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Identifying Indication of Depression of Twitter User in Indonesia Using Text Mining

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Abstract: In line with technological advances, the increasing number of internet users caused more and more social media users, one of which is Twitter. Twitter as a social media is generally used by its users as a place to express themselves, both positive and negative expressions. One example of such negative expressions is depression. According to WHO research, depression is a common mental disorder that can lead the sufferers to commit suicide. In an effort to suppress this issue, many studies seek to develop machine learning models that can identify depression, especially in social media such as Twitter. This research aimed to identify indication of depression of Twitter user in Indonesia using text mining. Tweets which portraying stress are marked by a psychologist and TF-IDF are used for feature extraction in Traditional Machine Learning (TML) and for Deep Learning (DL), word tokenizer is used. The classification methods used Multinomial Naive Bayes (MNB) and Support Vector Machine (SVM) for TML and Convolutional Neural Network for DL. Over-sampling and under-sampling methods and combination of both are used to deal with TML. The experimental results confirm that MNB, SVM and CNN can be used to detect tweet that has indication of depression in Indonesia. In addition, the use of Deep Learning (CNN) outperforms Traditional Machine Learning (MNB and SVM) in terms of performance scores with a longer calculation time. The highest accuracy of the model reached 91.23%.

Keywords: *depression, social media, text mining, twitter*

1. Introduction

Based on a survey conducted throughout 2019-2020 (Q2) by the Association of Indonesian Internet Service Providers (APJII) and the Indonesia Survey Centre [1], it is known that as many as 196.61 million Indonesians have become internet users out of a total population of 266.91 million. In percentage terms, this number is about 73.7% of the total population of Indonesia and experienced a growth of 8.9% from the number in the previous year which was only 64.8% or 171.17 million people.

Of the number of internet users in Indonesia, as many as 51.5% use social media as the main reason for using the internet [1]. The three most commonly used social media in Indonesia are Facebook, Instagram and Twitter [1]. Social media has become a place for people to express their thoughts and feelings [2].

There are nine benefits of social media, namely: media literacy, education, creativity, strengthening interpersonal relationships, sense of belonging and collective identity, strengthening and building communities, civic engagement and political participation, and well-being [3]. These benefits encourage people to actively engage in social media, and of course it is including self-disclosure or emotional-disclosure in social media.

Twitter, has been a major influence over the past few years where it is used to share current views and thoughts, comment on breaking news and events, and share interesting topics [4], which is the earliest, unedited voice, of ordinary people [5]. The presence of social media allows scientists to analyse these online behaviours in a large scale [6].

There are two needs that people want to fulfil when they are actively engaging in social media; emotional-disclosure and impression [7]. Big social media –like Facebook – tends to support people in displaying impression of themselves using positive emotions, while denser social media tends to support people in displaying expressions, where negative emotions get a larger portion.

The act of displaying positive and negative emotions in social media encourage researchers to do research about mental health of social media user. People who suffer from depression tends to have self-disclosure on social media, where they declare themselves as depression sufferer in Twitter and share their difficulties as depression sufferer there [2]. Another finding states that people in normal group – people who have never been assessed with depression by psychologist before – also show similar behaviour to the ones who diagnosed with depression [2], which leave a room for future research; identifying people with indication of depression in social media.

A study tried to analyse Instagram post to find sensitive self-disclosures, the responses, and social support in case of #depression. The finding of this research states that the reason people are doing self-disclosure on Instagram is to gain support from other people with the same problem – people who suffer from depression – on Instagram [8].

Through text mining, there are so many information that can be pulled from social media, such as, people’s opinion on events, news, or government new policy, trends, political movements, personality traits of the user, even mental health of the user [2].

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There is a lot of research on mental health of social media user, especially about depression. Many researchers believe that people who suffer from depression or at least have an indication of suffering depression will express themselves (self-disclosure or emotional disclosure) in social media.

Depression is a common mental disorder [9]. Globally, more than 264 million people of all ages suffer from depression [10]. Depression is a major cause of disability worldwide and is a major cause of the overall global burden of disease. Major depression will experience a tendency to self-harm up to suicide.

In Indonesia, data from National Institute of Health Research and Development shows that symptoms of emotional mental disorders as indicated by symptoms of depression and anxiety for ages 15 years and over about 6.1% of the total population of Indonesia or the equivalent of 11 million people. Teenagers (15-24 years) have a depression percentage of 6.2% [11].

With a lot of people using social media in Indonesia and many research about depression in social media, to investigate this issue further, research about identifying indication of depression of social media user in Indonesia is promising. Therefore, this research is aiming to identifying indication of depression among social media user, in this case Twitter, in Indonesia.

2. Theory and Method

2.1. Stress Theory

The term "stress" which is interpreted as "difficulty or suffering that is so heavy" can be found around the beginning of the fourteenth century, where the term "stress" is still based on an unsystematic emphasis [19].

In the eighteenth to the beginning of the nineteenth century, the word stress was more understood as strength, pressure, tension, or strong effort, which was more emphasized on material objects or organs or mental strength [19].

Cannon, who was the first researcher to introduce the concept of fight-or-flight response, defines stress as the body's response to something [19].

Fundamentally, stress is classified into three approaches: stimulus (stimulation), response, and transactional. Stress stimulus model is stress caused by a stimulus or stimulus that comes from outside someone (environment). E.g. Military soldiers who are carrying out war assignments experience stress due to the war situation that will be faced, so that the soldier's health condition decreases. While stress response model is stress that occurs because someone responds to stimuli or stimuli that come from outside (environment). E.g. When someone is experiencing something worrying, the body automatically responds to the threat. The body's response to threats is a stress response model. Last, stress of the transactional model is stress that arises due to the process of human interaction with the environment, where individual judgment is the cause of stress. Emotional response and cognitive processes are individual responses to stress in this model [19].

Stress sources can be divided into three: life events, chronic strain, and daily hassles. Life events is a source of stress that comes from changes in life that are so many and occur in a short time. E.g. Divorce, spouse's death, loss of family members, imprisonment, financial problems, etc. Chronic Strain is a source of stress that comes from difficulties that occur consistently in everyday life. E.g. Job demands, home demands, academic pressure, etc. Daily Hassles is a source of stress that comes from small events that occur in everyday life, which require adjustment in a short time. E.g. Traffic congestion, work deadlines, and others [19].

In addition, the source of stress is also an event or situation that exceeds the ability of the mind or body when dealing with such stress. Stress can go on to a more severe or gradually diminishing stage which is determined by how someone faces the source of stress [19].

Appraisal or assessment process is an act of evaluating, interpreting, and responding to existing events. There are two stages of assessment carried out by someone when experiencing stress: assessment of the initial stage (Primary Appraisal) and second stage appraisal [19].

The initial assessment can be divided into three stages: irrelevant, benign-positive, and stressful. Irrelevant occurs when a person is facing a situation that does not have any impact on his well-being (health), which means that no effort is needed in dealing with this situation because nothing is removed or received in this case. Benign-Positive occurs when the results of a situation faced by someone have a good impact on improving their welfare, such as feeling happy, feeling happy, and others. Stressful occurs when individuals do not have the personal ability to deal with stressful situations [19].

If an individual is at stressful stage, the individual will experience harmful, which is a sign that something dangerous is happening to the individual, threatening, which is a sign that there is a possibility that something harmful can continue occur in the future, and challenging, which is the involvement of individuals in the challenges that exist. These challenges can cause emotions such as expectations, desires, and beliefs [19].

In second stage appraisal, individuals will determine the type of coping that can be done in the face of existing threats. Coping method can be divided into two: problem-focused coping and emotion-focused coping. Problem-focused coping is a way to cope with stress that is focused on the problems faced, which is done by directly dealing with sources of stress or problems faced to avoid or reduce stress. Emotion-focused Coping is a way to cope with stress that involves emotions, which is done because there is nothing else that can be done to the source of stress [19].

Based on these studies, to find indication of depression of Twitter user, stress theory will be used as the guide to determine whether a tweet contains words which indicates stressful events.

2.2. Text Mining

Text Mining can be broadly defined as an intensive knowledge process where users interact with a set of text documents from time to time using a series of analysis tools [20].

Text Mining and Data Mining have a similar set of high-level architectures, both of which are used to find useful information from data sources through identification and exploration of interesting patterns. However, for Text Mining, interesting patterns are not found among formal database records, but are found in unstructured textual data sourced from the analysed documents [20].

Text mining can be grouped into seven areas; Information Retrieval, Clustering, Classification, Web Mining, Information Extraction, Natural Language Processing (NLP), Concept Extraction. Search and information retrieval area aims to search, retrieve text documents based on keywords, such as Google and Yahoo search engines. Document clustering area grouping words, terms, paragraphs, or documents is done by using the clustering method. Document classification area is the process of classification of documents that have not been labelled uses the text model of the training document. In web mining area, the excavation of information appears on the web is done. The purpose of information extraction is to extract structured data and unstructured data. Natural Language Processing (NLP) is a blend of the fields of linguistics (language) with computer science. In conducting text mining, NLP uses a statistical approach. Concept extraction area grouping words into groups that have similar meanings (semantics) is done [21].

The steps in text mining consist of four steps: Pre-processing task, core mining operation, presentation layer components, refinement techniques. Pre-processing task includes all processes and methods needed to prepare data for the next step of text mining, namely core mining operation. The tasks in this step are usually centred on the pre-processing data source. Core mining operation is the core of text mining activities and includes researching patterns or patterns, trend analysis and the use of algorithms for researching knowledge. Presentation layer components is a step to present the results of core mining. Generally using a GUI. Refinement techniques are methods that filter information that is excessive to represent a comprehensive, organized, and generalized approach aimed at optimizing findings. This technique has been referred to as post-processing [20].

2.3. Machine Learning and Deep Learning

The Machine learning is a branch of computer science that makes computers have the ability to learn things without being programmed. Machine learning begins with the extraction of human knowledge. In machine learning, observational data consists of features or attributes. Some examples of machine learning algorithms that are commonly used are Naive Bayes, Support Vector Machine, KNN, etc [22].

Deep learning is a subset of Machine learning based on Artificial Neural Networks (ANN). Deep learning is a fairly new thing in machine learning, and to distinguish the two, the term Traditional Machine Learning is usually used to refer to the old machine learning. Some examples of deep learning are Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM) etc [23].

2.4. Supervised Learning

Supervised learning, commonly called predictive modelling, is the process of determining predictions based on pre-labelled data. This data is usually called training data, which will be used to determine the label on the testing data [22].

2.5. Related Works

A study uses 95,046 Instagram photos that using tags contain depression utterance from 24,920 users during July 2014. The analysis of image and text content are using qualitative methods and statistical method. This research found that people with depression sometimes share their negative emotions through social media post, and the study reveals that this behaviour aim to find support and get support from other people who have the same experience [8].

Text analysis software: Linguistic Inquiry and Word Count (LIWC) is used to find about emotional disclosure on social networking and the psychological needs of it. The research uses three clusters of Facebook status data, first cluster contains posts of 441 students, second cluster contains post of 101 students, and the third cluster contains posts of 164 students. The findings are, there are two needs in social media. First is to vent and second is for impressions. Large social media tends to support people in displaying their impression, while dense social networks tend to support displaying negative emotions [7].

Moreover, another research also analysing the behaviour of people who is diagnosed with depression in Twitter and people who is never diagnosed with depression before using Fisher's Exact Test. This research finds that people who is diagnosed with depression tends to share their depression journey on social media, regarding their sleep pattern, pain, medication, and suicidal thoughts. Interestingly, around 40% of people who is never diagnosed with depression before, share the same behaviour with people who is diagnosed with depression; they share about their sleep pattern, pain, and suicidal thoughts. The conclusion is, social media is a place to express symptoms and problems that bothering a person, and this research also shows that people who have indication of depression might share their thought on social media [2].

From these studies, many other researchers have tried to detect depression on social media in more sophisticated ways. A study is conducted using social media to monitor mental health discussions. In this study, using autoregressive integrated moving average (ARIMA) models, the conclusion says that the spike in Twitter activity discussing an issue was in line with cases of depression and suicide that occurred in 2014 [12].

Another study tried to detect sentiment in text using several machine learning algorithms and classified them into positive and negative sentiments. The dataset used is a dataset from Kaggle. Using 800,000 training data and 200,000 test data with machine learning algorithm Baseline (Evaluation Metric), Naive Bayes and SVM. This research concludes that for various features, Naive Bayes and SVM have better results [13].

Another research also tries to detect emotions on Twitter using the Naive Bayes method and the Combination of Features, the Naive Bayes method used is Multinomial Naive Bayes for discrete data types and Bernoulli Naive Bayes for binary data types. The combination of features used in this study are linguistic features, orthographic features and combinations of N-gram features. The dataset used is the result of 2 weeks of API streaming data, with a total of 4396 tweets, of which 80% is training data and 20% is test data. The conclusions from this combination of features cover each other's weaknesses, not very significant because doesn't really affect the results [14].

Another research on similar field tries to detect depression, anxiety and stress candidates for Malay-language tweets. This study uses 165 Malay layman terms that describe depression, anxiety and stress. This study takes 1789 Malay-language tweets and finds 6 Twitter users as potential candidates because they have high frequency of layman terms. This study concludes that tweets can be used to detect candidates who experience depression, anxiety and stress, although this research has not used machine learning [15].

Another study on the detection of depression on tweets and a comparison test uses Naive Bayes and SVM and Deep Learning LSTM-RNN to predict tweets containing depression and anxiety. This research uses Tweet Scrap from TWINT, sentiment 140 and google word2vec. This study concludes that all algorithms have a fairly high accuracy with LSTM-RNN as the algorithm with the highest accuracy [16].

Another research used TF-IDF, Bag of Words (BOW) and Multinomial Naive Bayes and produced positive and negative sentiments on real-time twitter data. This study uses 10,314 data with 8,000 data used as training data and the rest as test data. This study concludes that the algorithm used is efficient and can be used to detect depression in tweet data. This study uses English tweets and states that the same model can be used in other languages. This study concludes that the Multinomial Naive Bayes algorithm is actually better than TF-IDF and Bag of Words [17].

Another study tries to conduct sentiment analysis to detect mental depression based on twitter data. This study uses NLP to process tweet data and Naive Bayes to perform analysis. The researchers argue that Naive Bayes is a fairly good and powerful algorithm to use if the classification algorithm you want to use is supervised learning. The results obtained are generally the same as other studies. This research also encourages other researcher to use another tweet languages [18].

A study tries to compare the accuracy between Convolutional neural networks from deep learning and Naive Bayes from traditional machine learning, this study uses 45,442 English tweets data with the topic "Turkey crisis 2018". This study concludes that the results of using the CNN classifier have a higher accuracy value than Naive Bayes [23].

Another study also tried to compare CNN and TML, using Moview review data and STS Gold dataset, this study concluded that the accuracy performance of twitter sentiment classification on CNN was better than TML such as Naive Bayes and SVM [24].

Another study tries to apply deep learning to stemmed Turkish twitter data. This research concludes that TML model is better in training-time and runtime than DL. However, DL is superior in terms of score [25].

Table 1. Comparison of Related Works

Research	Dataset	Method	Conclusion
[8]	95,046 Instagram Photos	Qualitative methods and statistical method	People with depression sometimes share their negative emotions through social media post
[7]	706 Facebook post in 3 clusters	Linguistic Inquiry and Word Count (LIWC)	Two needs in social media, to vent and for impressions
[12]	Tweets from 2011 to 2014	Auto Regressive Integrated Moving Average (ARIMA)	Spike in Twitter activity discussing an issue was in line with cases of depression and suicide that occurred in 2014
[13]	1,000,000 data from Kaggle	Baseline (Evaluation Metric), Naive Bayes and SVM	Naive Bayes and SVM better than Baseline
[14]	4396 tweets	Naive Bayes method and the Combination of Features	Combination of Features is not very significant
[15]	1789 Malay-language tweets	165 Malay layman terms	Malay language of Depression-Anxiety-Stress Scale (DASS) can be used to classify tweets
[16]	Tweet Scrap from TWINT, sentiment 140 (template dataset)	Naive Bayes, SVM and Deep Learning LSTM-RNN	All algorithms have a fairly high accuracy with LSTM-RNN as highest
[17]	10,314 real-time tweets	TF-IDF, Bag of Words (BOW) and Multinomial Naive Bayes	MNB is the best
[18]	Sentiment140 (template dataset)	Naive Bayes	Naive Bayes good for supervised learning, Exploratory Data Analysis (EDA) can be used to filter out possible slang language
[23]	45,442 English Tweets	Convolutional Neural Network (CNN) and Naïve Bayes (NB)	CNN has higher accuracy than NB
[24]	Movie Review and STS Gold Dataset	Convolutional Neural Network (CNN)	CNN can be used to measure sentiment analysis
[25]	3,000 and 10,500 Turkish twitter data	Deep Learning (CNN, RNN, HAN) and TML	DL outperform TML in performance score, otherwise TML outperform DL in training time and runtime

3. Research Framework

3.1. Research Framework

An overview of research framework applied to the research to identifying people with indication of depression in social media especially Twitter is shown in fig. 1.

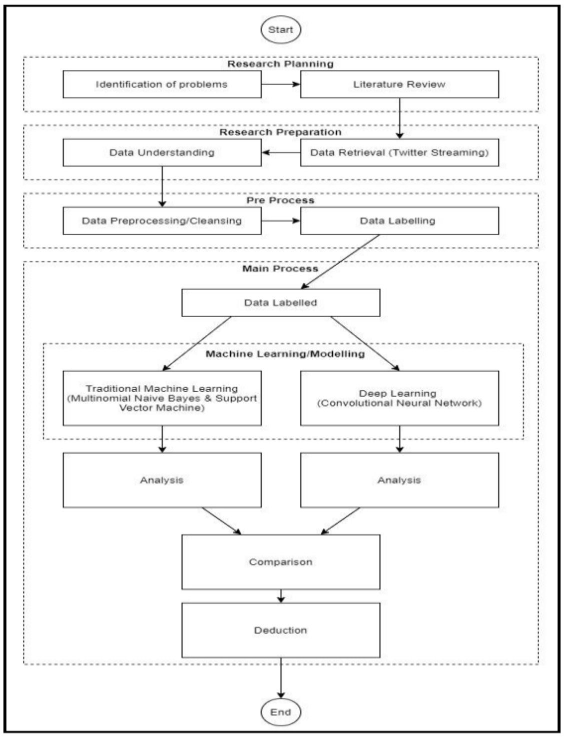

Fig. 1. Research Framework

3.2. Research Method

Fig. 2. explain research method of this research. Through explanation will be explained in this section.

3.2.1. Data Collection

In this study, the data to be used is tweet data obtained from Twitter using the Twitter API. The process of pulling tweet data from the Twitter API is called the crawling process. Crawling process is carried out between August and September 2021. These data are stored in csv format and only store tweet data only. As mentioned on scope of work in chapter 1, the data that will be used is tweet that is made in the geographical area of Indonesia and tweet that use Indonesian language. Data collection step is as shown on fig. 3.

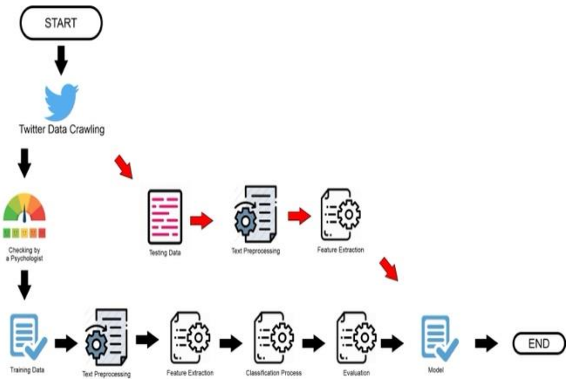

Fig. 2. Research Method

Fig. 3. Data Collection

3.2.2. Data Labelling

Data labelling process is a step to give a yes or no label to a Tweet based on the words contained in the Tweet. This step is done by looking at the words in the tweet that contains stress, since stress is what leads to depression. This process requires expert assistance from a psychologist who can determine whether the tweet contain stress or not. If indicated stress, then the tweet will be labelled with "yes" and if it is not, the tweet will be labelled with "no".

3.2.3. Text Pre-processing

Text pre-processing or data cleansing is a process that aims to clean and normalize research data so that the data used for research does not contain elements that are not needed in research. Below are text pre-processing steps, as shown in fig. 4.

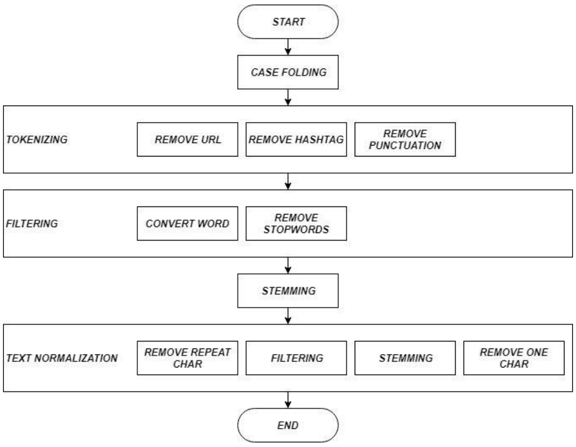

Fig. 4. Text Pre-processing

Case folding aims to convert all words to lowercase. The goal is to avoid being case sensitive when matching words with the dictionary. An example is changing the word "Bingung" to "bingung". Tokenizing is done by separating each word into a separate part. The separation of these words is done by cutting sentences based on spaces so that later a vocabulary can be made based on the unique words contained in the text. This process also includes data cleansing, all URLs, hashtags, retweet word, punctuation marks and numbers will be removed. Filtering aims to eliminate stop words or words that are considered meaningless. For example, the words "yang", "apa", "pun" are deleted because they have no meaning. Stemming is the process of mapping and decomposing various forms of words into their basic forms. The process of mapping and parsing is used to find the root word of a word that has affixes by removing or deleting the affixes. In this process, Sastrawi stemmer is used. Text normalization is the next process of pre-processing to normalize text, for example by eliminating repetitive words or words that have no meaning. Several previous processes were also repeated to ensure data cleanliness.

3.2.4. Feature Extraction

After text preprocessing, feature extraction will be done. TF-IDF method will be used to compare the count of the word occurrence with the whole text. TF-IDF process example is as shown on table 2.

T1: “John likes to swim. Mary likes to swim too.”

T2: “John also likes to play basketball.”

Table 2. Comparison of Related Works

Word	TF		IDF	TF*IDF	
	T1	T2		T1	T2
John	1/9	1/6	Log(2/2) = 0	0	0
Mary	1/9	0	Log(2/1) = 0.3	0.33	0
Likes	2/9	1/6	Log(2/3) = -0.18	-0.04	-0.33
To	2/9	1/6	Log(2/3) = -0.18	-0.04	-0.33
Swim	2/9	0	Log(2/2) = 0	0	0
Too	1/9	0	Log(2/1) = 0.3	0.33	0
Also	0	1/6	Log(2/1) = 0.3	0	0.05
Play	0	1/6	Log(2/1) = 0.3	0	0.05
Basketball	0	1/6	Log(2/1) = 0.3	0	0.05

TF-IDF Vector:

T1= [0, 0.33, -0.04, -0.04, 0, 0.33, 0, 0, 0]

T2= [0, 0, -0.33, -0.33, 0, 0, 0.05, 0.05, 0.05]

3.2.5. Classification Process

Classification process is divided into two process: modelling using traditional machine learning and deep learning. The algorithms used for traditional machine learning are multinomial naive bayes (MNB) and Support Vector Machine (SVM). As for Deep Learning, the algorithms used is Convolutional Neural Network. Machine learning process will be conducted using sklearn machine learning library. The details of classification process as shown on Fig. 5.

On classification process in traditional machine learning, data that has been labelled is separated into 80% data train and 20% data. The splitting process is carried out randomly. In case of data imbalance, over-sampling methods, under-sampling methods, and combination-sampling methods will be used.

Over-sampling methods use synthetic data generation in order to increase number of minor samples in data set. Algorithms that will be used for this method are SMOTE and ADASYN.

SMOTE algorithm finds n-nearest neighbors in the minority class then draws a line between neighbors an generate random sample on the line. ADASYN algorithm is an improved version of SMOTE. After generating random sample, this algorithm will add random value to make it more realistic.

Under-sampling methods reduce the majority class of data sets. Algorithms that will be used for this method are ENN (Edited Nearest Neighbor) and TOMEK-LINKS.

ENN algorithm removes instance of majority class whose prediction made by K-Nearest Neighbor is different from majority class. TOMEK-LINKS algorithm pairs sample of opposite class in close vicinity and removing majority of sample that is not in pair which provide better decision boundaries for classifier.

Combination method are the combination of under-sampling and oversampling method. Algorithms that will be used for this method are SMOTE-ENN and SMOTE-TOMEK.

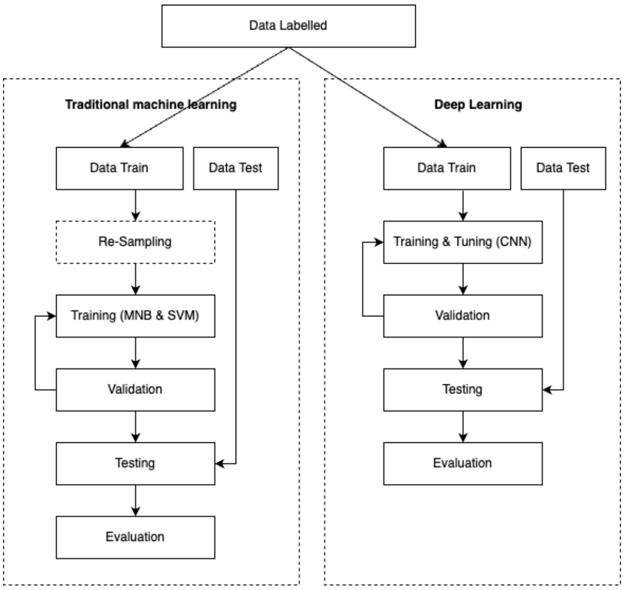

Fig. 5. Classification Process

SMOTE-ENN algorithm combines the ability of SMOTE which generate synthetic sample of minority class and the ability of ENN to remove instance of majority class whose prediction made by K-Nearest Neighbor is different from majority class.

SMOTE-TOMEK algorithm aims to clean overlapping data points for each of the classes distributed in sample space. After over-sampling is done by SMOTE, TOMEK will pair sample of opposite class. In this case, instead only removing majority class which have no pair, it is removing both class samples.

After the data is separated and re-sampling methods are applied, the training and modelling process is carried out using Multinomial Naïve Bayes and SVM. Multinomial Naïve Bayes is probabilistic method which based on number of occurrences of the data. Multinomial Naïve Bayes process examples are as shown on table 3 and 4. The calculation of probability is using multinomial naïve bayes formula as seen in (1).

$$(A|B) = P(A) * P(B|A)/P(B) \tag{1}$$

Table 3. Multinomial Naïve Bayes Process – Word List

Word count: 10.

Words	Stress
Lelah	yes
Mati	yes
Mati	yes
Lelah	yes
Capek	no
Capek	no
Lelah	no
Mati	yes
Capek	no
Mati	yes

Table 4. Multinomial Naïve Bayes Process – Calculation

Words	Count of yes	Count of no	P(B)
Lelah	1	2	3/10 = 0.3
Mati	4	0	4/10 = 0.4
Capek	0	3	3/10 = 0.3
Total	5	5	
P(A)	5/10 = 0.5	5/10 = 0.5	

P(Y|Lelah) = (1/5*0.5)/0.4 = 0.25

P(N|Lelah) = (2/5*0.5)/0.4 = 0.5

P(Y|Mati) = (4/5 *0.5)/0.4 = 1

P(N|Mati) = (0/5 *0.5)/0.4 = 0

Probability of Lelah as stress is lower, therefore when word Lelah occur, the probability it's stress is lower. Probability of Mati as stress is 100%, therefore when word Mati occur, the probability it's stress is 100%.

As for SVM will separates the sample according to the vector from TF-IDF process. Then it will find separating line between classes that is called hyperplane. In order to find the best hyperplane, SVM will locate sample closest to the line from both classes, which called support vectors. This distance is called margin and the goal of SVM is to maximize margin which will result in optimized hyperplane. This optimized hyperplane is the decision boundary which determine the class of new samples.

K-Fold Cross Validation will be used as validation method. K-Fold Cross Validation divides the input dataset into K groups of samples of equal sizes, called folds. For each learning set, the prediction function uses k-1 fold as test set and the rest of the folds as training set. Table 4. shows the example of five folds K-Fold Cross Validation.

Table 4. Multinomial Naïve Bayes Process Example

	K-1	K-2	K-3	K-4	K-5
1st iteration	Test	Train	Train	Train	Train
2nd iteration	Train	Test	Train	Train	Train
3rd iteration	Train	Train	Test	Train	Train
4th iteration	Train	Train	Train	Test	Train
5th iteration	Train	Train	Train	Train	Test

Similar with traditional machine learning process, for deep learning process, data that has been labelled is also separated into 80% data train and 20% data. The splitting process is also carried out randomly. CNN process will be conducted using Keras, a high-level neural network library that runs on top of tensorflow.

CNN that will be used is Sequential 1-Dimentional CNN with 3 epochs. For each epoch the dropouts is set to 0.5. ReLu activation function is used for the first and second epoch, and softmax activation function is used on the last epoch. Adam optimizer is used to increase the model performance, categorical cross entropy loss function is used to avoid overfitting.

The validation process is done by tuning those parameters throughout the iteration and the accuracy metric using keras accuracy metric which calculates how often predictions equal labels.

3.2.6. Evaluation Method

Evaluation method is done to get the accuracy value of the model that has been made. The evaluation method that is used for machine learning model is Confusion Matrix. The formula to find the accuracy of model using confusion matrix is as seen in (2).

$$\frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

True Positive (TP) is data that are positive and considered as positive. True Negative (TN) is data that are negative and as considered negative. False Positive (FP) is data that are positive but considered as negative. False Negative (FN) is data that are negative but considered as positive.

Evaluation method for deep learning model is based on loss function and other metrics that is set on training process.

4. Results

In total, 1424 tweets are successfully collected from Twitter which then labelled with label yes or no. Out of total data obtained, 169 tweets are labelled yes and the remaining 1255 tweets are labeled no by the expert. If the labelled result is calculated as percentage, the number of tweets indicating depression (yes label) is about 11.86% of the total data.

On traditional machine learning model, the experiment is divided into four for each algorithm; without re-sampling method, with over-sampling method, with under-sampling method, and with combination sampling method (MNB and SVM). Each experiment is run twice; the first experiment only run each process once, while the second experiment run each process ten times to get even better result. The accuracy results of traditional machine learning model is as shown on table 5.

As for deep learning model (CNN), the experiment is also done twice with both experiments using 3 epochs. The accuracy result of deep learning model is as shown on table 6.

Table 5. Traditional Machine Learning Accuracy Results

Traditional Machine Learning Accuracy	Multinomial Naïve Bayes (MNB)	Support Vector Machine (SVM)
Non Re-Sampling	88.07%	88.07%
Over-Sampling (SMOTE)	71.58%	87.37%
Over-Sampling (ADASYN)	71.58%	87.37%
Under-Sampling (ENN)	88.07%	88.07%
Under-Sampling (TOMEK-LINKS)	88.07%	88.07%
Combination (SMOTE-ENN)	70.53%	87.37%
Combination (SMOTE-Tomek)	72.28%	87.02%

Table 6. Deep Learning Accuracy Results

Deep Learning	Convolutional Neural Network (CNN)
Accuracy Score	91.23%

The results shows that CNN has higher accuracy result compared to MNB and SVM.

5. Conclusion

Multinomial Naive Bayes (MNB) and Support Vector Machine (SVM) have proven to be good classifiers for supervised learning in Traditional Machine Learning. In addition, the results of this study also prove that MNB and SVM can be used to conduct research on tweets that have indication of depression in Indonesia.

In future studies, we can improve and train the data model using more algorithms to get better results. As well as adding more training data using more validation input from several experts. With technological advances, this model can be developed into better model that can be used as tool for early detection of indication of depression by experts in clinical fields such as psychologists or psychiatrists also experts in non-clinical fields such as HR team in Indonesia.

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