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Development of Thai Picture Description Task for Alzheimer's Screening using Part-of-Speech Tagging

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***Abstract*— Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI) are among the most common health conditions in elderly patients. Currently, methods to diagnose AD and MCI are lengthy, costly and require specialized staff to operate. A picture description task was developed to speed up the diagnosis. It was designed to be suitable and relatable to the Thai culture. In this paper, we will be presenting two picture description tasks named Thais-at-Home and Thai Temple Fair. The developed picture set was presented to 90 participants (30 normals, 30 MCI patients, and 30 AD patients). Then, the recording in the form of spontaneous speech is converted to text. A Part-of-Speech (PoS) tagger is used to categorize words into 7 types (noun, pronoun, adjective, verb, conjunction, preposition, and interjection) according to the Office of the Royal Society of Thailand. Six machine learning algorithms were applied to train with the PoS patterns and their performances were compared. Results showed that the PoS can be used to classify patients (MCI and AD) and healthy controls using multilayer perceptron with 90.00% sensitivity, 80.00% specificity, and 86.67% accuracy. Moreover, the findings showed that healthy controls used more conjunctions and verbs but fewer pronouns than the patients.**

***Clinical relevance*— The picture description tasks using part-of-speech (PoS) to showed promising results in screening Alzheimer's patients.**

I. INTRODUCTION

A. *Alzheimer's disease*

The world is rapidly advancing into a community with more elderly people. Between 2000 and 2050, the percentage of population aged 60 or above is predicted to double from 605 million to 2 billion people and the countries that follow this trend the most will be middle and low income countries [1]. One of the most concerning problems is the increase in people developing dementia, and Alzheimer's disease (AD).

AD is the most common type of dementia including patients with behavioural impairments, memory loss, and cognitive deterioration and those suffering MCI. There will only be mild memory loss in the early stages of AD; however, individuals with late-stage AD tend to have difficulties performing daily activities. Although there is currently no known cure for AD, the severity of the disease can be delayed or stopped if the treatment is done correctly. An early and accurate diagnosis of AD is crucial for patients to start treatment early enough to prevent the symptoms from progressing towards critical stages [2].

Current clinical approaches to the diagnosis of AD include brain-imaging analysis tests such as MRI, CT scan, and PET scan [3]. However, these methods are complicated, costly, and require specialized staff, making them inconvenient in low and middle-income countries such as Thailand. Although neuropsychological tests such as the Mini Mental State Examination (MMSE) [4] and the Montreal Cognitive Assessment Test (MoCA) [5] are possible alternatives to screen for AD, theses methodologies have cultural elements that are not fully compatible with Thai society and culture. Therefore, a cheap, accurate, and fast diagnosis method to screen for MCI and AD is needed. In recent years, there has been a shift towards the use of spoken language as a marker of AD as it has been shown that AD affects the patient's use of language in several ways [6]. However, most of the neuropsychological tests do not emphasize the linguistic aspect.

Ahmed et al. [7] discovered that over 66% of the English-speaking patients show distinct changes in the production speech such as changes in lexical content, fluency, and semantic content, a whole year before testing positive for AD. This research, resultantly, conveys that certain language features can potentially be early markers for AD. Another study on standard assessments has also shown the reduction in syntactic complexity and the confirmation of semantic impairment in AD patients [8]. This promising use of English language features as a viable marker for AD combined with the improvement of computational linguistic tools has opened a way to new diagnostic methods such as Automated Spontaneous Speech Analysis (ASSA) as well as Spontaneous Speech (SS) [9].

ASSA methods involve the extraction of features from speech samples and machine learning (ML) algorithm to distinguish between AD patients and healthy controls. A study done by Thomas et al. [10] employed a "common N-grams" approach to classify spontaneous speech samples from English-speaking AD patients. The proposed method was able to distinguish between AD patients and healthy controls with an accuracy of 94.5%, and between MCI patients and healthy controls with an accuracy of 75.3%. Another study by Habash and Guinn [11] used English conversational speech samples from 31 AD patients and 57 healthy controls and achieved the best accuracy of

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79.5%. They discovered that measuring pauses, repetition of words, and incomplete enumeration of words were possible indicators that can be used in classifying between AD patients and healthy controls.

Picture description is one of several methods to detect Alzheimer's disease, i.e., it allows the patients to have more freedom, allowing their speech to be more natural, thus leading to a more accurate screening result. Shimada et al. [12] studied 17 English-speaking healthy control subjects and 23 English-speaking AD patients. The speech they made describing the picture was recorded, then analysed according to 3 main variables: amount of information, number of relevant and irrelevant descriptions, and efficiency of descriptions. There were significant differences in values of the 1st and 3rd variables, but no significant difference on the 2nd. Cummings [13] described the "Cookie theft" picture used to detect AD patients in the English language, that it contained several variables that were useful to distinguish patients: varying degrees of salience, different semantic categories, referential cohesion, causal and temporal relations. The recorded speech was analyzed and evaluated based on mental state language and structure of language and speech, as well as general cognition and perception. Results illustrated that there were differences in all variables between speech from AD patients and healthy controls.

Despite the progress in diagnosing AD, there is still a huge research gap as these methods may not be effective to the Thai language – a language with significant linguistic and semantic differences compared to other languages such as English [14]. Diagnosis of AD in Thailand still relies on conventional, inconvenient methods, and standardized examinations such as the Thai-MoCA [15]. This is extremely problematic in Thailand, especially in the rural regions, where AD patients far outnumber the number of medical specialists and the diagnostic equipment. Resultantly, many people in rural areas of Thailand are left untreated, resulting in the unavoidable progression of the disease, which eventually prevents them from carrying out daily activities.

Therefore, this study aims to develop a picture description task suitable for the Thai culture for screening patients (MCI and AD) and healthy controls using their verbal responses. The task aims to overcome the need for trained technicians and the expensive nature of conventional examinations, which are major hurdles in the rural areas of Thailand.

B. Picture description task

Patients with AD are shown to use certain types of words (PoS) in different patterns than the healthy controls. By having the patient describe a picture, the response will be in continuous form (spontaneous speech), which is the most effective way to produce diverse vocabularies and different types of words, allowing for a more accurate assessment. The work of Cummings [13] is adapted to design a picture set that best reflects common experiences of Thai culture [16]: (1) Thais-at-Home, and (2) Thai Temple Fair (shown in Fig. 1).

TABLE I: Major components for creating a descriptive picture proposed by Cummings [13].

Component	Cookie	Old1	Old2	At Home	Thai Fair
1. Salience of information	√	√	√	√	√
2. Semantic category	√	√	√	√	√
3. Referential cohesion	√	√	√	√	√
4. Causal and temporal relation	√	-	√	√	√
5. Mental state language	√	√	√	√	√
6. Structural language and speech	√	√	√	√	√
7. General cognition and perception	√	√	√	√	√

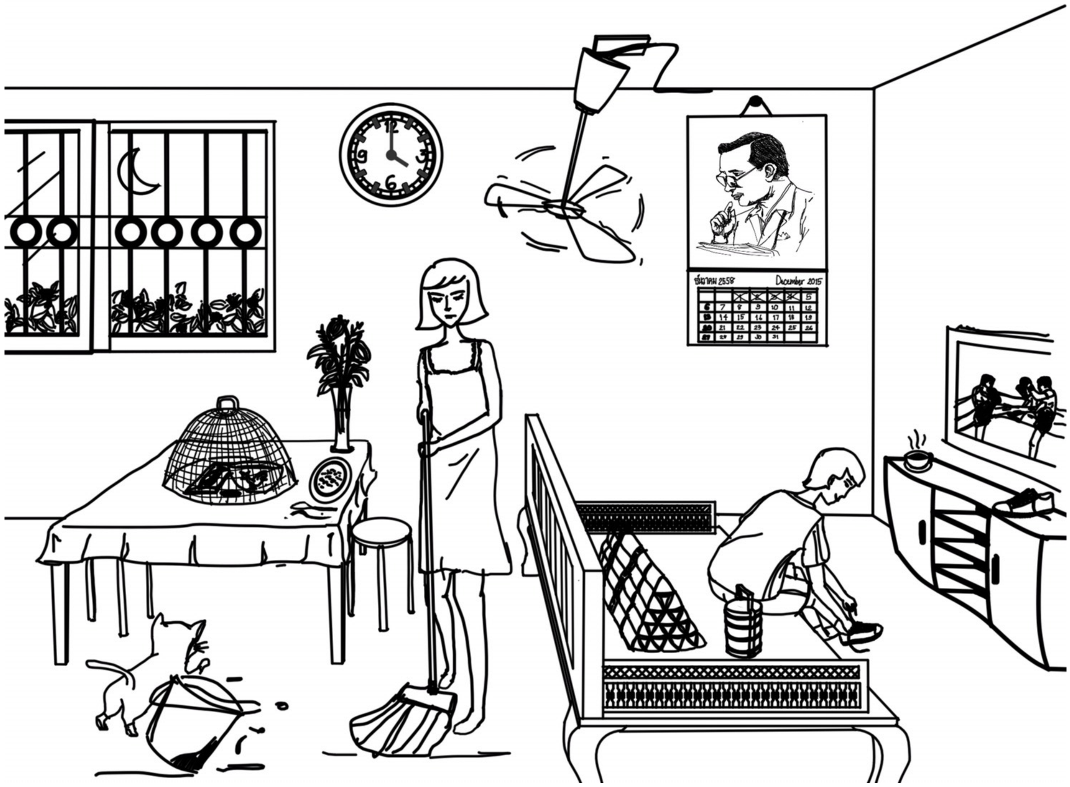
TABLE II: Different types of words (PoS) in Thai, proposed by the Office of the Royal Society of Thailand [17] and the ORCHID [18] .

PoS Tag	
Royal Society [17]	**ORCHID [18]**
NOUN	Proper noun, Cardinal number, Label noun, Common noun, Title noun, Unit classifier, Collective classifier, Measurement classifier, Frequency classifier, Verbal classifier , Determiner, cardinal number expression
PRONOUN	Personal pronoun, Demonstrative pronoun, Interrogative pronoun
ADJECTIVE	Ordinal number, Attributive verb, Determiner, ordinal number expression, Adverb with normal form, Adverb with iterative form, Adverb with prefixed form, Sentential adverb, Definite determiner, after noun without classifier in between, Definite determiner, allowing classifier in between, Definite determiner, between noun and classifier or preceding quantitative expression, Definite determiner, following quantitative expression, Indefinite determiner, following noun allowing classifier in between, Indefinite determiner, between noun and classifier or preceding quantitative expression, Indefinite determiner, following quantitative expression, Nominal prefix, Adverbial prefix, Ending for affirmative sentence, Ending for interrogative senten, Negator
VERB	Active verb, Stative verb, Pre-verb auxiliary, before negator, Pre-verb auxiliary, after negator, Pre-verb, before or after negato, Pre-verb auxiliary, in imperative mood, Post-verb auxiliary
CONJUNCTION	Coordinating conjunction, Interrogative pronoun, Subordinating conjunction, Comparative conjunction
PREPOSITION	Preposition
INTERJECTION	Interjection, Punctuation

The developed pictures were used to assess on subject's ability to verbally describe and explain the items and activities. The most effective aspects to differentiate people with AD from people without are: (1) magnitude of picture set or executed information to convey, where there are no more than 30 components in the picture, (2) number of words relevant and irrelevant to the description, and (3) efficiency of the words used for description, i.e., the ratio between the relevant and irrelevant words [19].

II. DEVELOPMENT OF DESCRIPTIVE PICTURES

There are several factors that should be considered for picture description task development. The objects in the image are required to be related to one another in order to elicit a variety of language aspects, shown in Table I.



(a)

(b)

Fig. 1: (a) Thais-at-Home Picture and (b) Thai Temple Fair Picture in our developed picture description tasks for Thai. Various items and actions in the pictures (e.g., King Rama IX illustration and Thai kick boxing) clearly relate to the Thai culture [16].

Cummings concluded that these components can be used to distinguish between patients with dementia and healthy controls [13]. These components were incorporated into the two pictures as follows.

Component 1: Salience of information is how different objects and actions that make up the image are ranked in different levels of significance. The less important aspects of the picture are normally put in the background of the image, where people recognize their details after explaining the more important, recognizable parts in the foreground of the picture.

Component 2: Semantic categories, which show how the picture must illustrate people, objects, and actions, where everything in the picture should be able to be described easily, as well as using different words for a single object or person with varying specificity, such as using the word 'women' or 'mother' to describe a person in the house.

Component 3: Referential cohesion refers to how the picture requires an action to happen in order to elicit the use of pronouns. Compared to healthy controls, AD patients find it harder to use a personal pronoun, for example "There is a man in the picture, and 'he' is putting his shoes on".

Component 4: Causal and temporal relations can help separate AD patients and healthy controls by having several incidents occurring that have a relationship with one another, e.g, A cat may spill water, therefore a person has to go clean it up. AD patients may have issues relating the events.

Component 5: Mental state language, where the picture used for description is required to show how a person in the picture is thinking or feeling, such as the words 'want', 'surprised'. Normal, people would naturally implement these words while describing the pictures, but AD patients have difficulties expressing how someone in the picture is feeling, such as the person is "angry" that the cat spilled some water on the floor.

Component 6: Structural language and speech requires the image to contain several parts to reflect how fluently the patient speaks, as well as patients' use of complex syntactic structures. AD patients might have problems choosing words to describe the picture, mispronouncing, or using incorrect grammar. Various parts in the picture may require more time for patients with AD to pause and collect their thoughts before responding.

Component 7: General cognition and perception also links with how the image is required to contain several parts. Healthy people will be able to recognize all major aspects of the picture, but AD patients have a different understanding and might forget that they had already described a certain aspect of a picture, and would repeat it again. For example, the clock (pointing at 4) in the Thais-at-Home picture should be described as 4 a.m. (judging from the moon seen from the window). Patients may have difficulty relating these two events together (the clock and the moon).

Our pilot study [16] was conducted with 32 participants (11 healthy controls; 11 MCIs; and 10 AD patients) using pictures from Cummings, the Cookie Theft [13] and 2 pictures (Designing Picture scenario old1: Old1 and Designing Picture scenario old2: Old2) from Marshall [20]. In agreement with early observations of a psychiatrist on our team, the findings clearly showed that elderly Thais have had unfamiliarity issues with some Western concepts and items in the picture (e.g., name of some furniture items). Therefore, we newly designed the two pictures in the set, including Thais-at-Home with a total of 28 different objects, and Thai Temple Fair with a total of 29 different objects (shown in Fig. 1). This study involves the use of continuous speech from Thai elderly describing the Thais-at- Home and the Thai Temple Fair (Fig. 1) to create a model for screening of Alzheimer's disease.

III. DATA COLLECTION

The data used in this work were obtained by recording Thai patients and healthy controls describing Thais-at-Home, and Thai Temple Fair pictures (Fig. 1). Spoken data are continuous (spontaneous speech), and there were a total of 90 participants (male = 28, female = 62) aged between 57−86 years old (mean = 70.3, SD = 6.8). Thirty-two participants did the paper based version and the rest (58) did it in the computer based version: 30 AD patients (male = 8, female = 22) aged between 61−86 years old (mean = 73.2, SD = 7.2), 30 with MCI (male = 13, female = 17) aged between 62−83 years old (mean = 71.9, SD = 6.3), and 30 healthy controls (male = 7, female = 23) aged between 57−77 years old (mean = 65.8, SD = 4.1) whose memorizing ability had deteriorated with age. The collection site was King Chulalongkorn Memorial Hospital under the institutional review board (IRB) review and approval no. 206/59.

IV. METHODOLOGY

A. Speech labeling and PoS tagging

After obtaining the recording, the speech was converted into texts by Google speech API [21] and Party [22]. Texts from these services are used as a baseline for well-trained linguists to compare and validate. Then, auto tagging converted texts into 47 types of words (PoS) using PyThaiNLP [23] based on guidelines from ORCHID [18]. The 47 PoS (shown in second column of Table II) were then grouped into 7 PoS (shown in first column of Table II). Separately, each word was sorted into one of the seven groups according to guidelines from the Office of the Royal Society [17]. Therefore, there were two sets of the same data; one was classified into 7 PoS types and the other into 47 PoS types. Frequency of each PoS set was used to create a machine learning model.

B. Machine Learning

The data from PoS Tagging were used to create a model using the 5-fold cross validation method. These data were randomly selected in 5 rounds to divide the data into 60 participants for training, 15 participants for validation and 15 participants for testing. Several machine learning classifiers (shown in Table III) were tested, where each one was used to create 2 models using the selected features from the 47 and the 7 PoS. The set of features for each round was

TABLE III: Average AUC from 6 classifiers with 5-fold cross validation. The highlighted rows signify a performance from selected features from 7 PoS and non-highlighted columns are selected features from 47 PoS.

Classifier	Patients (MCI and AD) vs Healthy controls		
	At Home AUC	Thai Fair AUC	At Home + Thai Fair AUC
Adaboost	0.7121 ± 0.0991	0.7000 ± 0.0787	0.7380 ± 0.1017
	0.6010 ± 0.1265	0.6885 ± 0.1129	0.6300 ± 0.0600
Logistic regression	0.7719 ± 0.1114	0.7120 ± 0.1157	0.7960 ± 0.1084
	0.5600 ± 0.0735	0.6800 ± 0.0812	0.6300 ± 0.0748
Multilayer perceptron	0.7760 ± 0.1076	0.7057 ± 0.0512	0.8480 ± 0.0968
	0.6434 ± 0.0924	0.6200 ± 0.2063	0.6500 ± 0.100
Naïve Bayes	0.7723 ± 0.0891	0.7517 ± 0.0500	0.8079 ± 0.0926
	0.5800 ± 0.0600	0.5800 ± 0.0678	0.5960 ± 0.1248
Random forest	0.7667 ± 0.0977	0.7292 ± 0.0624	0.7640 ± 0.0933
	0.6100 ± 0.0970	0.6300 ± 0.0927	0.6200 ± 0.1673
Decision tree	0.7240 ± 0.1214	0.6976 ± 0.0845	0.6800 ± 0.0748
	0.6494 ± 0.1000	0.6525 ± 0.0816	0.6700 ± 0.0245

selected by correlation-based feature selection along with Best-first search method by searching subspace using greedy hill climbing augmented with a backtracking facility [24] to find the critical classifier-independent features for machine classification models.

V. EXPERIMENTAL RESULTS

The two set of selected features: one from 7 PoS types and the other from 47 PoS types were used for developing each of machine classification models for patients (MCI and AD) and healthy controls. Table III shows that 5-fold cross validation with selected features from the 47 PoS model's performance is lower than the use of selected features from the 7 PoS because the former was probably using too many features with conflicting results, which prevented the model to learn from those features. The 7 PoS has the corresponding features which are pronouns, conjunctions and verbs as shown in Fig. 2.

The best classification results from six classifiers was the multilayer perceptron with selected features from the 7 PoS of two picture description tasks including Thais-at-Home and Thai Temple Fair (Fig. 1), where the average ± SD of the area under curve (AUC) is 0.8480±0.0968 for patients and healthy controls. The result of test with the best area under the curve (AUC) of multilayer perceptron classifiers have percentage of the sensitivity is 90.00%, the specificity is 80.00%, and the accuracy is 86.67%. Moreover, Analysis of Variance (ANOVA) from the selected features from the 7 PoS shows the same trend as that from machine classification models. There is a statistical significant difference between patients and healthy controls $[F(1, 149) = 6.63, p < 0.05]$.

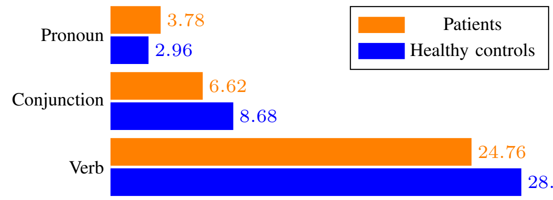


Fig. 2: Relative frequencies (%) of pronoun, conjunction and verb usage in patients (MCI and AD) and healthy controls.

VI. DISCUSSIONS AND FUTURE WORK

We have developed picture description tasks specifically for the Thai culture so that the elderly living in Thailand who are familiar with Thai culture and items can be able to describe pictures more effectively. The task consists of two pictures 1) Thais-at-Home with total of 28 different objects and 2) Thai Temple Fair with total of 29 different objects. Each picture exhibits the 7 components: salience of information, semantic categories, referential cohesion, causal and temporal relations, mental state language, structural language and speech, and general cognition and perception which Cummings [13] stated can be used for screening AD patients.

Since these variables affected the amount of information gained from patients versus healthy controls, the amount of information may affect the numbers of PoS produced from both groups. Our results showed that the PoS can be used as a promising marker for classifying between patients (MCI and AD) and healthy controls, especially with selected features from the 7 PoS. The results also showed that the Thais-at-Home description task can be more effective in classifying patients compared to the Thai Temple Fair description task because Thais-at-Home is generally simpler so that it is easier to describe every component in the picture. Its relative frequency of selected features from the 7 PoS between patients (pronoun is 3.38%, conjunction is 6.27%, and verb is 24.46%) and healthy controls (pronoun is 2.85%, conjunction is 8.31%, and verb is 27.77%) are different to the Thai Temple Fair which has relative frequency of selected features from the 7 PoS between patients (pronoun is 3.92%, conjunction is 7.00%, and verb is 25.27%) and healthy controls (pronoun is 3.45%, conjunction is 9.01%, and verb is 28.28%). Both picture description tasks follow the same direction, i.e., the patients use less conjunction and verb, but more pronoun than healthy controls. Furthermore, the results from Table III shows that the classification can be more accurate when considering Thais-at-Home and Thai Temple Fair together, as both groups (patients and healthy controls) have increased the number of PoS and relative frequency of selected features from the 7 PoS (shown in Fig. 2) are more different between patients and healthy controls. Based on the test results, we were able to classify all of AD correctly, but MCI and healthy controls were still not entirely perfect.

We found that AD patients tended to use simple or short sentences for describing each individual item (e.g.,

"นี่ รูปภาพ นี่ หน้าต่าง เนอะ (this-picture-this-window-right?)" 'This is a picture. This is a window, right?'), while healthy controls used more complex and longer sentences (e.g., "ตรง หน้าต่าง เรา มองเห็น พระจันทร์ แล้ว ริม หน้าต่าง จะ ปลูก ต้นไม้ (at-window-we-see-moon-and-by-window-will-plant-tree)" 'At the window, we can see the moon and by the window, there are trees present.') resulting in more usage of subject pronouns, especially the demonstrative pronoun such as "นี่" 'this' or "โน่น" 'that'. On the contrary, the average usage of conjunction and verb from patients is significantly lower than healthy controls.

Therefore, it can be concluded that the accuracy gained from developing classifiers using POS from two pictures (from the Thais-at-Home and Thai Temple Fair) can be used for preliminary screening to distinguish between patients and healthy controls. Importantly, this screening task takes a very short time to complete, with a maximum of 5 minutes for each picture.

In the future, we plan to increase the number of participants to provide more data for modeling, compare the speech to text converted by Google speech API [21] and Party [22] with text verified by well-trained linguists, measure how effectively the PoS classifier works and develop an application with simple instructions and a more user-friendly interface. Once the user completes the test and reaches the accuracy value, a distribution of scores will be displayed in each section with clear and precise evaluations in simple terminology. Also, the Automatic Speech Recognition (ASR) system will be redesigned in order to make this an automated process.

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