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Depression Detection Based On Twitter Using NLP and Sentiment Analysis

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ABSTRACT

Depression is the most common illness, serious disease, and underestimated by human beings. The serious depression will affect the emotion, physical condition, or cause suicide. Depression can be detected by reading their social media post. This research aims to develop a system that used to analyze the user depression status based on their social media post. This research will implement Recurrent Neural Network (RNN) model and Convolutional Neural Network (CNN) model in order to get the most accurate parameter for building the model and compare the accuracy of the prediction. The RNN (LSTM) 7-layer model are the most accuracy, precision, recall, F1 score of and less loss compare with other three model. The accuracy is 80.99%, F1 80.16%, and loss 45.0%. The RNN (LSTM) had selected 7-layer as the model in development the google chrome extension to perform the tweet sentiment analysis. The system will notify the user about their depression status; suggested to ask treatment with phycologist.

Keywords: NLP, CNN, LSTM, sentiment analysis, social media, Twitter, depression

1 INTRODUCTION

In this 21st century, depression is a serious and widespread public health challenge. which led to the increasing of suicide cases [1].. The suicide case caused by mental disorders contributes to 1.4% of all deaths worldwide. Research on the risk factors among people with mental disorders is crucial in the efforts to predict and prevent suicide death [2]. There are many people facing depression. According to the study that has been conducted in year 2017, Malaysian depressed people had increased from 17% in year 2011 to year 2017. Whereas 12% suicide case has been reported in 2011 and had increased to 29% in 2017 [3].Several methods can be used to diagnose depression. Face-to-face interview are often used by psychologist to diagnose depression. Although this is the most accurate method for depression diagnosis, mostly the individual who has depression they do not realize their depression status or somehow feel ashamed to admit that they had experience depression. More than 70% people in early stages of depression would not consult the psychological doctors, deteriorating their conditions. While others do not want to see or admit themselves as “depressed”. Majority of people choose to escape and ignore depression rather than having treatment at a psychological hospital. According to previous study, there are other methods to detect depression. Some of the researchers were using the NLP and sentiment analysis to detect potential depression at early stage [4] [5].

One of the efficient ways to detect depression is through social media. Social media can be one of the medium for user to express their feeling, user are likely to present their mental problems or illness with anonymity. The use of data from social media to estimate severity of depression in social media users has been studied before. There are some studies found that using data from social media can estimate severity of depression. For example, Tsugawa found that frequency of word usage in Twiter's tweet can be used to recognize depression among users [6]. De Choudhury also point out that machine learning can used to identify twitter user, which have depression using users' Twitter activity record. These research shows that potential of using Twitter data to recognizing depression symptoms [7]. Because of the unthreatening nature of computer mediated social networking, social network enables self-disclosure from individuals who would not normally disclose personal information in face-to-face interactions [8] [9]. Social media are widely used nowadays and the numbers of social media users are increasing rapidly globally. The number of users in January 2020 was increased 9% which is 3.8billion mark (321 million new users) compared to the 2019. There are over 60% of the world's population already uses social media [10].

Expanding the scope of current depression screening methods is critical for effectively detecting and treating the depression condition. New research suggests that monitoring social media activity may be one way to do so. By analyzing the language that have been used by social media users, it is somehow can assist to analyse the user depress status [11]. When the user has depression, they will use language differently. The depressed people will normally use the word such as loneliness, sadness, afraid, reckless, rejected, resigned, broken, crisis, crying, sadness, unhappy, upset or fear [12]. To analyse the words that have been posted by the users, there are several ways to do so. One of the techniques is by using NLP, there are different NLP methods that can be used for text analysis. The accuracy will be done by comparing the RNN-LSTM (Long short-term memory) and CNN-Conv1D model.

2 BACKGROUND STUDY AND METHOD

2.1 Background Study

This section will discuss about the background study and related works on depression. Languages, lifestyle or an unusual condition such as sleep disturbance to the depression patient has been discussed in this section.

2.1.1 Depression

Depression is a common mental disorder, the World Health Organization – WHO estimate there are 350 million people are having depression. The World Mental Health Survey conducted in 17 countries found that, on average about 1 in 20 people reported having an episode of depression in the year 2011. Normally, depressive disorders often start at a young age. Depression often comes with symptoms of anxiety. There are almost 1 million of people suicide due to depression in a year, which translate to 3000 suicide deaths every day. Depressed people may attempt 20 or more suicide to end his/her life [13].

Depression is more than just feeling sad or going through a rough patch. Depression can be devastating for the people who have it and for their families. Fortunately, with early detection, diagnosis and a treatment plan consisting of medication, psychotherapy and lifestyle choices, many people do get better. Some people having depression once in a lifetime, it last for few months to several years, but most of the people depression recurs [14].Nearly 75% of the severe events that occurred prior to depression episodes were interpersonal loss events [15].

2.1.2 Types of Depression

Like many other disorders, depression manifests itself in a variety of ways. First types of depression is major depression, which are characterised by a set of symptoms that make the patient suffered from unusual conditions such as difficult to work, sleep, eat, or enjoy formerly pleasurable activities. These incapacitating bouts of despair might happen once, twice, or multiple times over one's lifetime. Second types of depression is Dysthymia, a milder form of depression. Dysthymia is characterised by long-term, chronic symptoms that do not incapacitate you but prevent you from operating at full capacity or feeling happy. Dysthymia can lead to significant depressive episodes in certain persons. Finally, the third type of depression is manic-depressive illness, often known as bipolar disorder, is not nearly as common as other types of depression. It entails depressive cycles. [16]

2.1.3 Language and Depression

Language is having a great deal of information about someone. Typically, the depression people will have negative post. Different kind of people will have different word use. The word can contain some hint about themselves, such as status, age, sex, and motives. It is not a new concept to using people word use to diagnostic of their mental, social, and even physical state [17]. De Choudhury et al were able to distinguish depression among Twitter users by using frequent words that the first person pronouns and fewer allusions to third parties. Language features were the most utilised criteria that have been used in statistical modelling which produce the most accurate result [7]. People use word to express their felling. The depression people will normally use the negative adjectives and adverbs such as “lonely”, “sad” or “miserable” to express their emotion. The people who use absolutes words have better markers for mental health forums compare to the negative emotion words [18].

2.1.4 Sleep Disturbances and Depression

As discussed in previous section, depression patient will suffer from unusual condition or disorder. Depression patient will suffer from sleep disturbances (both insomnia and hypersomnolence) are so frequently observed in patients who is experiencing depression. There are 83% of depress patient to had at least one insomnia symptom. Depressed patients are often complaining about difficulty getting to sleep, frequent awakenings during the night, early morning awakening, or nonrestorative sleep. Patients with insomnia are up to 10 times more likely to have depression than normal sleepers, and individuals with persistent insomnia have a significantly higher risk of developing new-onset depression than those who have no sleep complaints. There is a questionnaire study about 2800 members of Depression Alliance (a UK-based charity for people with depression). There are 97% of patient declare about they had the sleep difficulties during depression [19] [20].

2.2 Method

This section will discuss about methods that can be used to detect and analyse text or words. Several methods have been studied and compared so that it can be implemented to this study.

2.2.1 Traditional and Modern Way to Detect Depression

Generally, professional collects the information manually and it only allow for analysis of a small subset of the public. This is the costly process and non-efficient way to do the analysist. The understanding metal health via social media are conduct by Harman et al. He found that it is the cheaper and more efficient way while using social media. There are two methodologies for analysing mental health signals in social media, one is linguistic signals, and the second is text classifier model [21] [22]. There is a large volume of written data available through social media, social media data can be used to measure the people's thought and felling. Early detection of user's mental health can be analysis by the user's social media texts [23]. Over the past decade, social networks have increasingly become a focus of research efforts to identify and characterize the incidence of various disorders. Example Prieto et al proposed a method to use Twitter, to measure the incidence of a set of health conditions [24]. There are many young adults using digital tech to vent their emotion. They rather express their emotion in social media instate their friend or parent [25].

2.2.2 Twitter

As discuss in the introduction section of this paper. Several methods can be used in order to detect depression. Social media can be the platform to detect the depression level among social media user. However, there are many social media applications such as Facebook, Instagram, Tiktok, twitter etc. Hence, this study will only focus on one type of social media, which is Twitter. Twitter is a microblogging service that was launched formally on July 13, 2006. Unlike other social media, Twitter is considered a microblog because its central activity revolves around posting short updates or tweets using the Web or mobile/cell phones [26]. Because of unlimited sources of post and freely access API. Twitter can be most appropriate platform for data scraping. Twitter become the first choice when conducted text classification analysis. Twitter has maximum of character length of 280 character [27].

2.2.3 Natural Language Processing (NLP)

NLP is a core interest in the field of artificial intelligence (AI) and computer science. NLP is aim of achieving the ability to understanding hu effective communication between human and computer in natural language. There are many breakthroughs in NLP, such as advance in machine translation, pattern matching, sentiment analysis, and speech recognition.

2.2.4 Sentiment analysis)

Sentiment analysis is use to classify the user where they have depressed or not. Natural language processing (NLP) and machine learning have been used to perform sentiment analysis of social media posts [28]. The NLP are commonly used in daily life, for example, google language translate, Microsoft word grammar check, Siri, and YouTube video categorize.

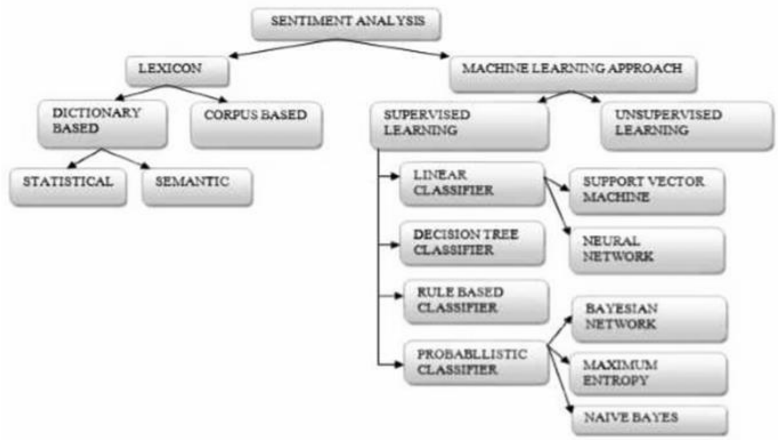

Figure 1: Sentiment Classification Techniques [29].

There are 2 sentiment classification use in NLP, which are Lexicon and Machine learning approach, both rely on the bag-of-words. Lexicon is the collection of word where the word indicates the positive, negative, neutral and objective nature of text. Machine learning approach is an automatic classification technique. Classification is performed using text features [30]. Linear classifier neural network will be applied in this study.

2.2.5 Machine learning approach

There are three type of machine learning approach which are reinforcement, supervised and unsupervised have been studied. Supervised learning – Linear classifier – Neural network are use in the this proposed system. Supervised learning needs a trained dataset which label with training example. It will compare and label a class with maximum matching when there is a word arrive. Linear classifier will base on the linear combination value of the characteristic to perform classification. Let W= {w1, w2, w3….} is word frequency, vector C= {c1, c2, c3….} is linear coefficient vecor and S is a scalar then output of linear predictor will be LP=W.C+S. (LP = linear predictor).

The neural network is the electronic network of neurons that similar to the neural structure of brain. Neuron is the basic element in this network. Neuron are place in three layers, which input and output is hidden [29]. There are two best model Convolutional Neural RNN (LSTM) & CNN (Conv1D). This study will use for the performance comparison between the prediction [31].

2.2.6 Recurrent Neural Networks (RNN) model

The RNN have the form of repeating chain module of neural network. The advantage of RNN are better capture the contextual information. When capture semantics of long text, this would be benefit. But there is an issue about RNN which including a feedback look which serves as a kind of memory. Figure 2 shown the RNN model.

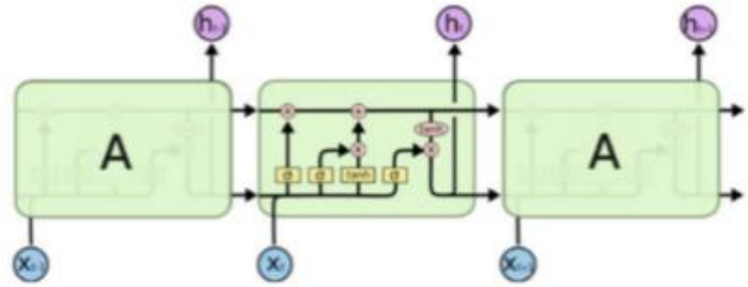

Figure 2: RNN - LSTM Model [32].

This study will use a variant of RNN that called Long Short Term Memory (LSTM) in the system. LSTM are the special kind of RNN where it able to learning long-term dependencies where introduce by [33] [34]. LSTM are specially design for avoid long-term dependency problem [32].

2.2.7 Convolutional Neural Network (CNN) model

CNN is a class of deep, feed-forward artificial neural networks. It uses the variation of multilayer perceptron designed to require minimal pre-processing. CNN model as in Figure 3, are normally use in computer vision, but it recently has been applying for NLP task, and the result are promising. The knowledge about the linguistic structure of a target language is not require by CNN. Because of this advantage, the CNN are able to predict various text analyses. [9]. When the special pattern is detected, the result of each convolution will fire. It will be varying the size of the kernel and concatenating their outputs. Patterns could be expressions (word n-grams?) like "I hate", "very good" and therefore CNNs can identify them in the sentence regardless of their position [12]. The sentiment analyst did not have a fix model in analyst, RNN (LSTM) are not always have the highest accuracy comparing to CNN. Table 1 shows the list of other studies have been done before the research.

Table 1: Related work comparing CNN and RNN (LSTM)

No.	Paper Title	Author	Result
1	A Hybrid CNN-LSTM Model for Improving Accuracy of Movie Reviews Sentiment Analysis [35]	Anwar Ur Rehman1 & Ahmad Kamran Malik1 & Basit Raza1 & Waqar Ali1	The result is plot in bar chart. The accurate are estimate. LSTM have the higher accuracy of ≈87.5% comparing to CNN have accuracy of ≈86%.
2	Twitter Sentiment Analysis using combined LSTM-CNN Models [36]	Pedro M. Sosa	LSTM have the higher accuracy of 72.5% comparing to CNN have accuracy of 66.7%
3	Evaluation of Deep Learning Techniques in Sentiment Analysis from Twitter Data [37]	Sani Kamış & Dionysis Goularas	Single LSTM Non-Regional have higher accuracy of 51% comparing to Single CNN Non-Regional have 49% of accuracy.

Because there is limited paper who used, LSTM & CNN as depression detection. So, we refer to the paper who used LSTM & CNN as comparison in NLP. By reading these articles, we are adapting their method to the research.

3 RESULTS AND DISCUSSION

Following is the research methodology that have been implement for this study. Next section will be discussed about the research methodology that have been implemented for this study.

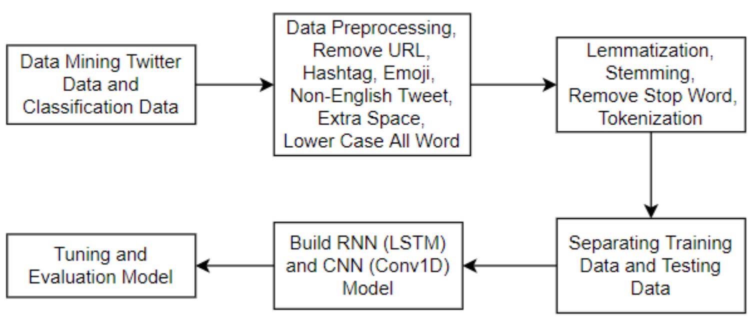

Figure 3: Research Methodology

3.1 Dataset and Data Mining

The depression and non-depression username dataset are created. The depression username dataset is the user tweet that contain “diagnosed” and “depress”. Non-depression username dataset is the random username that does not contain in depression username dataset. Both dataset’s user had been checked manually by reading through all their tweet, make sure all the users are not spam account. Each of the username dataset contain of 100 users. The tweet of depression user been scrape from the date they diagnosed depression until 1 month before diagnosed, and label by "1". The random user tweet dataset will also been scrape and label with "0". The figure 4 below show the number of depression and non-depression tweet.

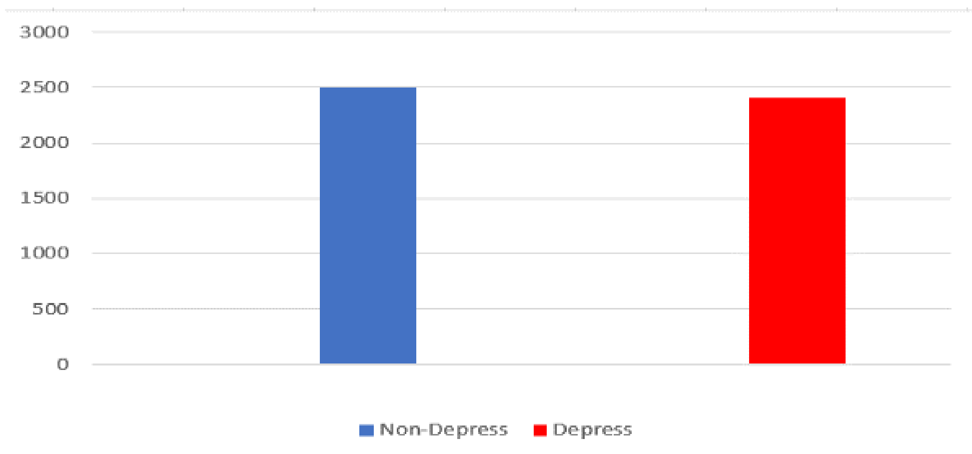

Figure 4: Number of depression and non-depression tweet

3.2 Preprocessing Data

In the data preprocessing stage, all the tweets will be cleansing by removing URL, hashtag, emoji, non-English word, extra space, and lower case all the word. After that, all the sentences will be lemmatization, stemming, remove stop word and tokenization. The data have been split by training data 80% and testing data 20%. Training data is the initial dataset used to train deep learning algorithms. Models create and refine their rules using this data. Test data is used to evaluate the performance or accuracy of the model.

3.3 Implement and Hyperparameters Tuning Model

Four (4) model have been implemented in this study. Which is RNN (LSTM) 4Layer, RNN (LSTM) 7Layer, CNN (Conv1D) 6Layer, and CNN (Conv1D) 9Layer. All the models will be hyperparameters tuning. The variable of hyperparameter tuning will be "activation", "dropout", "batch size" and "epochs". From the table 2 "batch size" and "epochs" compare. The lowest the "batch size" and higher the "epochs" will have more accuracy. Bigger batch size and lower epochs will be less accurate but faster training speed. From the table 3, all of the parameter tuning will have higher accuracy when the 'relu' and 'sigmoid' are used. The dropout rate of 0.5 is most suitable in the implementation.

Table 2: Hyperparameter tuning “batch size” and “epochs”

BATCH SIZE	EPOCHS	ACCURACY
6400	5	0.7627313
6400	10	0.7674828
6400	**15**	**0.7696367**
12800	5	0.7604156
12800	10	0.7650242
12800	15	0.7676156
25600	5	0.7536031
25600	10	0.7622414
25600	15	0.7635469

Table 3 Hyperparameter tuning “activation” and “dropout”

ACTIVATION	DROPOUT	ACCURACY
softmax & sigmoid	0.5	0.7625953
softmax & sigmoid	0.6	0.7602305
softmax & sigmoid	0.7	0.7576953
softmax & sigmoid	0.8	0.7542539
relu & sigmoid	**0.5**	**0.7662984**
relu & sigmoid	0.6	0.760507
relu & sigmoid	0.7	0.7518727
relu & sigmoid	0.8	0.7458211
tanh & sigmoid	0.5	0.7565992
tanh & sigmoid	0.6	0.7545828
tanh & sigmoid	0.7	0.752568
tanh & sigmoid	0.8	0.7493281
sigmoid & sigmoid	0.5	0.7502539
sigmoid & sigmoid	0.6	0.7478664
sigmoid & sigmoid	0.7	0.7424352
sigmoid & sigmoid	0.8	0.7393219

3.4 Evaluation, Result and Discussion

In the result, evaluation and discussion stage, an evaluation of accuracy, loss, precision, recall, F1, and training time will be carried out determine which model is most suitable for this study. F1 and Accuracy are important in this study, for avoid wrong depression detect. Table 4 are the confusion matrix for the performance evaluation.

Table 4: Confusion Matrix for performance evaluation

CLASSIFICATION CATEGORY	DEPRESS	NON-DEPRESS
DEPRESS	True Positive (TP)	False Negative (FN)
NON-DEPRESS	False Positive (FP)	True Negative (TN)

As the result, Table 5 shown the accuracy, loss, precision, recall, F1, and training time about the four model. The RNN(LSTM) 7Layer have the most accuracy, precision, recall, F1, and less loss compared to 3 other model. But the training time also the highest comparing other three model. The accuracy, precision, recall, and F1 of the RNN (LSTM) model is significantly higher than the CNN (Conv1D) model. The loss of RNN (LSTM) also significantly lower than the CNN (Conv1D). The training time are longer when compare with RNN (LSTM) with CNN (Conv1D). The RNN (LSTM) is more suitable for sentiment analysis compared to CNN (Conv1D).

Table 5: The accuracy, loss, precision, recall, and F1 value; comparison between RNN (LSTM) and CNN (Conv1D)

MODEL	ACCURACY	LOSS	PRECISION	RECALL	F1	TRAINING TIME (H:M:S)
RNN (LSTM) 4Layer	78.36%	45.59%	75.68%	83.66%	79.46%	1:19:04
RNN (LSTM) 7Layer	80.99%	45.01%	76.82%	83.81%	80.16%	2:19:47
CNN (Conv1D) 6Layer	76.48%	49.59%	74.69%	80.20%	77.34%	0:42:37
CNN (Conv1D) 9Layer	77.40%	47.46%	7548%	81.26%	78.26%	1:00:43

3.5 System Dashboard & Google Chrome Extension

The figure 5 to figure 10 show the system dashboard, it consists of 4 pages, which is user active tab, word cloud tab, topic frequency tab, and extension user data collect tab. The dashboard is describing the depression insight of user behavior, such as depression and normal user activity. The dashboard also shows the data hat collected from the user. The google chrome extension is for user to predict their depression status.

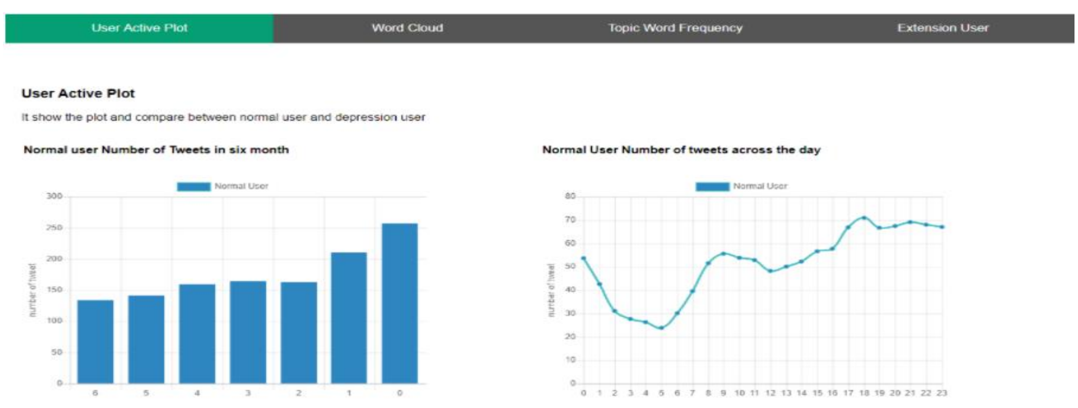

Figure 5: Visualize Dashboard 1

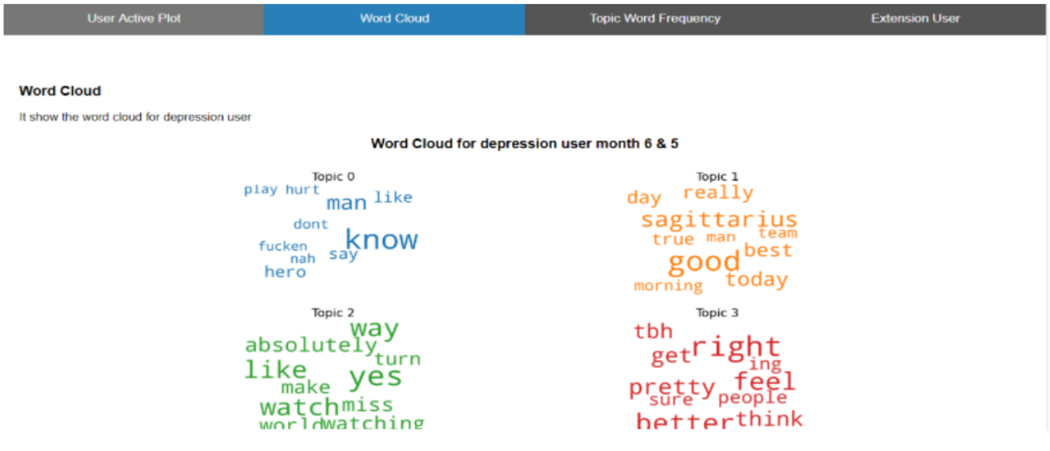

Figure 6: Visualize Dashboard 2

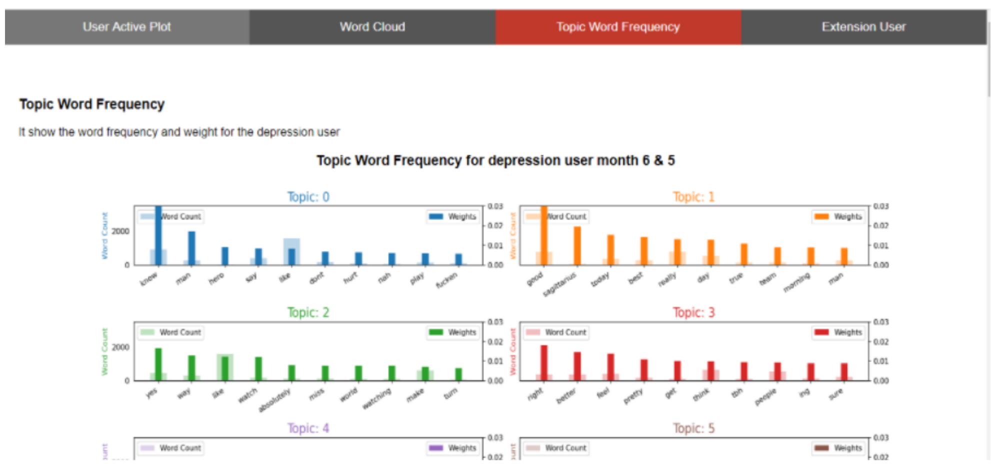

Figure 7: Visualize Dashboard 3

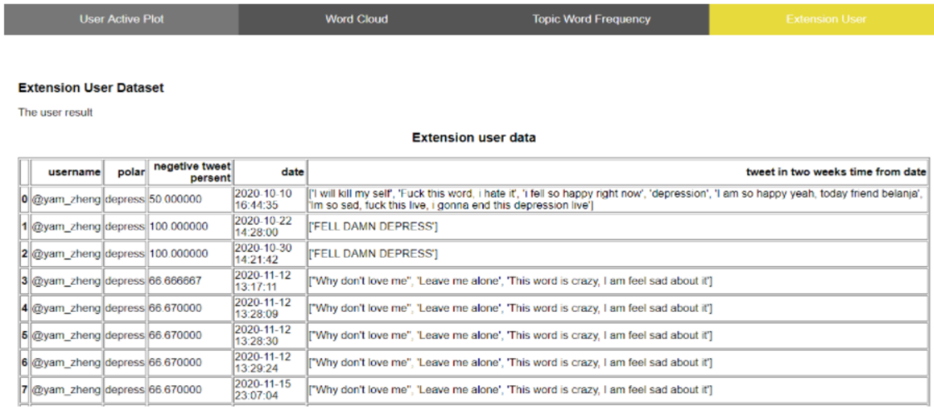

Figure 8: Visualize Dashboard 4

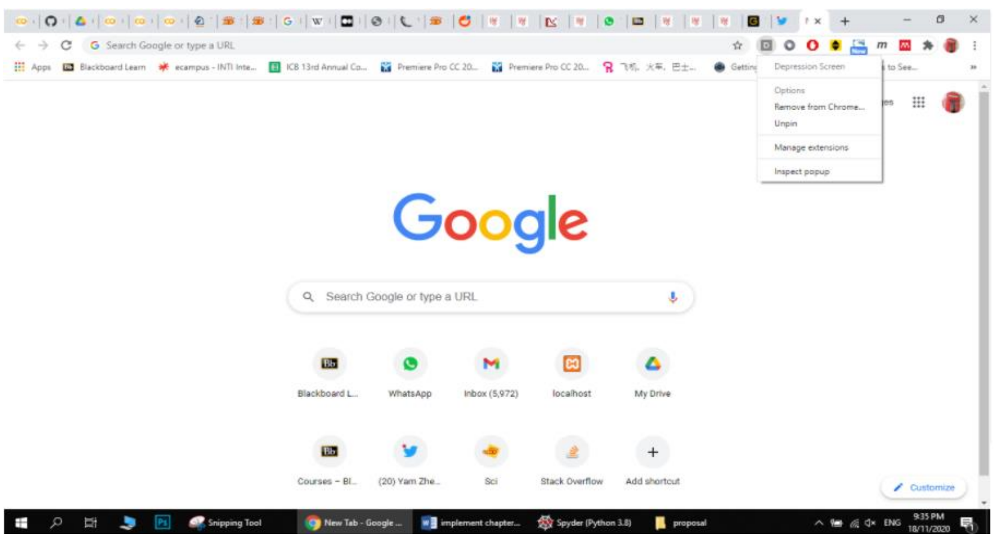

Figure 9: Disable to open Extension when it is not Twitter page

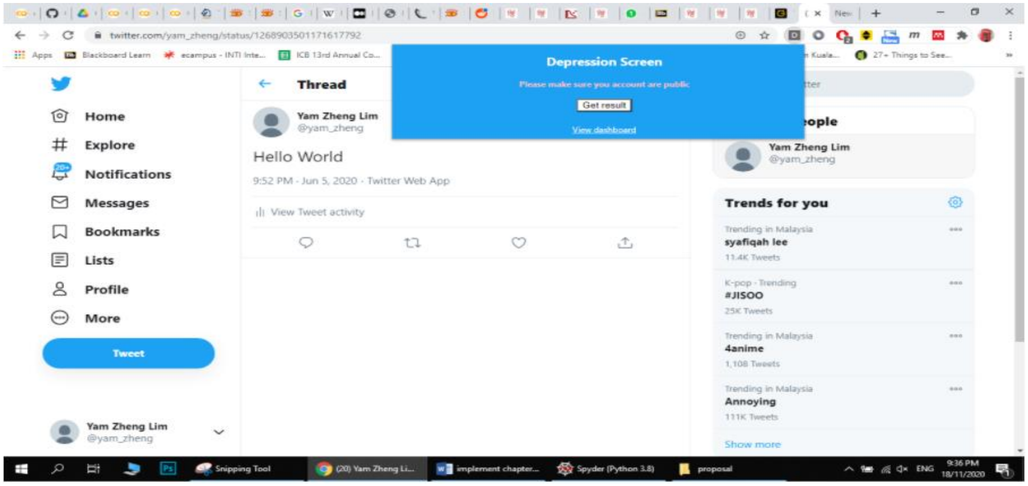

Figure 10: User can using the extension to get their depression status

4 CONCLUSION

As conclusion, the method of model evaluation has been explained. The accuracy, loss, precision, recall, and F1 is used to evaluation. The hyperparameter tuning is one of the important steps while building the model. From the comparison, the RNN (LSTM) 7-layer model are the most accurate, precision, recall, F1 score of and less loss compare with other 3 model. The accuracy is 80.99%, F1 80.16%, and loss 45.0%. The RNN (LSTM) had selected 7-layer as the model in development the google chrome extension to perform the tweet sentiment analysis. Refer to Table1 on this paper, this study obtains the same result as those three papers, which shown LSTM have highest accuracy comparing to CNN. For the future work, google chrome extension will be upload to Google Store, and the user private data will be opted in. We also want to implement our model to the other types of social media to compare the accuracy and detect the depression level on the other social media platform.

ACKNOWLEDGEMENT

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