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E-LEARNING TWITTER SENTIMENT ANALYSIS USING SUPPORT VECTOR MACHINE: A COVID-19 CASE STUDY

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Abstract*: It has been more than a year since the Covid-19 pandemic struck. It is evident that adoption of online teaching has changed the landscape of the education sector. However, the efficacy of online teaching is the main concern because it depends on the study of the present time as the method is evolving. Another problem is platform such as Sistem Pengurusan Aduan Awam (SISPAA) that exist to accept complaints and suggestions from the people is found to be very inefficient since not many people are familiar with it. Furthermore, it is quite complex to interpret the sentences and analysing the sentiments due to the granularities of words and phrases. As a solution, Sentiment Analysis can be conducted to analyse the sentiments of the people on Twitter platform. These sentiments will reflect the view and the efficacy of the new method by providing statistical analysis on the issue. Lexicon and rule-based tool, VADER is used to label the sentiments that later will be visualized, and further steps are taken to test the accuracy of Support Vector Machine (SVM) model against Linear Regression (LR) model. The analysis shows majority of the twitter users have a positive review for E-learning and the SVM is the better classifier because it has a higher accuracy percentage compared to LR. This project follows Data Science Life Cycle methodology and confusion matrix is used to visualize the accuracy testing for both models. The significance of this project is to provide a statistical analysis on the new approach based on Twitter data. Plus, the findings of this project can be used to improve the implementation of current online teaching method. For future research, Sentiment Analysis can be improved by tuning different parameter property and using another various technique with different machine learning models.*

Keywords*: e-learning, sentiment analysis, social media, support vector machine*

Introduction

In the beginning of 2020, the World Health Organization (WHO) declared that the coronavirus or better known as the Covid-19 outbreak as a global pandemic that posed a major threat to humanity. This pandemic has made a global shutdown of several prime activities including educational activities. This has caused a sudden action of migrating towards E-Learning

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platforms from the traditional method to keep the academic activities continuing despite the outbreak (Adedoyin & Soykan, 2020).

The emergence of E-Learning platforms has made many educators and researchers inclined towards online home-based learning as a new means to deliver lessons and interact with the students. It is a way of adaptation and improvement since institutions and schools must shut down temporarily to curb the outbreak. It has grown rapid due to its potential of providing more flexible access to content and instruction at anywhere and anytime (Castro & Tumibay, 2019). Online learning may not be totally foreign to some students in Malaysia since some institutions took actions to integrate the use of online student portals for study purposes in their learning activities. However, teaching activities through the student portal has not been conducted a hundred percent previously, it was used partially as an additional aide to further enhance the effectiveness of learning. Ever since the new approach is used, there were numerous mixed opinions regarding the approach. Some people liked it and some found it hard to adapt to certain issues.

Meanwhile there are pros and cons towards the e-learning method in different aspects, the most significant is the stress on the quality, making it harder to deliver and receive at the same time for both parties. Thus, it is imperative that the researchers consider, and examine the efficacy of online learning in educating students (Castro & Tumibay, 2019). In other words, reviewing the opinions of people involved in the approach can reflect the quality and the effectiveness of online learning which is the most crucial aspect in academics. Hence, finding out the opinion of this matter is important.

Microblogging on social media and websites became a trendy communication platform among internet users nowadays. Some of the most popular microblogging websites such as Twitter, Facebook and Tumblr generated millions of raw messages everyday turning it to be a rich source of data for opinion mining and performing Sentiment Analysis (Pak & Paroubek, 2010). Opinion mining can be done to extract raw data from social media and websites. It is useful because it can be converted into valuable information by using Sentiment Analysis. This allows us to see the classified opinions of people. Based on research, opinion lexicon methods are mostly used to analyze text sentiment in microblogging sites, mainly in twitter (Drus & Khalid, 2019). Next, data visualization will be done to the classified data, and it will represent the statistics of the opinion in which it will fall under the three categories which are either positive, negative and neutral provided. The formatter will need to create these components, incorporating the applicable criteria that follow.

Besides that, digital teaching is still not a common practice for the teachers and students in Malaysia. Since it is a new method, its effectiveness is the main concern. According to (Nguyen, 2015), the effectiveness of online learning is still inconclusive as the new method is still progressing and the only way to determine its efficacy is to conduct a research of the time it is implemented. Covid-19 pandemic has made a lot of education sectors to adopt the use of digital teaching as the main medium for teaching and learning.

“Sistem Pengurusan Aduan Awam” (SISPAA) is supposed to be the medium for delivering reviews and suggestions by the public to the government. However, since the system is not fully utilized, the data is found to be limited and it is not suitable to make analysis on it. A survey was conducted on 20th of April with 34 number of respondents participated in it. The main point of this survey was to find out the familiarity of the people with the web system SISPAA.

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Based on the results, only 17.6% of the respondents are familiar with the use of the platform. This shows that data gathered inside the existed system is too little to make an analysis since not many people know the existence of it. Twitter on the other hand act as a powerful medium for people to voice out their opinion with 76.5% agreed that Twitter is their main social media platform that they use to express opinions because it is easier and faster compared to SISPAA. In addition to that, using Twitter as the source for data mining is very useful since statistics from Statisca.com shows that in 2019 Twitter has approximately 2.4 million users in Malaysia and the number is predicted to keep increasing in the future.

Social media platforms are a rich place to conclude opinion of products. However, the tweets from Twitter are hard to interpret due to the granularities of words and phrases. The major problem is still related to the correct interpretation of context in which certain words are used. It is still however a challenge due to the raw data from twitter that does not have grammar and spelling check, with new slangs of words constantly emerging, short forms that are being written for the convenience of users and accents of native languages (Devi et al., 2020). Hence, it is still difficult for a vast majority of tools to precisely evaluate what truly is negative, neutral or a positive statement.

Related Works

E-Learning

Due to the worldwide spread of the COVID-19 virus, many institutions must come up with new ways to keep the teaching and learning process safe for all students. Almost 120 countries stopped the traditional face-to-face teaching method and the effect from this has caused roughly a billion students' education worldwide. Meanwhile, to curb the COVID-19 pandemic, all countries and including Malaysia chose to issue the order to shut down institutes such as the public school and higher education as an emergency measure to stop the infection (Shahzad et al., 2020).

According to (Tung et al., 2020) in Vietnam, almost all universities had to suspend their traditional teaching activities due to the government's social isolation warning. However, thanks to our technology development and education, a lot of teaching and learning methods can still be implemented during this time such as online training, distance learning and blended learning. These types of teaching methods do not require a direct human-to-human interaction and it is very essential and suitable in the current context where it is not safe to deliver lessons traditionally.

E-Learning is covered by a wider term of technology-based learning through websites, learning portals, video conferencing, online video-sharing platforms like YouTube, mobile apps and others for blended learning tools. Based on the news reports, many institutes such as universities, colleges, polytechnics utilize Massive Open Online Courses (MOOC). The growth of the online education market is skyrocketing with 16.4% annually more than the forecast period between 2016-2023. Synchronous with the development of technology and education that is moving quickly, it is expected that university teaching models might change in 10 to 15 years to come. Education quality and excellent facilities such as high-performance computer and IT equipment reception are now in high demand and with the use of intellectual resources, universities are adapting their teaching models (Shahzad et al., 2020). The advantages of E-Learning include having the flexibility for students to schedule their studies at their

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convenience, institutes can reuse prepared course materials and it is also relatively cheaper for institutions, maintaining content availability and it does not depend on the location.

However, as opposed to the benefits, E-Learning had many downsides that needed to be considered. One of them is, the process of preparing materials, it took a lot of time compared to the traditional method. Next, teachers' lack of confidence was found as a discouraging factor for ICT supported learning (Soni & Dubey, 2018). Additionally, inadequate bandwidth caused delays or connection failures and that seemed to be the main issue that everyone is facing worldwide. Broadband services for example did not cover the entire geographical area. This showed that there was a concerning gap that posed as a challenge to connect students and teachers (Ferri et al., 2020).

Due to the sudden switch to E-Learning, Sentiment Analysis was performed to analyse students' reviews on the approach. This analysis is vital to measure the efficacy and quality lessons being delivered to the students through new means.

Sentiment Analysis

Over the years, polls have been the primary way to address the question of "What do people think?". The traditional method of learning about large numbers of people was by careful sampling of the surveyed population and a structured questionnaire. However, the age of universal access to the internet and social media has recently introduced as a new way of learning human populations. Social media provides an important outlet for thoughts and feelings of people. It is a massive ever-growing source of texts that ranges from daily observations to observations. This study added to the field of analysis of sentiment, which it aimed to extract textual emotions and opinions (Mejova, 2012).

Sentiment Analysis and opinion mining is the machine study of thoughts, perceptions and feelings of people reflected in the text of natural language. Due to a large range of applications and many difficult issues, Sentiment Analysis had become a significant research field (Wu & Publishing, 2011). Sentiment Analysis and opinion mining has become a hotspot of study with the quick development of websites for social networks. For example, microblogging sites like Twitter were the typical social media network application with millions of users sharing their thoughts every day (Yuan, 2017).

There are varieties of methods to be used for Sentiment Analysis classification, ranging from free online sentiment classifier to machine learning classifier. There was no objectivity in choosing what kind of classifier for the project because every classifier had its own advantages and limitations. However, the technique must be feasible for the type of data that was collected. The most common machine learning classifiers used to find sentiment on social media are Naïve Bayes (NB) and Support Vector Machine (SVM). These two techniques were commonly used as a benchmark due to its potential to yield high accuracy level. Nevertheless, Support Vector Machine (SVM) classifier was chosen for this project rather than Naïve Bayes (NB) due to its characteristics which is far more suitable to be used for the text analysis.

Lastly, there are numerous types of visualization methods that existed to help display the data in a more convenient way. These visualization techniques depended on the three factors which were volume of data, data variety and data dynamic. Every technique displayed data in a different way according to the purpose of evaluation. These graphs were very interactive with the help of colour elements to assist the delivering of analysis in a more effective way.

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Nonetheless to say, these visualization techniques shared the same goal which was to make humans' work easier to identify patterns, trends and outliers in large datasets.

Proposed Works

This project followed the stages in data science lifecycle. Working with a project that required a big volume of data, it has always been a beneficial thing to closely follow a proper data science workflow. The lifecycle is divided into seven different stages: Business Understanding, Data Collection, Data Preparation, Exploratory Data Analysis (EDA), Modelling, Modelling Evaluation, Model Deployment, and repeat.

Business Understanding

Business understanding is the first step in Data Science Life Cycle, it plays an important role to make sure the project is successful. It is vital to understand the set of rules and goals in business in order to obtain the correct and accurate data. Data scientists required to probe questions such as why to shortlist number of knowledges to a precise data acquisition. The five questions typically are in the form of regression, classification, clustering, anomaly detection and recommendation. In this stage, the main objective of the project is identified alongside with variables that need to be evaluated.

Data Collection

For this project, tweets were scraped by using Twint. It is a scraping tool written in Python that allowed the scraping of Tweets from Twitter without using Twitter's API. The plan initially was to use official Twitter API as the medium to collect data. However, Twitter API has a few limitations such as being a limit of tweets that can be collected, the oldest tweets can only be from seven days before to the current time, personal information such as email and phone number are hidden. The second limitation is a major problem for the project since the project required to analyze tweets made from the day schools and institutions were closed by the government which is dated around March 2020. The project needs to collect tweets made about E-learning from the moment E-learning is enforced due to the pandemic.

Tweets were scraped from Twitter based on 13 different keywords which are identified to bring the same meaning as E-learning. Ever since E-learning was implemented, a variety of words such as blended learning, online learning, home-based learning, and other terms that reflect the use of digital teaching were chosen as the keywords to extract the tweets. These 13 different keywords were blended learning, online learning, distance learning, e-learning, ODL, online class, online distance learning, online lecture, open and distance learning, online course, home based learning, virtual class, and virtual learning. Combining all the tweets that had successfully scraped using 13 different keywords into one excel file brings out a total of 30,773 raw data.

Data Preparation

In this stage, raw tweets were filtered through the language column using excel filter feature. All the 30,773 raw data included other languages such as Thai, Tagalog, Bahasa Indonesia and many more were removed except for English language. After the filtration process, some of the unnecessary columns were removed and only 9208 raw tweets were left. The remaining raw tweets were then ready to be loaded into Jupyter Notebook for further cleaning process using python language.

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Firstly, all the necessary python libraries need to be imported inside the Jupyter. The first cleaning process for the raw tweets was to clean the special character such as @mentions, hashtag, RT, hyperlinks, and numerical value inside the tweets. These symbol and numerical value are considered insignificant value as they do not add up any meaning and it is better to have them removed to keep data trimmed and simple. To clean them, a function was created with the instructions to remove all the special character present in the tweets. Figure 1 shows the difference before and after special character is removed. Column 'special_character_removed' showed that the function worked, and it had successfully removed @, #, and numerical value from the tweets.

Next to be removed is the punctuation. Punctuation marks in the text are considered insignificant as it does not add any meaning to the text and pretty much useless for the analysis later. The basic approach to deal with this is to remove everything that is not a standard number or letter. Hence, for this step of cleaning, punctuation marks were removed from the tweets.
Stop words are common words such as 'if', 'but', 'we', 'he', 'she', and 'they' also need to be removed. They are available in abundance in any human language. By removing these words, we remove the low-level information from our text in order to give more focus to the important information These words need to remove from the data without changing the semantics of a text as in Figure 2.

	tweet	special_character_removed
0	FEU Tech is responding to the new normal in sc...	FEU Tech is responding to the new normal in sc...
1	We are excited to continue our partnership wit...	We are excited to continue our partnership wit...
2	Leadership #onlinelearning continue with @NFS...	Leadership onlinelearning continue with Lead...
3	Good dayIWe are researchers from 12 - Our Lady...	Good dayIWe are researchers from - Our Lady o...
4	Dr. Maszlee Malik always stand up for educator...	Dr. Maszlee Malik always stand up for educator...
5	Auto grad Bachelor in Online Learning nampak g...	Auto grad Bachelor in Online Learning nampak g...
6	#OnlineCSC has started! The Live QA was a gre...	OnlineCSC has started! The Live QA was a grea...
7	Online learning: 5 ways to make the most of th...	Online learning: ways to make the most of the...
8	@sowonthepb HAHAHA subway cookie 😂😂 I ate that...	HAHAHA subway cookie 😂😂 I ate that in my scho...
9	A language learning app that doubles as a #cal...	A language learning app that doubles as a cale...

Figure 1: Removing '@', '#', 'RT', hyperlinks and any numerical value

	removed_punctuations	removed_stopwords
0	feu tech is responding to the new normal in sc...	feu tech responding new normal schools launchi...
1	we are excited to continue our partnership wit...	excited continue partnership hso symphony onli...
2	leadership onlinelearning continue with lead...	leadership onlinelearning continue leadership ...
3	good daywe are researchers from our lady of ...	good daywe researchers lady mt carmel humbly a...
4	dr maszlee malik always stand up for educators...	dr maszlee malik always stand educators studen...
5	auto grad bachelor in online learning nampak g...	auto grad bachelor online learning nampak gayanya
6	onlinecsc has started the live qa was a great...	onlinecsc started live qa great success key ta...
7	online learning ways to make the most of the ...	online learning ways make student support role...
8	hahaha subway cookie 😂😂 i ate that in my scho...	hahaha subway cookie 😂😂 ate school almost ever...
9	a language learning app that doubles as a cale...	language learning app doubles calendar organiz...

Figure 2: Stop words successfully removed from the tweets

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In this process of calculating sentiments, VADER (Valence Aware Dictionary and sEntiment Reasoner) was used to calculate the sentiments of tweets and label them accordingly to three classes which are negative, positive, and neutral. VADER is a lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media. VADER used a combination of sentiment lexicon, a list of lexical features (e.g., words) which are generally labeled according to their semantic orientation which is either positive or negative. SentimentIntensityAnalyzer() is an object and polarity_scores is a method which will give us scores of positive, negative, neutral and compound.

According to (Hutto & Gilbert, 2014), the label settings for the compound score is set as positive sentiment: (compound score >= 0.05), negative sentiment: (compound score <= -0.05), neutral sentiment: (compound score > -0.05) and (compound score < 0.05).

Exploratory Data Analysis (EDA)

In this process, both stacked bar chart and bar chart were used to perform initial investigations on data as to discover patterns and hypothesis with the help of summary statistics and graphical representations. Figure 3 shows the number of tweets for each of the sentiment class after the tweets are successfully labelled by VADER.

```
Positive    4264
Neutral     3420
Negative    1344
Name: Analysis, dtype: int64
```

Figure 3: Number of tweets for each of the sentiment classes

A simple statistical analysis output on the number of sentiments belong to each of the classes is made. Figure 4 shows the bar chart of sentiment count for each of the classes.

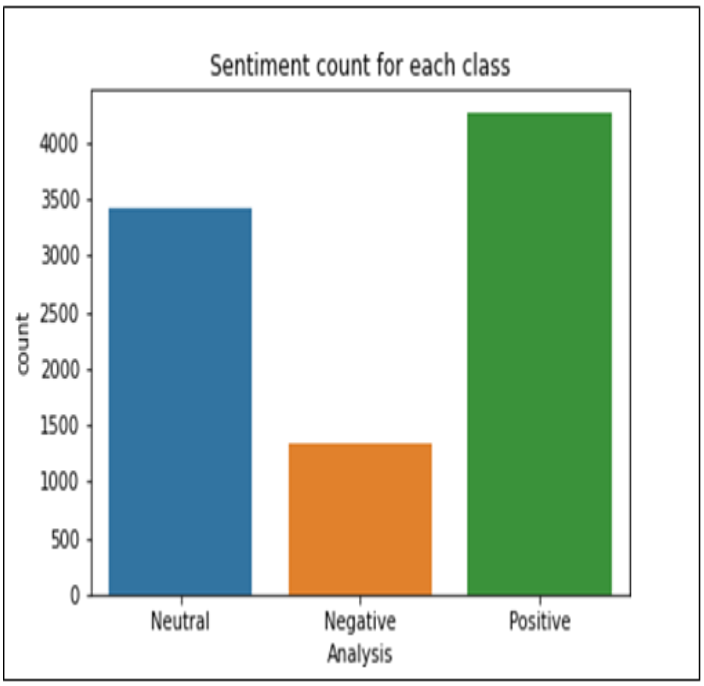

Figure 4: Classification of the tweets

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The result was transformed with the use of bar chart by using Matplotlib. It was plotted to represent the number of sentiments belong to each of the classes in a more interactive way. As seen from the Fig4, more than 4000 tweets were identified as positive sentiments, meanwhile neutral was the second runner up with less than 3500 tweets were classified under the class and negative sentiment with the least value which made up of less than 1500 tweets.

Data Modeling and Fitting

The main model that is used to evaluate the accuracy of the dataset was Support Vector Machine (SVM). This model is used as it is proven by many researchers that it is very good at handling text data and provides much better accuracy compared to the other models. The second model which is Logistic Regression model was used to compare both models' accuracy based on the same value parameter.

The dataset was spilt into two types which were test and train set with the ratio of 80:20. After splitting, vectorizing the data was performed by using CountVectorizer(). It is used to transform a given text into a vector based on the frequency (count) of each word that occurs in the entire text. CountVectorizer is a way to convert a given set of strings into a frequency. This process called feature extraction or sometimes may be known as vectorization. Scikit-learn's CountVectorizer is used to convert a collection of text documents to a vector of term or token counts. Both of train and test datasets is vectorized before data is modelled with the SVM and LR.

In this phase, parameter that became the manipulative variable is C parameter in Support Vector Machine and Logistic Regression model. The C parameter tells the SVM optimization how much a user wants to avoid misclassifying each training example. Then, SVM model was built with different C parameter value which were 0.01, 0.05, 0.25, 0.5, 0.75, 1.00. These parameter value is set according to (Imelda et al., 2015) previous project with a little tweak on the value to give a more varieties. The train dataset was fit into the model and tested for their accuracy. The value of C parameter that give the highest accuracy percentage was chosen for model fitting for the test dataset. The same process took place for LR model with the same C parameter values is set as SVM model. Table 1 shows the accuracy results for both SVM and LR models.

Table 1: Accuracy results for both SVM and LR models

C Parameter Value	Support Vector Machine (SVM) Accuracy	Logistic Regression (LR) Accuracy
0.01	0.77	0.71
0.05	0.83	0.76
0.25	0.86	0.82
0.5	0.86	0.84
0.75	0.86	0.84
1.00	**0.87**	**0.84**

Both of 1.00 C parameter value for both models gave the highest accuracy. Therefore, C parameter 1.00 was used to fit the test data set to the SVM model and LR model. A hypothesis can be made based on the results according to (Imelda et al., 2015), the larger the value of C parameter, the higher the accuracy percentage it would yield. In other words, higher C value

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means that the model cared more about every single point and smaller C means it focused more on the margin or the boundary which may have resulted in some classification errors and giving up a few points.

Model Deployment and Evaluation

Both models SVM and LR were evaluated by using confusion matrix. The best parameter value based on the previous steps were used to fit the model against the train dataset. The results are as shown as in Figure 5 and Figure 6. Based on the results, the accuracy percentage for SVM model is higher than LR model by 3%.

The results showed a bias finding towards the positive sentiments. It dominated the analysis with the amount of 4264, meanwhile 3420 classified as neutral sentiments and negative sentiments with only 1344 tweets. Positive sentiments made up of 47.23% which is almost half of the tweets meanwhile neutral sentiments composed of 37.88% and 14.89% for negative sentiments. The positive sentiments over here can be concluded that the public is accepting the E-learning method with words such as “happy”. “grateful” and “simple” are found in most of the tweets collected. This shows that they are happy, feeling grateful and finds digital teaching simple and not complicated. Based on the results, it is proven that people’s review on the use of E-learning are very positive and indicates that the approach is successfully effective as a medium for teaching and learning during the time of lockdown.

From the evaluation, SVM model gained 87% whereas LR model gained 84% accuracy. The overfitting risk in LR could possibly be the reason why it is less accurate compared to SVM. Unlike LR, the risk of overfitting in SVM is possible but much less due to its process of classification that is different than LR. SVM chose a specific hyperplane that separated data and LR computes probability values that ranged from 0 and 1.

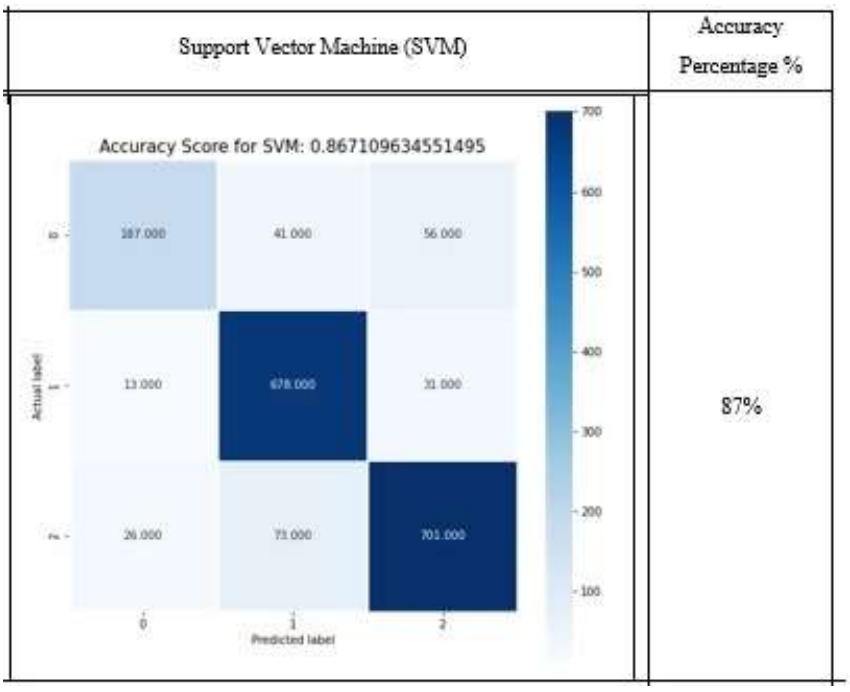

Figure 5: Confusion Matrix for SVM

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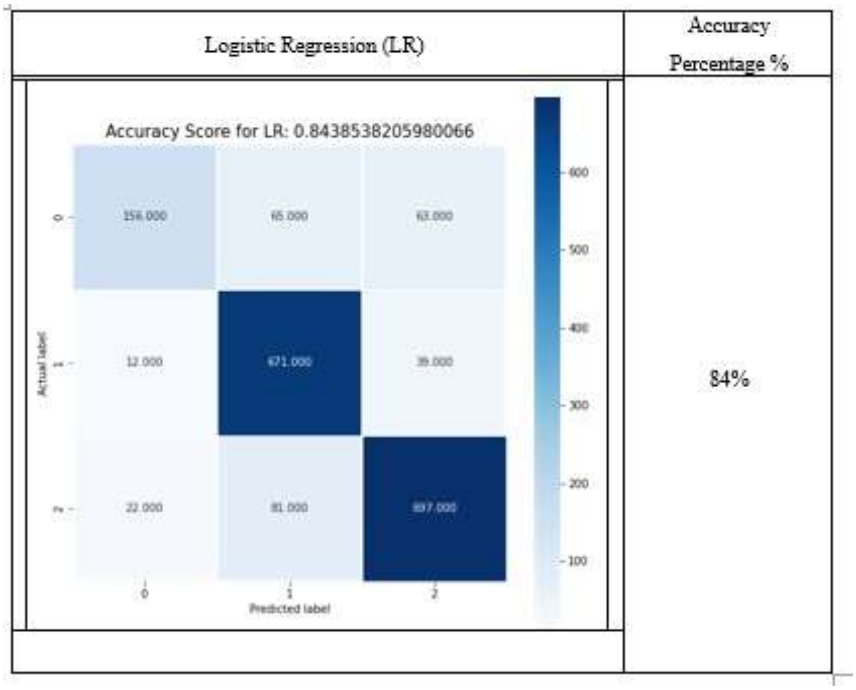

Figure 6: Confusion Matrix for LR

Conclusion and future works

The purpose of this study is to conduct a sentiment analysis on E-learning based on Twitter data using Support Vector Machine. Overall, it can be concluded that SVM was the better and more accurate algorithm for this project as it yielded a higher percentage compared to LR algorithm by 3% more. Further research can be done on other parameters functions in SVM and LR since the only parameter that was tuned in this project was C parameter alone with different values. By doing so, it would elaborate an extensive understanding on which parameter tuning will give a better classification result.

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