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Enhancing Fintech P2P Lending Analysis: Integrating LSTM Algorithm and SERVQUAL Model for Aspect-Based Sentiment Analysis

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Abstract. This research aims to aspect-based sentiment analysis based on the customer satisfaction theory SERVQUAL model of the Fintech P2P Lending application on the Google Play Store. The massive technological developments in digital money lending are not supported by optimal service and guaranteed data security. The poor service to customers has caused many complaints and bad reviews for the application. Therefore, a method is needed that can measure how good the services of digital fund-offering service providers are. The SERVQUAL model allows companies to measure the performance of their services from an internal and external perspective of the company. This research uses 1000 review data that is given by users that are labeled based on the 5 aspects of the SERVQUAL model. Then it is processed to obtain a machine learning model that can classify whether a review contains SERVQUAL aspects. The data that has been obtained is going to be lemmatized to get clean data in the form of essential words for preprocessing. The algorithm used is Long-short Term Memory (LSTM) which can study the full context of a review. The result is the highest accuracy obtained is 79%.

Keywords: Fintech, P2P Lending, SERVQUAL, LSTM.

1 Introduction

FinTech or Financial Technology is an innovation that unites financial services business processes with technology services. Customers who previously needed to make transactions with cash in person, now only need to go through an Automated Teller Machine or through a mobile-based application and it can be done in seconds [1].

FinTech itself refers to the latest technology that can initiate transformation in the financial world [2]. In general, FinTech companies provide the most innovative financial services in the form of digital technologies that can be developed and evolved to bring new benefits to users, individual consumers, large companies or SMEs [3]. Several FinTech companies also act as platforms that create and mediate markets in serving lending requests (peer-to-peer lending) and insurance.

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According to [4], the application of the term Fintech 3.0 can apply in 3 different, interrelated fields. First, in the field of systems, banks and several other financial institutions use technology to improve and update the company's systems and business processes both internally and in a joint project. Second, in the field of Business-to-Business or B2B, where banks act as clients or partners of a FinTech company. Banks can buy, invest, or develop a FinTech product to modernize services or create new services provided to customers. Third, in the field of Business-to-Consumer or B2C, FinTech companies compete with conventional banks and other financial service institutions to get market attention. FinTech companies transform services (such as payment and lending services) by offering product advantages and a convenient user experience. They can also use technology to build markets to address unmet needs by conventional financial service providers. Several FinTech companies also act as platforms that create and mediate markets in serving lending requests (peer-to-peer lending) and insurance [4].

This study tries to focus on sentiment analysis at the aspect level or Aspect-based Sentiment Analyst (ABSA). ABSA is a sentiment analysis technique that focuses on identifying and evaluating sentiments related to certain aspects of the text [5]. The aspects to be analysed are based on the theory of the SERVQUAL model which compares what customers want with what is evaluated by service providers [6]. The SERVQUAL model assesses the level of customer satisfaction with 5 aspects, namely reliability, assurance, tangibles, empathy, responsiveness [7].

The algorithm that will be used to perform sentiment analysis is LSTM or Long Short-Term Memory. Deep learning networks such as LSTM are especially useful with large and high dimensional data, which is why neural networks can outperform ordinary machine learning algorithms for most applications where there are text, image, video, speech, and audio data that need to be processed [8].

Because ABSA aims to classify sentiments related to aspect terms in sentences, the LSTM method is important for modelling aspect patterns in a whole sentences. LSTM is a model further developed from RNN or (Recurrent Neural Network). Simple RNNs have limitations caused by gradients that may vanish (close to zero) or explode (become very high) [9]. This limitation has been corrected with the introduction of the LSTM network [10].

2 Literature Review

2.1 A Subsection Sample

Peer-to-peer lending or P2P business lending is one of the most popular business models in the FinTech industry. P2P lending fintech allows individuals and businesses to lend and borrow from each other. With its streamlined structure, FinTech P2P lending can offer lower interest rates and a better lending process for both lenders and borrowers. The difference from banks is that these FinTech are not technically involved in the lending itself, as they only match lenders with borrowers, and charge fees from users. Due to this difference, FinTech P2P lending currently does not need to meet capital requirements that affect the total loan amount [11].

2.2 A Recurrent Neural Network (RNN)

RNN has a structure that allows information to flow from the previous layer to the next layer in the network which allows processing of data in sequence [12].

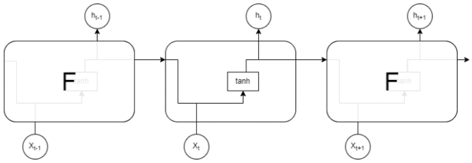

Fig. 1. RNN Architecture

In modeling data can be seen in **Figure 1**, an X value will be fed into function F in one timestep. Then a value will be generated that will be entered into the next timestep, symbolized by an arrow from F towards to next F [13], [14]. RNN has 2 types of development, namely LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit), each of which has advantages but can be used simultaneously to maximize accuracy.

2.3 Long Short-Term Memory

The LSTM architecture augments the basic RNN architecture with a "cell state" that allows a sentence context to be understood not just step by step, but across a sequence of steps. Thus, using LSTM in bidirectional is very useful for understanding sentiment in a text [13], [14].

Figure 2 shows the LSTM architecture in one timestep. [9] in his blog explains that LSTM could add or remove information in the cell state which is symbolized by a straight line that passes through the top of the diagram, adding or deleting information is regulated by the cell gate. There are 3 types of cell gates in the LSTM, namely the forget gate which controls the amount of information received from the previous step, the input gate which controls the amount of information the cell state will receive from the cell memory at the current time step, and the output gate which controls the output which will become a hidden state with multiplication between elements [9].

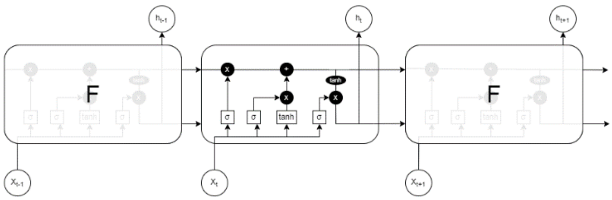

Fig. 2. LSTM's architecture

2.4 SERVQUAL Model

SERVQUAL is a technology for measuring and managing service quality. Since 1985, when this technology was published, the innovators, Parasuraman, Zeithaml and Berry, have further developed, disseminated, and promoted the technology through a series of publications.

SERVQUAL is based on the view that the customer's assessment of service quality is the most important. This rating is conceptualized as the gap between what customers expect and their evaluation of the performance of a particular service provider. In its original formulation, SERVQUAL had ten main components: reliability, responsiveness, competence, access, courtesy, communication, credibility, security, knowing/knowing the customer, Tangibles.

Then [7] summarized the SERVQUAL model into 5 main components. The last two components (assurance and empathy) are a combination of the other 7 original components. Shown in **Table 1** below:

Table 1. SERVQUAL Model explainations

Components	Explainations	Example
Reliability	Ability to perform the promised service reliably and accurately	In the P2P Lending's business, providers must ensure that the interest rates offered to borrowers and investors are consistent and transparent.
Assurance	Knowledge and courtesy of employees and their ability to convey something. Including giving confidence and trust to customers.	P2P lending platforms must have a strong security system to protect personal data of borrowers and investors.
Tangibles	Availability of facilities, equipment, personnel and communication materials.	The P2P lending application must be responsive and the user interface attractive and easy to use.
Empathy	Availability of care and individual attention to customers.	Platforms must actively listen to suggestions and complaints from borrowers and investors.
Responsiveness	Availability to help customers and provide prompt service.	When a borrower applies for a loan or an investor makes an investment, the platform must have a fast and efficient verification process.

2.5 Aspect-Based Sentiment Analysis

Sentiment analysis at the document level and sentence level is very useful in many applications, but it does not provide more detailed information within an application. Comments or text reviews with positive sentiments about an application do not mean that the author has positive sentiments about all the features of the application. In some cases, users write positive and negative sentiments related to an application feature. To get these hidden details, we need to open Aspect Based Sentiment Analysis [5]. In aspect-based analysis there are 3 stages, namely extraction of target opinion, detection of aspect categories, and sentiment polarity [10]. The purpose of target opinion extraction is to get the subject of a review sentence. Shown in **Figure 3** below:

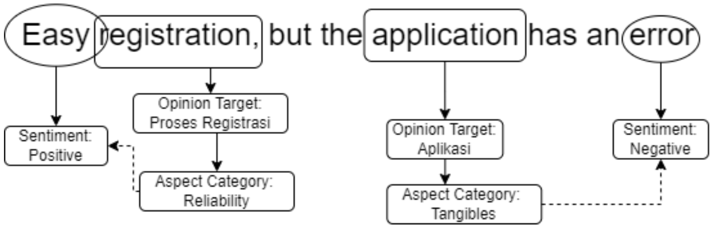

Fig. 3. Three ABSA subtask

3 Methodology

3.1 Data Crawling

In this research, the data is a collection of application user reviews which are FinTech peer-to-peer lending applications on the Google Play Store using the Google-Play-Scrapper library and carried out on Google Colab. After obtaining the raw data, then all columns that are not needed are removed leaving a user review column that will be used for analysis. The data that has been obtained is then manually labeled according to the five aspects based on the SERVQUAL Model theory, reliability, assurance, tangibles, empathy, and responsiveness.

3.2 Data Preparation

The dataset obtained and labelled must then be pre-processed to ensure the quality of the data used for analysis. The first process is Lemmatization, which is the process of removing prefixes, endings in words to get their basic form (lemma). Then the lemma goes into the process of converting words into tokens and tokens into sequences so that they can be used by the model. This sequence is usually generated by grouping tokens in one review data. Data that is ready to be processed is then divided into test data and train data.

3.3 Modelling

The model will be trained using certain optimization techniques such as Adam (Adaptive Moment Estimation). During the training process, the model will update its parameters, such as accuracy and loss, based on the data provided to minimize error from the prediction results.

After the training phase is complete, then the accuracy and loss functions are analyzed for each epoch with several scenarios. The final stage is that the model will be tested with data that has never been seen before (test data) at the modeling stage to find out how accurate the resulting model is.

4 Analysis and Data Processing

4.1 Collecting Data

Table 2. Table captions should be placed above the tables.

Content	Reliability	Assurance	Tangibles	Empathy	Responsiveness
Mau ganti nomer aja ribet.	0	0	1	0	0
Saya mengajukan pinjaman buat Usaha tapi malah di Tolak. Kenapa ini? apakah Dananya habis?	1	0	1	0	0

Table 3. Label Explaination

Label	Explanation
0	Unrelated with aspect
1	Negative Aspect
2	Positive Aspect

The first step is to collect data. The data used is primary data, collected from reviews of one of the P2P Lending applications available on the Google Play Store from January 25, 2023 - January 27, 2023. This dataset is extracted in Excel format, which has a total of 1000 rows of data. The dataset is given 5 additional columns as aspect labels based on the theory of the SERVQUAL model, namely reliability, assurance, tangibles, empathy, and responsiveness.

It can be seen in **Table 2**, each review is labeled with an integer 0, 1, or 2; one review can contain several aspects. Explanation of labels can be seen in **Table 3**.

4.2 Preprocessing Data

Lemmatization. At the Lemmatization stage, the Sastrawi library will transform words in the form of inflections into basic words or root words (lemma) and eliminate capitalization of letters. The basic word is a standard word form and contains the core meaning of the word. Shown in **Table 4** below:

Table 4. Comparison between Before and After Lemmatization

Before Lemmatization	After Lemmatization
Data saya sudah di daftarkan. sudah verifikasi email untuk pembuatan rekening Tapi ternyata setelah proses malah balik lagi ke awal seperti	*data saya sudah di daftar sudah verifikasi email untuk buat rekening tapi nyata telah proses malah balik lagi ke awal seperti itu*

itu terus menerus diminta buka rekening Berarti kalau kaya begitu pengajuan saya tidak di acc kah? Kalau iya tolong hapus data saya dari akun tunaiku. Saya tidak ingin data saya di salah gunakan	*terus terus minta buka rekening arti kalau kaya begitu aju saya tidak di acc kah kalau iya tolong hapus data saya dari akun tunai saya tidak ingin data saya di salah guna*

Tokenizer. The tokenizer will build an internal dictionary that maps each token to its numerical representation. To create a dictionary containing tokens, the *tf.keras.preprocessing.text.Tokenizer* module from the TensorFlow library (one of the libraries for neural networks) is used to convert text into token sequences.

{'<OOV>': 1, 'saya': 2, 'tidak': 3, …..,'binatang': 1599}

Sequencing. Transformation of text into a sequence of numeric tokens is important in NLP, because many NLP models and algorithms use these numerical representations as input for subsequent analysis or modeling. Shown in **Table 5** below:

Table 5. Comparison between Before and After Sequencing

Before Sequencing	After Sequencing
data saya sudah di daftar sudah verifikasi email untuk buat rekening tapi nyata telah proses malah balik lagi ke awal seperti itu terus terus minta buka rekening arti kalau kaya begitu aju saya tidak di acc kah kalau iya tolong hapus data saya dari akun tunai saya tidak ingin data saya di salah guna	[4, 2, 7, 5, 50, 7, 117, 94, 56, 71, 36, 19, 104, 95, 28, 40, 284, 24, 62, 202, 138, 63, 47, 47, 96, 75, 36, 375, 58, 203, 237, 8, 2, 3, 5, 20, 534, 58, 535, 11, 14, 4, 2, 59, 127, 37, 2, 3, 149, 4, 2, 5, 46, 43]

Padding of Sequence. This is useful when using token sequences as input for neural network models that require uniform input lengths, as opposed to using typical machine learning algorithms which do not require uniform length sequences. In this research, padding text using the tf.keras.preprocessing.sequence library from TensorFlow, this function used to equalize the length of the sequence, with parameters *truncating=”pre”* and *padding=”pre”*.

4.3 Data Modelling

The model developed is a sequential model using the Keras library by TensorFlow. This model is designed to address specific tasks involving sequential data, where the order and relationship between data elements is critical. In this study, we will test scenarios when the data is trained using single layer LSTM and multi-layer LSTM.

LSTM is becoming a very effective tool for doing this task. LSTM will remember any information from the past to be used as input for the current timestep which is carried out forward and backward. Next, in order to compile the model on *TensorFlow*

Keras, it is necessary to use the compile() function available on the model object. Some of the main arguments used in the model are Optimizer using Adam or Adaptive Moment Estimation, Loss using *binary_crossentropy*, and Metrics using accuracy.

4.4 Training Model

The model training process uses the fit() method on the model object. The model will go through a training process. Training and testing data will be used to train the model for 100 epochs. During training, the model will be evaluated using the test_seq and test_labels validation data. In this study, the model will be trained with different batch sizes and number of LSTM layers to find out which accuracy is best.

The pre-processed training data and labels are then sampled in one batch. One batch shows the number of samples processed by the model in one iteration. This data will be an input for the LSTM network which will produce output. The next process is calculating the loss of the output data and labell with *binary crossentropy* then optimized with Adam's algorithm. One time the above process runs is the same as one iteration and will continue to be repeated until it reaches 100 epochs for later analysis.

5 Result and Discussion

5.1 Analysis of test scenario results

First, testing will be carried out by varying the batch size in the LSTM model. In this scenario, several different batch size values will be used, namely 16, 32, and 64, to evaluate their effect on the accuracy of the single layer LSTM model. In the second scenario, three tests will be carried out by adding an LSTM layer to the sequence model. The first test is when the data is trained using a single layer LSTM, the second test is when the data is trained using a stacked 2-layer LSTM, and the third test uses a stacked 5-layer LSTM. Shown in **Table 6** below:

Table 6. Scenarios Result

Scenario	LSTM		
	Single -layer	2-layer	5-layer
Batch_size 16	79,00%	65,75%	67,75%
Batch_size 32	76,13%	65,50%	66,50%
Batch_size 64	71,38%	67,00%	62,50%

The result is that the model with single layer LSTM has an accuracy of above 70% in each test with different batch sizes. Batch size 16 has the highest accuracy compared to all test models at 79%. Based on the results obtained from the test scenario, a simple model with a single layer LSTM and low batch size can have higher accuracy and lower loss than a more complex model such as a multi-layer LSTM. Shown in **Figure 4** below:

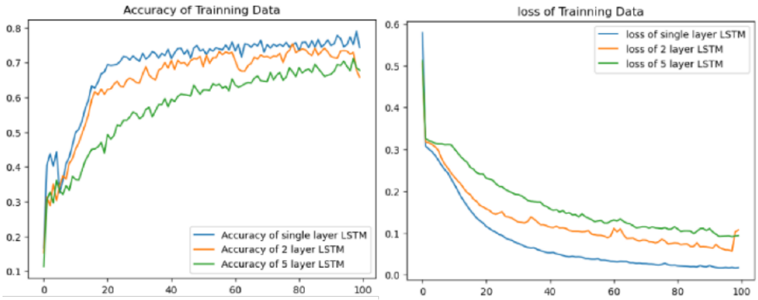

Fig. 4. Loss and Accuracy of Training Data

5.2 Model Implementation

The reviews used for classification trials are data that is exclude from the training data with total three row dataset. The review sentences are preprocessed first into a sequence containing tokens which are then padded so that they can finally be classified by the model. Shown in **Figure 5** below:

```
array([[2.1280473e-06, 1.6723676e-01, 4.9056813e-05, 2.0511861e-01,
        4.2332683e-04, 1.4887225e-05, 7.0931774e-01, 3.9211024e-08,
        7.8928360e-04, 5.7214458e-02],

       [9.9997556e-01, 2.9634798e-16, 8.1093114e-09, 6.7879770e-16,
        3.9143256e-15, 1.2853417e-18, 5.0600178e-08, 2.0582261e-21,
        5.3758126e-06, 1.0233114e-09],

       [6.7673656e-10, 3.7723999e-03, 7.4674088e-01, 2.5849292e-10,
        1.5255948e-07, 1.2495909e-08, 3.2045420e-09, 4.1974957e-19,
        9.9902356e-01, 5.3196113e-06]],
```

Fig. 5. Array that contains probabilities each aspect

There are three array rows that represent each new review. In the first row, there is one result in 7th place with a probability of 70.9%. The second row has one result in first place with a probability of 90.9%. The second row has two results in 3rd place with a probability of 74.6% and 9th place with a probability of 9.99%. With these results, the first review has the empathy aspect with a negative sentiment, the second review has the reliability aspect with a negative sentiment, and the third review has the assurance aspect with a negative sentiment and the responsiveness aspect with a negative sentiment.

6 Conclusion

This research focuses on analyzing aspect-based sentiment based on the SERVQUAL Model customer satisfaction theory in the popular Fintech P2P Lending application available on the Google Play Store. Customer satisfaction is one of the most prominent topics in Fintech literature. The predominance of reviews that have negative sentiments on every aspect of SERVQUAL is an indicator of dissatisfaction with the service of one of the P2P Lending applications from Indonesia registered on the Google Play

Store, which is related to the realization and expectations given to users through their advertisements, although some users think positively. Based on the two scenarios that have been carried out, the model with batch size 16 and using single layer LSTM managed to achieve the highest accuracy of 79.00%. Suggestions for further research are to have sufficient data to avoid overfitting that occurs in the model and increase model accuracy. P2P Lending service developers can utilize models to analyze user satisfaction based on the SERVQUAL model theory so that they can improve service quality in the P2P Lending sector.

References

1. Departemen Komunikasi Bank Indonesia, "Mengenal Financial Teknologi," bi.go.id. Accessed: Nov. 19, 2022. [Online]. Available: https://www.bi.go.id/id/edukasi/Pages/mengenal-Financial-Teknologi.aspx
2. A. V. Thakor, "Fintech and banking: What do we know?," *Journal of Financial Intermediation*, vol. 41, p. 100833 (2020)
3. N. R. Mosteanu and A. Faccia, "Fintech frontiers in quantum computing, fractals, and blockchain distributed ledger: Paradigm shifts and open innovation," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 7, no. 1, pp. 1–19, (2021)
4. R. Bates, "Banking on the future: an exploration of FinTech and the consumer interest," (2017)
5. N. K. Laskari and S. K. Sanampudi, "Aspect Based Sentiment Analysis Survey," vol. 18, no. 2, pp. 24–28 (2016)
6. F. Buttle, "SERVQUAL: review, critique, research agenda," *Eur J Mark*, vol. 30, no. 1, pp. 8–9, (1996)
7. a Parasuraman, V. a Zeithaml, and L. L. Berry, "SERQUAL: A Multiple-Item scale for Measuring Consumer Perceptions of Service Quality," *Journal of Retailing*, vol. 64, no. September 2014, p. 28 (1988)
8. C. Janiesch, P. Zschech, and K. Heinrich, "Machine learning and deep learning," *Electron Markets*, pp. 685–695, (2021)
9. C. Olah, "Understanding LSTM Networks." Accessed: Aug. 10, 2023. [Online]. Available: http://colah.github.io/posts/2015-08-Understanding-LSTMs/
10. H. H. Do, P. W. C. Prasad, A. Maag, and A. Alsadoon, "Deep Learning for Aspect-Based Sentiment Analysis: A Comparative Review," *Expert Syst Appl*, vol. 118, pp. 272–299 (2019).
11. I. Lee and Y. J. Shin, "Fintech: Ecosystem, business models, investment decisions, and challenges," *Bus Horiz*, vol. 61, no. 1, pp. 35–46, (2018).
12. U. Kamath, J. Liu, and J. Whitaker, *Deep Learning for NLP and Speech Recognition*. Springer International Publishing (2019).
13. Safitra, M. F., Lubis, M., & Fakhrurroja, H. (2023). Counterattacking Cyber Threats: A Framework for the Future of Cybersecurity. Sustainability, 15(18), 13369.
14. L. Moroney, *AI and Machine Learning for Coders*, 2nd ed. O'Reilly Media, Inc., (2020).