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Proactive depression detection from Facebook text and behavior data

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ABSTRACT

This paper proposes a proactive method to detect the clinical depression affected person from post and behavior data from Facebook, called text-based and behavior-based models, respectively. For a text-based model, the words that make up the posts are separated and converted into vectors of terms. A machine learning classification applies the term frequency- inverse document frequency technique to identify important or rare words in the posts. For the behavior-based model, the statistical values of the behavioral data were designed to capture depressive symptoms. The results showed that the behavior-based model was able to detect depressive symptoms better than the text-based model. Regarding performance, a detection model using behaviors yields significantly higher F1 scores than those using words in the post. The k-nearest neighbors (KNN) classifier is the best model with the highest F1 score of 1.0, while the highest F1 score of the behavior-based model is 0.88. An analysis of the predominant features influencing depression signifies that posted messages could detect feelings of self-hatred and suicidal thoughts. At the same time, behavioral manifestations identified depressed people who manifested as restlessness, insomnia, decreased concentration.

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1. INTRODUCTION

Clinical depression is a mood disorder that negatively affects a patient's feelings, thinking, and action [1]. Its symptoms (including losing interest or pleasure in most activities [2] and having recurrent suicidal thoughts [3]) vary from person to person. To diagnose the disorder, a doctor may choose to do lab tests [4] and psychiatric evaluations [5]. Although lab testing may not directly detect the disorder, it can help rule out other causes to make similar symptoms, such as malfunctioning of the thyroid. For psychiatric evaluation, a question-answering session or asking to fill out a questionnaire may be applied [6]. The often used questionnaire to determine depression includes a depression checklist (K10) [7] and patient health questionnaire-9 (PHQ-9) [8], [9]. The questionnaires are also available online for public access so concerned people can reach a screening test and get the result from anywhere. However, this screening method is passive since it needs patients to access and answer the questionnaire by themselves voluntarily. Hence, some patients who cannot access the service or yet realize their own depression risk may not be diagnosed and treated in time.

Aside from direct examination of a patient's physical and mental states for detecting the disorder, several researchers apply artificial intelligence methods to detect people with a risk of depression from online social network platforms. This detection method has the advantage of covering more populations with automated monitoring of social network users for their signs of depression from their posted text details. The existing works can be categorized into two groups. The first is works that analyze the posted texts to detect and learn keywords related to depression symptoms such as worthless, lonely, suicidal thoughts, feel sad, and anxiety feelings [10], [11]. The second is to use a machine-learning technique to create a classification model for depression users from annotated social network text data [12]–[14].

The works from the first group use statistical calculation and machine learning methods to analyze natural language texts to indicate signs of suicides for users and to find posts with suicide-related thoughts. For example, the process using the natural language processing (NLP) method such as term frequency [15], [16] and latent semantic analysis (LSA) [17] helps to identify the most frequent terms in a dataset and generate a ranked list of used terms representing suicidal thoughts.

For the group of work using machine-learning techniques to create a classification model, annotated data are mandatory for indicating depression patients. Since Twitter and Reddit are the widely used English-based social network platforms, their English text messages are collected and annotated for depression status as positive and negative. Then, they are used for the training of a classification model with text analysis methods to identify depression users with acceptable accuracy [18]. These works showed the promising results of automatic detection of depression-positive users from online messages.

Results of the aforementioned works indicate that text data from social media can be used to detect mental disorders and their symptoms. However, they are limited to the users who made posts in textual expression. In fact, depression does not only affect patient’s communication but also behavior [19]. According to the PHQ-9 [8], [9] several self-assessed questions involve behavioral aspects such as losing interest or pleasure in doing things and having trouble falling or staying asleep. Hence, it is essential to include those aspects in detecting clinical depression from social network data.

In this work, we propose a proactive, predictive model to help screening depression using data from the social network in a daily life environment rather than waiting for at-risk persons to make a test. Unlike existing works, contents and activities in the social network are considered to determine users’ depression status. We design a set of features regarding behavior/activity in a social network platform to cover more range of depression symptoms such as sleeping problem and losing pleasure in doing things that are scarcely realized by analyzing textual contents. This work focuses on detecting depression-positive users in Thailand; thus, we select Facebook social network service to gather users’ data since it is the most used service for Thai people. The classification results as detecting efficiency are studied and discussed. The rest of this paper is organized as follows. Section 2 explains research methods, including data collection, design of features, and classification model. Section 3 provides the results of the proposed methods and findings of influential features. Last, section 4 gives a conclusion of the research including findings and remarks.

2. RESEARCH METHOD

This work defines depression detection as a classification problem. Data for this work include text data and behavior data from Thai Facebook users. The features for training a classification model are thus designed to match available Facebook functions.

2.1. Facebook data collection

Facebook is an online social media and social networking service accessible from internet-connectable devices, including personal computers, tablets, and smartphones. Registration is needed for a user to create a profile that serves as an ID for an account. Users are allowed to make textual posts along with images and another multimedia which is shared with other users. In this work, Facebook data refer to a content of a post and users’ reaction to posts of another user. For the posted text, the applied data are textual posts only, while other contents including images, stickers, emoticon, and other multimedia are removed. For users’ reaction to posts of another user as behavior data, statistical information of how often posts are made and the reactions of users is collected to represent user behavior data on the Facebook platform.

To gather participants, we asked for Thai volunteers who have owned an active Facebook account for over 12 months. The volunteers were asked to test with the Thai version of PHQ-9 [8], [9] to identify their depression state. Then, we assigned the result as depression state to the user for ‘depression-positive’ and ‘depression-negative’. With the given criteria, 160 applied volunteers in this study. Their statistical information is provided in Table 1.

The PHQ-9 test results showed that 120 participants are depression-negative, and 40 participants are depression-positive. The Facebook data were collected for 14 days. Since the experiments involve human volunteers to provide their Facebook data, personal information, and their depression-diagnosis status, a Certificate of Ethical Approval from the Human Research Ethics Committee of Walailak University with the Project No. WU-EC-IN-0-187-62 are granted for this work.

Table 1. Voluntary participants and their statistical information

Depression-state	Age 18-22 (56)		Age 23-35 (53)		Age 36-50 (44)		Age <50 (7)	
	Male	Female	Male	Female	Male	Female	Male	Female
depression-positive	16	26	15	24	13	20	3	3
depression-negative	5	9	4	10	4	7	0	1

2.2. Feature design

For a textual post from Facebook, content is a set of Thai character strings that appeared in a post. To perform a text classification with a machine learning technique, words in a post must be recognized to represent the meanings of the post. However, since this work handles the Thai language, which is a language without a visible word boundary [20], we need to apply Thai word segmentation or tokenizer to realize words in a text content. The word segmentation service selected in this work is Lexto-plus [21], provided by National Electronics and Computer Technology Center (NECTEC), Thailand, for its ability to segment words at a concept level. Unfortunately, the word segmentation performance is not perfect, and some rare and unknown terms are not properly segmented. Hence, a manual post-edit process is required for maintaining input quality. Then, typos and misspelling words are manually corrected. Last, stop words, which are functional words used for representing grammatical function with little to no meaning, are removed to maximize text processing performance in terms of computational complexity from less search space.

We transform words in the Facebook post in the form of a word vector [15] using a bag of word approach [22] to represent word frequency statistics. A post is separately handled as a text document. Furthermore, we generate a wordlist from whole set of documents. We select term frequency (TF) and inverse document frequency (IDF) to represent significance of terms. TF and IDF are defined as given in (1) and (2), respectively.

$$\text{TF} = N(w,p) \quad (1)$$

$$\text{IDF} = N(w,p) \times log(|P|/N(p,w)) \quad (2)$$

Where $N(w,p)$ refers to the number of occurrences of each word (w) in a post (p), while IDF is logarithmic scale value of the collection of the entire posts (P) divided by the number of posts that contained the word (w). Then, w a multiplication of TF and IDF is calculated for TF-IDF value. The higher of the TF-IDF shows the higher the significance of the term.

For the behavior aspect, the features are designed based on available Facebook functions. The features are to represent a statistical value of how a user acts and interacts with other accounts regarding making a post, a comment, a share, and a reply to a comment. For clarification, making a post refers to an act in Facebook of making a post by an account owner. Making a share is an act of sharing another account's post. Making a comment is an act to create a text replying to another person's post. Last, making a reply is an act of making a response to another person's comments in own post. These actions of the user are then numerated and recorded to represent a value of the designed feature. In addition, we also collect the timestamp of the actions to calculate a gap between each action. In fact, we only count the actions, but the content of these actions is not recoded since they are private information. Unlike other actions, since the obtained comments for each person are vary as some posts may not get a comment to reply to or some may have many comments, counting the reply may not apparently represent the actual circumstance. Hence, the percentage of replying is calculated from a total number of obtained comments from other users instead of counting. We then use the action information to calculate and represent behavior feature in Facebook as shown in Table 2.

The value of the features given in Table 2 is a numerical value. To balance the number, we [23] to scale the data into a value ranged between 0 and 1. The formula for applied min-max normalization method is given in (3):

$$\acute{x} = \frac{x-\min(x)}{\max(x)-\min(x)} \quad (3)$$

where x is an original value and $\acute{x}$ is a normalized value. To apply the value in classification process, we perform discretization of the normalized value (0-1) into 5 frequent categories. The categories are very low (less than 0.2), low (from 0.2 to less than 0.4), moderate (from 0.4 to less than 0.6), high (from 0.6 to less than 0.8) and very high (over 0.8).

Table 2. Features based on Facebook behavior data

Aspect	Features
Function	Average number of daily posts (PA)
	Standard deviation of daily posts (PS)
	Average number of daily shares (SA)
	Standard deviation number of daily shares (SS)
	Average number of daily comments (CA)
	Standard deviation number of daily comments (CS)
	Average percentage of daily replies (RA)
	Standard deviation number of daily replies (RS)
Time	Average number of actions done between Monday to Friday (WdA)
	Average number of actions done in weekend (WeA)
	Average number of actions done in morning (06:01 to 12:00) (MnA)
	Standard deviation of actions done in morning (MnS)
	Average number of actions done in afternoon (12:01 to 18:00) (AnA)
	Standard deviation of actions done in afternoon (AnS)
	Average number of actions done in evening (18:01 to 24:00) (EvA)
	Standard deviation of actions done in evening (EvS)
	Average number of actions done in late night (00:01 to 06:00) (LnA)
	Standard deviation of actions done in late night (LnS)
Consecution	Number of actions done consecutively within 1-minute gap (G1 m)
	Number of actions done consecutively within 5-minute gap (G5 m)
	Number of actions done consecutively within 10-minute gap (G10 m)
	Number of actions done consecutively within 15-minute gap (G15 m)
	Number of actions done consecutively within 20-minute gap (G20 m)

2.3. Proactive depression detection model

The features and their values are trained for a supervised classification model towards a depression detection. The training dataset includes feature data as input data and their depression state labels as a response value. In a training process, the main task is to specify and map a set of feature values to a class label, and the mapping then is used as a classification model. The new unseen data then are compared to the model to make predictions. With the supervised data, a classification model can be trained by mapping an input to an output based on example input-output pairs. Since there are two classes as 'depression-positive' and 'depression-negative,' binary-class classification is applied. In this work, we select five commonly used machine-learning techniques as support-vector machine (SVM) [24], naive Bayes classifier (NB) [25], neural network (NN) [26], decision tree (DT) [27], and K-nearest neighbors (KNN) [28]. In this research, the machine learning process is conducted via RapidMiner version 9.6. The parameters of these machine-learning techniques are set as default. Though we select five machine learning approaches to train the depression detection, we do not plan to compare the techniques for performance but aim to demonstrate how the designed features are usable in a task of detecting depression using Facebook data.

3. RESULTS AND DISCUSSION

In this part, we give the results of the proposed method. First, the statistic of the newly invented features of Facebook behavior data is calculated and compared to indicate their discriminative potential in representing the depression status of users. Second, detection results using the proposed method are provided. Last, we rank the features from classification results to find the most influential features indicating depression status.

3.1. Statistics of Facebook behavior data

The collected data from the designed behavior features are numerical values. Their statistics are transformed in the range of 0 to 1 with min-max normalization. The Facebook behavior data regarding depression status for function, time, and consecution aspects are given in Figures 1 to 3, respectively. The abbreviations on the graph are mentioned in Table 2.

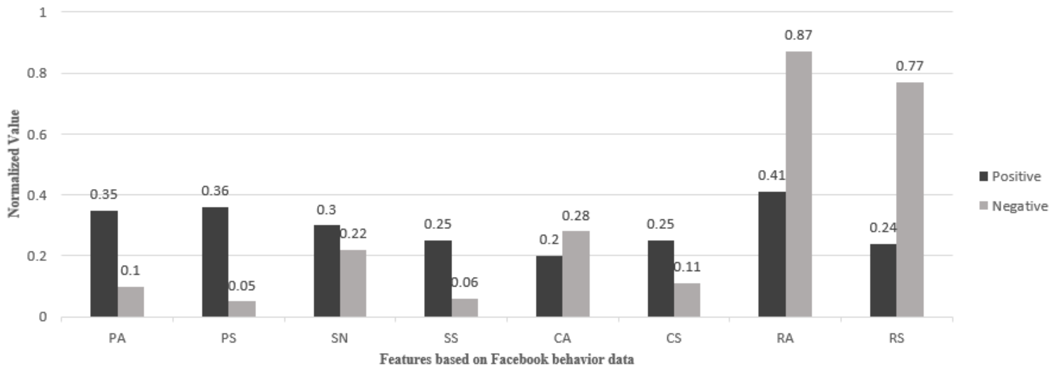

Figure 1. Statistical data in function aspect

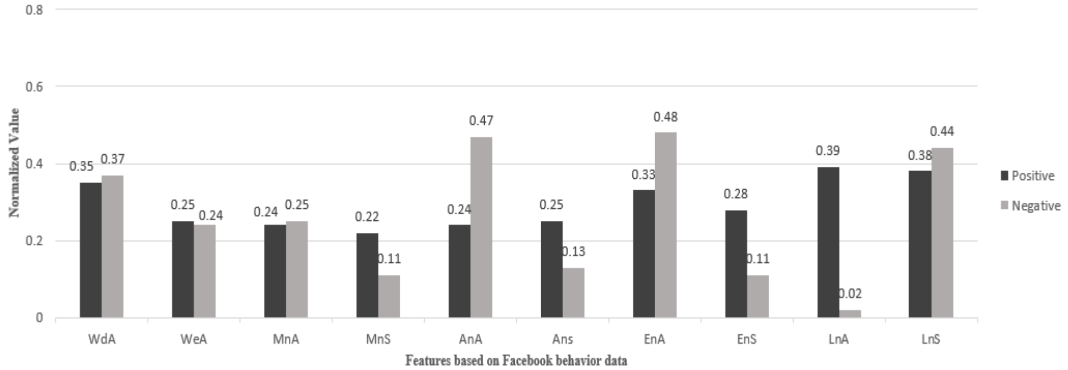

Figure 2. Statistical data in time aspect

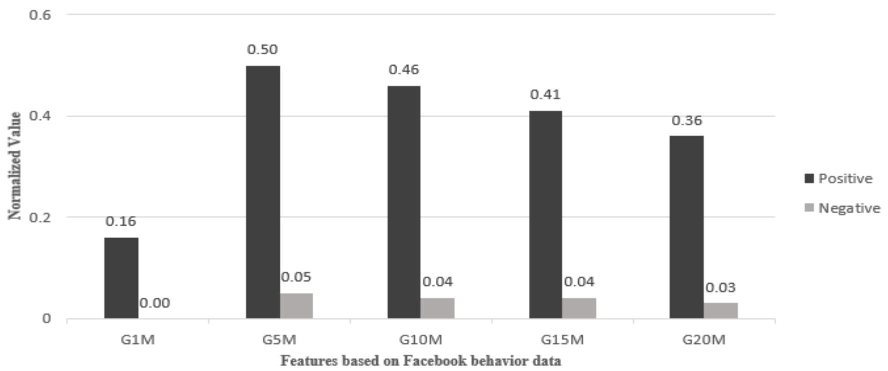

Figure 3. Statistical data in consecution aspect

From the data, standard deviation values of daily posts and shares were different between the two groups, while the average number of posts and shares was slightly different. This finding indicates that depression-negative users tentatively had consistent daily posts and shares while depression-positive users may have inconsistent daily posts and shares. The inconsistent behavior, which is called 'peak liming,' results from an unstable mood [29] from depression. Moreover, for replying, it is obvious that depression-positive users rarely reply to other comments. According to time-based features, the two groups are active in a different timeframe. The depression-positive users had more activity numbers during the late-night. This can be explained as the night time is a time when depression is more likely to occur based on sky color theory [30] that mentioned the effect of daylight and depression symptoms. Accordingly, depression-affected people usually spend more time online late at night or early in the morning from a known symptom of having a troubling sleep [29]. Furthermore, the data indicate that depression-positive users had made action within a gap of 1 minute as it shows a sign of unstable moods, leading to restless behavior or lack of concentration [31]. Thus, the behavior data can greatly represent distinctive differences of depression symptoms and are expected to perform well as features in a classification model.

3.2. Detection results

To find out the potentials of the proposed method, we set up an experiment to see the performance in detecting positive-depressed persons via Facebook social media. Since the proposed method has two distinct input parts for depressing detection as textual posts and usage behavior, both have experimented separately for comparison. Data in this experiment are text-posts and behavior data made by 160 Facebook users. The classification model is to determine positive and negative depression users. This experiment applies 5-fold-cross-validation fashion to assess the effectiveness of the generated model. The 5 folds are assured to distribute the same amount of both classes. To evaluate the model, we choose precision (A), (P), recall (R), and F-measure (F1) score for measuring the result.

For settings, proactive depression detection using text-based Facebook data applies three different n-grams to the bag-of-word as uni-gram, bi-gram, tri-gram, and a combination of the aforementioned n-grams. The original data are the collected data that have not been statistically processed. The normalized data are processed with the min-max normalization method to scale the numerical values between 0 and 1. The typing data are processed with the min-max normalization method and discretization as mentioned in section 2.2. The data settings of behavior-based Facebook data have three types: without normalization, with normalization, and with normalization and discretization. The performance results of text-based Facebook data and behavior-based Facebook data are given in Tables 3 and 4, respectively.

Table 3. Performance comparison among uni-gram, bi-gram, tri-gram and their combination for text base detection

	Uni-Gram				Bi-Gram				Tri-Gram				Combination			
	A	P	R	F1	A	P	R	F1	A	P	R	F1	A	P	R	F1
NB	0.73	0.97	0.75	0.84	0.74	0.98	0.75	0.85	0.87	0.97	0.87	0.88	0.73	0.97	0.75	0.85
NN	0.77	0.97	0.78	0.87	0.8	0.97	0.81	0.88	0.71	0.66	0.94	0.78	0.8	0.97	0.8	0.88
SVM	0.76	0.95	0.78	0.86	0.75	1	0.75	0.86	0.75	1	0.75	0.86	0.75	0.98	0.76	0.86
DT	0.8	0.87	0.86	0.87	0.75	0.75	0.9	0.82	0.45	0.29	0.95	0.45	0.8	0.89	0.86	0.87
KNN	0.76	1	0.76	0.87	0.46	0.38	0.81	0.52	0.43	0.25	0.94	0.41	0.76	1	0.76	0.86

Table 4. Performance comparison of behavior data in three sets: (1) without normalized, (2) with normalization, and (3) with normalization and discretization

	Without normalized				With normalized				Normalized + discretizing			
	A	P	R	F1	A	P	R	F1	A	P	R	F1
NB	0.98	0.98	1	0.99	0.98	0.98	1	0.99	0.99	0.99	0.98	0.98
NN	1	0.99	0.99	0.99	1	0.99	0.99	0.99	1	0.98	0.99	0.98
SVM	0.94	0.75	1	0.85	0.75	1	0.91	0.95	0.94	1	0.90	0.94
DT	0.99	0.99	0.99	0.99	0.98	1	0.99	0.99	0.91	0.98	0.98	0.98
KNN	0.91	0.99	0.99	0.99	1	1	1	1	1	1	1	1

The experiment results by naive Bayes with trigram data is 0.88 of F-score and performed the best. While F-score from many settings of depression detection using behavior data is 1 with the k-nearest neighbor. The experimental results signify that model from behavior data perform better than models of post data in overall. The behavior-based models receive the high evaluation results on every applied machine learning technique.

Furthermore, we analyzed the result and noticed the topics to discuss from experimental results. The designed behavior-based features are informative to discriminate between depression-positive and depression-negative users. In fact, the statistics shown in Figure 1 displays several distinctive values of Facebook behavior data between depression-positive and negative users. These noticeable differences effectively help with classification for higher accuracy. For post-based models, we found that posts made by depression users were both a normal post and a depression related post because the symptoms of the depressive disorder, especially mildly depressed person, can be mild and do not always manifest [29]. Additionally, normal Facebook users may feel irritable and use similar words to those depression keywords [18] and cause the distribution of words to be ambiguate and confusing a classification. Thus, to improve the text-based detection, it is advised to train from a large corpus of only posts involving the depression content annotated by experts to reduce noises in a classification model.

3.3. Influential features from behavior and post

We exploit statistical information called 'information gain' (IG) used during a classification model generation to indicate influential features from both models. IG is calculated within the range between 0 and 1 to measure how much information about the class that one feature gives [32], while 1 refers to the highest informative value as a highly impacted feature, and 0 is vice versa. The IG score of features thus can help to determine the impact of the features for positive-depression Facebook users by sorting the IG value.

The features of the text-based classification are words in the posts, and the top-ranked features are a list of words which depression users often use. The behavior-based feature is an action in a defined duration or usage style of users, and the top ranked features are the common actions that may differentiate depression users from normal users. We list the top-10-ranked features of both sides with their IG values in Table 5.

Table 5. Top-10 features with the highest information gain

Rank	Text-based features	Behavior-based features
1	ไร้ค่า [useless] (0.97)	Standard deviation number of daily replies (RS) (0.94)
2	ตาย [die/dead] (0.92)	Average percentage of daily replies (RA) (0.93)
3	เครียด [stressed] (0.87)	Number of actions done consecutively within 20-minute gap (G20m) (0.93)
4	เบื่อ [boredom/boring] (0.87)	Standard deviation of daily posts (PS) (0.87)
5	เกลียด [hate/dislike] (0.86)	Standard deviation of actions done in late night (LnS) (0.82)
6	แคร์ [care/mindful] (0.86)	Number of actions done consecutively within 15-minute gap (G15m) (0.81)
7	เหงา [alone/lonely] (0.86)	Number of actions done consecutively within 10-minute gap (G10m) (0.76)
8	ไม่ไหว [unbearable] (0.85)	Number of actions done consecutively within 5-minute gap (G5m) (0.74)
9	โดดเดี่ยว [alone/lonely] (0.83)	Average number of actions done in late night (LnA) (0.72)
10	เรา [we/I] (0.72)	Standard deviation of actions done in morning (MnS) (0.71)

These features are determined to impact words for the depression-positive user regarding IG score highly. Most of the words (rank 1st to 9th) are terms with a negative feeling from the analysis. These words signify that depression users often expressed their negative feelings on social media and can be used to detect depression effectively [10]. For behavior-based features, the top-ranked influential features are aligned with the finding in previously mentioned behavior data since these features can explicitly represent symptoms of clinical depression and clearly distinguish behavior between depression-positive and negative users [2].

4. CONCLUSION AND REMARKS

Detecting clinical depression, especially on an early state, is an important task to find the patients for early treatment. An automate classification using a supervised machine learning technique is thus exploited to generate a model to predict the depression status of Facebook users as proactive depression detection. There are two different types of Facebook data in this work as features for the classification model. First is a text-based data extracted from posts user made. The text is an expression containing meaning and intention from a post owner; thus, words in the posts are used as features to determine a difference between depression-positive and negative person. In addition, words are transformed into a vector to represent their term-frequency and inverse-post frequency. Second is statistical data of actions made by Facebook users. The information includes several posts, comments, and replies a user made daily, along with time and frequency information of these actions. These data are collected to create a user behavior profile indicating the difference between depression-positive and negative person. Finally, the features are trained for a classification model using a supervised machine learning approach.

One hundred sixty volunteer participants were selected and asked to provide their Facebook data and to answer the PHQ-9 questionnaire for experiments. The experimental results indicated that the model generated by Naïve Bayes with trigram data performed the best for 0.88 F-score. In contrast, models from the k-nearest neighbor obtained a maximum of 1.0 F-score from many settings of depression detection using behavior data. While the classification model is generated, features used to train models are analyzed for their significance. A list of top-ranked significant terms and Facebook usage behavior from Thai users are found from the experiment. The knowledge of depression disorder reveals that the found significant features are matched to depression disorder symptoms. Depression patients commonly have negative feelings, and they are shown in their frequently used terms. In addition, a sign of disturbed sleep and feeling irritable and intolerant of others are noticeable from influential behavior features.

The proposed method has the advantage of allowing a healthcare provider to monitor depression-at-risk persons instead of passively waiting for patients. Furthermore, using social media data such as Facebook can cover most of the population in their ordinary environment. Some depression symptoms can exclusively be detected regarding behavior in the social network, such as sleep changes and loss of interest in daily activities. Besides, we realize that both text-based and behavior-based methods have their advantages and support one another since some users may have low numbers of activities. Still, their post containing the depression-sign terms, or some may not express their feeling through words but action. Since depression has several symptoms and some may manifest at a time, it is essential to have better coverage methods. We expect this work to help keep the user in check and prevent suicidal loss from clinical depression.

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