Facebook Social Media for Depression Detection in the Thai community

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Abstract **- Depression is one of the leading mental health problems. It is a cause of psychological disability and economic burden to a country. Around 1.5 Thai people suffer from depression and its prevalence has been growing up fast. Although it is a serious psychological problem, less than a half of those who have this emotional problem gained access to mental health service. This could be a result of many factors including having lack awareness about the disease. One of the solutions would be providing a tool that depression could be easily and early detected. This would help people to be aware of their emotional states and seek help from professional services. Given Facebook is the most popular social network platform in Thailand, it could be a large-scale resource to develop a depression detection tool. This research employs Natural Language Processing (NLP) techniques to develop a depression detection algorithm for the Thai language on Facebook where people use it as a tool for sharing opinions, feelings, and life events. Results from 35 Facebook users indicated that Facebook behaviours could predict depression level.**

Keywords—depression detection; depression screening; psychological tool; social media mental health; health tech;

I. INTRODUCTION

Depression is a common mental illness. It is one of the most concerning public health problems worldwide. In 2015, over 300 millions world population have suffered from this mental problem [1]. Depression is characterized by having a persistent feeling of sadness, hopelessness, low energy level, low self-esteem, empty mood, anxious mood, reduced or increased appetite, sleeping problems, guilty feeling, self harm as well as suicidal thoughts. This emotional disturbance affects daily functions as it also disturbs one's memory and an ability to concentrate [2]. Not only it affects one's ability to live normally, it also is a burden to the society in general [3].

In Thailand, Depression is a significant cause of years of life lost (YLL) which refers to a number of years of premature mortality. A report by Thailand National Mental Health Survey (TNMHS) stated that there were approximately 1.5 million Thai people who had suffered from depression which suggested that 3 out of 100 Thais had experienced with depression. In 2013, it appeared that depression was the number one caused of years of life lost due to disability (YLD) [4] and a caused of suicidal. It was found that the suicidal rate in Thailand was 5.98 per 100 000 population. Mental health disorders have serious economic consequences. It was reported that depression had an impact on the economic worth approximately over 800 billion USD in 2010 and this number is estimated to be doubled by 2030 [5]. Depression does not only impact psychological but also physical health. It associates with diabetes, high blood pressure and back pain [6]. Depression also put the patients at risk of heart disease by 67% and an increase in a risk of cancer by 50% [7]. Moreover, this mental illness is also a burden to family, friends, caregivers and other relationship in form of stress, marital breakdown, or homelessness [8]. Thus, it is reasonable to make an effort and investment in depression prevention and medication. It was evaluated that every investment of 1 USD on depression treatment would make 4 USD in return. This is because depression treatment would enhance overall well-being and work performance [9].

Depression is a curable disease. An early detection and intervention would shorten the treatment course [10]. Unfortunately, the rate of accessibility to treatment is surprisingly low. It was reported that less than 50% of those who have this mental illness gained access to mental health service. The barriers include a lack of knowledge and awareness in depression, having negative perception about mental health services and a limit numbers of mental health professions [1]. To help increase the rate of accessibility to mental health service, it is necessary that an advanced technology and proactive technique should be used. More importantly, to encourage people to be aware of their emotional well-being including depression, there should be a valid depression detection system available on the internet where most of the people are able to use. A Statista survey reported that Facebook is the most popular social network in Thailand and the users use it as a tool to share opinions, feeling, as well as life events [11], [12]. Thus, Facebook seems like a suitable platform to develop the depression detection system.

Taken together, this research aims to provide a depression detection tool on Facebook, the most popular social network by applying Natural Language Processing (NLP) techniques to psychological assessment and developing the depression detection algorithm for the Thai language and Thai culture.

Depressive signs were extracted from Facebook use behaviours including a number of posts, interaction with others, privacy settings, and day and time of posting.

II. Literature Review and Related Work

In the mental health services, standardized tools are widely used for depression screening and assessment. The tools include using questionnaire, psychological tests, clinical interview as well as brain scanning. A brief explanation of each technique is illustrated here;

Professional interviews: This methodology is operated by trained mental health professions. The interviewer must have strong knowledge of depressive signs and symptom along with observational skills. A diagnostic interview conducted by a qualified psychiatrist is regarded as a gold standard. This technique can also be conducted by other qualified mental health professions such as clinical psychologist and mental health nurse. However, this technique is time consuming as it requires one on one interview session.

Brain Scanning: Brain scanning techniques are used to detect the depression by investigating brain, neuron, and neurotransmitter activities. For instance, PET imaging and functional MRI capture brain functions. CT scan (computed tomography) and MRI (magnetic resonance imaging) visualize brain shape and size. The brain scanning techniques allow the defected and damaged brain and its function to be detected. Although highly accurate, it comes with high cost and limit numbers of the scanning machines.

Depression questionnaires : There is a substantial number of standard questionnaire available in the Thai language. For example, the Patient Health Questionnaire (PHQ) [13], Beck Depression Inventory-Thai [14], and 2q 9q 8q [15] developed by Department of Mental health Thailand. The Thai Mental Health Questionnaire (TMHQ) is among the widely use self-report that measure five aspects of psychopathologies including Somatization, Anxiety, Psychotic, Social function and Depression [16]. For depression domain, it comprises of 20 items measuring depressive symptoms such as dysphoric affect and mood, lack of motivation and loss of vital energy and thoughts of death and suicidal ideation [16].

Although there are several questionnaires available, evaluating depression using this method has its own limitation. Responses ascertain by this method might not represent the real symptoms and severity as it might affect from biases such as self-report bias which refers to a misunderstanding about what is being measured and social desirability bias [17] where the self-rater wants to ‘look good’ to others [18]. To detect depression passively from daily living activity could be a solution to somewhat resolve limitations from the discussed methods. It was hypothesized that the way people behave online might be a good source for self-reflection. During the past decade, literature in psychology and online behaviors has been rapidly increased. This includes emotional aspect.

Munmund et.al [19] examined whether social media would be able to detect and diagnose the major depressive disorder or not. Data such as social engagement, emotion, language styles, ego network, and mentions of antidepressant medications were collected from Twitter users over one year. They found some significant online behaviours that could predict the onset of depression. They reported that decrease in social activity, increase negative emotion, highly clustered ego networks, heightened relational and medicinal concerns, and greater expression of religious involvement were predictors of the onset of depression. They also reported that the model developed from this study has could predict depression before its onset with 70% accuracy and 0.74 precision. They suggested that this method could be a new approach to identify people who are at risk of depression.

Xinyu Wang et. al [20] detected social network users' depression by applying data mining to psychology knowledge. They employed a sentiment analysis method. Vocabulary and man-made rules were utilized for calculating tendency. Their depression detection model included 10 selected features based on related literature. The 10 features could be categorized into three dimensions which are micro-blog, interactions and behaviours. Validated by Bayes, Trees and Rules, ROC Area and F-measure, they reported that the proposed model has 80% accuracy in detecting depression. They also reported that in cases of incorrect prediction, it was caused by the insufficient data in microblogs.

Andrew G. Reece and Christopher M Danforth [21] employed machine learning for depression screening on Instagram. Colour analysis, metadata components, and algorithmic face detection were performed in order to develop a model. They found that their proposed model had 70% accuracy in predicting depression even before being diagnosed. They highlighted that this could be a new method for depression screening and detection.

To summarize, the previous literature indicates that online behaviours could predict depression. As stated that Facebook is the most popular social media among Thai people, it could be used as a tool for mental health monitoring and screening.

III. System Architecture

This research studied the possibility to detect depression in Thai community through Facebook social media. We intended to develop a detection algorithm as a new psychiatric instrument. This study examined whether the proposed algorithm could determine whether individuals were depressed or not by evaluating their Facebook posts.

To follow the ethics of Artificial Intelligence, the research protocol has been granted the ethical approval by Mahidol University Central Institutional Review Board (IRB) with the COA No. MU-CIRB 2017/143.1809. Facebook users who were aged over 18 years old and willing to share their microblogs for depression research were recruited into the study through the internet. Participation was voluntary and the volunteers did not receive any incentive for taking part in this research. Our system architecture is described in Fig. 1. The volunteers were asked to complete 20 items self-report depression screening derived from the Thai mental health questionnaire (TMHQ); depression domain. The detail of this measure can be found in [16]. Total scores were classified into two groups; depress and nondepressed. This classification is used as depression criteria in this research.

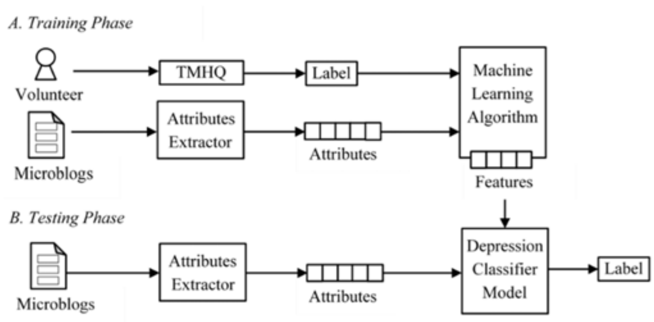

Figure 1. System Architecture

After the completing the TMHQ, all microblogs which were created during a period of one month prior to the date completing the questionnaire were collected. The microblogs are represented in the Graph API JSON format [22]. Attributes Extractor Module parsed the microblogs to list of attributes.

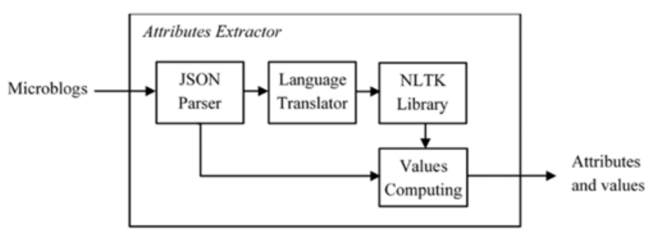

Figure 2. Attributes Extractor Architecture

All attributes are listed in Table I. Some attributes were transformed into numerical values by the values computing module such as N_allPost which refers to a total number of posts collected one month prior to the date the participant answered the TMHQ depression domain. Some language-related attributes, however, required more complicated processing such as N_Neg which refers to a total number of Negative posts. In order to process the value of the attribute value under the lack of NLP resource in the Thai language, we translated the post into English first. Then, system segmented the words, tagged part of speech and analyzed sentiments in order to determine the values of language-related attributes. We used Google Cloud Translation API [23] as a language translator and NLTK python library [24] as the NLP resources to manipulate the translated text. The examples of language-related attributes were N_Pos which is the total number of all positive sentimental posts, and N_First-person which is the total number of using a singular first-person pronoun.

In Machine Learning Algorithm module, we applied various algorithms. The three most accurate algorithms which were Support Vector Machine (SVM), Random Forest and Deep Learning were selected. We found relevant features and a depression classifier model is constructed in this process. In the testing phase, the microblogs were processed without labels. The extracted attributes were fed as the input of the depression classifier model. The prediction label indicated the possible presence of depression of the user.

TABLE I: Attributes Dictionary

Attributes	Description
N_allPost	Total number of posts
Content	
N_Message	Total number of posts has composed and posted by themselves
Len_Message	Total number of characters of the status message in the post composed and posted by themselves
N_emoMsg	Total number of posts contain emoticons
N_Emo	Total number of emoticons for all posts
N_Pos	Total number of Positive posts
N_Neg	Total number of Negative posts
N_Nor	Total number of Neutral posts
N_First-person	Total number of First person pronoun
Interactions with others	
N_allStory	Total number of posts posted on the user's behalf because of an action they have taken
N_shareOth	Total number of posts that shared others' posts
N_shareOwn	Total number of posts that added or shared a life event and a memory
N_With	A total number of posts contained profiles tagged as being 'with' the publisher of the post.
N_atPlace	Total number of posts contained any location information attached to the post.
Privacy Setting	
N_pvSelf	Total number of posts set privacy to 'Myself'
N_pvEverone	Total number of posts set privacy to 'Public'
N_pvCustom	Total number of posts set privacy to discard someone
N_pvAllFriend	Total number of posts set privacy to 'Friend'
Online user Behaviors	
N_Sun	Total number of posts posted on Sunday
N_Mon	Total number of posts posted on Monday
N_Tue	Total number of posts posted on Tuesday
N_Wed	Total number of posts posted on Wednesday
N_Thu	Total number of posts posted on Thursday
N_Fri	Total number of posts posted on Friday
N_Sat	Total number of posts posted on Saturday
N_NightPost	Total number of posts posted between 12 AM and before 6 AM
N_DayPost	Total number of posts posted between 6 AM and before 12 AM

IV. Experimental Setup and Results

Thirty-five Facebook users who aged over 18 years old and willing to donate their microblogs for this research were classified by TMHQ into 2 groups which were 22 depressed and

13 non-depressed. These TMHQ profiles were used as a gold label for this study. 1105 posts were collected and attributes were extracted which can be found in Table 1. A data set was then created.

A. Experiment 1: Weka with SVM algorithm

Weka [25] is used to implement sequential minimal optimization algorithm (SMO) for training a support vector classifier. Nonetheless the size of collected data was too small, we could not separate training and test sets as conventional validation without losing significant modelling. Eight-cross-validation was applied to estimate model prediction performance. The evaluation results are presented in Table II. Accuracy of the SVM model was slightly better than the majority vote which was used as baseline for evaluation. More experiments are considered.

TABLE II: SVM Model Prediction Performance

Method	Accuracy	Precision	Recall	F-Measure
Baseline (Majority vote)	62.85	-	-	-
SVM Model	68.57	0.674	0.686	0.664

B. Experiment 2: RapidMiner with Random Forest algorithm

To gain a better insight, we also employed RapidMiner with Random Forest algorithm to train and evaluate the model. The performance is described in Table III.

The supported factors for the depression detection model are visualized in green colour in Figure 3. The model states that people who post a lot of micro-blog on Monday with neutral sentiment possible suffer from depression.

TABLE III: Random Forest Model Prediction Performance

Method	Accuracy	Precision	Recall	F-Measure
Baseline (Majority vote)	62.85	-	-	-
Random Forest	84.6%	84.6%	88.9%	88.9%

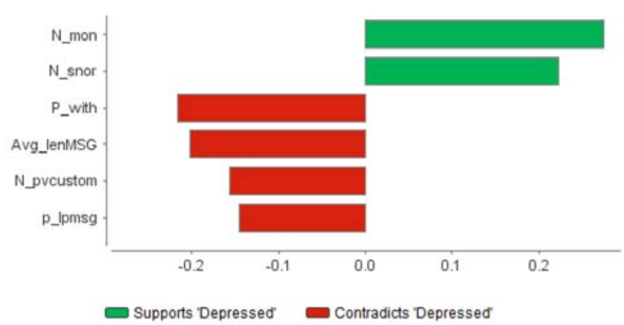

Figure 3. Important factors recognized by Random Forest

C. Experiment 3: RapidMiner with Deep Learning algorithm

Deep Learning algorithm was applied with automatic parameters optimization for getting another insight of the data set. The sentiment polarity was simplified into 2 groups; A_Pos represents Total posts with positive sentiment and A_Neg represents Total posts with negative sentiment. Some lookup attributes are explicitly calculated; Without_Msg is computed by N_allPost minus N_Message. It is the total number of micro-blogs that composed by others. A_NonEmoMSG is the total number of messages without Emoticons. It is computed by N_allPost minus N_emoMsg. A_ShareOwn, A_day, A_pvself and A_with are the normalized form of N_shareOwn, N_dayPost, N_pvself and N_with accordingly. The meaning of the attributes are described in Table I

Table IV illustrates performance of the model. The confidence for this prediction is 62.64%. The most important support for this prediction was yielded from Negative Sentiment (A_Neg). 84.62%. For depressed class prediction, it covers 100.00% of those cases. In addition, it is correct with 80.00% of all predictions for class Depressed.

TABLE IV: Deep learning Model Prediction Performance

Method	Accuracy	Precision	Recall	F-Measure
Baseline (Majority vote)	62.85	-	-	-
Deep Learning (positive class: Depressed)	85%	80%	100%	88.9%

Figure 4 shows some important factors recognized by Deep Learning model. It states that people who post negative sentimental microblog without using Emoticon and set privacy to be 'only me' tended to suffer from depression. In contrast, for those who frequently forwarded others' posts, shared their own memory, actively posted between 6 AM and 12 AM and usually tagged friends were more likely not suffer from depression.

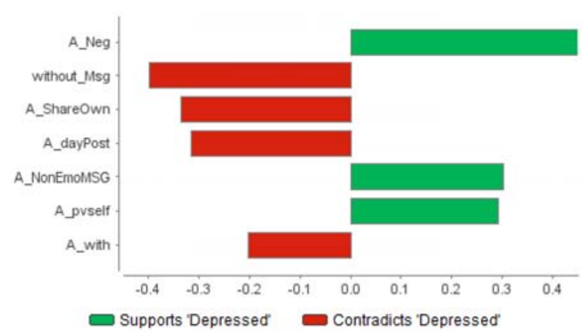

Figure 4. Important factors recognized by Deep Learning

V. Conclusion

The experiments results show that the use of behavioural information on Facebook, both in forms of messages and activities, could predict depression. However, the sample of this research is relatively small because Facebook has limited their permission to collect personal information and the process of gaining approval has become more complicated. Thus, the results getting from this study might not cover all relevant factors. Moreover, as the language-related features had to be translated from Thai to English for analyzing the process, there might be some errors due to this process because some important sentiment polar words might have been eliminated during the translation process.

For the future research, we intend to collect more data to get more relevant and valid features. Manual annotating all complex attributes using crowdsourcing and deeper dimensions should also be analysed in order to be able to create a better depression detection algorithm.

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