

# User Sentiment Analysis in the Fintech OVO Review Based on the Lexicon Method

Abertus Dwiyoga Widianoro  
Information system Department  
Soegijapranata Catholic University  
Semarang  
yoga@unika.ac.id

Adi Wibowo  
Department of Informatics Universitas  
Diponegoro Semarang, Indonesia  
bowo.adi@live.undip.ac.id

Bernardinus Harnadi  
Information system Department  
Soegijapranata Catholic University  
Semarang Indonesia  
bharnadi@unika.ac.id

**Abstract**—User reviews are important in the new approach to fintech services. To learn this information, a simple sentiment analysis can make the right observations to support the OVO fintech system in analyzing the success of the fintech system. The analysis has several stages, starting from how to extract comment data from the play store, extracting meaningful information from the play store platform, and extracting the data into valuable information. Moreover, accurate topic modeling and document representation is another challenging task in sentiment analysis. We propose a lexicon-based topic modeling in observing user sentiment simply by looking at the number of words that appear. The proposed system retrieves OVO fintech comment data from the Play Store, removes irrelevant content to extract meaningful information, and generates topics and features from the extracted data using NLTK. Data processing using google collab in Python language where data is used freely. Data analysis using the word cloud method, Exploratory Data Analysis (EDA), correlation analysis between words, ordering the number of words in sentences revealed that OVO comments in that period tended to be negative

**Keywords**—*fintech, lexicon-based, review, OVO-fintech*

## I. INTRODUCTION

Natural language processing (NLP) performs sentiment analysis in the form of classification, where words are grouped into positive, negative, and neutral classes. The traditional way of performing processing tasks is based on the sentiment lexicon [1,2].

Sentiment dictionaries can serve as a word-level basis, lexicon analyzes the sentiment of unlabeled documents or sentences, in order to obtain discrete information such as the polarity and strength of the words they contain.

The lexicon-based method utilizes features that are able to provide information such as the total number, the maximum number of positive and negative words that can be summarized [3]. The sentiment lexicon forms a polarity in every word that is the same, if the word is in a different domain then it has a different polarity, so it has a different power weight. for example "hot", expresses a positive meaning in comments on popular songs while comments have a negative meaning if the word is interpreted in a meeting room.

Machine learning based methods rely on data because most of them are trained in a certain corpus, this is the output of the current research. Natural Language Toolkit (NLTK), is a library in the Python programming language used in natural language processing (NLP) that is capable of both symbolic and statistical processing. NLTK is capable of displaying graphical demonstrations and requires sample data to process

it. The fields of empirical linguistics, cognitive science, artificial intelligence, information retrieval, and machine learning are fully supported in this NLTK. The process of semantic reasoning, classification, tokenization, stemming, tagging, and parsing functions can be completed by NLTK.

This simple sentiment analysis will specifically analyze the OVO fintech application in Indonesia within a certain period of time, namely data taken in September-December 2020. The data is taken from comments from OVO fintech users who write comments on the OVO application on the PlayStore.

This method still ignores the problem of semantic composition. Semantic composition can be expressed in several ways such as negative reversal (e.g., unattractive), negative shift (e.g., not good), and intensification (e.g., very good).

Sentiment Analysis (SA) or Opinion Mining (OM) is known as the computational study of people's opinions, attitudes and emotions towards a particular entity. An entity can be an individual, a specific event, or a specific topic. The two expressions SA or OM can have mutual meanings. However, some researchers consider that OM and SA are slightly different [4].

Opinion Mining extracts documents and then analyzes a person's opinion about an entity, while Sentiment Analysis identifies the sentiments expressed in the text and analyzes them. Finding opinions, identifying expressed sentiments, and then classifying polarities are the main targets of Sentiment Analysis. This porosity is in the form of product reviews, sentiment identification, certain feature groupings, sentiment classification, sentiment polarity) [5,6].

Sentiment analysis is generally defined as a method to identify and categorize the polarity of the text according to a certain meaning [7], with the aim of categorizing according to standards to determine a certain document has positive, negative and neutral values [8].

Fintech, which can also be called financial services / financial technology / payment technology [9], is a subject that combines finance, technology management, and innovation management viewed from various cross-disciplinary fields.

Fintech refers to innovative ideas to improve financial service processes by using technological solutions in accordance with existing business models. Fintech refers to mobile devices including wireless, digital assistants, radio frequency devices, and NFC-based communication devices that are utilized in the payment of goods and services utilized

by individuals and organizations [10]. Systems that integrate payments with mobile devices allow users to initiate, authorize, and complete financial transactions [11].

Fintech is part of a growing financial innovation, which theoretically proves to be risky but worthwhile [12], that fintech generates substantial value for investors [13].

The fintech sentiment in this case is the comments of OVO fintech users on the PlayStore. User or consumer comments are important for developers to see the level of user acceptance.

The lexicon is the required opinion words along with the sentiment score in the lexicon-based approach. In machine learning supervisor (SML), a large amount of labeled data, which will be annotated by the annotator, is required for classification training.

The problem faced in this research is that the number of user reviews on the OVO fintech application needs to be dug deeper, to get reviews that are easier to read or view in groupings based on the number of words. This review will be processed using the Lexicon approach.

The structure of this paper is presented, Section 2 presents related works, Section 3 describes the proposed method, Section IV on data analysis and discussion and Section 5 draws conclusions).

## II. RELATED WORK

Opinion mining has been studied for a long time, and many methods are used to analyze user reviews in the form of emotions and opinions from social media [14]. Social media such as Facebook, Twitter, and other media produce user reviews that have many topics, so many researchers are interested in digging deeper into the content contained in these reviews.

Natural Language Programming (NLP) is able to analyze various kinds of sentiments in detail using the document level classification method [15] and at the phrase level [3]. The method used in the analysis is the ML method and the lexicon-based method. The ML method uses more support vector machine (SVM), Naïve Bayes (NB), logistic regression, and multilayer perceptron (MLP). This method requires a dataset to be prepared as training to learn the model from the corpus data, and requires a dataset as a test to verify the proposed model.

The lexicon method based on a dictionary of words and phrases with positive and negative values SentiWordNet is a lexicon that is widely used in sentiment analysis [2]. In some domains the lexicon approach does not work well, because it has different meanings, so usually use the desired domain. Machine learning approaches, neural word insertion, and fuzzy logic are used to obtain optimal results in performing information extraction and sentiment analysis, including lexical knowledge [16,17].

Fintech data processing and fintech comment extraction are still little discussed [16,18]. Users submit reviews in the form of opinions on the PlayStore regarding various obstacles and conveniences related to fintech being used (for example, difficulty sending, difficulty logging in, and ease of use. However, these opinions are about fintech users specifically at fintech banks.

For this research, explore user messages and focus on fintech OVO. What is contained in the message during that time. Is the message related to the Ovo app or something else.

## III. METHODOLOGY

OVO application comment processing uses sentiment analysis using the GoogleColab Python language. User comment data that has been scraped are included in Google Drive to facilitate data processing. The stages of processing comment data are as follows.

### A. Data Cleaning consists of:

Import data from google drive after that clears unused columns. Using python literature for the steaming process. Using Google translate: Change non-Indonesian text to Indonesia. Clean up / extra text for words. Deletion of unnecessary/meaningless words. Remove duplicate data.

### B. Word Processing

Use NLTK to tokenize to remove words that have an emphasis. Suppose the word no .. becomes the word no.

Clean text extra, which removes words that still appear but are not needed in digging up words that are important in sentiment. For example ['ovo', 'dan', 'di', 'lalu', 'dari', 'ingin', 'apa', 'karena', 'sama', 'ke', 'tentu', 'saja'] .

Creating a word dictionary, importing lexicons, and removing negation words from the lexicon, the lexicon is a combination of several sources, which are combined into one, and include the swear word that has the most negative score. Checks if there are words in the dictionary that are not included in the lexicon.

### C. Creating a word cloud

Create a word cloud to see the main types of words that often appear in comments on the use of OVO fintech.

### D. EDA: Exploratory Data Analysis (EDA)

EDA is part of the data science process. EDA is very important before performing feature engineering and modeling because at this stage we have to understand the data first. Exploratory Data Analysis allows understanding the contents of the data used, starting from distribution, frequency, correlation.

### E. Discussion

Discusses the results obtained from the processing of sentiments and lexicons

### F. Conclusion:

Draw conclusions from the word processing stages.

## IV. DATA ANALYSIS AND DISCUSSION

The data used in this study, using data from 18 September - 4 October 2020, is a very crucial time in Indonesia because at that time OVO was used for pre-employment payments and the main thing was the government's recommendation to use online transactions to avoid physical contact with others.

The data was taken by scraping method by collecting data in Indonesian. The data used in this study were 1099 fintech OVO reviews.

Data processing using Python programming using google colab service. The scraped data is also placed in Google Drive so that reading data is easier.

Python Sastrawi is a simple library that can change words with Indonesian affixes into their basic form. Literature can also be installed via "pip".

The cleansing process is the process of eliminating duplication so that there are no duplicate sentences. And the language is done by removing the duplication of existing data into 1068 sentences. After the process of removing duplication, the next process is to use Google Translate to translate it into Indonesian if English is included in the sentence.

The tokenization process uses a process nltk in which a large amount of text is divided into smaller parts called tokens. Python Sastrawi is a simple library that can change Indonesian affixed words into their basic form. Word processing using NLTK is used to remove affirmation words, so they become normal words. The word dictionary is used to help the lexicon process break down sentences into words that can be taken from lexicons that have been labeled positive, negative, and weighted [19] [20].

After all sentences are preprocessed, lexicon, and broken down into meaningful base words for OVO sentiment analysis, the following are the results of the analysis using several forms, namely word cloud, and EDA

In Figure 1 Wordcloud in the image below shows words that have a large number of comments will appear larger, and those that look small have a low number of comments. It is seen that the negative sentiment words which have a greater number ie, gagal, lama, nunggu. Meanwhile, positive sentiments that have a lot of numbers are stars, can, and love. Bintang in this case is giving the sentence a star which means giving good quality. While kasih is taken from gratitude which means being satisfied with the service.



Fig. 1. Word Cloud OVO

Exploratory Data Analysis (EDA) looks at the data distribution, it can be seen that the histogram is upright, meaning that the sentiment is normally distributed. In Figure 2 the highest data density is 0.05. The distribution of the data is close to normal, where the sentiment value between positive (greater than zero) and negative sentiment (less than zero) is nearly balanced. Density level where the data is normally distributed at the 0.01 position.

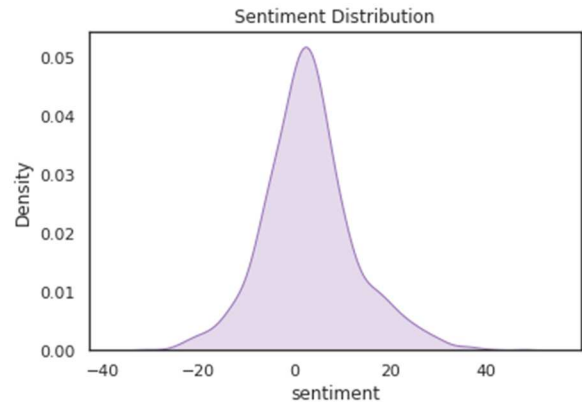


Fig. 2. EDA OVO

In Figure 3, the correlation analysis in the image below explains whether or not there is a relationship between the two variables. The correlation is positive, which means that if you add to the X value, the Y value will also increase. A negative correlation explains the relationship between each increase in X value, then there is a decrease in the Y value. A weak correlation explains that these two variables have nothing to do with it. The correlation is very strong if the value exceeds 0.7 a strong correlation is seen in the orange box. The highest value of the relation is 1. If the correlation value reaches 1 then it is considered a perfect relationship. Weak correlation is seen in black images.

The word smga correlates with the word Berjaya, the word related has a strong correlation with the word Buat, said part has a strong correlation with the word annoyed with a value of 0.894343. The word has a positive sentiment analysis rate.

However, when viewed from the sentiment analysis, the analysis of the words has not shown positive sentiment if the value is above 0. This is evident in the word fishing correlates with the word emotion with a value of 0.894343, and the sentiment value is above 0 but the word is classified as a negative sentiment.

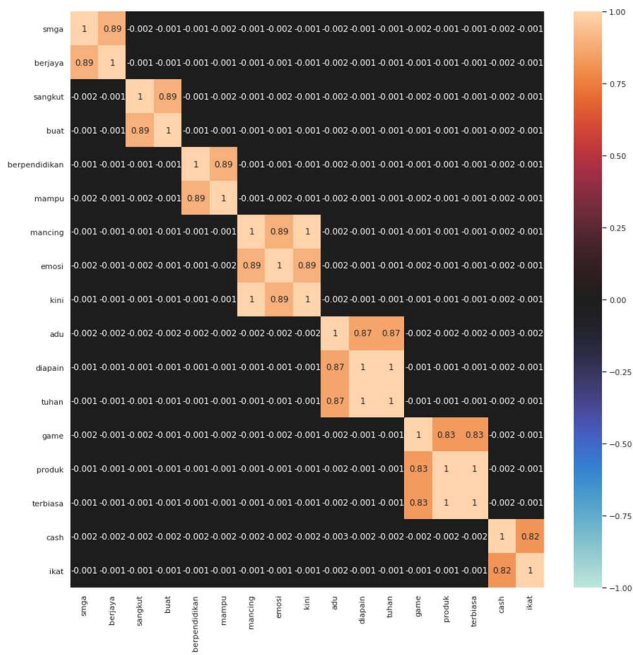


Fig. 3. Image Plot OVO

The Figure 4, below is 15 words that appear, sorted according to large to small numbers. See from the picture below that the word is mentioned in the sentence. The number indicates the number of sentences containing the word. The word that is often mentioned in each sentence is the “lama”, it’s mean a very long process with a total of 257 sentences, the word tolong have word count 184 sentences and mohon have word count 143 sentences. From the big 3 words are the negative sentiment words that often arise. Meanwhile, the top 4 positive sentiments were “kasih” words what it means is thank you totaling 132 sentences, both 120 sentences, 120 more sentences, and “cepat” words it’s means is that the process is fast totaling 112 sentences.

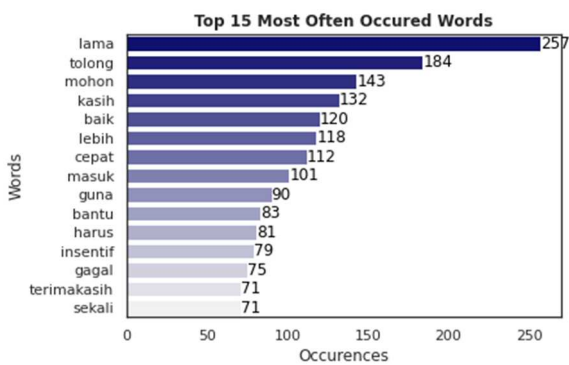


Fig. 4. Image to 15 word

## V. CONCLUSION

The OVO service on 18 September - 4 October 2020, is a very crucial time in Indonesia because at that time OVO was used for pre-work payments and the main thing was the Government's recommendation to use online transactions to avoid physical contact with others.

Judging from the processing data, it can be seen that the sentiment analysis based on the OVO app review on the Playstore tends to be negative.

The lexicon method by displaying data and graphics can process sentiment analysis well. However, there are still many words that must be removed to find the main hidden message.

## REFERENCES

- [1] Y. Kim, “Convolutional neural networks for sentence classification,” EMNLP 2014 - 2014 Conf. Empir. Methods Nat. Lang. Process. Proc. Conf., pp. 1746–1751, 2014, doi: 10.3115/v1/d14-1181.
- [2] S. Baccianella, A. Esuli, and F. Sebastiani, “SENTIWORDNET 3.0: An enhanced lexical resource for sentiment analysis and opinion mining,” Proc. 7th Int. Conf. Lang. Resour. Eval. Lr. 2010, vol. 0, pp. 2200–2204, 2010.
- [3] B. X. Agarwal, I. Vovsha, O. Rambow, and R. Passonneau, “Semantic Sentiment Analysis of Twitter Data,” arXiv, 2017.
- [4] M. Tsytsarou, T. Palpanas, and P. Descartes, “Survey on mining subjective data on the web,” no. May, 2017.
- [5] M. I. Hanafri, A. Budiman, and N. A. Akbar, “Game Edukasi Tebak Gambar Bahasa Jawa Menggunakan Adobe Flash CS6 Berbasis Android,” vol. 5, no. 2, pp. 50–53, 2015.
- [6] W. Medhat, A. Hassan, and H. Korashy, “Sentiment analysis algorithms and applications : A survey,” Ain Shams Eng. J., vol. 5, no. 4, pp. 1093–1113, 2014, doi: 10.1016/j.asej.2014.04.011.
- [7] L. F. S. Coletta, N. F. F. De Silva, E. R. Hruschka, and E. R. Hruschka, “Combining classification and clustering for tweet sentiment analysis,” Proc. - 2014 Brazilian Conf. Intell. Syst. BRACIS 2014, no. January, pp. 210–215, 2014, doi: 10.1109/BRACIS.2014.46.
- [8] E. S. Tellez, S. Miranda-Jiménez, M. Graff, D. Moctezuma, O. S. Siordia, and E. A. Villaseñor, “A case study of Spanish text transformations for twitter sentiment analysis,” Expert Syst. Appl., vol. 81, pp. 457–471, 2017, doi: 10.1016/j.eswa.2017.03.071.
- [9] E. Z. Milián, M. D. M. Spinola, and M. M. De Carvalho, “Fintechs : A Literature Review and Research Agenda,” Electron. Commer. Res. Appl., p. 100833, 2019, doi: 10.1016/j.elerap.2019.100833.
- [10] W. A. Alkhowaiter, “Digital payment and banking adoption research in Gulf countries: A systematic literature review,” Int. J. Inf. Manage., vol. 53, no. February, p. 102102, 2020, doi: 10.1016/j.ijinfomgt.2020.102102.
- [11] S. Chandra, S. C. Srivastava, and Y.-L. Theng, “Evaluating the Role of Trust in Consumer Adoption of Mobile Payment Systems: An Empirical Analysis,” Commun. Assoc. Inf. Syst., vol. 27, no. 1, 2010, doi: 10.17705/1cais.02729.
- [12] A. V. Thakor, “Incentives to innovate and financial crises \$,” J. financ. econ., vol. 103, no. 1, pp. 130–148, 2012, doi: 10.1016/j.jfineco.2011.03.026.
- [13] M. A. Chen, Q. Wu, and B. Yang, “How Valuable Is FinTech Innovation?,” Rev. Financ. Stud., vol. 32, no. 5, pp. 2062–2106, 2019, doi: 10.1093/rfs/hhy130.
- [14] M. Alam, F. Abid, C. Guangpei, and L. V. Yunrong, “Social media sentiment analysis through parallel dilated convolutional neural network for smart city applications,” Comput. Commun., vol. 154, no. February, pp. 129–137, 2020, doi: 10.1016/j.comcom.2020.02.044.
- [15] S. Liu and I. Lee, “Discovering sentiment sequence within email data through trajectory representation,” Expert Syst. Appl., vol. 99, pp. 1–11, 2018, doi: 10.1016/j.eswa.2018.01.026.
- [16] A. Yadav, C. K. Jha, A. Sharan, and V. Vaish, “Sentiment analysis of financial news using unsupervised approach,” Procedia Comput. Sci., vol. 167, no. 2019, pp. 589–598, 2020, doi: 10.1016/j.procs.2020.03.325.
- [17] J. X. Shen et al., “Dual memory network model for sentiment analysis of review text,” Knowledge-Based Syst., vol. 188, 2020, doi: 10.1016/j.knosys.2019.105004.
- [18] V. Balakrishnan, P. Y. Lok, and H. Abdul Rahim, “A semi-supervised approach in detecting sentiment and emotion based on digital payment

reviews,” *J. Supercomput.*, no. 0123456789, 2020, doi: 10.1007/s11227-020-03412-w.

- [19] F. Koto and G. Y. Rahmanningtyas, “Inset lexicon: Evaluation of a word list for Indonesian sentiment analysis in microblogs,” *Proc. 2017 Int. Conf. Asian Lang. Process. IALP 2017*, vol. 2018-Janua, no. December, pp. 391–394, 2018, doi: 10.1109/IALP.2017.8300625.
- [20] R. Ferdiana, F. Jatmiko, D. D. Purwanti, A. S. T. Ayu, and W. F. Dicka, “Dataset Indonesia untuk Analisis Sentimen,” *J. Nas. Tek. Elektro dan Teknol. Inf.*, vol. 8, no. 4, p. 334, 2019, doi: 10.22146/jnteti.v8i4.533.