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Predicting Depression Using Social Media Posts

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Abstract: The use of Social Network Sites (SNS) is on the rise these days, particularly among the younger generations. Users can communicate their interests, feelings, and everyday routines thanks to the availability of social media sites. Many studies show that properly utilizing user-generated content (UGC) can aid in determining people's mental health status. The use of the UGC could aid in the prediction of mental health, particularly depression, where it is a significant medical condition that impairs one's ability to work, learn, eat, sleep, and enjoy life. However, all information about a person's mood and negativism can be gathered from their SNS user profile. Therefore, this study utilizes SNS as a data source by using machine learning models to screen and identify users in categorizing users based on their mental health. The performance of three machine learning models is evaluated to classify the UGC: Decision Forest, Neural Network, and Support Vector Machine (SVM). The results show that the accuracy and recall result of the Neural Network model is the same as the Support Vector Machine (SVM) model, which is 78.27% and 0.042, but Neural Network performs better in the average precision value. This proves that the Neural Network model is the best model for making predictions to determine the level of depression by using social media posts.

Keywords: Social media, machine learning, decision forest, neural network, Support Vector Machine (SVM)

1. Introduction

The vast volume of information available on social media, which corresponds to user behavioral characteristics, might be utilized [1]. Using that data to anticipate a social media user's mental health status can assist a psychiatrist, family member, or friend in providing timely medical advice and therapy to a sad user [2]. According to the World Health Organization (WHO) [3], depression affects roughly 350 million people worldwide today. Depression is one of the world's most deadly disorders [4]. Furthermore, almost two-thirds of depressed persons do not seek adequate treatment, resulting in serious repercussions [5]. Medical science relies on asking patients questions about their circumstances, which does not allow for a precise diagnosis of depression [6]. During two weeks, the patient must attend more than one session. A False Positive problem exists when a non-depressed condition is classified as depressed [7]. Researchers discovered, however, that electronic health record (EHR) systems are not well-suited to merging behavioral health and basic care. Documenting and tracking data for behavioral health problems such as depression is not supported by EHRs [8].

According to eMarketer [9], the number of social media users in 2015 was about 2 billion, and it is growing every day. The majority of people use social media to convey their feelings, emotions, and day-to-day activities. Social media has been proven to be a safe space for many people to vent their negative feelings by sharing material that reflects those emotions [10]. Many studies have demonstrated that data from social media can be utilized to help people maintain their mental health. Researchers can gain a thorough picture of a user's natural behavior by mining

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users' social media posts [11]. By using machine learning models, researchers can gather all information about a person's mood, activities, sleep hours, thinking style, interactions, guilt feelings, worthlessness, loneliness, and helplessness from a user's social media profile. Retrieving such behavioral attributes reveals depression symptoms in social media users, which could be utilized to determine whether or not the user is depressed [12]. The use of machine learning models can help Psychiatrists, parents, and friends detect their early symptoms and prevent the user's depression, which would save time before the depressed person enters the serious depression stage.

2. Project Background

Depression is a type of mood illness characterized by a persistent sense of melancholy and loss of interest. There are several different types of depressive disorders, each with its own set of symptoms. Major Depressive Disease (MDD) is the most frequent type of depressive disorder, and it affects people's ability to work, study, eat, sleep, and have fun. To diagnose a major depressive episode, the patient must exhibit five or more of the following nine symptoms for at least two weeks and virtually every day [13], [14]. The first sign is having a sad mood for the majority of the day. The second symptom is a general lack of interest in practically all activities. The third sign is weight loss or increase, as well as excessive sleeping. Body agitation or retardation is the fourth symptom [15]. The sixth symptom is exhaustion or a lack of energy. The sixth is a feeling of remorse or worthlessness. Finding concentration, thinking, or making a decision becomes tough is the seventh symptom. The seventh symptom is difficulty sleeping or sleeping too much. The ninth and last symptom is the only one that does not have to occur daily. It is the thought of death, a suicide attempt, or a plan to commit suicide.

Asking patients questions about their symptoms cannot precisely diagnose depression, indicating that medical science does not have complete confidence in the approaches employed to diagnose depression [2]. Nowadays, the usage of social media is on the rise, particularly among the younger population. Users can access their SNS at any time and from any location using their Smartphones, PCs, or laptops [16]. Users can communicate their interests, feelings, and everyday routines thanks to the availability of social media sites. User-generated content (UGC) from any social media platform could be used to study human health behaviors [17]. Many studies have shown that by using UGC correctly it can help people maintain their mental health or identify at an early stage. This way may be able to gain a complete picture of a user's natural behavior by mining their social media posts, which could aid in the prediction of depression. This study might be able to get a precise result of the user's mental health by using approaches that identify social media users' depression phases based on their individually authored content. To overcome this problem, there must be a method to predict the level of patient depression through social media. So, the objective of the study is to analyze depression on a dataset collected from an online public source. Then data collected will be analyzed, and the performance of machine learning models will be compared on predicting depression levels. Two scopes have been set up to guide this project toward its objectives. For the scope project, user data is extracted from social media (Twitter). User posts can help to classify users according to mental health. The patient's natural behavior will be created out of their written posts. The data of the user is collected from the Kaggle website.

3. Related Studies

Many researchers have used machine learning techniques such as the Random Forest Tree (RFT), the Support Vector Machine (SVM), and the Convolution Neural Network (CNN) to collect and classify data from websites to predict depression. Table 1 presents the results of the comparison with relevant studies from other articles.

Table 1- Comparison result between various articles

References	Related	SNS	Method	Result	
				Total Accuracy (%)	Total Precision
[18]	Depression Detection by Analyzing Social Media Posts of User	Twitter & Facebook	SVM	78%	1.000
			Naïve Bayes	74%	1.000
[19]	Social media as a measurement tool of depression in populations	Twitter	SVM	73%	0.820
[20]	Predicting Depression via Social Media	Twitter	SVM	70%	0.705
[21]	Detecting Arabic Depressed Users from Twitter Data	Twitter	Random Forest	83%	85.7
			Naïve Bayes	75%	75.8

			AdaBoostM1	55%	56.4
			Liblinear	87.5%	87.6
[22]	Predicting Anxiety, Depression, and Stress in Modern Life using Machine Learning Algorithms	-	Decision Tree	Anxiety: 73%	0.458
				Depression: 78%	0.731
				Stress 63%	0.599
			Random Forest	Anxiety: 71%	0.431
				Depression: 79%	0.881
				Stress: 72%	0.731
			Naïve Bayes	Anxiety: 73%	0.459
				Depression: 85%	0.822
				Stress: 74%	0.548
			Support Vector Machine	Anxiety: 67%	0.403
				Depression: 80%	0.820
				Stress: 66%	0.672
			K Nearest Neighbour	Anxiety: 69%	0.449
				Depression: 72%	0.750
				Stress 71%	0.719

Different researchers have used different machine learning algorithms to predict psychiatric diseases, and the results of the algorithms have varied depending on the context. There was no single algorithm has been determined to be the best in all circumstances. Therefore, many machine learning algorithms were used to identify the symptoms of anxiety, depression, sadness, and stress in the current study. The performance of those machine learning algorithms drives this research's motivation to select some of the popular algorithms for the selected datasets.

4. Methodology/ Framework

This project follows the standard process of conducting experiments and simulations by selecting the CRISP-DM model as the methodology for this research study. The CRISP-DM [23] (Cross-Industry Standard Process for Data Mining) is the standard method used by most researchers in the data mining area to guide data mining activities. It comprises descriptions of common project phases, tasks associated with each phase, and an explanation of the interconnections between these activities as a methodology [24]. CRISP-DM presents an overview of the data mining life cycle as a process model.

4.1 Data Collection

The author obtained datasets for this study, Narendra Sahu, collected from Twitter, including posts from several random users. The dataset contains posts that have been scrapped from the Twint tool to detect all the tweet posts that are related to depression. Keywords used are hopeless, depressed, suicide. The dataset consists of the tweet from more than 10,314 users. This dataset contains six fields, including "ID", "Username". "Tweet Text", 'Prediction Score" and "Sentiment". A more detailed description of the contents of the data set is described in Table 2 below.

The author used the dictionary to contain words with their polarity. Each word taken from the tweet is compared with the dictionary and given a score. The sum of polarity is added for each tweet, and if it is above 0, then it is a negative tweet that stands for a non-depressed post. If it is equal to 1, it is a positive tweet that declares that post as a depressing tweet. In this way, tweets are classified as negative and positive. Evaluated tweet posts were used to be incorporated into the machine learning model.

Table 2 - Description of each column field contained in the dataset

Fields	Description
Id	An index value of a tweet
Username	Handle of account or person that their text had been identified on Twitter
Tweet Text	The message on which the sentimental analysis needs to be performed
Prediction	0 stands for NO = “non-depressed” and 1 stands for YES = “depressed”
Sentiment	0 = negative, 1 = positive

4.2 Creating Prediction Model

In this part, the Microsoft Azure Machine Learning (Classic) was used to create the prediction models by selecting Decision Forest, Neural Network, and Support Vector Machine (SVM) classifier for two-class models, which is suitable for classification with discrete features. The two-class technique classifier takes three parameters to compare each of this classifier: accuracy, precision, and recall. This classifier was fitted according to the training dataset. The experimental design for each model is shown in Fig.s 1 and 2.

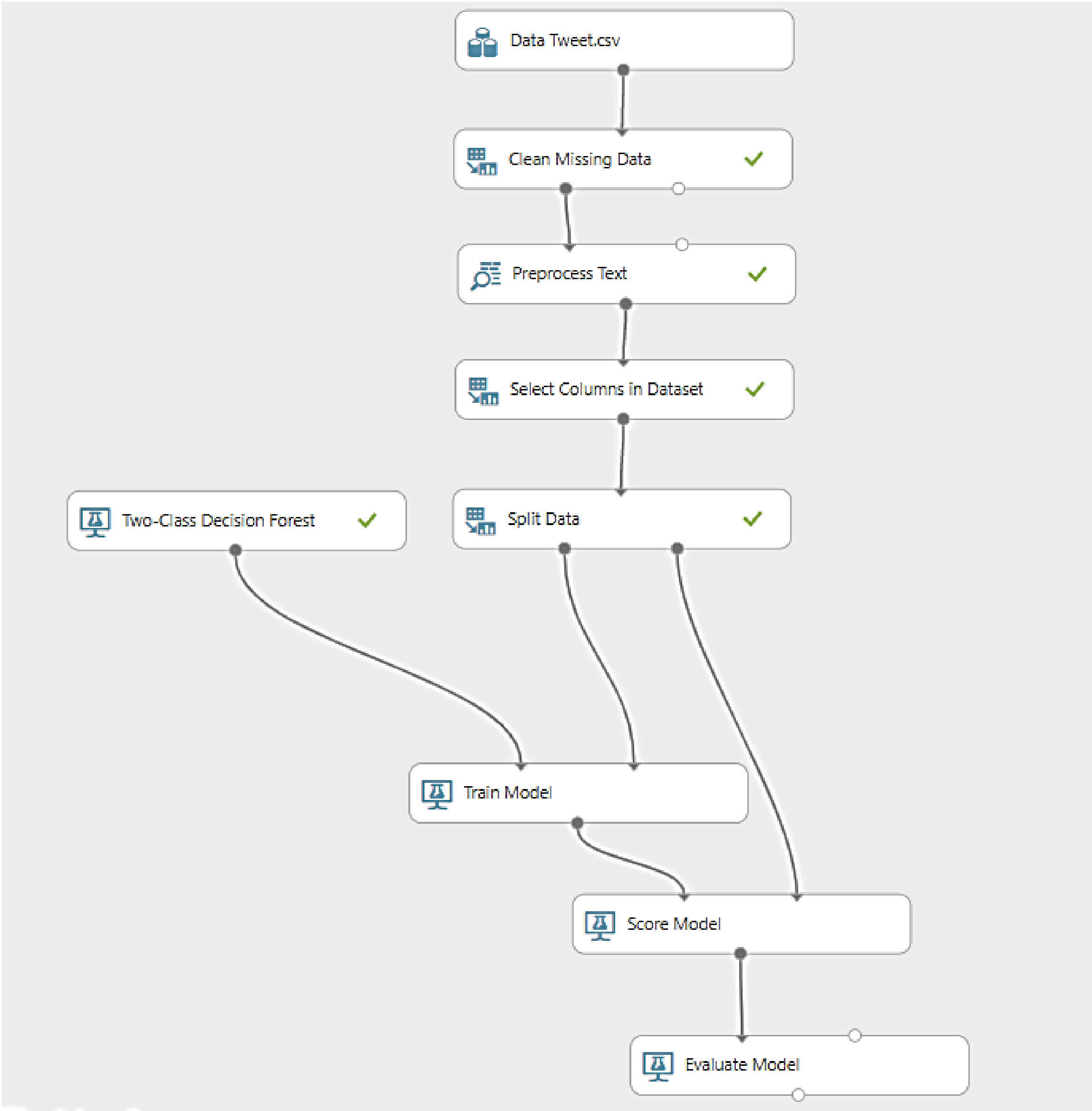

Fig. 1 - Model building using Decision Forest classifier.

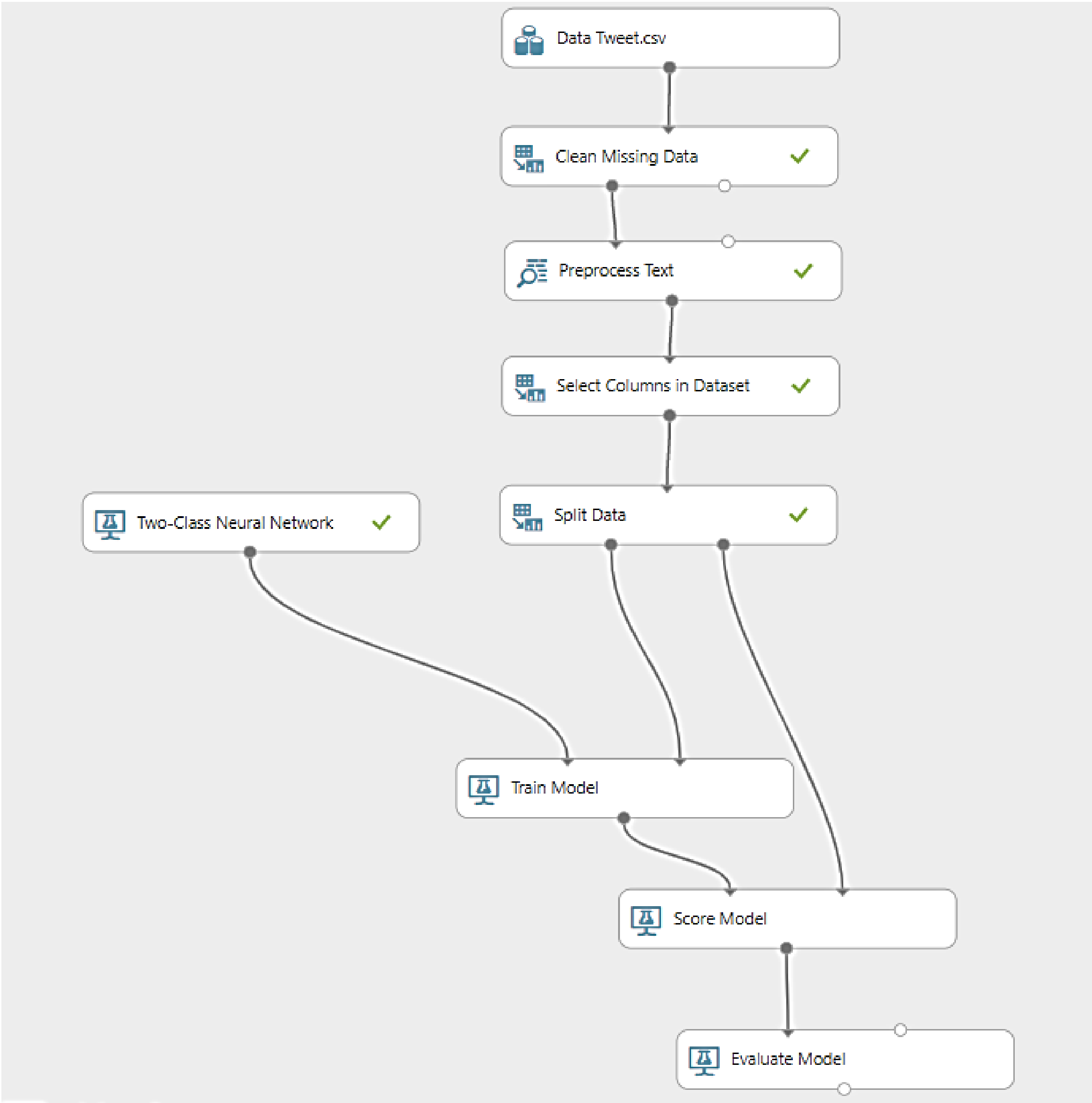

Fig. 2 - Model building using Neural Network classifier.

4.3 Data Cleaning

Data cleaning is the process of identifying parts of data that are incorrect, incomplete, incorrect, irrelevant, or missing, and then altering, replacing, or deleting them as needed. For analysis and machine learning, data is the most valuable resource. There are several missing values identified in the data set that has been used in this study. Therefore, a data cleaning process was used for this data set to avoid any errors during the training and testing period of the data. Data cleaning eliminates a row of missing values with a minimum missing value ratio of 0 and a maximum missing value ratio of 1.

4.4 Pre-processing Text

A dataset usually requires some pre-processing before it can be analyzed. This process also applied to this dataset using pre-processing text in Microsoft Azure for each model machine learning. This pre-processing text help in analyzing text to removing twitter handles (@user, removing links, removing punctuations, numbers, and special characters, remove stop words and lowercase words.

4.5 Split Data

This section discusses the process used to construct a data set with basic permission label information on whether a tweet post indicates depression. The data set is divided into training and testing models. The classifier changes the model from Decision Forest Classification to Neural Network Classification and Support Vector Machine (SVM) classification each time a test is recorded. In the test section, a trained model is applied to the monitored data set. Machine learning will evaluate models that link training data sets and test data sets to provide predictive results. Therefore, the three main metrics used to evaluate a classification model are accuracy, precision, and recall. The difference value of the algorithm is shown in the result section.

4.6 Evaluate the Model

This section uses the classification method to perform a prediction using an Azure Machine Learning Studio (classic). There are four types of outcomes that will be evaluated:

- **True positives** are when predict an observation belongs to a class and it does belong to that class.
- **True negatives** predict an observation that does not belong to a class and does not belong to that class.
- **False positives** occur when predicting an observation belongs to a class when in reality, it does not.
- **False negatives** occur when predicting an observation does not belong to a class when in fact, it does.

5. Analysis and Results

This section explains the analysis results of simulations that have been done for this study. The performance of three selected machine learning algorithms is compared on the same datasets selected to determine the best models that can make predictions. This section will show the result value of accuracy, precision, and recall for each machine learning model with different algorithms during the training and testing data. This result will also be used in comparing which model is better in making predictions. All the algorithms and results are recorded in the table as shown in Table 3, Table 4, and Table 5.

Table 3 - Accuracy results for Decision Forest, Neural Network, and SVM

Split Data		Accuracy (%)		
Training	**Testing**	**Decision Forest**	**Neural Network**	**SVM**
5	95	77.8	78.1	78.1
10	90	77.9	78.0	77.9
15	85	77.4	78.0	78.0
20	80	77.6	78.0	78.0
25	75	77.6	78.0	78.0
30	70	77.7	77.9	77.9
35	65	77.5	77.9	77.9
40	60	77.4	78.1	78.1
45	55	77.8	78.2	78.2
50	50	77.6	78.5	78.5
55	45	78.1	78.7	78.7
60	40	77.7	78.5	78.5
65	35	77.7	78.6	78.5
70	30	77.7	78.5	78.5
75	25	77.2	78.2	78.2
80	20	77.3	77.9	77.9
85	15	76.7	78.0	78.0
90	10	77.4	78.7	78.7
95	5	78.1	79.5	79.5
Average		**77.58**	**78.27**	**78.27**
Standard Deviation		**0.316**	**0.396**	**0.387**

Accuracy measures the goodness of a classification model as the proportion of true results to total cases. Based on Table 3 as shown below, the following are the results for the accuracy value for each machine learning model that has been used in this study. From the results of the accuracy, the average value for Neural Network and SVM machine learning model has the same average accuracy of 78.27%. Meanwhile, the Decision Forest machine learning model recorded a different average accuracy value of 77.58%. A difference of 0.69% for the average accuracy results for the Neural Network and SVM machine learning models shows that the Neural Network model is more accurate than SVM. Next, the calculation results for the standard deviation for the three machine learning models give different results. The standard deviation value for the Decision Forest machine learning model is 0.316%.

Meanwhile, the Neural Network model recorded a standard deviation value of 0.396%, which is higher than the standard deviation value for the SVM model, which is only 0.387%. This difference value shows the percentage of standard deviation for the Decision Forest model was the lowest, while the Neural Network machine learning model recorded the highest standard deviation value. The more detailed difference of accuracy result for each model is also shown in Fig. 3 in the form of a graph.

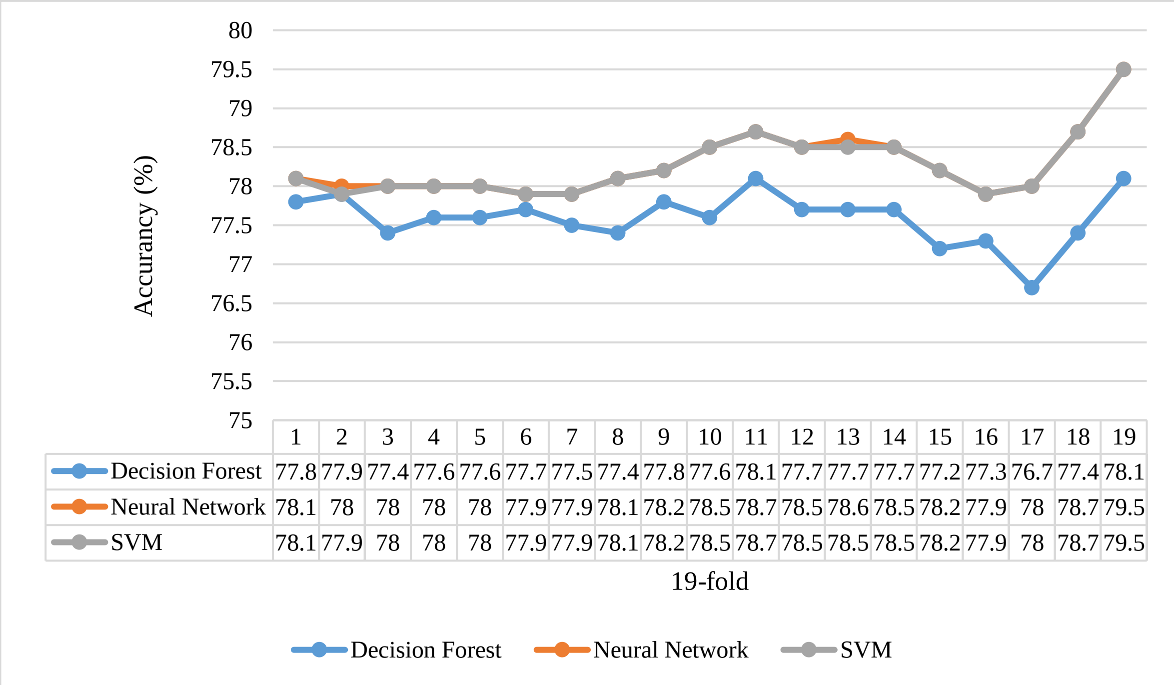

Fig. 3 - Graph of accuracy result for Decision Forest, Neural Network, and SVM

Precision is the proportion of true results overall positive results. Based on Table 4, shown below, the following are the results for the precision value for each machine learning model used in this study. The average value of precision for each model indicates a different value. The decision Forest model produces a high average precision value which is one compared to the Neural Network and SVM models. Next, the average value of accuracy for the Neural Network model is 0.981. The difference in the value of 0.007 when compared to the average value of accuracy for the Support Vector Machine (SVM) model, the average value is 0.974. This shows that the Neural Network model is the second-highest model for the average value of precision in making predictions. Meanwhile, for standard deviation calculation for model decision forest is 0 while model Neural Network and Support Vector Machine (SVM) record the standard value of the same deviation, which is 0.026.

Table 4 - Precision results for Decision Forest, Neural Network, and SVM

Split Data		Precision		
Training	**Testing**	**Decision Forest**	**Neural Network**	**SVM**
5	95	1.000	1.000	1.000
10	90	1.000	1.000	1.000
15	85	1.000	0.894	0.894
20	80	1.000	1.000	1.000
25	75	1.000	1.000	1.000
30	70	1.000	0.978	0.978
35	65	1.000	0.980	0.980
40	60	1.000	0.980	0.980
45	55	1.000	0.981	0.981
50	50	1.000	0.981	0.981
55	45	1.000	0.979	0.979
60	40	1.000	0.977	0.977
65	35	1.000	0.936	0.976

70	30	1.000	1.000	0.951
75	25	1.000	1.000	0.949
80	20	1.000	1.000	0.935
85	15	1.000	0.955	0.955
90	10	1.000	1.000	1.000
95	5	1.000	1.000	1.000
Average		**1**	**0.981**	**0.974**
Standard Deviation		**0**	**0.026**	**0.026**

A recall is the fraction of all correct results returned by the model. Based on Table 5 which shows the results for the recall value for each machine learning model that has been used in this study. There are differences in the standard deviation values for these three models to produce recall results. The average value for the Decision Forest model is 0.011. Meanwhile, the average recall value for the Neural Network and Support Vector Machine (SVM) models is similar. The value is 0.042. However, the value of the difference can be seen for these two models in the standard deviation value that is the value for the Neural Network model is 0.014 while for the Support Vector Machine (SVM) model is 0.015. The difference gap is only a small amount of 0.001. Finally, the standard deviation value for the Decision Forest model is 0.007, significantly different from the value of the Neural Network and Support Vector Machine (SVM) model.

Table 5 - Recall results for Decision Forest, Neural Network, and SVM

Split Data		**Recall**		
Training	**Testing**	**Decision Forest**	**Neural Network**	**SVM**
5	95	0.004	0.019	0.019
10	90	0.016	0.021	0.020
15	85	0.000	0.030	0.030
20	80	0.012	0.027	0.027
25	75	0.012	0.028	0.028
30	70	0.015	0.027	0.028
35	65	0.012	0.032	0.032
40	60	0.004	0.036	0.036
45	55	0.019	0.041	0.041
50	50	0.000	0.044	0.044
55	45	0.019	0.045	0.045
60	40	0.011	0.045	0.045
65	35	0.012	0.054	0.049
70	30	0.017	0.053	0.056
75	25	0.015	0.059	0.062
80	20	0.029	0.058	0.060
85	15	0.003	0.058	0.058
90	10	0.009	0.064	0.064
95	5	0.009	0.070	0.070
Average		**0.011**	**0.042**	**0.042**
Standard Deviation		**0.007**	**0.014**	**0.015**

Based on the result accuracy, precision, and recall that has been recorded in each training test and testing for each model that has been developed. A comparison that can be made for the best model in making predictions for this study is the Neural Network model. However, the result for the accuracy and recall result of the Neural Network model is the same as the Support Vector Machine (SVM) model, which is 78.27% and 0.042. However, a significant difference in value can be seen in the average precision value for these two models, which is 0.007. This proves that the Neural Network model is the best in making predictions to determine the level of depression by using social media posts.

6. Conclusion

The study's show this way can determine whether there is a link between SNS users' activity and mental illness. This study also shows that social media activity can disclose mental disease in its early stages. The psychiatrist cannot obtain complete information from the depressed patient using typical questioning tactics. The SNS-based system has the potential to solve the self-reporting issues. From the user's social activities, machine learning can help researchers get closer to the natural behavior of the depressed patient and his/her way of thinking and better classify the mental levels. This result of the prediction level of depression could help psychiatrists, family, and friends of the depressed patient identify early symptoms of depression and help them prevent some accidents from happening.

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