	17	6	14	9	6	5	10	9	25	5	24	14	9
Tap 3	2	2	9	3	2	2	2	4	21	14	4	7	5	5	9	35	12	38	6	9	3
Tap 4	2	1	4	5	3	5	1	3	7	26	10	10	5	2	7	13	19	4	4	12	2
Tap 5	2	1	6	4	2	3	6	4	10	15	35	4	11	3	19	30	19	7	11	5	14
Total time	10	9	33	20	18	20	16	19	65	65	71	35	34	21	76	98	80	62	48	43	32

Note: H and L correspond to high and low MMSE categories, respectively.

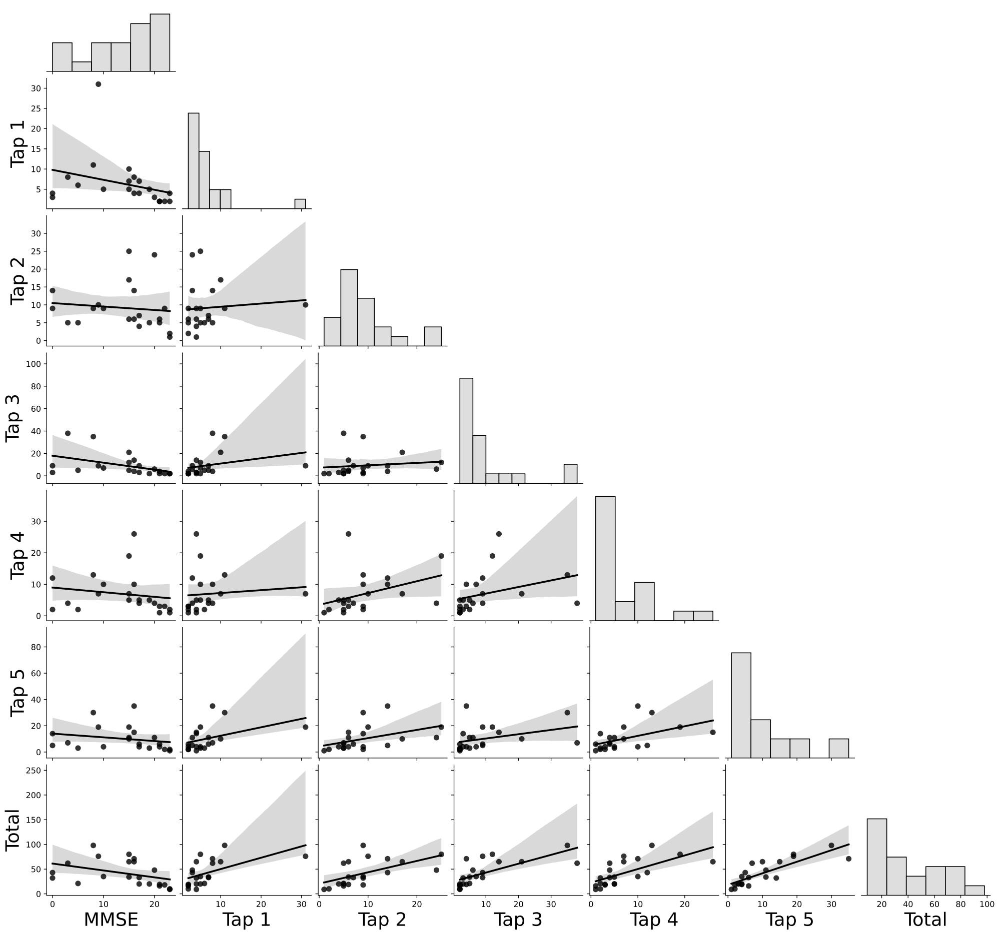


Figure 4. Histograms and pairwise relationships of reaction times and MMSE scores

machine learning algorithm, 10,000 bootstrap iterations were executed. Each iteration consisted of (i) sampling the dataset with replacement to create a bootstrap sample (with an approximate size of 64% of the instances) for model training; (ii) creating an out-of-bag set for model evaluation with an approximate size of 36% of the instances; (iii) building a classifier model; and (iv) evaluating the model in terms of accuracy. For each machine learning model, the mean and median accuracy as well as 95% confidence intervals were computed. The machine learning models were built using statsmodels (for logistic regression) and scikit-learn (for decision trees and support vector machines) both Python libraries. It should be noted that default model parameter values were used.

The logistic regression analysis was conducted using statsmodels to explore whether there is a significant effect of the reaction time from tap 1 on the cognitive status of PwD. It should be noted that only the effect related to the reaction time from tap 1 was explored because the logistic regression models trained with the reaction time from tap 1 yielded the best median accuracy (see Section 4 for details).

Except for the correlation analysis, the machine learning models and the regression analysis were conducted using a scaled dataset due to the presence of outliers (see Figure 5). The dataset was scaled using scikit-learn's robust scaler.

4. Results

To assess statistical significance, hypothesis test results with a p-value less than 0.05 were considered significant. Statistical analysis was conducted using scipy, a Python library.

4.1 Correlation between MMSE score and reaction time

According to Spearman's rank correlation coefficients (see Table 3), there is a relatively moderate and negative monotonic association between the (i) MMSE score of PwD and (ii) the reaction times from taps (except for tap 2) and the total time. In general, as the reaction times from taps increase, the MMSE scores decrease or vice versa. However, it should be noted that causality should not be inferred from these results.

4.2 Feasibility of machine learning models for classifying people with dementia based on reaction times

The bootstrapped accuracy results reported in Table 4 show that the median accuracy attained by all the machine learning models was greater than 0.500 (i.e., better than random guessing) regardless of the machine learning algorithm used or whether the model was built using all features (namely, reaction times from tap 1 to tap 5 and total time) or only the reaction time from tap 1. However, for each model, the lower bound of its 95% confidence interval was less than 0.5, see Figs. 6, 7, and 8.

It is worth mentioning that the decision tree models and the support vectors machine models achieved the same median accuracy regardless of whether the models were built with all features or only the reaction time from tap 1 (see Figs. 6 and 7). However, the logistic regression model built with only the reaction time from tap 1 achieved a higher accuracy than the logistic regression model built with all features (see Figure 8). In fact, the logistic regression model trained with only the reaction time from tap 1 yielded the best accuracy results with a mean accuracy of 0.665 and a median accuracy of 0.667 (see Figure 8b). Nevertheless, while the upper bound of its 95% confidence interval is 1.000, its lower bound is less than 0.5.

The median accuracies achieved by the machine learning models suggest that it may be feasible to automatically classify PwD as individuals with a relatively low or high MMSE score based on the reaction times from taps. However, the lower bounds of the 95% confidence intervals do not allow drawing definitive conclusions. Hence, data from more participants must be collected to confirm or refute this finding.

4.3 Logistic regression analysis of reaction times to predict MMSE categories

As indicated by the result of the likelihood-ratio test (reported in Table 5), the logistic regression model provides a better fit to the data than the intercept-only model, i.e., the logistic regression model is statistically significant (p-value < 0.05). Also, the result of a Wald test rejects the null hypothesis (at a significance level of 0.05) for *tap 1*'s coefficient, then the alternative hypothesis that there is a significant effect of the reaction time from *tap 1* on the cognitive status of PwD is accepted. In addition, since the coefficient for *tap 1* is negative (-1.9624), it can be concluded that as the reaction time of an individual increases, the probability of being categorized as a PwD with a relatively high MMSE score decreases.

5. Discussion

This study explored the use of reaction times from a relatively simple activity performed on a wide touch screen to appraise the cognitive status of PwD. The present study involved a representative group of PwD corresponding to the majority of patients attending a day center in Sonora, Mexico. Although this sample is relatively small, the logistic regression analysis concluded that there is a significant effect (p-value < 0.05) of the reaction time from *tap 1* on the cognitive status of PwD. In addition, statistically significant Spearman's rank correlation coefficients were found between the MMSE scores and the reaction times from 4 (out of 5) taps. However, with respect to the feasibility of machine learning models for classifying PwD, the results should be interpreted in the context of the relatively small dataset used to train the models. This is because

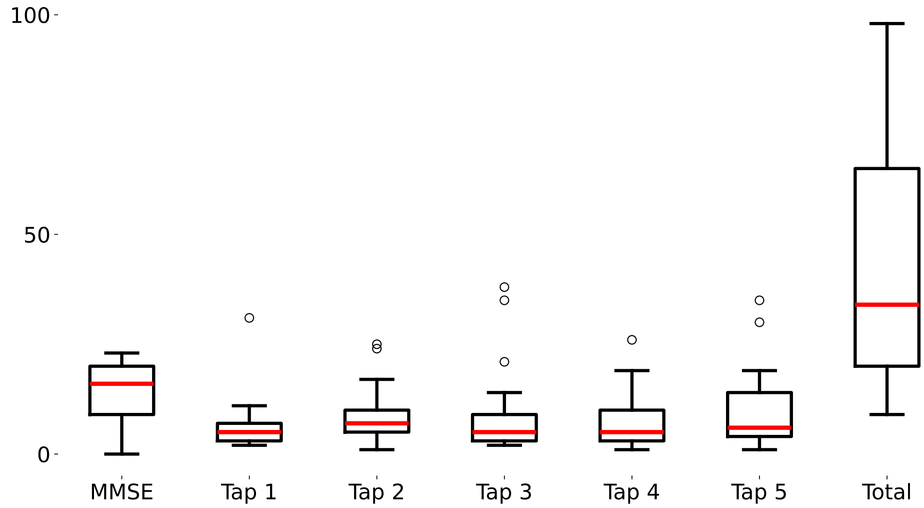


Figure 5. Data distribution (box plots) of reaction times and MMSE scores

Algorithm 1 Bootstrap Evaluation of a Machine Learning Model

Require: A *dataset* of people with dementia including reaction times and MMSE scores

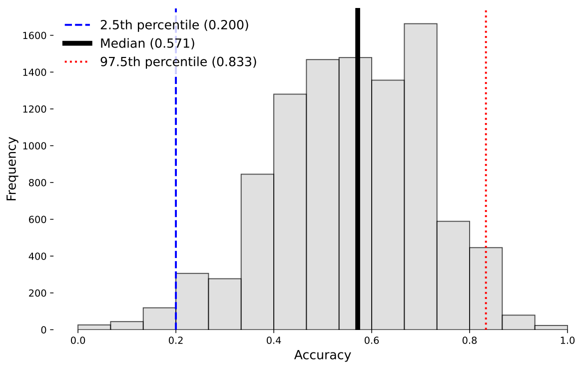
```
Scale dataset
n ← 10000 // bootstrap iterations
accuracyScores ← [ ]
for i = 1 to n do
    Create a bootstrap sample from the dataset for model training
    Create an out-of-bag set for model evaluation
    Train a model using the bootstrap sample
    Evaluate the model using the out-of-bag set
    Append the accuracy score to accuracyScores
end for
Using accuracyScores, compute mean and median accuracy as well as its 95% confidence interval
```

Table 3. Spearman correlation results

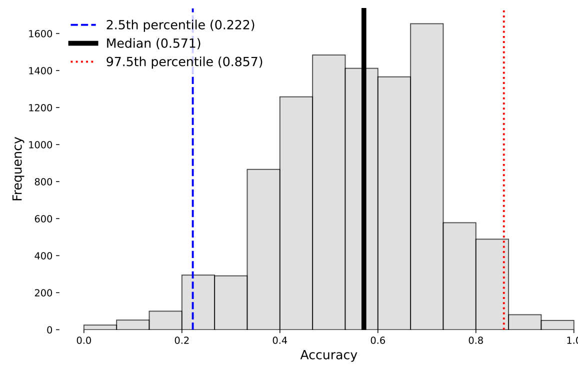
	Coefficient	**p-value**
Tap 1	-0.567	0.0073
Tap 2	-0.379	0.089
Tap 3	-0.645	0.0015
Tap 4	-0.437	0.047
Tap 5	-0.492	0.023
Total time	-0.6282	0.0023

Table 4. Bootstrapped accuracy results of the machine learning models

Model	**Features**	***Mean accuracy***	***Median accuracy***	**95% CI**
Decision tree	Reaction times from taps 1-5 and total time	0.547	0.571	(0.200, 0.833)
Decision tree	Reaction time from tap 1	0.549	0.571	(0.222, 0.857)
Support vector machine	Reaction times from taps 1-5 and total time	0.549	0.571	(0.167, 0.857)
Support vector machine	Reaction time from tap 1	0.558	0.571	(0.167, 0.875)
Logistic regression	Reaction times from taps 1-5 and total time	0.591	0.600	(0.250, 0.875)
Logistic regression	Reaction time from tap 1	**0.665**	**0.667**	**(0.333, 1.000)**

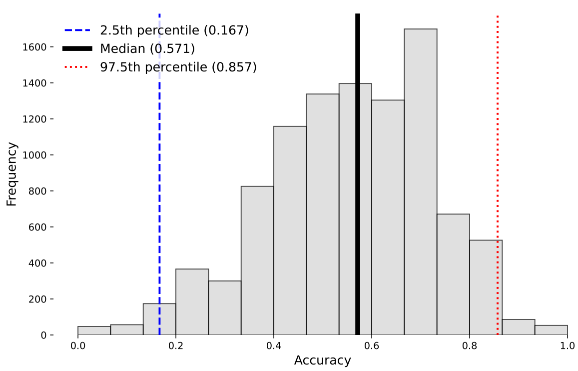


(a) Using taps 1-5 and total time

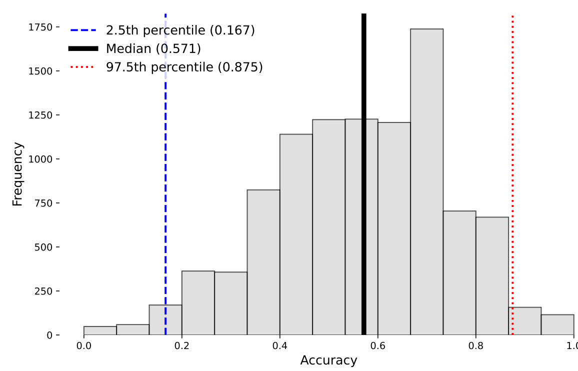


(b) Using only tap 1

Figure 6. Bootstrap sampling distributions of the accuracy of the decision tree models.



(a) Using taps 1-5 and total time



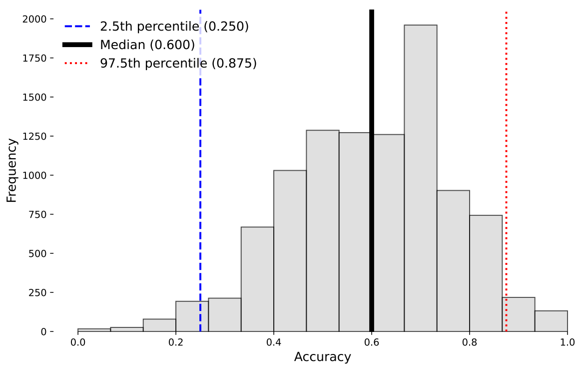
(b) Using only tap 1

Figure 7. Bootstrap sampling distributions of the accuracy of the support vector machine models.

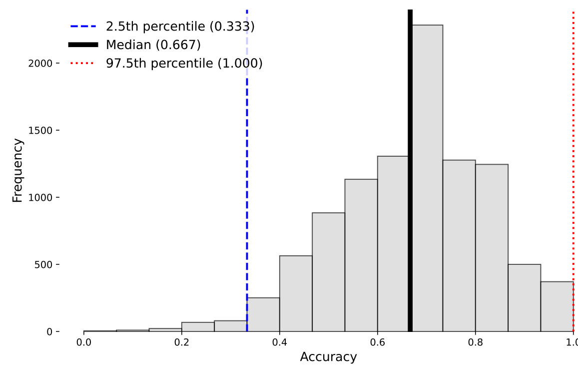
Table 5. Results of the logistic regression analysis

Likelihood-ratio test (vs. null model) p-value: 0.007311

	Coefficient (β)	**Std error**	**z**	**P-value**	**95% confidence interval**
Constant	0.2378	0.522	0.455	0.649	(-0.786, 1.261)
Tap 1	-1.9624	0.987	-1.988	0.047	(-3.897, -0.028)



(a) Using taps 1-5 and total time



(b) Using only tap 1

Figure 8. Bootstrap sampling distributions of the accuracy of the regression logistic models.

whereas the median accuracy attained by the best performing model (namely, the logistic regression model) was 0.667 with an upper bound of its 95% confidence interval of 1.000, its lower bound was 0.333.

In addition, it is acknowledged that the sample of participants may have included patients with common comorbidities such as arthritis, tremors, or visual difficulties, which may have influenced their reaction times. However, it should be noted that people of advanced age commonly have those comorbidities and that all participants (involved in this study) were able to complete the touch interaction task. Nonetheless, a study involving a relatively large sample may allow grouping participants, for instance, by comorbidity (if any) and conducting separate analysis for each group.

This preliminary study presented models built from three commonly used machine learning algorithms: decision trees, support vector machines, and logistic regression. Each algorithm has a set of hyperparameters that can be tuned to improve their performance, for instance, in decision trees, the quality of a split can be measured using criteria such as gini or entropy. Then, there is, in fact, the possibility of improving the performance of the models presented. In addition, exploring other (deep) machine learning algorithms may help improve model performance. However, this preliminary study focused on exploring the use of reaction times from a relatively simple activity to appraise the cognitive status of PwD.

6. Conclusions

The significance of the present work is that it is among the first studies (to the best of authors' knowledge) to (i) appraise the cognitive status of people with dementia using reaction times from touch interaction tasks and (ii) identify significant relationships between the MMSE score of people with dementia (PwD) and the reaction time from taps.

From the empirical results (obtained from the present study involving 21 PwD), it can be concluded that there is a negative relationship between the MMSE score of PwD and the reaction times from taps, i.e., as the MMSE score decreases, the reaction times from taps increase or vice versa. Nevertheless, no causality should be inferred. In addition, the bootstrapped mean accuracy results of the classifiers suggest that it may be feasible to automatically classify PwD as individuals having a relatively *low* or *high* MMSE score based on reaction times from taps. However, the lower bounds of the 95% confidence intervals do not allow drawing definitive conclusions and more experiments should be conducted to confirm or refute this finding.

Future work will focus on designing and implementing cognitive activities for the wide touchscreen to explore the performance of PwD and its relationship to the MMSE score. Another direction for future research is to explore whether the performance of PwD in other touch interaction tasks, for example, tasks involving drag & drop gestures, is related to their MMSE scores. Also, future work will focus on incorporating more sensors (such as microphones and cameras) into the hardware for touch interaction so as to collect and analyze sounds and gestural movements of PwD.

Ethics Statement

This study was reviewed and approved by the Ethics Committee of Instituto Tecnologico de Sonora under protocol number 393. All participants provided written informed consent in accordance with the Declaration of Helsinki.

CRediT authorship contribution statement

Marco Esquer-Rochin: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review editing, Visualization. **Luis-Felipe Rodriguez:** Conceptualization, Project administration, Supervision. **J. Octavio Gutierrez-Garcia:** Conceptualization, Project administration, Supervision.

Declaration of Generative AI and AI-assisted technologies in the writing process

This manuscript was written without the assistance of generative AI tools. All content, including figures and text, was produced by the authors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

Acknowledgements

The authors thank day center *Dorita de Ojeda* for their support. This work was supported by PROFAPI 2024. J. O. Gutierrez-Garcia gratefully acknowledges the financial support from the Asociación Mexicana de Cultura, A.C.

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