Sentiment Analysis of TikTok and Instagram Reviews on Google Play Store

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***Abstract*—In today’s digital era, social media is one of the most used media right now since it connects and entertains people. With how fast TikTok and Instagram grow, both apps still receive backlashes, where for Instagram, it receives backlash for losing their identity as a photo shared social media and TikTok for its controversial user data security problem since 2020. The more people use social media, we could see how expressive they are in terms of reviewing. This study will do a sentiment analysis on TikTok and Instagram Google Play Store review with Multinomial Naïve Bayes method, because both TikTok and Instagram went through a significant growth in the past few years. This research aims to analyze how accurate the method can predict the positive sentiment and negative sentiment with dataset for Instagram and TikTok is 261.554 each, where Instagram’s sentiment accuracy is 74% and TikTok’s sentiment accuracy is 88%. The result shows that even though Multinomial Naïve Bayes is one of the most effective ways to do sentiment analysis method.**

***Keywords—Multinomial Naïve Bayes, Sentiment Analysis, TikTok, Instagram, Review***

# INTRODUCTION

In today's digital era and with how fast social media developed, it became a crucial thing to connect people around the world. Not only connecting them, but social media also provides entertainment for people [1]. In 2024, there are approximately 5.16 billion active social media users worldwide with the most popular social media activities including watching videos, reading news, and interacting with friends and family [2]. The most popular social media platforms right now are Facebook with 3.04 billion users (61.05%), YouTube with 2.5 billion users (48.45%), WhatsApp and Instagram 2 billion users (38.76%), and TikTok 1.5 billion users (19.38%), which shows that Instagram and TikTok are one of the most used social media platforms today [2].

Younger users especially Gen Z has a view where the amount of time they spend on social media as a time saver because while on it, they are still connected to each other without having to reach out individually, or to simplify, they feel like they have social life by spending time on these apps especially TikTok and Instagram [3]. TikTok and Instagram are very popular in various circles and both platforms are mostly similar in terms of user experience and the features they have.

TikTok and Instagram are one of the newest social media platforms yet have the most impressive progress where they are open with users’ feedback and always up to new features and trends for their application. But even with this excellent progress, both platforms still get some bad ratings and reviews from their users. For example, Instagram is having an identity crisis because the reels feature on it made Instagram lean more into video and share more recommended posts from accounts that the users don’t follow [4], similar to TikTok’s For You Page feature. As for TikTok, it received a backlash because of the user data security issue which grew into a global backlash in 2020 [5]. The Google Play store offers the TikTok and Instagram app for Android users to download. There is a review feature in the Google Play Store that lets you assign a star to an app, movie, e-book, and other products [6].

Research about TikTok and Instagram analysis itself is not a new thing. There are a lot of papers who already did this sentiment analysis with different methods. There is a sentiment analysis using RNN classification where this paper is interested to know how worried the users are with their user data security [7]. The other example is using CNN method, where it talks about how users should be more aware with how they use the apps [8], or the last example is using Decision Tree algorithm to find possible threats and privacy risk from social media [9].

From the research that have been done, this paper will investigate the sentiment of user reviews for TikTok and Instagram on Google Play Store to find out what are the prevailing sentiments in users’ reviews for both apps, and to examine how user experiences and perceptions shape the review and ratings on Google Play Store. The reason we did this research is because we found it interesting how sentiment analysis could predict which one is the positive sentiment and which one is the negative sentiment. This study will investigate the sentiment of user reviews for TikTok and Instagram on Google Play with Multinomial Naive Bayes algorithm. Through this research, we aim to provide practical insights for both platforms to enhance their services and better meet user needs.

# LITERATURE REVIEW

In the research of TikTok Social Media Sentiment Analysis Using the Naive Bayes Classifier Algorithm published in 2022, they use Naïve Bayes Algorithm to analyze TikTok sentiment. The data for this research was taken from 600 random comments from TikTok users, and the data is obtained from a web page that exports TikTok comments from videos or content uploaded that contain negative and positive comments. The algorithm achieved an accuracy of 80% for sentiment analysis, however its AUC value was just 46%. The algorithm found 26 bad, 464 neutral, and 76 positive comments out of 565 cleaned comments [10].

While in The Effect of Feature Weighting on Sentiment Analysis TikTok Application Using the RNN Classification published in 2023, they compare the effectiveness of Word2Vec feature weighting, TF IDF, and TF RF on RNN classification for TikTok sentiment analysis. The data for this study is from 5000 reviews of the application, from April 5 to April 15, 2023, on the Google Play Store. The result of the experiment shows that TF RF and TF IDF approaches produce excellent accuracy, with TF RF doing marginally better. The Word2Vec approach performed less than optimally with accuracy and loss values that varied [7].

Then, in Comparison of TikTok User Sentiment Analysis Accuracy with Naïve Bayes and Support Vector Machine published in 2023, they compare the accuracy of the sentiment analysis of TikTok application users with Naïve Bayes Algorithm and Support Vector Machine. The data set comes from comments from TikTok users on Twitter where the data set was divided into three sets. Testing was done by dividing the data by 70% for training data and 30% for test data. The results showed that the accuracy of the Naïve algorithm was 89.35% and 94.08% using the Support Vector Machine algorithm [11].

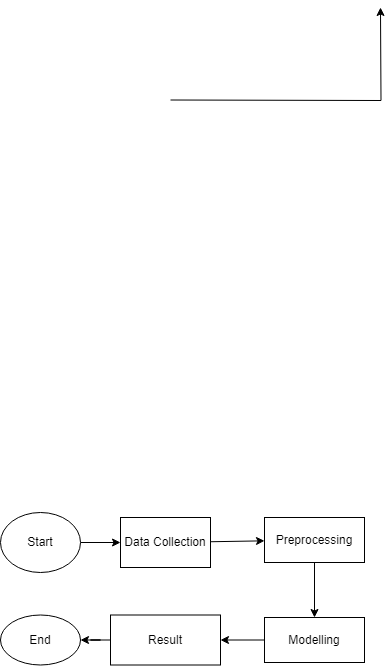
In Sentiment Analysis of Social Media Platform Reviews Using the Naïve Bayes Classifier Algorithm published in 2023, they aim to find out public opinion on social media platforms with sentiment analysis on the Google Play Store review of Twitter, Instagram and TikTok. The dataset was taken based on ratings from user reviews on the Google Play Store using the NBC (Naïve Bayes Classifier) method with Python programming language. Based on testing of 1000 comments for each application, the majority gave positive sentiment and negative sentiment with an accuracy rate of 85.6% for Twitter, 83.6% for Instagram and 84.8% for TikTok [12].

And the last one, Google Play Store Users Comment Review Classification Using SVM Classifier and Random Forest published in 2023, highlighted the pioneering efforts to address a significant gap in sentiment analysis within social media commentary. This study uses Word2vec for preprocessing and leveraging the Random Forest classification model. The study successfully classifies comments on a detailed 1-5 rating scale resulting in a 60.4% accuracy score. Despite having a low score, the study marks substantial progress in understanding the nuanced sentiments embedded in user-generated content [13].

These papers show that social media sentiment analysis research has been done a lot of times. These papers has been done greatly but there are also some minus points from these papers such as how choosing the wrong feature will lead to bad results [7], or not all methods good enough to be used, depending on whether precision or recall holds special significance in the context of the problem [13]. For these reasons, we decided to do our research to see if we can do a better job in testing the model or will we still be lacking and find out what’s lacking with Multinomial Naïve Bayes algorithm where this algorithm is one of algorithm model that was used to classify data with the help of calculation and probability [14].

# METHODOLOGY

For this study, our flow of research is shown in Figure 1 below.



1. Flowchart

As shown in Figure 1, we will work on the research gradually from collecting data to finally do the modelling and evaluate it to figure out what are our limitations during the research. We will do sentiment analysis classifications with Multinomial Naïve Bayes model for our research with 421108 reviews as our dataset.

1. *Data Collection*

The data used in this research was obtained from Kaggle. It consists of reviews from the TikTok and Instagram applications in the Google Play Store. The data is formatted in a CSV file and includes three attributes: *review description, rating, and review date*. The *review description* attribute contains the comments on the applications, the *rating* attribute provides the rating for the applications, and the *review date* attribute indicates the date the review was made.

1. *Preprocessing*

Preprocessing is the first step of data processing for sentiment analysis, and its goals are to eliminate unnecessary words or phrases and standardize word forms to lower the vocabulary volume. Here are the steps to preprocessing:

* + - 1. Case Folding

Case folding is a process to filter unnecessary punctation, which also converts all uppercase to lowercase characters and removes emoticons.

* + - 1. Filtering

Filtering is a process to eliminate stop words (common words like "and," "the," "is," etc.), punctuation, special characters, and numerals from the text.

* + - 1. Stemming

The process of stemming involves converting attached words into basic words. The goal is to reduce dimensionality by grouping many variants of the same word together for analysis as a single item.

* + - 1. Tokenizing

Tokenizing is a process of dividing text into individual words or tokens. Tokenization divides the text into manageable pieces that can be processed and examined further, and it is essential for text analysis.

1. *Modelling*

Sentiment Analysis, or sometimes called opinion mining, is a natural language process where it classifies texts based on the apparent emotion they convey [12]. This type of analysis is widely used for customer feedback and recommender system [13]. Typically, it uses machine learning approaches to categorize documents according to a set of features that are derived from the text using other NLP techniques [14]. The outcomes can be used to improve recommendation systems [12]. In this research, we use Multinomial Naïve Bayes, which is a foundational variant of the Naïve Bayes algorithm. Naïve Bayes Classifier is a machine learning algorithm that applies Bayes’ rule which is used for classification such as text classification [15]. Naïve Bayes seeks to model the distribution of inputs of a given class or category. By observing the values of a given set of features, Naïve Bayes classifier can calculate the probability [16]. Naïve Bayes classifier assumes that each feature is independent and equal [17] which simplifies a classification problem by making it understood by computer [18]. The resulting classifier uses a linear model. Multinomial Naïve Bayes is a probabilistic and efficient algorithm based on Bayes’ theorem. Multinomial Naïve Bayes is one of Naïve Bayes classifier that is often used as a baseline for text classification or Sentiment Analysis [19]. Multinomial refers to the type of data distribution assumed by the model, normally used to estimate the likelihood of seeing a specific set of word counts in a document [20]. Multinomial Naïve Bayes operates under a couple of key assumptions, where it assumes that predictors are conditionally independent or unrelated and assumes that all features contribute equally to the outcome [18].

1. Multinomial Naïve Bayes

Multinomial Naïve Bayes is a probabilistic and efficient algorithm based on Bayes’ theorem. Multinomial Naïve Bayes is one of Naïve Bayes classifiers that is often used as a baseline for text classification or Sentiment Analysis [19]. Multinomial refers to the type of data distribution assumed by the model, normally used to estimate the likelihood of seeing a specific set of word counts in a document [20]. Multinomial Naïve Bayes operates under a couple of key assumptions, where it assumes that predictors are conditionally independent or unrelated and assumes that all features contribute equally to the outcome [18]. Multinominal Naïve Bayes can be formulated:

Where is the probability of the appearance of a text document (). N is the number of documents and is the polarity. To calculate the polarity value, you can use the given equation

1. Confusion Matrix

Confusion matrix provides information about the actual and predicted classifications given by a classifier.

|  |  |  |
| --- | --- | --- |
| Actual | Positive | Negative |
| Positive | TP | FN |
| Negative | FP | TN |

Where:  
TP (True Positive): The number of correct classifications of the positive examples

FN (False Negative): The number of incorrect classifications of the positive examples

FP (False Positive): The number of incorrect classifications of the negative examples

TN (True Negative): The number of correct classifications of the negative examples

The main metric is classification accuracy, which is calculated by dividing the number of correctly classified cases by the total number of cases in the test set. Recall and precision quantify the degree of accuracy and completeness of the positive class classification. Precision (p) is the ratio of occurrences that are truly classified as positive out of all instances classified as positive. Recall (r) is the ratio of real positive instances correctly identified out of all actual positive instances. The harmonic mean of precision and recall is known as the F1 score.

# RESULT

This section will show the result from our finding using *Multinomial Naïve Bayes.* Before the data that we already collected used in our research, it must go through some process.

## Data Collection

The data that we used in our research is from *Kaggle.* We use 2 datasets, for TikTok Google Play Review and Instagram Google Play Review. The raw dataset for TikTok contains 460.288 entries, but we are using 210.542 entries. For Instagram, there are 210.542 entries, and we use the entire dataset. We reduced the TikTok dataset to match the size of the Instagram dataset. There are 3 attributes that we use in our dataset, there are *review\_description, rating, review\_date.* Both datasets are in csv format.

TABLE I. Data Collection

|  |  |  |
| --- | --- | --- |
|  | TikTok | Instagram |
| Raw Dataset | 460.288 | 210.542 |
| Used | 210.542 | 210.542 |

## B. Preprocessing

1. Case Folding

Case folding is used to filter comments with unnecessary punctation, changed all the uppercase letter to lowercase letters, and emoticons are deleted. Table II shows the result before and after case folding process for some comments.

TABLE II. Case Folding

|  |  |
| --- | --- |
| **Before** | **After** |
| Perfect 🥰 | perfect |
| I WISH I COULD GIVE THIS A 100 PERCENT RATING I LOVE THIS!! 💕 😘 | i wish i could give this a 100 percent rating i love this!! |
| Being able to express yourself | being able to express yourself |

1. Filtering

After the case folding process, the next step is to filter the comments to eliminate stop words. Table III shows the result before and after filtering process for some comments.

TABLE III. Filtering

|  |  |
| --- | --- |
| **Before** | **After** |
| The app is good for connecting with friends, family and even potential business partners. However... | app good connect friend family even potential... |
| Used to be my favorite social media app, but "improvements" have made it harder and harder to use and I find myself using less and less. The... | use favorite social media app improv made harder... |
| Instagram is the best of all the social media. IG is not just a posting platform, it facilitates the.. | instagram best social media ig post platform... |

1. Stemming and Tokenizing

The next step is stemming and tokenizing. Stemming is a process to change affixed words into basic words and tokenizing is the separator between words to be used. Table IV shows the result before and after stemming and tokenizing process for some comments.

TABLE IV. Stemming and Tokenizing TikTok

|  |  |
| --- | --- |
| **Before** | **After** |
| This app keeps blocking me from making my account. It wont let me continue, its annoying. I will take this rate.... | [app, keep, block, make, account, wont, let, continue,...] |
| Used to be my favorite social media app, but "improvements" have made it harder and harder to use and I find myself using less and less. The... | [use, favorite, social, media, app, improv, made, ...] |
| Instagram is the best of all the social media. IG is not just a posting platform, it facilitates the.. | [instagram, best, social, media, ig, post, platform, ...] |

## C. Modeling

After preprocessing, the modeling is carried out using Multinomial Naïve Bayes. We are using 80% data for training and 20% data for testing. After data modelling is finished, the last step is to evaluate the model of the data process. A confusion matrix is needed to establish the model’s evaluation criteria for this case. A customized table that provides an overview of an algorithm is called the Confusion Matrix.

**A graph of positive and negative

Description automatically generated**

1. Labeling Training and Testing Data for TikTok

Figure 2 is a graph for labeling training and testing data for TikTok. The outputs are 111.115 for positive comments (52.77%), 90.806 for neutral comments (43.13%), and 8.621 for negative comments (4.09%).

**A bar graph with different colored squares

Description automatically generated**

1. Labeling Testing Data for TikTok

Figure 3 is a graph for labeling testing data for TikTok. The outputs are 33.461 for positive comments (79.46%), 6.899 for neutral comments (16.38%), and 1.747 for negative comments (4.14%).

**A bar graph with different colored squares

Description automatically generated**

1. Labeling Training and Testing Data for Instagram

Figure 4 is a graph for labeling training and testing data for Instagram. The outputs are 111.902 for positive comments (53.14%), 56.016 for neutral comments (26.60%), and 42.624 for negative comments (20.24%).

A graph of different colored squares

Description automatically generated

1. Labeling Testing Data for Instagram

Figure 5 is a graph for labeling testing data for Instagram. The outputs are 12.692 for positive comments (30.14%), 5.307 for neutral comments (12.60%), and 24.110 for negative comments (57.25%).

## D. Evaluation

The following process is to evaluate by comparing the accuracy of TikTok and Instagram Google Play Stire review using Multinomial Naïve Bayes algorithm to do sentiment analysis. We test how accurate is this method to predict whether the review is a positive, negative, or neutral comments. We divided the dataset for training and testing. The result for precision, recall, f1-score, and accuracy is shown in the table IV.

TABLE IV. Precision Value Results, Recall, F1-Score

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | TikTok | | | Instagram | | |
| **precision** | **recall** | **F1** | **precision** | **recall** | **F1** |
| 0 | 0.95 | 0.34 | 0.51 | 0.75 | 0.54 | 0.63 |
| 1 | 0.91 | 0.55 | 0.68 | 0.94 | 0.75 | 0.84 |
| 2 | 0.68 | 0.98 | 0.81 | 0.81 | 0.96 | 0.88 |
| **accuracy** | 88% | | | 74% | | |

Table IV performance differences between TikTok and Instagram’s sentiment analysis models. TikTok’s precision values range from 0.68 to 0.95 signifying efficient identification of pertinent instances, particularly within specific classes. However, its recall varies greatly (0.34 to 0.98), indicating that positive instances may occasionally be overlooked. While Instagram scores hinger on F1 (0.63-0.88) than TikTok (0.51–0.81), suggesting a more balanced performance in terms of recall and precision. Instagram's slightly lower accuracy of 74% is accompanied by more consistent performance metrics across various sentiment categories, while TikTok achieves a higher overall accuracy of 88%.

# CONCLUSIONS

In this paper, we’re using Multinomial Naïve Bayes Classification Algorithm to do sentiment analysis on TikTok and Instagram Google Play Store review, where we test how accurate this method to predict whether the review is a positive sentiment, a negative sentiment, or a neutral sentiment. With all the datasets we have, we divided the dataset into a training and testing dataset. After all process, the data that are used for TikTok are 42107 that had been cleaned and good to use. There are 33.461 for positive comments (79.46%), 6.899 for neutral comments (16.38%), and 1.747 for negative comments (4.14%). For Instagram, 42109 data have been cleaned and are good to use. There are 12.692 for positive comments (30.14%), 5.307 for neutral comments (12.60%), and 24.110 for negative comments (57.25%). Although we encountered some errors during the experiment, at the end we had the accuracy result of 85% for TikTok and 74% for Instagram. Multinomial Naïve Bayes itself is one of the Naïve Bayes methods that is easy to use. But even though it is easy and more efficient, there are maybe some limitations in our paper that can be improved in future research.

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