

# Automated Vader Lexicon Labeling on Sentiment Analysis Against The E-Wallet

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**Abstract**— In Indonesia, e-wallets have gained immense popularity due to their user-friendly interfaces and attractive features. Despite their convenience, user opinions about e-wallet applications remain polarized, with sentiments ranging from highly positive to critically negative. This study seeks to analyze these diverse user sentiments by leveraging the VADER Lexicon model, a powerful tool for sentiment analysis. The Naïve Bayes Classifier, a well-established probabilistic model renowned for its efficacy in text-based classification tasks, is employed to categorize user reviews. The sentiment analysis yielded promising results, with the model achieving an impressive accuracy rate of 92.02%. Additionally, the precision of the model, indicating the ratio of correctly predicted positive sentiments to all predicted positive sentiments, stood at 83.23%. The recall, representing the ratio of correctly predicted positive sentiments to all actual positive sentiments, was recorded at 86.80%. Beyond the statistical metrics, the qualitative findings reveal critical areas of user dissatisfaction, particularly regarding facial verification failures and transaction delays. These insights offer actionable recommendations for fintech developers to optimize application features and elevate user experience.

**Index Terms**— *E-wallet; sentiment analysis; Naïve Bayes Classifier; VADER Lexicon model; Financial technology.*

## I. INTRODUCTION

The evolution of transactional methods globally has been significantly impacted by the emergence of technological devices, wireless communication, and electronic payment systems [1], [2]. Electronic wallets, often referred to as mobile wallets or digital wallets, serve as payment mechanisms through various electronic platforms, including computers, laptops, and mobile devices [3]–[6]. This innovation has profoundly transformed traditional banking, offering users convenient and cost-effective payment services [3], [7].

These financial technology products make all our transaction activities much easier and more practical. We can transfer money to relatives or friends without visiting a bank or an ATM. In Indonesia, digital wallets, or e-wallets, have increased during the COVID-19

pandemic, indicating a trend towards digital transactions in the country [4], [8]. This aligns with the goals of Bank Indonesia to innovate and promote the National Non-Cash Movement. The continuous surge in digital commerce has led to a substantial transformation in the business models of many enterprises, with noteworthy scholarly attention directed towards the adoption of e-wallets [9]–[11]. Shin [12] and Nizam et al. [13] assert that the e-wallet is an innovative and novel approach capable of supplanting traditional payment methods.

One popular e-wallet application in Indonesia is DANA. DANA is a financial technology (fintech) company that provides transaction services using users' smartphones [14], [15]. Users can transfer money to other DANA users and bank accounts through the DANA app. DANA also aims to fulfil various needs through cashless and mobile payment transactions. The app offers various services, including paying for mobile credit and data packages, electricity bills, health insurance (BPJS Kesehatan), and many more. Currently, almost all Indonesian people use the internet for the purpose of carrying out financial transactions. According to survey statistics conducted by Kominformo, around 65.4% of respondents use digital devices most often [16]. The following are data results sourced from Ipsos and Bank Indonesia [17].

With the multitude of services and features the e-wallet app provides, it naturally elicits user feedback. Users can express their opinions and experiences using the e-wallet app on the Google Play Store. However, despite the services offered by the e-wallet app, some users express dissatisfaction and leave negative feedback on the Google Play Store, resulting in two types of opinions: positive and negative. Google Play Store is a digital content service built by Google to provide a platform for app and game developers to upload their creations for other users. Users can leave opinions about their experiences using the downloaded applications in the Google Play Store. These opinions can serve as references for other users interested in trying the app, as well as feedback for the app

developers to improve their creations in the future [18], [19].

TABLE 1. ESTIMATED E-WALLET MARKET SHARE IN INDONESIA (DATA IN MILLION (USD))

E-Wallet Players	TPV market share	Estimated monthly transaction	Transaction market share	Value per transaction
LinkAja	8%	27	7%	3.9
DANA	14%	55	14%	3.3
Gopay	21%	86	22%	3.2
OVO	25%	106	27%	3.1
ShopeePay	32%	114	29%	3.7

Reviews on Google Playstore often come with ratings ranging from 1 to 5. The usefulness of star ratings from these reviews is limited to the progress team as scores reflect the average for the entire app and will incorporate positive and negative evaluations of its unique features [20], [21]. However, it is common for users to provide ratings that do not entirely align with the sentiments expressed in their reviews. Consequently, the ratings alone may not adequately represent the true quality or user experience of the e-wallet application. The sentences in the reviews carry valuable information as they describe how users react to the e-wallet application in more detail. These reviews can have a significant impact on potential visitors or users who are considering downloading the application. By reading the users feedback, potential users can gain insights into the actual experiences and opinions of existing users, which can influence their decision to download and use the application. Therefore, analyzing the reviews and sentiments expressed therein is crucial in understanding users' reactions and perceptions towards the e-wallet application. To enhance the accuracy of sentiment analysis, leveraging semi-supervised learning techniques is crucial. By using these techniques, a more refined annotation corpus can be created for opinion analysis, which in turn provides a comprehensive and sufficient training dataset. This approach leads to more effective sentiment value analysis and enables more precise identification of sentiment elements within the data [22]–[24]. That Vader in the annotation process produces superior accuracy values compared to manual annotation [25], [26].

To analyze these sentiments, a method is needed to analyze the reviews of e-wallet users obtained from the Google Play Store. Sentiment analysis systems are capable of gathering and organizing unstructured data by aggregating public opinions on various subjects, such as services, products, policies, brands, and more [27], [28]. In this research, the data scraping of user reviews is carried out using the DataMiner extension on Google Chrome. Then, in the sentiment extraction stage, each review will be scored using the VADER

model. Finally, the Naive Bayes Classifier algorithm is utilized in the data analysis processing stage. This sentiment analysis research aims to understand the users' response to the features and services of the e-wallet app on the Google Play Store.

## II. METHOD

This study analyzes user sentiments towards the e-wallet application on the Google Play Store platform. The research process is divided into two main stages, each crucial in achieving the overall objective. The initial stage involves the creation of a comprehensive dataset, which serves as the foundation for conducting sentiment analysis. This dataset is constructed by gathering user reviews of the e-wallet application from the Google Play Store, ensuring it captures diverse opinions and experiences. The dataset used is the sentiment toward the DANA application because DANA is a popular e-wallet in Indonesia. Sentiment analysis encompasses crucial stages, notably preprocessing, feature extraction, and classification methods. Foremost among these is the pivotal preprocessing phase, dedicated to rectifying inconsistent data. Its primary goal is to optimize classification accuracy. This stage involves various processes, including the removal of redundant elements, case folding, tokenization, elimination of stopwords, and stemming as outlined [29], [30].

The completed dataset will be used in the second stage to train the Naïve Bayes Classifier model. This training regimen is meticulously devised to extract and elucidate underlying sentiment patterns latent within the dataset. Its primary aim is to forge a classification model that discriminates between positive and negative sentiments based on salient features embedded within user review texts. The model's learning process will undergo meticulous testing employing previously unseen test data, a critical phase facilitating the assessment of the Naïve Bayes Classifier model's precision and efficiency in sentiment prediction. The ultimate fruition of this stage will yield invaluable insights into the efficacy of the Naïve Bayes Classifier algorithm tailored explicitly for sentiment analysis, notably within the domain of e-wallet applications on the Google Play Store. By delving into user sentiments comprehensively, this research aspires to furnish meaningful inputs for the refinement of e-wallet applications, potentially serving as a catalyst for further explorations into the applicability of the Naïve Bayes Classifier across diverse machine learning tasks involving dynamic and distributed data.

### A. Dataset creation

The initial phase of this study centres around creating a comprehensive dataset, which serves as a fundamental pillar in conducting an efficient sentiment analysis of the e-wallet application on the Google Play Store platform. The dataset generation process

comprises six distinct and carefully structured steps, meticulously curated to ensure the data collected possesses high quality and diversity and accurately portrays the users' opinions and experiences. The six stages are (1) Literature Review, (2) Scraping, (3) Preprocessing, (4) Sentiment Extraction, (5) Labeling, and (6) Write to CSV. The steps or flowchart for creating a dataset can be seen in Figure 1.

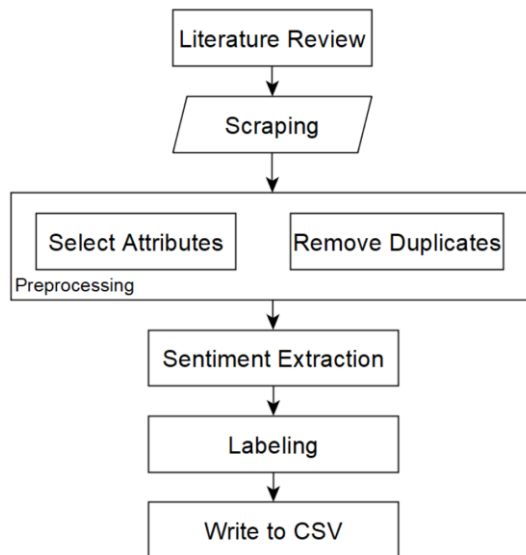


Fig. 1. The steps for creating a dataset.

The first stage of the research encompassed a comprehensive literature review. During this phase, the scholars conducted an extensive search in academic databases and credible sources focusing on topics related to sentiment analysis, Vader's Lexicon, and the specific applications of e-wallet.

Web scraping is essential at the data collection stage for e-wallet user reviews, specifically targeting the Google Play Store page. Web scraping is crucial in automatically extracting valuable information from online sources [20]. In this case, the Google Play Store page is a valuable resource for gathering user feedback, opinions, and sentiments about the e-wallet application. Researchers utilize specific tools to automate extracting relevant data during web scraping. One such tool is the DataMiner extension, a powerful web scraping tool in Google Chrome. DataMiner empowers researchers to navigate web pages, identify relevant data elements, and efficiently extract them. By leveraging this extension, researchers can access reviews related to e-wallet and discover the expressions of sentiments shared by users on the Google Play Store page.

The initial phase of preprocessing involves two essential steps: Selecting attributes and removing duplicates. The Select Attributes stage determines which attributes or columns are relevant for further analysis. In large datasets, numerous attributes may not significantly contribute to the intended analysis and are considered irrelevant. By carefully choosing the

appropriate attributes, complexity and processing time can be reduced, allowing for more precise and efficient analysis. On the other hand, the Remove Duplicates step is crucial for ensuring high-quality data before proceeding with further analysis. It involves identifying and eliminating duplicate entries from the dataset. The data's integrity is upheld, and potential biases or inaccuracies caused by duplicate information are mitigated. This preparation ensures a solid foundation for subsequent analyses.

Following the preprocessing stage, the data proceeds to the Extract Sentiment stage. Review sentences are analyzed and scored based on their sentiments in this phase. The resulting sentiment score will play a significant role in determining the review's class. The assignment of classes to each review takes place in the labelling stage. The next stage in the process is Labeling, where the e-wallet user review data is classified. The Labeling stage utilizes the Lexicon VADER (Valence Aware Dictionary Sentiment Reasoner), an automatic classification tool. The VADER, introduced by Hutto and Gilbert in 2014, is specifically designed for sentiment analysis in the English language [25], [31]. Lexicon analysis is a simpler method for analyzing opinion data compared to machine learning. It utilizes pre-built sentiment lexicons to evaluate sentiment scores of words and sentences. While more complex, machine learning requires extensive algorithms and computing power to analyze sentiment on a larger scale. The choice depends on task complexity and available resources. Lexicon analysis is quick and straightforward, while machine learning offers higher accuracy but requires more computational resources [26], [32], [33]. The last step in the data preparation is the Write to CSV stage. CSV (Comma-Separated Values) format is a widely used file format for storing data in a tabular form, with values separated by commas. This step involves saving the processed and prepared datasets into CSV files, enabling easy access and usability with various data analysis tools.

### B. Naïve Bayes Classifier (NBC)

The NBC is a specific implementation of the Naïve Bayes algorithm, a widely recognized probabilistic method used in supervised learning, with particular applications in sentiment analysis and text classification [34], [35]. This model relies on Bayes' theorem, which connects the conditional probabilities of an event. In the context of sentiment analysis, Bayes' theorem is used to determine the likelihood of a particular sentiment class based on the presence of specific words or features in the text.

The data analysis process using the NBC algorithm involves a sequence of five detailed steps. To begin, the Retrieve Dataset step is crucial, as it entails accessing the necessary dataset for the analysis from relevant data sources, ensuring that the data is both comprehensive

and suitable for the task at hand. Following this, the Split Data step is carried out, where the dataset is systematically divided into two distinct portions: training data and test data. This division is critical, as the training data will be employed to construct the NBC model in the subsequent Model stage. In this stage, the model is built under the assumption that each feature within the data is conditionally independent of the sentiment or class being predicted, a key principle of the NBC algorithm. After the model is adequately trained, it is then applied to the unseen test data in the Apply Model stage, where the model's predictive capabilities are tested on new, previously unencountered data. Finally, the process culminates in the Evaluation stage, where the performance of the model is thoroughly assessed using a range of evaluation metrics such as accuracy, precision, and recall, providing a comprehensive understanding of the model's effectiveness and reliability in making predictions. This structured approach ensures that the analysis is both methodical and robust, leading to meaningful and actionable insights. Figure 2 provides the form of a flowchart.

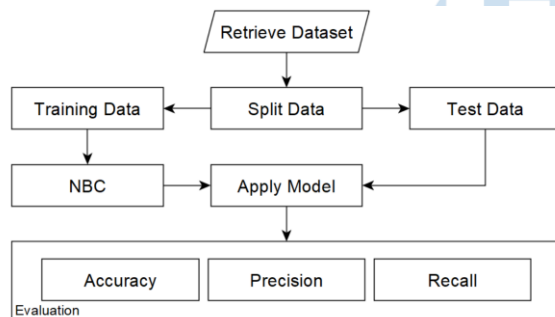


Fig. 2. The steps for Naïve Bayes Classifier Model

In the Split Data stage, the dataset is divided into two parts: training data and test data. The training data is used to implement the NBC algorithm to build a predictive model. This model is then applied to the test data in the Apply Model stage, where its effectiveness is evaluated.

During the Evaluation stage, key metrics such as precision, recall, and accuracy are calculated for the test data. This stage is essential for assessing the performance of the model and determining whether the NBC algorithm is appropriate and effective for the dataset. The evaluation results guide the decision-making process regarding the suitability of the algorithm for practical application.

### III. RESULT AND DISCUSSIONS

The study utilizes review data from users of the e-wallet application, extracted through web scraping from the Google Play Store website. The dataset comprises 4,520 reviews, which will be used for analysis. Table 1 provides sample examples of the review data obtained through this process. The dataset is expected to contain

user feedback, opinions, and experiences related to the e-wallet application, which will be analyzed using appropriate techniques, such as sentiment analysis or other natural language processing methods, to gain valuable insights and feedback for the application's improvement and user satisfaction.

TABLE 2. EXAMPLE OF REVIEW DATA FROM SCRAPING RESULTS

Users	Date	Review Text
SSBH	May 24, 2021	It used to be a great app, but recently I can't use "send" feature and it always stuck before the last process. Had already contacted the CS by WA, but it wasn't helpful at all. Waiting for hours and the only answer they gave was to update the apps and wait. Well, I did and nothing happened. I don't know, are you in the "surrender" stage? since your service quality is already going down the sink.
FZ	July 19, 2022	The features offered are attractive and easy to use and the flexibility of the application is also great, but please fix the bug problem in the application. I often experience bugs when the application is opened, there are frequent errors and reloads and exits from the application itself. I'm afraid it will interfere with the transactions that I will make and the security of the funds we have
GOO	Oct 30, 2019	Bad system. The promotion of cashback doesn't go well as you expected in reality. Didn't get the cashback at all in the last 2 months. I also didn't get the chance to open the envelope even though I've made several transactions (more than 20k off course). Contact the CS doesn't help at all. Just wasting my time and mobile credits. Not recommended for digital wallet apps.

Based on the information provided in Table 2, there is a presence of duplicate reviews, potentially arising from instances of attrition. Addressing this issue necessitates the implementation of a data filtration process aimed at systematically removing these duplicate entries. This critical step precedes the preprocessing stage, where the attribute select operator comes into play, pinpointing and isolating specific attributes with a primary focus on user reviews. The objective here is to refine the dataset, strategically streamlining it for subsequent in-depth analysis and exploration.

To achieve the removal of duplicate data, the remove duplicate operator is used. As a result of this step, the data set was refined, and duplicate views were eliminated, leaving 1,636 unique data entries. The results of the preprocessing stage can be seen in Table 3, showing the dataset after the process of removing duplicates and selecting attributes has been applied.

TABLE 3. EXAMPLE OF DATA AFTER PREPROCESSING STAGE

No	Review Text
1	It used to be a great app, but recently I can't use "send" feature and it always stuck before the last process. Had already contacted the CS by WA, but it wasn't helpful at all. Waiting for hours and the only answer they gave was to

No	Review Text
	update the apps and wait. Well, I did and nothing happened. I don't know, are you in the "surrender" stage? since your service quality is already going down the sink.
2	Can't support older app version Service is great with occasional slow transaction speed, but I really don't like how the app won't open on older versions. It's understandable if I didn't update it for three or four versions but it's only one version off and it won't open. I can't just delete important apps just to update this app.

Each sentence or review is scored based on its sentiment value in the extract sentiment stage. The Lexicon VADER model is utilized for sentiment analysis in this research, which takes into account the polarity (positive / negative) and intensity (strength) of emotions [31]. Each word in the review sentence is evaluated during this stage, and the cumulative score determines whether the review belongs to the negative or positive sentiment class.

The outcomes of the extracted sentiment and labeling processes are displayed in Table 4, showcasing the resulting data after assigning sentiment scores and classifying the reviews into their respective sentiment classes.

TABLE 4. EXAMPLE OF DATA AFTER EXTRACT SENTIMENT AND LABELING STAGE

Score	Scoring string	Review Text	Sentiment
1.538	great (0.79) helpful (0.46) well (0.28)	It used to be a great app, but recently I can't use "send" feature and it always sticks before the last process. Had already contacted the CS by WA, but it wasn't helpful at all. Waiting for hours and the only answer they gave was to update the apps and wait. Well, I did and nothing happened. I don't know, are you in the "surrender" stage? since your service quality is already going down the sink.	Positive
0.487	bad (-0.64) well (0.28) chance (0.26) help (0.44) wasting (-0.44) credits (0.38) recommended (0.21)	Bad system. The promotion of cashback doesn't go well as expected in reality. Didn't get the cashback at all in the last 2 months. I also didn't get the chance to open the envelope even though I've made several transactions (more than 20k off course). Contact the CS doesn't help at all. Just wasting my time and mobile credits. Not recommended for digital wallet apps.	Positive

Following the data cleansing process, the subsequent step involves labeling, constituting the primary classification stage. Label attributes have been obtained from the data in Table 4, which are the main requirements for processing data analysis using the Naïve Bayes Classifier algorithm. The data will be written into CSV format using the write to CSV operator in RapidMiner after the data is in CSV. The

dataset will be imported into RapidMiner to become a dataset that can be processed.

Then enter the analysis data processing stage with the Naïve Bayes Classifier algorithm. At this stage, the dataset will be retrieved to be processed. Before retrieving, the attribute sentiment (positive or negative) will change its role to label. The data is split or divided into a test data class of 20% and a training data class of 80% so that 326 test data are obtained and 1,304 training data. The data division here uses the data split operator on RapidMiner. After dividing the data, the training data will be applied with the Naïve Bayes Classifier algorithm using operators in RapidMiner. The output of the Naïve Bayes Classifier operator will be entered into the Apply Model operator as a model from the training data. Meanwhile, the test data from the split data is directly entered into the Apply Model as unlabeled data or data to be tested using the training data model.

Then the data will be applied to the performance operator. When RapidMiner is run, the test data will display the result in precision, recall, and accuracy. In addition, the data analysis results will produce a true positive and true negative value. True positive results from the data label and prediction sentiment point to the same positive class. Likewise, true negative means the label and prediction sentiments point to the negative class. Meanwhile, there are false positives and negatives, meaning the label and prediction point to a different class. In Table 4, the examples demonstrate true positive (TP) and true negative (TN) cases. TP indicates that the model correctly predicted a positive sentiment for positive reviews and negative sentiment for negative reviews. Similarly, TN indicates that the model correctly predicted negative sentiment for negative reviews and positive sentiment for positive reviews. Table 5 illustrates false negatives (FN) and false positives (FP). FN indicates that the model incorrectly predicted a negative sentiment for a review that is positive. On the other hand, FP means that the model incorrectly predicted a positive sentiment for a review that is negative.

TABLE 5. EXAMPLE OF A TEXT REVIEW RESULT

Sentiment	Prediction	Review Text
Negative	Negative	very bad, too much lag, bug, etc. so bad, really bad. fix it asap please, it's really annoying and so uncomfortable. i can't log in, after i got in, it always says 'SYSTEM BUSY'. really bad.
Negative	Negative	the complain resolution is bad! THERE IS NO FOLLOW UP! done topup but not reflected in balance. complain using message but no response, using email also useless, call the agent but no solution, told me to wait. UNRELIABLE *already waited for 24h, but nothing happened. why not you just put a robot instead of hire a person who only give default answer. just wasting time

Sentiment	Prediction	Review Text
Positive	Positive	good app, very fast to send money
Positive	Positive	The functional of the app is quite good. You can compare this to other apps when it comes to payment and things like that. But, i think the major flaw that ive seen is the user experience. I felt some lags when i tried to move from a page to another page. Not a big deal but it feels so annoying. Hope you make big improvement later. And if it doesnt lag anymore, undoubtedly i will change the stars as well.
Positive	Negative	The function is great. But, for you to be a premium member, they got the dumbest face verification of all e-wallet app. They use the dumb blink shutter. I got old smartphone with me that doesn't have any autofocus feature for front camera, so the image always comes out as blur as my future. There's no alternative solution like changing to main camera, or upload an existing image.
Positive	Negative	I recently uninstalled the app because it was a bit laggy and couldn't even make a transaction. After I reinstalled the app again I couldn't log in with the number used in my account, EVEN WITH THE EXACT SAME PHONE! It says 'Phone number is already used by another customer. Please check your number again'. Then how do I sign in to my account if there is no alternative way I can do in this app?

Evaluating the model's performance using TP, TN, FP, and FN will be crucial in understanding the model's accuracy, precision, and recall. These metrics help to assess the effectiveness of the sentiment analysis model in predicting sentiment accurately based on the review data.

TABLE 6. PERFORMANCE RESULT

	True Negative	True Positive	Class precision
Prediction Negative	129	26	83,23%
Prediction Positive	0	171	100,00%
Class Recall	100,00%	86,80%	

From Table 6, the value of the negative class recall is 100%, meaning that all negative sentiment classes are correctly predicted to the negative class. The value of the positive class recall is 86.80%, meaning that out of all positive sentiment classes predicted, 26 data fall into the false negative category or are predicted as negative class. The precision of the negative class is 83.23%, meaning that of the entire negative class, 26 data are predicted to be negative classes but are not included as a negative class in the sentiment label. The value of the positive class precision is 100%, meaning no data is included as a false positive. From these data, the accuracy value of

the data mining method is 92.02%. From this, it can be judged that the Naïve Bayes Classifier algorithm is feasible for the e-wallet application user sentiment analysis process.

#### IV. CONCLUSION

This research demonstrates the effectiveness of the Naïve Bayes algorithm in analyzing user reviews of e-wallet applications. A comprehensive dataset of 4,520 user reviews was initially gathered, with 1,636 refined reviews being viable for analysis after preprocessing. These reviews were categorized into positive and negative sentiments, and formatted into a CSV file for analysis. The dataset was divided into training and test classes in an 80:20 ratio, and the Naïve Bayes algorithm was used to develop a sentiment classification model. Performance assessment of the model showed promising results, with an overall accuracy of 92.02%. Specifically, the negative class recall was 100%, positive class recall was 86.80%, positive class precision was 100%, and negative class precision was 83.23%. These metrics affirm the algorithm's robust capability in accurately classifying user sentiments.

However, the study also highlights some limitations, such as the presence of typos and misspellings in the Google Play Store reviews, which hinder accurate sentiment analysis using the VADER model. Additionally, certain phrases with negative implications were incorrectly classified as positive due to the nuances in language that the model could not fully capture.

Overall, the Naïve Bayes algorithm proves to be a suitable tool for sentiment analysis of e-wallet user reviews, providing significant insights into user feedback. This research underscores the potential of sentiment analysis in enhancing user experience and guiding the development of e-wallet applications. Future work could focus on improving preprocessing techniques and refining sentiment models to handle linguistic nuances more effectively.

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