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Sentiment Analysis of Gojek Application User Reviews Using the Long Short-Term Memory (LSTM) Algorithm

Ahmad Firdaussani[1*], Hardian Oktavianto[2], Wiwik Suharso[3]
[1,2,3] Teknik Informatika, Universitas Muhammadiyah Jember, Jember, Indonesia

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ABSTRACT

This study was conducted to perform sentiment analysis by identifying patterns or trends in user reviews of the Gojek application using the Long Short-Term Memory (LSTM) algorithm, which was implemented in the form of a simple web-based application or dashboard. In today's digital era, technological advancements have significantly influenced various aspects of life, particularly the mobile-based transportation service industry. One of the most widely used online transportation services in Indonesia is Gojek. It is essential for Gojek to listen to customer reviews; therefore, sentiment analysis is required to identify patterns or trends within user feedback so the application can better respond to user needs. This research utilizes the Long Short-Term Memory (LSTM) algorithm, a variant of the Recurrent Neural Network (RNN) that incorporates a cell state and gating mechanisms (input, forget, and output gates) to regulate the flow of information. This structure enables LSTM to retain relevant information while discarding irrelevant data, allowing it to capture both short-term and long-term patterns in text reviews. The model was used to analyze sentiment within a dataset collected from 2021 to 2024.
The experimental results show that LSTM achieved an optimal accuracy of 78% using a 70:30 dataset split, providing balanced performance across both majority and minority classes, with a significant improvement in the f1-score for each class (0: 0.73; 1: 0.75; 2: 0.85) after applying the SMOTE technique to address class imbalance. Without SMOTE, the highest accuracy reached 83% with the same split (70:30); however, the neutral class could not be detected (f1-score = 0). With SMOTE, although accuracy slightly decreased, the overall performance became more balanced as the neutral class could be properly recognized.

1. INTRODUCTION

The development of the digital era has had a significant impact on various aspects of life, particularly within the mobile-based transportation service industry. Transportation is a fundamental need for Indonesian society to support daily activities (Alghifari et al., 2022). The Gojek application offers several features such as online motorcycle taxis, food delivery, and goods delivery services. With these diverse features, Gojek enables users to conveniently fulfill their transportation and service needs (Indrawati & Februatiyanti, 2023). The increasing number of smartphone users and vehicles has contributed to the growing number of people using the Gojek application. This rapid growth in smartphone users also leads to higher expectations regarding the quality of Gojek's services (Muttaqin & Kharisudin, 2021).

Therefore, to meet user expectations and maintain its position in a competitive market, Gojek must continuously pay attention to customer reviews. These reviews provide valuable insights into user perspectives, allowing the company to identify issues and improve its services (Rahman et al., 2024). Hence, sentiment analysis is needed to identify patterns or trends within user reviews, enabling Gojek to better respond to user needs by detecting positive, negative, and neutral sentiments.

The Long Short-Term Memory (LSTM) algorithm is one of the architectures of Recurrent Neural Networks (RNN), widely used in deep learning applications (Rahman et al.,

* Corresponding Author: Ahmad Firfaussani: firdaussaniahmad08@gmail.com

2024). LSTM is capable of storing information from sequential data, allowing it to capture context and meaning from user opinions.

This study aims to analyze the sentiment of user reviews on the Gojek application using the LSTM algorithm, without comparing it to other methods, in order to obtain a clearer understanding of user sentiment to support future service development.

2. LITERATURE REVIEW

Online Transportation

Online transportation refers to public transportation services used by communities in Indonesia through a smartphone-based booking system. The advancement of Indonesia's transportation systems has driven the development of various service models, including the emergence of online transportation services (Sugianto & Kurniawan, 2020). Providers of online transportation applications operate as electronic system organizers that connect vehicle owners with service users (Tuti et al., 2021).

Text Mining

Text mining is the process of extracting in-depth information through specific methods to analyze data or documents (Rania & Syah, 2024). The text mining process involves several stages, such as data cleaning, natural language processing, and statistical analysis.

Sentiment Analysis

Sentiment analysis is a process used to evaluate people's views, feelings, and emotions with the aim of categorizing the sentiments expressed in statements that convey opinions or perspectives (Hidayat et al., 2021). In the context of the Gojek application, sentiment analysis is conducted to assess user comments and feedback in order to understand customer experiences. Through this process, the company can identify areas that require improvement as well as features most desired by consumers for future product and service development. Sentiment analysis is generally divided into four categories: hierarchical, emotion detection, aspect-based, and multilingual analysis (Larasati et al., 2022).

SMOTE Oversampling

The Synthetic Minority Over-sampling Technique (SMOTE) is a method used to address class imbalance in a dataset. SMOTE operates by resampling the minority class and generating new synthetic samples to balance the amount of data without creating duplicates. Data imbalance often causes the model to focus on the majority class while neglecting the minority class, which can reduce prediction accuracy (Gunawan et al., 2025).

Long Short-Term Memory (LSTM) Algorithm

Long Short-Term Memory is a variant of the Recurrent Neural Network (RNN) that is capable of retaining information over long periods (Prawinata et al., 2024). LSTM can learn sequential data and produce more accurate and informative text representations compared to traditional methods (Wibowo et al., 2024). LSTM introduces a memory unit called a *cell*, equipped with gating mechanisms that allow the model to control the flow of information.

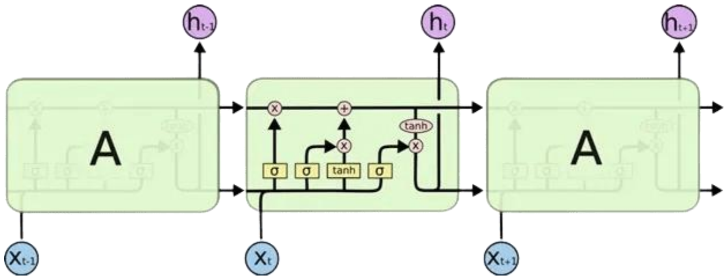

Figure 1. LSTM Structure

According to Pardede & Pakpahan (2023),

a. Forget Gate, which determines the amount of information to be removed from the memory cell. The formula for the Forget Gate is presented below.

$$ft = \sigma(W\,x\,f\,.\,xt + whf\,.\,(ht\text{-}1) + bf)$$

b. Input Gate, which determines the amount of new information that needs to be stored in the memory cell. The formula for the Input Gate is presented below.

$$it = \sigma(Wxi\,.\,xt + Whi\,.\,(ht - 1) + bi)$$

$$Ct = \tanh(W\,x\,C\,.\,xt + Whc\,.\,(ht - 1) + bC)$$

c. Cell State, the process of updating the previous cell state (C_{t-1}) into the new cell state (C_t) by integrating the new information obtained from the input and the previous hidden state.

$$Ct = ft * (Ct - 1) + (it\text{-}1 * Ct)$$

d. Output Gate, which applies the Sigmoid activation function to generate the output value for the hidden state, while the cell state is processed using the Tanh function. The formula for the Output Gate is shown below.

$$Ot = \sigma(Wxo\,.\,xt + Who.(ht\text{-}1) + bo)$$

$$ht = ot * \tanh\,(Ct)$$

Confusion Matrix

A confusion matrix is a table that stores information used to evaluate the performance of a model and serves as a reference for assessing the classification results of an algorithm during the evaluation stage (Fadli & Hidayatullah, 2021). The confusion matrix consists of four values: true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

Tabel 1. Confusion Matrix

	Predicted Positive	**Predicted Negative**	**Predicted Neutral**
Actual Positive	TP (True Positive)	FN (False Negative)	FN (False Negative)
Actual Negative	FP (False Positive)	TN (True Negative)	FP (False Positive)
Actual Neutral	FN (False Negative)	FP (False Positive)	TN (True Negative)

The testing method produces calculations using the following formulas.

1. Accuracy
   Accuracy is used to measure the correctness of the algorithmic model being applied.

$$\text{Accuracy} = \frac{TP+TN+TN}{TP+FP+FN+TN}\ x\ 100\%$$

2. Precision
   Precision measures the accuracy between the predicted target data and the actual data in the sentiment analysis results.

$$\text{Precision} = \frac{TP}{TP+FP}\ x\ 100\%$$

3. Recall
   Recall functions to measure the ability of the algorithmic model to successfully identify relevant information.

$$Recall = \frac{TP}{TP+FN} \times 100\%$$

4. F1-Score
   The F1-Score is an evaluation metric used to measure the performance of a classification model, particularly in problems involving imbalanced class distributions.

$$F1\text{-}Score = 2 \times \frac{\text{Precision x Recall}}{\text{Precision + Recall}}$$

3. METHOD

Research Flow

This research involves a series of modeling steps that are visually illustrated in the flowchart shown in the figure below, which outlines the stages of the research process.

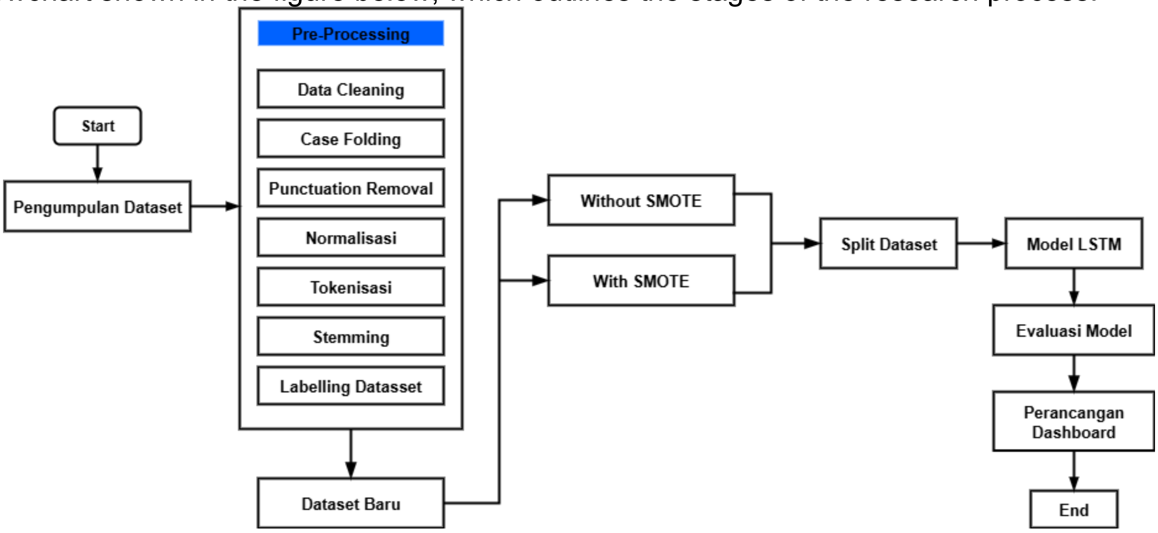

Figure 2. Research Flow

Dataset Collection

The dataset was collected by obtaining user review data of the Gojek application from the Kaggle platform at https://www.kaggle.com/datasets/ucupsedaya/gojek-app-reviews-bahasa-indonesia, with a total of 225,002 entries covering Gojek services from 2021 to 2024. The dataset contains a compilation of user reviews that represent users' opinions regarding the services provided by the Gojek application.

Preprocessing

The preprocessing stage consists of several steps, including data cleaning, case folding, punctuation removal, stopword removal, normalization, stemming, and SMOTE oversampling. Preprocessing aims to establish a solid foundation for the modeling algorithm to be applied (Mutmatinah et al., 2024).

Dataset Labeling

In the dataset labeling stage, each review is assigned a label based on the rating provided by the user. The ratings range from 1-5. This stage aims to classify the reviews into three sentiment categories: Negative, Neutral, and Positive. The labeling is determined as follows:

1. Ratings 1 and 2 (Negative)
   Reviews with these ratings contain words that reflect user disappointment and dissatisfaction with Gojek's services.
2. Rating 3 (Neutral)
   These reviews describe user experiences without indicating significant satisfaction or dissatisfaction with the Gojek application.
3. Ratings 4 and 5 (Positive)
   These ratings reflect user satisfaction and appreciation toward the services provided by the Gojek application.

SMOTE Oversampling

After the text data has completed the preprocessing stage and is transformed into numerical representations, the next step is to balance the classes using the Synthetic Minority Oversampling Technique (SMOTE). With the dataset consisting of 161,371 positive reviews, 9,460 neutral reviews, and 54,171 negative reviews, this class imbalance causes the model to focus more on the majority class while neglecting the minority classes, resulting in reduced prediction accuracy. SMOTE is applied to address this imbalance by generating new synthetic samples for the minority classes.

Dataset Splitting

After the text data has undergone preprocessing and class balancing using SMOTE (Synthetic Minority Oversampling Technique), the next step is dataset splitting. This technique is applied to separate the data into two main parts: training data and testing data.

Long Short-Term Memory (LSTM) Model

The dataset that has undergone the preprocessing stage is then divided into training and testing data to ensure proper model generalization. The LSTM model is used to analyze the sentiment of user reviews from the Gojek application. The LSTM model is designed by taking into account the structure of the processed text data.

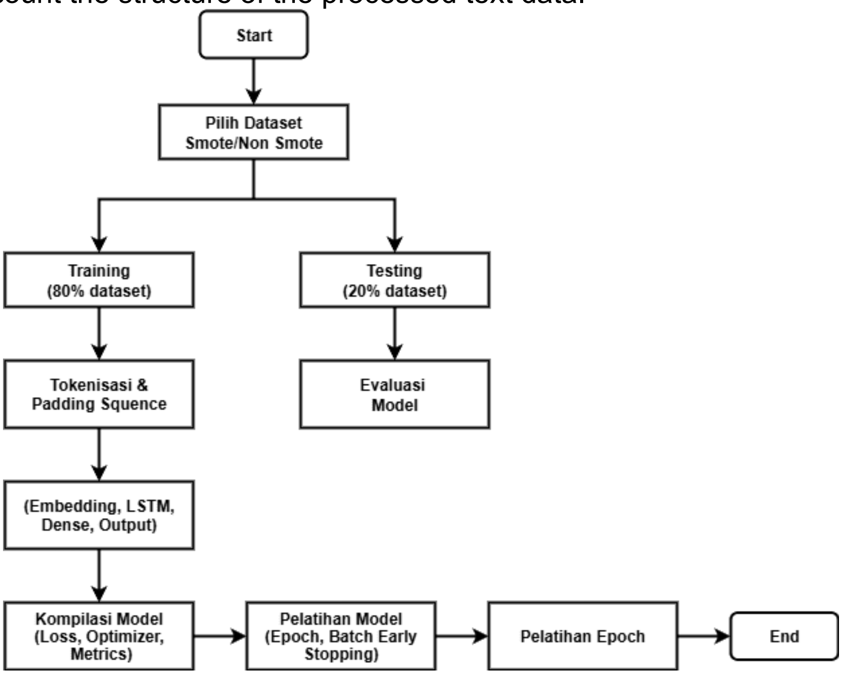

Figure 3. Long Short-Term Memory Model

Model Evaluation

The performance evaluation is conducted using a confusion matrix to measure the levels of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The evaluation process aims to assess the accuracy, precision, and recall obtained from the experimental results (Al-Areef & Saputra, 2023).

Table 2. Example of Model Evaluation Calculation

	Predicted Positive	**Predicted Negative**	**Predicted Neutral**
Actual Positive	TP = 80	FN = 10	FN = 5
Actual Negative	FP = 15	TN = 70	FP = 10
Actual Neutral	FN = 5	FP = 10	TN = 100

Dashboard Design

The design of the dashboard interface aims to create a simple yet functional layout that allows users to easily view the results of the sentiment analysis. The website will display clear visualizations, such as bar charts or pie charts, illustrating the distribution of sentiments (positive, negative, and neutral) from user reviews.

4. RESULT AND DISCUSSION

In the analysis stage, the data then undergoes preprocessing to identify duplicate entries or irrelevant reviews. After removing the irrelevant reviews, the total number of data entries was reduced from 225,002 to 122,039 rows.

Dataset Labeling

In the dataset labeling stage, each review is assigned a label based on the user's given rating. Using a rating scale of 1 to 5, ratings 1-2 are categorized as negative reviews, rating 3 as neutral, and ratings 4-5 as positive reviews. The validation process is performed automatically using a Python mapping function. The results of this rating-to-label mapping are stored in the Target_Binary column, aiming to systematically group the data according to the sentiment contained in each review.

	hasil_ulasan	score	Target_Binary	Sentiment
0	akun gopay saya di blok	1	0	Negatif
1	lambat sekali sekarang ini bos apk gojek engga...	3	1	Netral
2	kenapa sih dari kemarin saya buka aplikasi goj...	4	2	Positif
3	baru download gojek dan hape baru terus top lu...	1	0	Negatif
4	bagaimana ini kak pin saya salah terus padahal...	1	0	Negatif
...	...	...	...	...
122034	bapak gojek baik antar dengan sabar cari alama...	5	2	Positif
122035	makin kesini makin mahal dan vouchernya makin ...	5	2	Positif
122036	kenapa harus baru mulu hedeh payah	1	0	Negatif
122037	gofood biaya lai enggak ngotak mending hujan b...	1	0	Negatif
122038	gojek lama lama enggak jelas lagi pesan masa m...	1	0	Negatif

122039 rows × 4 columns

Figure 4. Dataset Labeling Results

SMOTE Oversampling

In this study, the SMOTE (Synthetic Minority Oversampling Technique) method was applied to increase the number of samples in minority classes, thereby achieving a more balanced class distribution prior to the classification process. SMOTE generates new synthetic samples by constructing data points based on the proximity of instances within the minority class. This approach prevents the model from relying solely on majority-class data and enhances its ability to produce more accurate and representative predictions across all sentiment categories.

Table 3. Minority Class Identification

Class	Data Quantity
0	50.380
1	8.070
2	63.589

Based on the table above, Class 1 is identified as the minority class because it contains the smallest number of samples. This indicates that the dataset is imbalanced. To address this issue, SMOTE is applied to generate synthetic samples by identifying the nearest neighbors from the same class, thereby improving class distribution prior to model training.

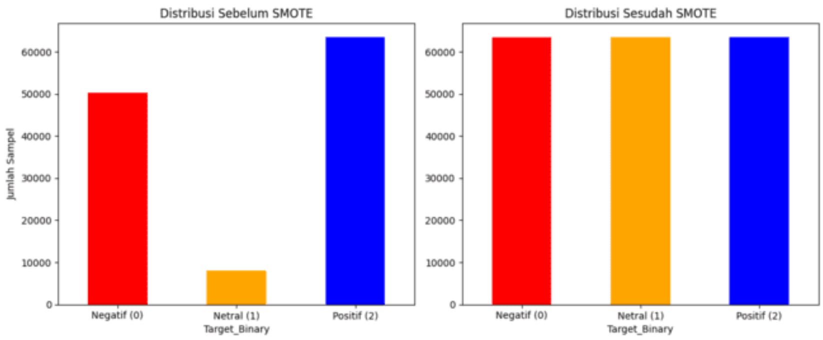

Figure 5. Distribution of Data Before and After Applying SMOTE

After applying SMOTE, each class (Positive, Neutral, and Negative) becomes balanced, with 63,589 data points in each category. SMOTE generates new synthetic samples between existing data points, thereby increasing the variation within the minority class. This process enhances the model's performance by producing a more representative and balanced dataset.

Split Dataset

Before dividing the testing data into four proportions (20%, 30%, 40%, and 50%), two experimental scenarios were conducted, namely with SMOTE and without SMOTE, to compare their impact in addressing class imbalance and improving model performance.

Building the Long Short-Term Memory Model

The LSTM model consists of an Embedding layer with 1,000,000 parameters to map tokens into 43–dimensional vectors, followed by an LSTM layer with 128 units and 117,248 parameters to capture sequential patterns in the text data. Subsequently, a Dense layer with 64 units and 8,256 parameters serves as the hidden layer, followed by a Dropout layer to prevent overfitting. Finally, a Dense output layer with 3 softmax units and 195 parameters is used to classify sentiment into three categories.

Table 4. LSTM Model Results

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, 100, 43)	1,000,000
lstm_1 (LSTM)	(None, 128)	117,248
dense_2 (Dense)	(None, 64)	8,256

Layer (type)	Output Shape	Param #
dropout_1 (Dropout)	(None, 64)	0
dense_3 (Dense)	(None, 3)	195

LSTM Model Training

The LSTM model was trained using both SMOTE-augmented data and non-SMOTE data, with testing data allocated according to the specified proportions. Training was conducted for a maximum of 10 epochs using a batch size of 64 and early stopping. *Accuracy* and *loss* represent the model's performance on the training data, while *val_accuracy* and *val_loss* indicate performance on the validation data. An increase in accuracy and a decrease in loss demonstrate that the model is learning effectively, whereas a decrease in *val_accuracy* accompanied by an increase in *val_loss* signals the occurrence of overfitting.

1. **Training Results for the 70:30 Dataset Split**

   a. Without SMOTE Oversampling

   The training results for the 70:30 dataset split show that the training accuracy increased from 70.05% to 82.93%, while the loss decreased from 0.7355 to 0.3764. The lowest validation loss was recorded at epoch 4 (0.4846). Therefore, with an early stopping patience of five epochs, the model selected at epoch 4 represents the optimal balance between accuracy and loss.

Table 5. Training Results for the 70:30 Dataset Split Without SMOTE

Epoch	Accuracy	Loss	Val_Accuracy	Val_Loss
1	0.7005	0.7355	0.7662	0.6937
2	0.7484	0.5909	0.8191	0.4995
3	0.7660	0.4924	0.8244	0.4861
4	**0.7778**	**0.4551**	**0.8264**	**0.4846**
5	0.7898	0.4423	0.8269	0.4862
6	0.8006	0.4230	0.8262	0.4884
7	0.8070	0.4045	0.8260	0.4967
8	0.8193	0.3918	0.8238	0.5093
9	0.8293	0.3764	0.8230	0.5214

   b. **Using SMOTE Oversampling**

   Training the 70:30 dataset split with SMOTE increased the training accuracy from 48.34% to 78.48% and reduced the loss from 0.9725 to 0.5512. The lowest validation loss was recorded at epoch 5 (0.6085), and with an early stopping patience of five epochs, this epoch was selected as the best model.

Table 6. Training Results for the 70:30 Dataset Split with SMOTE

Epoch	Accuracy	Loss	Val_Accuracy	Val_Loss
1	0.4834	0.9725	0.5723	0.8248
2	0.5905	0.8190	0.6679	0.7436
3	0.6685	0.7464	0.7058	0.6802
4	0.7092	0.6847	0.7384	0.6350
5	**0.7401**	**0.6372**	**0.7540**	**0.6085**
6	0.7542	0.6103	0.7650	0.5909
7	0.7685	0.5875	0.7696	0.5796
8	0.7767	0.5704	0.7742	0.5720
9	0.7807	0.5587	0.7772	0.5686
10	0.7848	0.5512	0.7776	0.5685

Accuracy and Loss Curves of the Model

The accuracy and loss curves illustrate the training process of the LSTM model under the 70:30 dataset split scenario.

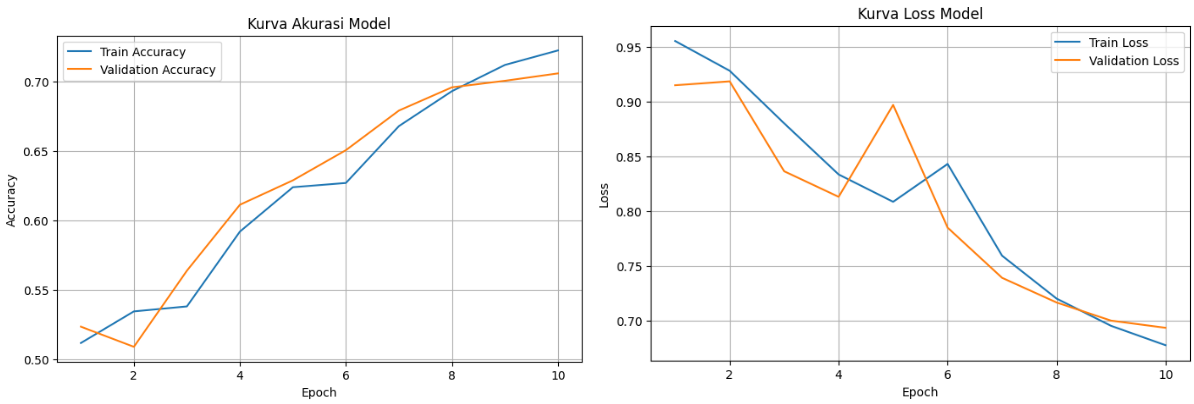

Figure 6. Accuracy and Loss Curves of the Model

1. In the accuracy graph, both training accuracy and validation accuracy consistently increased from approximately 0.52 to over 0.70. This indicates that the model is progressively learning to recognize data patterns effectively without significant overfitting, as the training and validation accuracies remain closely aligned.
2. In the loss graph, both training loss and validation loss decreased from around 0.95 to 0.68 as the number of epochs increased. Although there were slight fluctuations in the validation loss at certain points, the overall trend remained downward. This suggests that the model's errors decreased and that the training process was stable.

Overall, both graphs indicate that the model learned effectively, maintained stability, and was able to improve its performance throughout the training process.

Model Evaluation

The model's performance was evaluated using a confusion matrix in the 70:30 dataset split scenario. The confusion matrix provides a detailed overview of the model's predictions, facilitating comparison between the performance of models trained with SMOTE and those without, in order to determine the most effective approach.

1. Evaluation Results for the 70:30 Split

a. Without SMOTE Oversampling

The 70:30 dataset split without SMOTE achieved an accuracy of 83%, with high F1-scores for the majority classes (0: 0.83; 2: 0.88) but very low for the minority class (1: 0.00) due to data imbalance.Table 7. Evaluation Results for the 70:30 Dataset Split Without SMOTE

Label	Precision	Recall	F1-Score
0	0.76	0.93	0.83
1	0.00	0.00	0.00
2	0.90	0.85	0.88
Accuracy		**83%**	

b. Using SMOTE Oversampling

The 70:30 dataset split with SMOTE achieved an accuracy of 78%, with a more balanced F1-score between the minority class (1: 0.75) and the majority classes (0: 0.73; 2: 0.85), demonstrating that SMOTE effectively balances model performance.

Table 8. Evaluation Results for the 70:30 Dataset Split with SMOTE

Label	Precision	Recall	F1-Score
0	0.72	0.73	0.73
1	0.75	0.75	0.75
2	0.85	0.85	0.85
Accuracy		**78%**	

Website Interface

1. Dashboard Display

   The dashboard presents the results of sentiment analysis on Gojek application user reviews, showing 56.2% positive reviews (78,033 reviews), 6.1% neutral reviews (8,432 reviews), and 37.7% negative reviews (52,354 reviews). These results indicate that the majority of users provided positive feedback, although a considerable portion of negative reviews remains, which should be addressed by Gojek. Visualizations such as bar charts, pie charts, and word clouds support these findings, highlighting dominant positive words like “Gojek,” “driver,” and “helpful” in positive reviews, and words like “cannot,” “expensive,” and “not” in negative reviews.

Figure 7. Website Dashboard Display Results

2. Dataset Display

   This page presents a list of Gojek application user reviews that have undergone preprocessing and sentiment labeling. The sentiment analysis results are shown in the *sentiment* column, categorized into three classes: positive, negative, and neutral. This table allows users to directly view the content of the reviews along with their corresponding classifications.

Figure 8. Website Dataset Menu Display

5. CONCLUSION

Conclusion

The evaluation of the 70:30 dataset split with SMOTE application provided the best balance between performance on majority and minority classes. The LSTM model achieved relatively high F1-scores for each class (0: 0.73; 1: 0.75; 2: 0.85) with an overall accuracy of 78%. This demonstrates that LSTM is effective in sentiment analysis of Gojek user reviews, particularly after addressing class imbalance. Furthermore, the LSTM algorithm can be practically implemented on a web platform to facilitate the display of sentiment analysis results for Gojek application services.

Recommendations

Based on the LSTM algorithm and the presentation of analysis through a web platform, it is recommended to improve accuracy for the neutral sentiment class, for example, by balancing the data further and exploring alternative models such as Bi-LSTM or Attention mechanisms. Additionally, the application system can be enhanced by adding features such as dataset uploading and real-time review classification based on direct text input. This would allow users to type or paste reviews into the application, and the system would automatically provide the sentiment analysis results (positive, negative, or neutral).

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