A Predictive Model for Depression Risk in Thai Youth during COVID-19

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***Abstract*—The risk of depression in youth affects future development of the learning process. Therefore, it is important to study on preventing the risk of depression in youth. The purpose of this research was (1) to study the risk situation of youth' depression in Thailand, and (2) to develop a model for predicting depression among youth in Thailand. The data used in the research were 1,413 samples from 9 faculties at the Rajabhat Maha Sarakham University, and Phadungnaree School at Mueang District of Maha Sarakham Province, Thailand. Research tools and procedures used were the data mining principles to analyze and develop prototype models. It includes the decision tree, naïve bayes, and artificial neural networks techniques. The results showed that the majority of the respondents had no depressive risk conditions with 1,059 samples (74.95%). However, there are still three risk groups that need to be monitored: mild level with 260 samples (18.40%) moderate level with 78 samples (5.52%), and severe level with 16 samples (1.13%). The observations were taken to develop a prototype model. It was found that the highest accuracy model was the artificial neural networks technique with an accuracy value of 97.88%. Based on such success, the researchers hope to develop a future application in preventing youth' risk depression.**

***Index Terms*—predictive model, depression risk analysis, learning analytics, machine learning**

I. Introduction

There are many factors that affect the academic achievement of the students. One is the depression crisis that affect more than 264 million people worldwide [1], [2]. Depression is a chemical disorder in the brain resulting in mood disorders. It results in having negative behaviors in one's daily life. It is coupled with the current situation that students at universities and secondary schools are more likely to be at a higher risk of depression [1], [3]-[5]. Some researchers suggest that depression occurs in high numbers with students. The agency should provide appropriate interventions in institutions to monitor the learning process and to detect and treat these disorders, particularly paying attention to those exposed to a higher level of risk [4], [5].

However, there are also scientists and artificial intelligence technologists trying to study and develop tools to predict the behavior of people at risk for depression [6], [7]. But there are no research works that have studied and developed any practical models for managing risk of depression in the field of education or educational institutions. Thus, this research was aimed (1) to study the risk situation of youth' depression in Thailand, and (2) to develop a model for predicting depression among youth in Thailand. The population of this research was youth in the Mueang District of Maha Sarakham Province. The samples in this research were obtained from 1,413 representatives from secondary schools and Rajabhat Maha Sarakham University. The key expectation of this research is to study the potential impact of the coronavirus disease 2019 (COVID-19) epidemic situation on Thai youth. Moreover, researchers strongly believe that artificial intelligence technology can help analyze potential impacts on Thai youth through this research.

The COVID-19 pandemic has created a crisis within the crisis. It is a mental health emergency. According to the World Health Organization, around 40 million people in Europe suffer from depression. Many people with depression struggle with social isolation and serious health problems [8]. In addition, the depression has a huge impact on individuals and on society. The effects and consequences of depression have a wide spectrum of impact on humanity. It affects personal relationships, productivity, and physical health. Depression is associated with symptoms including stress, headaches, and back pain, as well as a range of life-threatening conditions.

In the social and learning dimension, it affects the stopping and slowing down of the learners' learning. The examples of the impact from the depression to the learner are the following: lack of motivation, irritability during class, fatigue needed to sleep, and loss of concentration [9]. There are also a number of articles on the effects of depression on learning management [10], [11].

The depression crisis that affects all dimensions has brought about an initiative reason and inspiration for the researchers to conduct a research study on this phenomenon.

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II. Research Methodology

The research methodology follows the theory of data mining and machine learning analysis, which is the CRISP-DM: Cross-Industry Standard Process for Data Mining [12], [13]. There are 6 phases of the CRISP-DM cycle: business understanding, data understanding, data preparation, modeling, evaluation, and deployment. The conceptual framework is shown in Fig. 1. In addition, the researcher chose a psychological questionnaire as the tool for gathering data and analysis. It's known as the Thai Version of The Patient Health Questionnaire for Adolescents: PHQ-A Questionnaire [14]. To find the performance of the model, the researchers used cross-validation methods, and confusion matrix performance techniques including accuracy, precision, and recall for determining the model's efficiency. The research methodology is shown in Fig. 1.

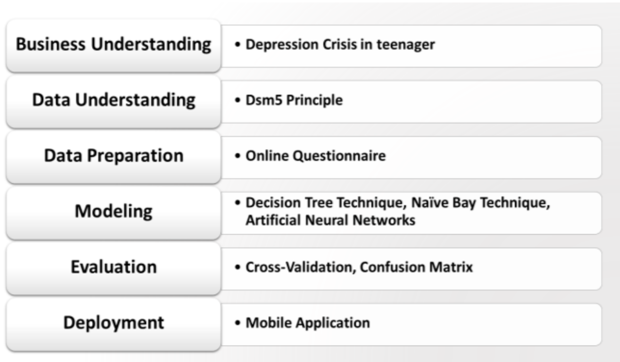

Figure 1. Research methodology.

A. Business Understanding

Business Understanding phase is the process of understanding the problems and situations that create a research problem.

The current situation and necessity of universities in Thailand are that most students are prone to depression [15]. The concern of many universities for students' depressive tendencies has therefore formulated policies and strategies for tackling depression that requires the authors to do research that would contribute to the health and wellbeing of the nation's future generation. The key goal of this research is to develop a model for predicting the university students' chances of getting into a state of depression. The researchers gathered the problems and found solutions in this study.

B. Data Understanding

Data Understanding phase is to understand the data, understand the nature of the data. The researchers discovered that university students are young people who are growing up and being heavily engaged with the many social media applications in the digital world. Numerous studies have identified problems with technology addiction, ADHD: Attention Deficit Hyperactivity Disorder, and decreased learning efforts [16]-[18]. For this reason, the research aimed at collecting the university students' inputs by using an online questionnaire to collect the data.

The data collection was consistent with the Thai Version of The Patient Health Questionnaire for Adolescents: PHQ-A Questionnaire. It is a self-assessment form consisting of 9 items for symptoms occurring during at least 2 weeks. Each item has four levels: 0 means has never happened to the respondents at all, 1 means it has happened to the respondents sometimes, 2 means it has happened to the respondents at a large level or a good part of time, and 3 means it has happened to the respondents most of the time. After the respondents complete the questionnaire, the scores in each item will be taken to calculate the total result with interpretation as follows: The total score is between 0-4 means no depression or minimal depression, 5-9 means mild depression, 10-14 means moderate depression, 15-19 means moderately severe depression, and 20-27 means severe depression.

C. Data Preparation

Data Preparation phase is the process of preparing and converting data into a format that is ready for model analysis. Data is gathered from the online questionnaire that the university students answered.

The population of this research was youth in the Mueang District of Maha Sarakham Province. The samples in this research were obtained from 1,413 representatives from secondary schools and Rajabhat Maha Sarakham University. These samples were targeted from nine faculties at the Rajabhat Maha Sarakham University and one school: Faculty of Agricultural Technology (AGT), Faculty of Education (EDU), Faculty of Engineering (ENG), Faculty of Humanities and Social Sciences (HUSO), Faculty of Information Technology (IT), Faculty of Law, Faculty of Management Science (FMS), Faculty of Political Science and Public Administration (PSPA), Faculty of Science and Technology (SCI), and Phadungnaree School.

TABLE I. Data Collection

No.	Affiliation	Gender		Total:
		Female	Male	
Rajabhat Maha Sarakham University				
1.	AGT	11 (11.70%)	83 (88.30%)	94 (6.65%)
2.	EDU	92 (37.70%)	152 (62.30%)	244 (17.27%)
3.	ENG	11 (21.15%)	41 (78.85%)	52 (3.68%)
4.	HUSO	25 (32.89%)	51 (67.11%)	76 (5.38%)
5.	IT	37 (36.27%)	65 (63.73%)	102 (7.22%)
6.	LAW	18 (9.38%)	174 (90.63%)	192 (13.59%)
7.	FMS	52 (16.30%)	267 (83.70%)	319 (22.58%)
8.	PSPA	3 (11.54%)	23 (88.46%)	26 (1.84%)
9.	SCI	45 (38.14%)	73 (61.86%)	118 (8.35%)
Phadungnaree School				
10.	High School	142 (74.74%)	48 (25.26%)	190 (13.45%)
	Total:	436 (30.86%)	977 (69.14%)	1,413 (100%)

Table I shows the data collection. It was found that the Faculty of Management Science (FMS) had the highest number of respondents, with 319 samples (22.58%). The second was the Faculty of Education (EDU), with 244 samples (17.27%). The third was the Faculty of Law, with 192 samples (13.59%). The total data collected was 1,413 samples from 9 faculties and 1 school. In addition, the majority of respondents were 977 males (69.14%), while 436 female respondents (30.86%).

TABLE II. DATA COLLECTION CLASSIFED BY AGE

No.	Affiliation	Age					
		18	19	20	21	22	23
Rajabhat Maha Sarakham University							
1.	AGT	3	7	37	33	7	7
2.	EDU	14	120	39	43	21	7
3.	ENG	0	9	18	12	10	3
4.	HUSO	2	4	10	11	13	36
5.	IT	4	12	19	42	20	5
6.	LAW	0	1	26	64	95	6
7.	FMS	3	152	50	92	18	4
8.	PSPA	0	2	7	5	11	1
9.	SCI	4	32	45	24	10	3
Phadungnaree School							
10.	High School	186	2	1	1	0	0
	Total:	216	348	278	329	202	40

From Table II, the data collected revealed that most of the 348 respondents (24.63%) were 19 years of age. The second was 329 respondents (23.28%) aged 21 years. The second was 278 respondents (19.67%) aged 20 years.

D. Modeling

Modeling phase is the process of taking the collected data, selecting the data, and converting the data into a ready-to-analytical form for analysis to create a model [10].

The tools used to develop the model were selected data mining techniques using machine learning with supervised learning type. It consists of three techniques: decision tree [8], naïve bayes, and artificial neural networks [19] techniques . The results of the development of the three models are summarized and discussed in the following sections.

E. Evaluation

Evaluation phase is the process of analyzing the model that has been constructed to determine the model's performance. The tools and techniques used to analyze model performance consist of two parts. The first part is used to divide the data in the test model, it is known as cross-validation methods. The second part is used to analyze test results, it is known as confusion matrix performance. It contains of accuracy, precision, and recall.

F. Deployment

Deployment phase is the last step of the CRISP-DM cycle. It is responsible for implementing an appropriate and efficient model for further development. In this section, the researchers plan to develop mobile applications by taking the most suitable model for further development.

III. RESEARCH FINDINGS

The research findings consisted of two parts: (1) reporting on the depression risk analysis, and (2) reporting on the development of models for each technique.

A. Depression Risk Analysis

A total of 1,413 samples were collected for depressive risk analysis, as summarized in Table I and Table II. It can summarize the analysis results as shown in the Table III.

TABLE III. DEPRESSION RISK ANALYSIS

No	Affiliation	Depression Risk			
		Normal	Mild	Moderate	Severe
Rajabhat Maha Sarakham University					
1.	AGT	78 (82.98%)	13 (13.83%)	3 (3.19%)	0 (0.00%)
2.	EDU	211 (86.48%)	24 (9.84%)	7 (2.87%)	2 (0.82%)
3.	ENG	39 (75.00%)	8 (15.38%)	5 (9.62%)	0 (0.00%)
4.	HUSO	49 (64.47%)	21 (27.63%)	6 (7.89%)	0 (0.00%)
5.	IT	42 (41.18%)	52 (50.98%)	7 (6.86%)	1 (0.98%)
6.	LAW	145 (75.52%)	37 (19.27%)	9 (4.69%)	1 (0.52%)
7.	FMS	292 (91.54%)	22 (6.90%)	5 (1.57%)	0 (0.00%)
8.	PSPA	23 (88.46%)	2 (7.69%)	1 (3.85%)	0 (0.00%)
9.	SCI	78 (66.10%)	34 (28.81%)	6 (5.08%)	0 (0.00%)
Phadungnaree School					
10.	High School	102 (53.68%)	47 (24.74%)	30 (15.79%)	11 (5.79%)
	Total:	1,059 (74.95%)	260 (18.40%)	78 (5.52%)	16 (1.13%)

Table III shows the data collection classified by depression risk analysis. It was found that the majority of respondents were at a normal risk in 1,059 samples (74.95%). However, there are still three instances of risk that need to be monitored: The first level was the normal level with 260 samples (18.40%). The second level was the mild level with 78 samples (5.52%). The third level was the severe level with 16 samples (1.13%). The data in this section were analyzed to predict depression risk models.

B. Model Development Results

The purpose of this section is to present a comparison of the three techniques used to compare and select models with the highest accuracy. The results of the model development of each technique are as follows.

1) Decision tree classification model

This section reports the analysis with the decision tree technique. It categorizes analytical methods according to the Cross-validation principle which consists of 10-Fold Cross-validation, 50-Fold Cross-validation, 100-Fold Cross-validation, and leave-one-out Cross-validation as detailed the model analysis as shown in Table IV and Table V.

TABLE IV. DECISION TREE ANALYSIS

Decision Tree Level	Cross-Validation Methods (k-Fold)			
	10-Fold	50-Fold	100-Fold	Leave-one-out
2	86.20%	86.19%	86.20%	86.20%
3	87.12%	87.97%	88.11%	88.18%
4	89.03%	88.25%	88.74%	88.75%
5	90.73%	90.44%	90.79%	90.66%
6	92.15%	91.50%	91.36%	91.15%
7	92.78%	91.86%	91.69%	91.51%
8	93.21%	93.75%	93.34%	92.92%
9	94.27%	94.34%	94.45%	94.34%
10	94.27%	94.91%	94.40%	94.20%
11	94.76%	94.77%	94.60%	94.13%
12	94.55%	95.05%	94.96%	94.83%
13	94.13%	94.89%	95.03%	94.83%
14	94.34%	94.83%	95.04%	94.83%
15	94.48%	95.05%	94.61%	94.83%
16	94.98%	94.47%	94.84%	94.83%
17	94.48%	94.89%	94.50%	94.83%
18	94.27%	94.69%	95.06%	94.83%
19	94.69%	94.62%	95.04%	94.83%
20*	95.05%	95.33%*	94.99%	94.83%

Table IV shows the analysis with the decision tree technique. It shows 19 decision tree models with different levels of model depth. It can be seen that models with increased depth have increased accuracy, where the decision tree model with the highest accuracy is the decision tree model with a depth of 20. It has an accuracy of 95.53%. Therefore, this model was selected for comparison with other data mining analysis techniques. The details of testing this model with the confusion matrix are shown in Table V.

TABLE V. DECISION TREE ANALYSIS

Accuracy: 95.53%	True Moderate	True Severe	True Mild	True Normal	Class Precision
Pred. Moderate	62	5	10	0	80.52%
Pred. Severe	4	11	0	0	73.33%
Pred. Mild	12	0	231	13	90.23%
Pred. Normal	0	0	19	1046	98.22%
Class Recall	79.49%	68.75%	88.85%	98.77%	

2) Naive bayes classification model

This section reports the analysis with the naive bayes technique. It has detailed model analysis in Table VI and Table VII.

TABLE VI. NAÏVE BAYES ANALYSIS

Cross-Validation Methods (k-Fold)			
10-Fold	50-Fold	100-Fold	Leave-one-out
88.82%	88.53%	88.39	88.54*

Table VI shows the analysis with the naïve bayes technique. The results showed that the most effective naive bayes model was the model with leave-one-out Cross-validation. It has an accuracy of 88.54%. The details of testing this model with the confusion matrix are shown in Table VII.

TABLE VII. NAIVE BAYES ANALYSIS

Accuracy: 88.54%	True Moderate	True Severe	True Mild	True Normal	Class Precision
Pred. Moderate	77	3	36	0	66.38%
Pred. Severe	1	13	0	0	92.86%
Pred. Mild	0	0	224	122	64.74%
Pred. Normal	0	0	0	937	100.00%
Class Recall	98.72%	81.25%	86.15%	88.48%	

3) Artificial neural networks model

This section reports the analysis with the artificial neural networks technique. It has detailed the model analysis in Table VIII and Table IX.

TABLE VIII. ARTIFICIAL NEURAL NETWORKS ANALYSIS

Cross-Validation Methods (k-Fold)			
10-Fold	50-Fold	100-Fold	Leave-one-out
97.88%*	96.16%	97.44%	97.10%

Table VIII shows the analysis with the artificial neural networks technique. The results showed that the most effective artificial neural networks model was the model with 10-Fold Cross-validation. It has an accuracy of 97.88%. The details of testing this model with the confusion matrix are shown in Table IX.

TABLE IX. ARTIFICIAL NEURAL NETWORKS ANALYSIS

Accuracy: 97.88%	True Moderate	True Severe	True Mild	True Normal	Class Precision
Pred. Moderate	62	10	0	0	86.11 %
Pred. Severe	0	2	0	0	100%
Pred. Mild	16	4	260	0	92.86 %
Pred. Normal	0	0	0	1059	100%
Class Recall	79.49%	12.50%	100%	100%	

At the end of this section, here is a report on the results of a youth depression risk prediction model analysis report. There are three techniques comprising the decision tree technique, the naïve bayes technique, and the artificial neural networks techniques. The results of these three techniques will be discussed for further discussion in the research discussion section.

IV. RESEARCH DISCUSSIONS

There are two perspectives to discuss on with regards to the findings: data collection discussion, and discussion of model development results.

A. Data Collection Discussion

The target population in this research was youth in Muang District, Maha Sarakham Province. The researchers were able to collect 1,413 samples from one university and one secondary school as shown in Table I and Table II.

In addition, the results of the depression assessment using the DASS-21 questionnaire found that the majority of respondents had no depression symptoms during the COVID-19 pandemic as concluded in Table III.

Please note that there is still information that needs to be monitored and tracked. It is the number of respondents who are at risk for depression as classified into three parts: mild level with 260 samples (18.40%), moderate level with 78 samples (5.52%), and severe level with 16 samples (1.13%). With this caution, the researchers have developed a model to select the most efficient model and develop it into future applications.

B. Discussion of Model Development Results

There are three analytical techniques for developing a prototype model: decision tree technique, naïve bayes technique, and artificial neural networks techniques. Where the results of each technique are shown in Table IV to Table IX. The results of model development and model performance testing with cross-validation principle and confusion matrix techniques of all three techniques revealed that the prototype model from artificial neural networks techniques has the highest accuracy. It has an accuracy value of 97.88% as detailed in Table IX. whereas the second efficient model is from the decision tree technique, with an accuracy value of 95.53% as detailed in Table V. The last efficient model is from the naïve bayes technique, with an accuracy value of 88.54% as detailed in Table VII.

The impact of the COVID-19 epidemic can manifest itself in many dimensions. Depression in youth as a result of the COVID-19 epidemic has been covered in several studies [6], [10], [16], [17]. The huge urgency and importance of youth prevention planning are immense, so this research aims to develop a model for predicting the likelihood of youth impacted by the COVID-19 pandemic. It was successful researchers were able to develop models with data mining techniques and artificial intelligence technologies as reported above. Finally, in order to expand the research findings and put their results for public benefit, researchers are committed to developing applications to support and plan youth prevention for moderately and severe depression with the expectation that it will continue to benefit humanity.

V. Conclusion

This paper was aimed (1) to study the risk situation of youth' depression in Thailand, and (2) to develop a model for predicting depression among youth in Thailand. The results showed that the majority of the respondents had no depression problems with 1,059 samples (74.95%) as detailed in Table IV. However, there are still three risk groups that need to be monitored: mild level with 260 samples (18.40%) moderate level with 78 samples (5.52%), and severe level with 16 samples (1.13%).

The data used in the research were 1,413 samples from nine faculties at the Rajabhat Maha Sarakham University, and one Phadungnaree school as detailed in Table I. The research tools and procedures were applied with the data mining principles to analyze and develop prototype models. It includes decision tree technique, naïve bayes technique, and artificial neural networks techniques. Whereas the best predictive prototype model has a high level of accuracy 97.88%, with artificial neural networks technique. Other results of the three-part model performance analysis are presented in Tables IV to Table IX.

The results of the research can be concluded to attest that it qualifies to be further developed into an application, in which the researchers intend to develop in the future.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Wongpanya Sararat Nuankaew conducted the research by defining research frameworks, designing research methodology, analyzing, modeling, and writing the paper. Patchara Nasa-ngium, and Prem Enkvetchakul conducted the research by collecting data and preparing the data for modeling. Pratya Nuankaew conducted the research by editing the paper, reviewing models, and discussing the findings. All authors had approved the final version.

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