ANALYSIS OF DEPRESSION IN COLLEGE STUDENT DURING COVID-19 PANDEMIC USING EXTREAM GRADIENT BOOST

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Abstract—*The Covid-19 pandemic that spreads in Indonesia causes health, economic, and social problems in the community, including mental health. Of course, this mental health problem also hit students. Seeing these conditions, we conducted research on students of the Faculty of Computer Science, University of Singaperbangsa Karawang using the Patient Health Questionnaire-9 which measures a person's level of depression. In this study, we used Extreme Gradient Boost or XGBoost to classify students' depression tendencies. We break down the dataset into training data and testing data with 4 data sharing combinations, they are 80 : 20, 50 : 50, 90 : 10, 70 : 30. The combination of 90 : 10 data sharing has the best performance with accuracy, precision, recall, and F1-scores respectively 92.86%, 94.29%, 92.86% , and 92.06%. This method also has better performance than K-Nearest Neighbor, Random Forest, Multi Layer Perception, Support Vector Machine and Decision Tree .*

Keywords—*Depression, PHQ-9, XGBoost*

Intisari—Pandemi Covid-19 yang terjadi di Indonesia menyebabkan permasalahan kesehatan, ekonomi, dan sosial yang ada di masyarakat, termasuk kesehatan jiwa. Tentu saja permasalahan kesehatan jiwa ini juga melanda mahasiswa. Melihat kondisi tersebut kami melakukan penelitian kepada mahasiswa Fakultas Ilmu Komputer Universitas Singaperbangsa Karawang menggunakan kuesioner *Patient Health Questionnaire*-9 yang mengukur tingkat depresi seseorang. Pada penelitian ini menggunakan *Extream Gradient Boost* atau XGBoost untuk melakukan klasifikasi kecenderungan depresi pada mahasiswa. Penulis memecah dataset menjadi data latih dan data test dengan 4 kombinasi pembagian data, yaitu 80 : 20, 50 : 50, 90 : 10, 70 : 30. Kombinasi pembagian data 90 : 10 memiliki performa yang paling baik dengan *accuracy*, *precission*, *recall*, dan *F1-score* masing-masing 92.86%, 94.29%, 92.86%, dan 92.06%. Metode ini juga memiliki performa lebih baik dibanding dengan *K-Nearest Neighbor, Random Forest*, *Multi Layer Perception*, *Support Vector Machine* dan *Decision Tree.*

Kata Kunci*:* Depresi, PHQ-9, XGBoost.

INTRODUCTION

The spread of Covid-19 in Indonesia as of August 25, 2021, shows that 257,677 positive cases have been confirmed, 3,639,867 cases have recovered and 129,293 people have died (Satuan Tugas Penanganan Covid-19, 2021). The growth of Covid-19 cases, which creates anxiety about when this pandemic will end, has a negative impact on the community. The impact of the Covid-19 pandemic includes health, economic, and social problems in the community, including mental health (Lempang et al., 2021).

Based on survey data regarding Psychological Problems in the Covid-19 Pandemic Era to self-check users from Perhimpunan Dokter Spesialis Kedokteran Jiwa Indonesia (Perhimpunan Dokter Spesialis Kedokteran Jiwa Indonesia, 2020), 68% experienced anxiety problems, 67% experienced depression and 77% experienced psychological trauma. In one study it was explained that people aged 18-29 were more susceptible to anxiety due to COVID-19 than other age groups. (Indra et al., 2020). In another study, 21.1% of 147 students had mild depression, 17% moderate depression and 3.4% had severe depression (Hasanah et al., 2020).

Seeing these conditions, we conducted research on students of the Faculty of Computer Science, University of Singaperbangsa Karawang to find out if they had problems related to mental health by providing a Patient Health Questionnaire-9 survey that measured a person's level of depression. Depression is a feeling disorder that is common to everyone. According to WHO data in 2018 the number of people with depression ranged from 300 million people (Kusuma et al., 2021).

The Patient Health Questionnaire-9 is a nine-point questionnaire that helps in early diagnosis of depression and helps in selecting and monitoring

treatment. The advantages of using PHQ-9 are that it can be done quickly, has good psychometric properties, can be given repeatedly, the results will show improvement or worsening of depression during the treatment period (P. D. Kusuma et al., 2018). In addition, in one study, the results of the PHQ-9 survey on 235 ITEKES Bali Nursing Students showed 45.5% had mild depression, 1.7% had severe depression and 29.4% did not experience depression (Kusuma et al., 2021).

In a study that analyzed several machine learning algorithms including Random Forest, Naive Bayes, Support Vector Machine, K-Nearest Neighbors to detect mental stress in students from Jaypee Institute of Information Technology with 206 data (Ahuja & Banga, 2019). The algorithm with the best accuracy is the Support Vector Machine with 85.71%. Then in another study that aims to analyze whether a person is depressed or not with a machine learning approach (Kumawat et al., n.d.). machine learning algorithms used include XGBoost Tree, Random Trees, Neural Network, SVM, Random Forest, C5.0, and BayNet. From these results, it is evident that the C5.0 classifier provides the highest accuracy with 83.94% and for each classifier, the results are derived based on no pre-processing.

To support this research, we use the XGBoost algorithm to model the data we have with the help of the Python programming language. XGBoost is a technique or method of data modeling to solve regression and classification problems based on the Gradient Boosting Decision Tree efficiently and operate in parallel (Karo, 2020). In research, the classification of breast tumor types using the Extreme Gradient Boost algorithm has an accuracy rate of 97.60% to 97.80% (Handayani et al., 2017).

MATERIALS AND METHOD

The research methodology used is Knowledge Discovery in Database (KDD) which has 5 stages, namely Data Selection, Preprocessing, Transformation, Data Mining, and Evaluation (Gullo, 2015). The flow of the research carried out is as shown in Figure 1.

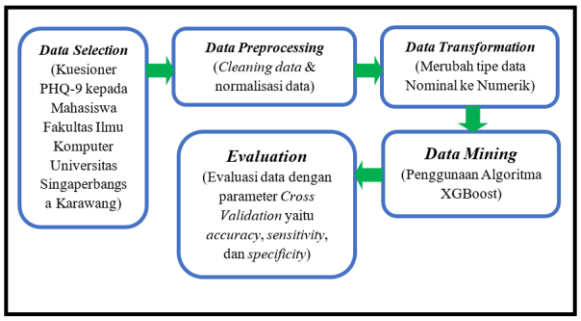

Figure 1. Research Flow

Data Selection

Based on data from Pangkalan Data Pendidikan Tinggi (Kemdikbud, 2021) the number of students at the Faculty of Computer Science, Singaperbangsa Karawang University is 1272. This data will be used to measure the number of samples to be used. The method of determining the sample in this study uses Simple Random Sampling. This method takes a random sample from the population regardless of the strata in the population and is commonly used in similar or homogeneous populations (Arieska & Herdiani, 2018). To determine the number of samples in this study, the author uses the Slovin formula with a population size of N = 1272 and an estimator error of d = 8%, so the number of samples is 140. The following is the Slovin formula:

$$n = \frac{n}{N.d^2+1} \quad \text{.....(1)}$$

Description :
n = sample size
N = population size
d = forecast error (tolerable error rate)

The dataset used by the study was obtained through a questionnaire based on PHQ-9 to students of the Faculty of Computers Sciences Unsika. The data that have been collected are 140 data with 9 questions as shown in table 1 while in table 2 are the types of depression tendencies which will be used as the target class.

Table 1. PHQ-9 Questions

No	Variable	Descriptions
1	X1	Lack of interest or enthusiasm in doing anything
2	X2	Feeling down, sad, or hopeless
3	X3	Difficulty sleeping / waking up easily, or sleeping too much
4	X4	Feeling tired or lacking energy
5	X5	Lack of appetite or eating too much
6	X6	Lack of confidence or feel that you are a failure or have let yourself or your family down
7	X7	Difficulty concentrating on something, for example reading the newspaper or watching television
8	X8	Move or speak so slowly that others notice them. Or vice versa; feeling restless or restless so that you move more often than usual.
9	X9	Feeling better off dead or wanting to hurt yourself in any way.

Source: (Prabowo, et al, 2021)

Table 2. Depression Tendency Class

No	Class	Type of Depressive Tendency
1	0	Symptoms of mild depression
2	1	Mild depression
3	2	Moderate depression
4	3	Severe depression

Source: (Prabowo, et al, 2021)

Data Validity Test

The validity test is useful to determine the suitability of the questionnaire in measuring and obtaining research data from the respondents. Validity is a measurement to prove the accuracy of research tools/instruments in measuring what you want to measure in research (Budiastuti & Bandur, 2018). The level of suitability of the data was assessed using the significance value. A data can be said to be valid if it obtains a significance value < 0.05. Tests were carried out using SPSS software using Bivariate Pearson correlation (Pearson Moment Product).

Correlations

		X01	X02	X03	X04	X05	X06	X07	X08	X09	Total
X01	Pearson Correlation	1	.616**	.464**	.548**	.275**	.424**	.393**	.295**	.327**	.678**
	Sig. (2-tailed)		<,001	<,001	<,001	,001	<,001	<,001	<,001	<,001	<,001
	N	140	140	140	140	140	140	140	140	140	140
X02	Pearson Correlation	.616**	1	.459**	.636**	.448**	.593**	.450**	.418**	.435**	.800**
	Sig. (2-tailed)	<,001		<,001	<,001	<,001	<,001	<,001	<,001	<,001	<,001
	N	140	140	140	140	140	140	140	140	140	140
X03	Pearson Correlation	.464**	.459**	1	.604**	.476**	.386**	.343**	.250**	.341**	.712**
	Sig. (2-tailed)	<,001	<,001		<,001	<,001	<,001	<,001	,003	<,001	<,001
	N	140	140	140	140	140	140	140	140	140	140
X04	Pearson Correlation	.548**	.636**	.604**	1	.426**	.492**	.392**	.349**	.361**	.773**
	Sig. (2-tailed)	<,001	<,001	<,001		<,001	<,001	<,001	<,001	<,001	<,001
	N	140	140	140	140	140	140	140	140	140	140
X05	Pearson Correlation	.275**	.448**	.476**	.426**	1	.474**	.371**	.363**	.312**	.687**
	Sig. (2-tailed)	,001	<,001	<,001	<,001		<,001	<,001	<,001	<,001	<,001
	N	140	140	140	140	140	140	140	140	140	140
X06	Pearson Correlation	.424**	.593**	.386**	.492**	.474**	1	.428**	.358**	.385**	.739**
	Sig. (2-tailed)	<,001	<,001	<,001	<,001	<,001		<,001	<,001	<,001	<,001
	N	140	140	140	140	140	140	140	140	140	140
X07	Pearson Correlation	.393**	.450**	.343**	.392**	.371**	.428**	1	.387**	.271**	.648**
	Sig. (2-tailed)	<,001	<,001	<,001	<,001	<,001	<,001		<,001	,001	<,001
	N	140	140	140	140	140	140	140	140	140	140
X08	Pearson Correlation	.295**	.418**	.250**	.349**	.363**	.358**	.387**	1	.357**	.588**
	Sig. (2-tailed)	<,001	<,001	,003	<,001	<,001	<,001	<,001		<,001	<,001
	N	140	140	140	140	140	140	140	140	140	140
X09	Pearson Correlation	.327**	.435**	.341**	.361**	.312**	.385**	.271**	.357**	1	.595**
	Sig. (2-tailed)	<,001	<,001	<,001	<,001	<,001	<,001	,001	<,001		<,001
	N	140	140	140	140	140	140	140	140	140	140
Total	Pearson Correlation	.678**	.800**	.712**	.773**	.687**	.739**	.648**	.588**	.595**	1
	Sig. (2-tailed)	<,001	<,001	<,001	<,001	<,001	<,001	<,001	<,001	<,001	
	N	140	140	140	140	140	140	140	140	140	140

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 2. Validation Test Result

It can be seen from Figure 2, all the numbers show numbers below 0.05, then the data is valid and feasible to use.

Cronbach Alpha Reliability Test

Test Reliability or reliability is the consistency of a series of measurements made for research. Reliability is a benchmark for data to determine whether the data is relevant if it is done repeatedly. Reliability is essentially a tool to measure a questionnaire which is an indicator of a variable or construct (Ghozali, 2013).

Case Processing Summary

		N	%
Cases	Valid	140	100.0
	Excluded[a]	0	.0
	Total	140	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.861	9

Figure 3. Reliability Test Result

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
X01	8.7214	27.368	.596	.847
X02	8.8929	25.909	.740	.834
X03	8.2143	25.076	.599	.846
X04	8.6214	25.230	.692	.836
X05	8.7714	25.516	.569	.849
X06	8.6500	24.833	.635	.842
X07	8.9786	26.654	.537	.851
X08	9.3571	28.015	.487	.855
X09	9.5071	27.734	.489	.855

Figure 4. Overall Statistic Result

In Figure 3 shows the value of Cronbach's Alpha = 0.861, it can be said that the data is reliable. Then for details in Figure 4, the data sample with the lowest reliability is in the X02 sample with 0.834. The factors that influence the level of validity and reliability of a measuring instrument other than the instrument are the user of the measuring instrument who takes the measurement and the subject being measured (Sugiyono, 2014). The results of this reliability measurement can be used as a benchmark in the future if you want to conduct a similar research basis.

Data Preprocessing

In data mining research, the process of data collection and pre-processing of data consumes most of the energy required for research. There are even some studies that say that 80% of data mining is data collection and pre-processing of data (Karo, 2016).

Pre-processing on the data is carried out to overcome conditions that are not ideal in the dataset such as the custom of missing data or scaling on data that is not the same. Pre-processing on the dataset is done by equalizing the existing scale in the dataset. This can be done by normalizing the

data. Data normalization is done to standardize the data in the dataset, so that every value in the dataset variable has the same scale. This study uses the z-score normalization method, with the following equation:

$$Z = \frac{x - \mu}{\sigma} \quad \text{.....(2)}$$

Description:
Z = normalized value
x = amount of data
μ = average value
σ = standard deviation

Data Transformation

At this stage the categorical data in the form of answers from respondents is converted into numerical data as can be seen in table 3. In each question the respondents choose one of the 4 available options, namely: Never symbolized 0, Several days is symbolized 1, More than half The time in question is denoted 2, and Every day is symbolized 3. Then an example of a dataset that has been transformed can be seen in table 4.

Table 3. Questionnaire Rating

No	Value	Description
1	0	Never
2	1	A few days
3	2	More than half the time in question
4	3	Every day

Source: (Prabowo, et al, 2021)

Table 4. Example of Transformation Result

X1	X2	X3	X4	X5	X6	X7	X8	X9	Class
1	1	1	1	1	1	1	1	0	0
1	1	3	1	1	1	1	0	1	1
1	0	1	0	0	0	1	0	0	0
2	1	3	1	2	3	0	0	3	2
1	1	2	2	2	2	0	0	0	1
1	1	2	1	1	1	1	1	0	0
1	1	1	1	0	0	0	0	0	0
1	2	3	3	3	1	2	1	3	2
1	1	2	1	2	1	0	0	0	0
1	1	0	1	0	0	2	0	0	0

Source: (Prabowo, et al, 2021)

Data Mining

After normalizing the dataset, the dataset already has a value with the same scale. The next step is to break the data into two parts, namely the training data used to build the classification model and the test data used to test the model obtained from the training data. In this study, we tried to divide the data with several combinations. The first combination is 80% training data and 20% test data. The second combination is 50% training data and 50% test data, the third combination is 90% training data and 10% test data, the fourth combination is 70% training data and 30% test data. The classification modeling process in this study was carried out using the Extreme Gradient Boost (XGBoost) method.

Extreme Gradient Boost is a classification algorithm that is enhanced by gradient boosting decision trees and can also build boosted trees efficiently and operate in parallel (Chen, 2016). XGBoost is part of a family of trees (Decision tree, Random Forest, bagging, boosting, gradient boosting). XGBoost is an ensemble method with the aim of reducing bias as well as variance. In the interior of the regression tree, inside nodes represent values for the test attribute and leaf nodes represent decisions. The prediction result is the number of scores predicted by the tree (Cherif, 2019).

$$\hat{y}l = \sum_k^K f_k(x_i), f_k \, \mathcal{E} \, F \quad \text{.....(3)}$$

$$obj(\theta) = \sum_{i=1}^n l\left(y_i, \hat{y}l\right) + \sum_k^K \Omega\left(f_k\right) \quad \text{.....(4)}$$

Where a is $\sum_{i=1}^n l\left(y_i, \hat{y}l\right)$ differentiable loss function to measure whether the model is suitable for the training data set and $\sum_k^K \Omega\left(f_k\right)$ is an item that determines the complexity of the model. As the complexity of the model increases the corresponding score is reduced.

Evaluation

The model that has been made of course must be checked with several parameters to determine the quality of the model in classifying according to the truth. Accuracy alone is not enough to validate a classification model (Karo, 2020), so that other parameters are needed to validate the model. In this study, the authors use the accuracy, Precision, Recall, and F1-Score values to be included in the confusion matrix. TP is the class that is recorded as true and the model results are correct. FN is a class that is recorded as correct, but the model predicts wrongly, FP is a class in the data incorrectly, while the model results predict correctly and TN is a wrong class and the model also predicts incorrectly as shown in table 5.

Table 5. Model Validation

Class	Class 1 (Prediction)	Class 2 (Prediction)
Class 1 (Actual)	TP (True Positive)	FN (False Negative)
Class 2 (Actual)	FP (False Positive)	TN (True Negative)

Source: (Prabowo, et al, 2021)

Accuracy is the ratio of 'True' (positive and negative) predictions to the overall data. Accuracy in answering the question "What percentage of depression categories are correctly predicted and not depressed from the overall trend of depression

data", Precision is the ratio of positive correct predictions compared to the overall positive predicted results. Precision answers the question "What percentage of students have a tendency to be depressed out of all students who are predicted to have a tendency to depression". Recall/Sensitivity is a ratio of correctly positive predictions compared to the overall data that are correctly positive (Martin & Nilawati, 2019). Recall answers the question "What percentage of students are predicted to have a tendency to depression from all students who actually have a tendency to depression". and F1 score is a compares weighted mean precision and recall. The parameters used for model evaluation can be seen in the following equation.

$$accuracy(y, \hat{y}) = \frac{1}{n_{sample}} \sum_{i=0}^{n_{sample}-1} 1(\hat{y}i = y_i) \quad (5)$$

$$precission = \frac{tp}{tp+fp} \quad (6)$$

$$recall = \frac{tp}{tp+fn} \quad (7)$$

$$F_\beta = (1 = \beta^2) \frac{precission\ x\ recall}{\beta^2 precission+recall} \quad (8)$$

RESULT AND DISCUSSIONS

XGBoost

The trend of depression dataset using the PHQ-9 questionnaire used in this study has 9 variables. As an initial reference, the authors divide the dataset into 80% training data and 20% test data to be tested using the XGBoost classification method. Next, the writer will divide the dataset with other combinations and also compare it with other classification methods to choose the best data combination and classification method to be tested with 4 parameters, namely accuracy, precision, recall/sensitivity, and F1-score. The results are as shown in table 6.

Table 6. Evaluation Result of XGBoost (80 : 20)

Method	Accuracy	Precision	Recall	F1-Score
XGBoost	83,33	85,92	83,33	83,02

Source: (Prabowo, et al, 2021)

This information is then continued by measuring the model using a confusion matrix with 3 parameters, namely precision, recall, and F1-score for each class. Then we get the results listed in table 7.

Table 7. Confussion Matrix (80 : 20)

Validation Method	Class	Value (%)
Precission	Class 0	91
	Class 1	75
	Class 2	100
	Class 3	50
Recall	Class 0	95
	Class 1	75
	Class 2	50
	Class 3	100
F1-Score	Class 0	93
	Class 1	75
	Class 2	67
	Class 3	67

Source: (Prabowo, et al, 2021)

Based on the evaluation of the model, it shows that the model does not yet have accurate results, then the author tries to use other combinations of data sharing, namely the distribution of 50% training data and 50% test data, then 90% training data and 10% test data, and the last is a combination distribution. 70% training data and 30% test data. From the data sharing experiment, the results are shown in table 8 and table 9.

Table 8. Evaluation Result of XGBoost

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Data Split(%)
XGBoost	75,71	77,65	75,71	76,09	50 : 50
XGBoost	92,86	94,29	92,86	92,06	90 : 10
XGBoost	83,33	85,92	83,33	83,02	70 : 30

Source: (Prabowo, et al, 2021)

Table 9. Confussion Matrix

Data Split(%)	Validation Method	Class	Value (%)
50 : 50	Precission	Class 0	94
		Class 1	58
		Class 2	50
		Class 3	100
	Recall	Class 0	86
		Class 1	75
		Class 2	40
		Class 3	75
	F1-Score	Class 0	90
		Class 1	65
		Class 2	44
		Class 3	86
90 : 10	Precission	Class 0	100
		Class 1	80
		Class 2	100
		Class 3	100
	Recall	Class 0	100
		Class 1	100
		Class 2	50
		Class 3	100
	F1-Score	Class 0	100
		Class 1	89
		Class 2	67
		Class 3	100
70 : 30	Precission	Class 0	91
		Class 1	75

		Class 2	100
		Class 3	50
	Recall	Class 0	95
		Class 1	75
		Class 2	50
		Class 3	100
	F1-Score	Class 0	93
		Class 1	75
		Class 2	67
		Class 3	67

Source: (Prabowo, et al, 2021)

Based on the results of the evaluation of the model from the 4 combinations of data sharing that have been carried out. Then it can be seen in table 8 that the combination of data sharing with 90% training data and 10% test data has the best model evaluation results compared to other data sharing combinations with 92.86% accuracy, 94.29% precision, 92.86% recall/sensitivity and F1- score 92.06%.

In the next step, the writer predicts the class on the test data which amounts to 10% using the model with the best performance, namely the model with a combination of training data and test data of 90: 10 each. Then the results are as shown in table 10.

Table 10. Prediction Result

Index	Actual Class	Prediction Class
4	1	1
11	0	0
99	0	0
75	2	2
1	1	1
129	0	0
109	0	0
134	0	0
80	3	3
72	0	0
82	2	1
24	1	1
28	0	0
125	1	1

Source: (Prabowo, et al, 2021)

In table 10 it can be seen that the model managed to predict almost all classes correctly except for data 82, the model incorrectly predicted the actual class that should be 2 but the XGBoost model made predicts the class in data 82, namely 1. The XGBoost model that was made was able to become a tool in conduct early diagnosis and screening of students who have a tendency to depression. However, development is needed in the future to get better performance on the XGBoost Model made.

The next step is to create a visualization on the XGBoost model with the best performance. Because XGBoost is part of a tree family (Decision tree, Random Forest, bagging, boosting, gradient boosting), the final XGBoost result is visualized in the form of a tree, as shown in Figure 5.

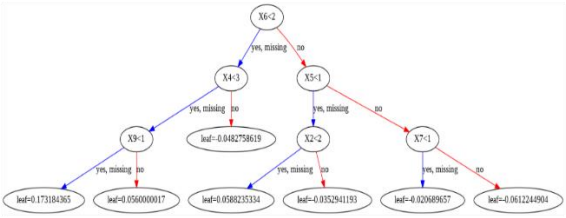

Figure 5. XGBoost Tree

Comparison with Other Algorithms

In this section, the author also performs a performance comparison with several other classification models. The algorithm used by the author to compare is K-Nearest Neighbor, Random Forest, Multi Layer Perception, Support Vector Machine and Decision Tree. Then the author also conducted several tests with the 4 combinations of data sharing described previously. The results of the model evaluation are described in table 11.

Table 11. Algorithm Comparison Result

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Data Split (%)
KNN	76,19	78,32	76,19	73,32	80 : 20
SVM	88,10	89,04	88,10	87,25	
Random Forest	85,71	86,23	85,71	84,99	
XGBoost	83,33	85,92	83,33	83,02	
Multi Layer Percepton	88,10	89,04	88,10	87,25	
Decission Tree	83,33	83,33	83,33	81,99	
KNN	77,14	76,37	77,14	75,32	50 : 50
SVM	80,00	80,30	80,00	79,64	
Random Forest	82,86	83,84	82,86	82,70	
XGBoost	75,71	77,65	75,71	76,09	
Multi Layer Percepton	85,71	88,60	85,71	84,86	
Decission Tree	78,57	78,98	78,57	78,61	
KNN	64,29	52,86	78,57	55,46	90 : 10
SVM	85,71	86,61	85,71	84,76	
Random Forest	85,71	86,61	85,71	84,76	
XGBoost	92,86	94,29	92,86	92,06	
Multi Layer Percepton	85,71	86,61	85,71	84,76	
Decission Tree	85,71	86,61	85,71	84,76	
KNN	76,19	78,32	76,19	72,32	70 : 30
SVM	88,10	89,04	88,10	87,25	
Random Forest	80,95	82,24	80,95	80,02	
XGBoost	83,33	85,92	83,33	83,02	
Multi Layer Percepton	85,71	84,92	85,71	84,87	
Decission Tree	83,33	83,30	83,33	81,99	

Source: (Prabowo, et al, 2021)

CONCLUSION

Depression trend dataset using the PHQ-9 questionnaire on computer science students at the University of Singapore with 9 variables and 140 total data. In making the classification model, the distribution of the dataset affects the process of making the Extream Gradient Boost classification model. The best combination of data distribution is to divide it into 90% training data and 10% test data so as to produce an evaluation of the accuracy, precision, recall/sensitivity model, and the F1-scores are 92.86%, 94.29%, 92, 86% and 92.06%. This method is also still better than other methods, both in terms of model evaluation results and overall performance in each combination of dataset distribution. This shows that the model will predict more accurately if it is formed with many datasets. The more data that is trained, the easier it is for the model to predict new data. The dataset used in this study can still be added to the number of samples to improve model performance and also minimize generalizations on the model. The Extreme Gradient Boost model that was made, although it could not be a standard goal for students' depression tendencies, was able to become a tool for early diagnosis and screening of students with depression tendencies. The Extream Gradient Boost model that is made can still be developed in the future to get better performance.

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