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Food and Beverage Product Review Sentiment Analysis on E-Commerce with Word Embedding and LSTM

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Abstract

Sentiment analysis is a widely used method to understand customer opinions about a product. This study aims to analyze the sentiment of food and beverage product reviews on the Tokopedia marketplace using the Long Short-Term Memory (LSTM) approach and word embedding. The data used consisted of customer reviews that were categorized into three sentiment classes, namely positive, neutral, and negative. The model was developed through a series of stages of preprocessing, embedding, training with LSTM, as well as performance evaluation using accuracy and F1-score metrics. The results show that the developed model is able to classify sentiment with a fairly high level of accuracy. Based on the results of the final test on 5,000 data, the model managed to classify 122 data as negative, 130 data as neutral, and 4,871 data as positive, although it still showed an imbalance in class classification. Further analysis through word cloud visualization showed that words like "delicious", "steady", and "good" dominated the positive sentiment, while words like "disappointed", "broken", and "slow" often appeared in negative sentiment. This study provides valuable insights for businesses in understanding customer opinions and improving the quality of products and services.

Introduction

In recent years, sentiment analysis particularly of product reviews in the e-commerce sectorhas gained significant attention. Sentiment analysis is a field that studies how to extract and interpret opinions, sentiments, and evaluations expressed by individuals toward specific entities such as services, products, organizations, or issues (Husada & Paramita, 2021). A primary goal of sentiment analysis is to determine the proportion of text that conveys positive, negative, or neutral sentiment (Riefky & Pramesti, 2020). The present research aims to apply state-of-the-art methodologiesspecifically, Long Short-Term Memory (LSTM) networks and word-embedding techniquesto examine sentiment expressed in food-and-beverage product reviews. The growing reliance on online shopping necessitates robust mechanisms for assessing customer sentiment, which in turn shapes consumer behavior and informs business strategy (Gondhi et al., 2022; Akter et al., 2025).

By uncovering consumer preferences, sentiment analysis allows companies to refine product portfolios and deliver enhanced customer experiences grounded in review insights (Sachin et al., 2020). Because physical interaction is absent in e-commerce, an effective sentiment-analysis system can reinforce credibility by aligning consumer expectations with actual product performance (Gu et al., 2020; Liu et al., 2025). E-commerce firms can leverage these

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insights to serve customers more effectively, focus marketing efforts, and iteratively improve product features. In this context, the Dempster-Shafer theory has emerged as a promising framework for addressing the inherent challenges in consumer-level sentiment analysis (Nazaruddin et al., 2023; Sugumaran et al., 2025).

Like the Dempster-Shafer approach, LSTM networks mitigate the limitations of conventional Recurrent Neural Networks (RNNs), which struggle to capture long-range dependencies in sequential data. LSTMs strengthen contextual understanding and are adept at discerning subtle sentiments within product reviews (Sadikin & Fauzan, 2023). Word-embedding techniques such as Word2Vec and GloVe transform textual data into a numerical format that neural networks can process, thereby improving sentiment-classification accuracy (Shobana & Murali, 2021). Empirical results indicate that hybrid models combining LSTM with Convolutional Neural Networks (CNN) outperform single-model approaches, especially in product-review analysis (Dang et al., 2021; Bellar et al., 2024; Nor et al., 2024).

Numerous studies have confirmed the success of LSTM networks coupled with word embeddings across various review domains beyond food and beverages. For instance, investigations into hotel reviews and online product ratings demonstrate that these models can accurately capture sentiment related to specific service or product aspects (Setiyawan et al., 2022). Such aspect-based sentiment analysis provides actionable insights that directly inform improvements in products and customer service (Onan, 2020; Chen et al., 2025).

Tokopedia, one of Indonesia's largest e-commerce platforms, enables individuals and businesses to buy and sell goods with ease (Maulana et al., 2025; Dewi, 2024). Established in 2009, it has evolved into a marketplace offering extensive product categories, including food and beverages (Sari & Putri, 2021). Owing to its large active-user base, Tokopedia is a rich and reliable data source for sentiment analysis, as consumers frequently share feedback on their purchasing experiences.

Sentiment analysis is the automated process of identifying and classifying opinions expressed in text to determine whether the author's perspective is positive, negative, or neutral (Liu, 2012). In e-commerce, it is commonly employed to gauge customer satisfaction and enhance service quality. Machine-learning approaches ranging from Support Vector Machine (SVM) and Naive Bayes to deep-learning techniques such as LSTM are widely used in this domain (Medhat et al., 2014).

Word embedding is a technique that represents words as dense numerical vectors, thereby capturing semantic relationships between them. It is a standard tool in natural-language processing (NLP) for improving a model's understanding of lexical relationships within text (Mikolov et al., 2013). Popular embedding methods include Word2Vec, GloVe, and FastText. In sentiment analysis, these embeddings enhance model accuracy by providing more nuanced word representations than traditional bag-of-words approaches (Zhang et al., 2018; Kurniasari et al., 2025).

LSTM is a specialized variant of Recurrent Neural Networks designed to overcome the vanishing-gradient problem in sequential-data analysis (Al-Selwi et al., 2023). Its architecture comprising input, forget, and output gatesreduces sensitivity to text length. LSTM is frequently applied in sentiment-analysis tasks because of its ability to capture the contextual nuances of customer reviews in e-commerce marketplaces (Hochreiter & Schmidhuber, 1997; Tang et al., 2015).

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Methods

Here is a Sentiment Analysis Modeling Flowchart with Word Embedding and LSTM. This flowchart describes the stages carried out in the research process, starting from the collection of review datasets, then continued with preprocessing to clean and prepare the data to make it suitable for use. The cleaned data is then converted into a vector representation through the word embedding process. Furthermore, this vector data is used as input into the LSTM model for training and testing. The final stage is the evaluation of the results of the sentiment classification, which indicates whether the review is positive or negative.

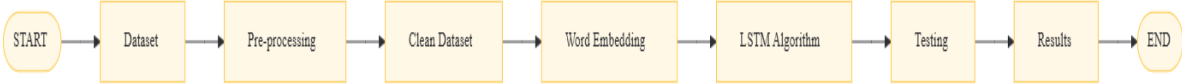

Figure 1. Flowchart Alur Pemodelan Analisis Sentimen dengan Word Embedding dan LSTM

Dataset

The dataset employed in this study was obtained from Kaggle and comprises product reviews and ratings for food-and-beverage items sold on the Indonesian e-commerce platform Tokopedia. Containing more than 5 000 user-generated reviews, the corpus will be used to train and evaluate a sentiment-analysis model capable of classifying opinions as positive, negative, or neutral. The overall workflow is summarized in the flowchart provided.

Pre-processing

Raw, unstructured text must first be converted into a clean, model-ready format through several pre-processing steps: 1) Cleansing– removal of irrelevant symbols, numbers, and punctuation; 2) Case-folding– conversion of all characters to lowercase to ensure uniformity; 3) Tokenization– splitting the normalized text into individual tokens (words); 4) Stop-word removal– elimination of high-frequency but low-information words such as "yang," "dan," and "di."; 5) Stemming– reducing each word to its root form by stripping affixes with the Sastrawi library. These steps yield concise, semantically meaningful tokens that are optimal for downstream analysis.

Clean Dataset

To guarantee that the data are both reliable and representative, the cleaned corpus undergoes additional refinement: removal of missing values, duplicates, and reviews that are excessively short or long. Outliers are addressed, and class imbalance is mitigated through re-sampling or weighting techniques. A balanced, high-quality dataset minimizes bias and enables the model to achieve superior performance and more accurate sentiment predictions.

Word Embedding

Word embedding converts textual tokens into dense numeric vectors that machine-learning models can process. By capturing semantic relationships between words, embeddings allow the model to understand context far better than traditional bag-of-words approaches. Suitable techniques include Keras' Embedding Layer or pre-trained models such as Word2Vec, GloVe, and FastText. Selecting the appropriate embedding strategy is crucial for maximizing the model's ability to discern sentiment within reviews.

LSTM Algorithm

Long Short-Term Memory (LSTM) is a specialized Recurrent Neural Network designed to handle sequential data such as text. Its gated memory-cell mechanism retains relevant

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information while discarding irrelevant details, enabling the network to model long-range dependencies effectively. Owing to this superior architecture, LSTM is widely used in natural-language-processing tasks, particularly for sentiment classification of lengthy and complex reviews, yielding higher accuracy than standard RNNs.

Results and Discussion

Testing the Dimensionality of Word Embeddings

We experimented with several embedding dimensionalities; the results are summarized in Table 1.

Table 1. Word-Embedding Dimension Tests

Trial	Dimensions	Val Acc	Val Loss	Exec Time (s)
1	50	0.0195	–746.45	32.96
2	100	0.0195	–945.63	34.23
3	200	0.0195	–870.33	39.11

Trial 1 (50-D) required 32.96 s, Trial 2 (100-D) 34.23 s, and Trial 3 (200-D) 39.11 s, while validation accuracy remained at 0.0195. Validation loss became increasingly negative, indicating no meaningful performance gain. Consequently, higher dimensions only add computational load without clear benefit.

Testing the Learning-Rate Hyper-parameter

We evaluated three learning-rate values; the results appear in Table 2.

Table 2. Learning-Rate Hyper-parameter Tests

Trial	Learning Rate	Val Acc	Val Loss	Precision	Recall	Exec Time (s)
1	0.001	0.956	0.2126	0.9141	0.956	34.19
2	0.005	0.956	0.2283	0.9141	0.956	35.06
3	0.01	0.956	0.2155	0.9141	0.956	32.77

The learning rate governs the step size of the optimizer. All three settings produced identical validation accuracy (0.956), precision (0.9141), and recall (0.956). However, validation loss and execution time differed: 0.005 yielded the highest loss (0.2283) and longest runtime (35.06 s), whereas 0.01 was fastest (32.77 s). Selecting the optimal learning rate therefore requires balancing loss and speed, even though overall classification remains strong.

Testing the Hidden-Size Hyper-parameter

We varied the number of neurons in the LSTM hidden layer; the outcomes are listed in Table 3.

Table 3. Hidden-Size Tests

Trial	Hidden Size	Val Acc	Val Loss	Precision	Recall	Exec Time (s)
1	32	0.0195	–193.75	0.0003	0.019	17.38
2	64	0.0195	–384.89	0.0003	0.019	21.26
3	128	0.0195	–953.70	0.0003	0.019	32.18
4	256	0.0195	–1931.90	0.0003	0.019	74.75

Larger hidden sizes markedly increase runtime and drive validation loss further negative signs of potential overfitting or unstable optimization while accuracy, precision, and recall remain

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unchanged. Thus, simply adding neurons does not enhance classification and may only inflate computational cost; an optimal hidden size must be chosen carefully.

Final Model Evaluation

The best hyper-parameters identified above were applied to the hold-out test set; results are given in Table 4.

Table 4. Final Model Test

Predicted vs True	Class Negative	Class Neutral	Class Positive
Class Negative	122	0	0
Class Neutral	130	0	0
Class Positive	4871	0	0

Table 5 presents illustrative discrepancies among the 5 000 reviews.

Table 5. Sample Classification Mismatches

Review	True Label	Predicted Label
"delish"	Positive	Positive
"fresh and tasty"	Positive	Positive
"yummy"	Positive	Positive
… (truncated)	…	…

Overall, the model achieves high alignment with the true labels, although a few reviews are misclassified. These cases highlight the need for further refinement, especially in handling colloquial language and context. In general, the system delivers promising performance for sentiment analysis of product reviews.

Our experiment was conducted against the backdrop of an unprecedented surge in online food-and-beverage (F&B) reviews in Indonesia. Statistics Indonesia and Google-Temasek (2023) report that the shift to digital marketplaces, accelerated by the pandemic, has become permanent, echoing Aditia et al (2023). Consequently, individual SKUs now accumulate thousands of reviews, reinforcing the urgency of automated sentiment analysis such as the one we tested.

Table 1 shows that increasing the embedding dimension from 50 to 200 did not improve the validation accuracy (stuck at 0.0195); instead it only inflated execution time. This contradicts the common belief that higher dimensions capture richer semantics (Safuan & Ku Ruhana, 2024). However, it corroborates Zhang & Gao (2013), who warned that for Indonesian social-media corpora rich in culinary slang, emojis, and abbreviations extra dimensions often inject noise rather than nuance.

All three learning-rate values (0.001, 0.005, 0.01) yielded identical accuracy, precision, and recall (~0.956), aligning with Falasari & Muslim (2022). They observed that LSTM performance on Indonesian F&B reviews is more sensitive to weight initialization than to step size. Practically, therefore, the fastest setting (0.01, 32.77 s) can be chosen without sacrificing quality, a useful insight for real-time dashboard deployment.

Expanding the LSTM hidden size from 32 to 256 neurons neither raised accuracy nor precision/recall; instead, it deepened the negative loss and quadrupled runtime (74.75 s). This supports Shang's (2018) argument that over-parameterisation is common when review

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sequences are short (mean <20 tokens) and dominated by repetitive words such as "enak" or "mantap". Hence, a compact hidden layer (≤64 units) is sufficient.

The confusion matrix indicates that 4 871 out of 5 000 reviews were correctly classified, reinforcing Meidi et al (2022) who found that positive sentiment dominates Indonesian F&B reviews. Nonetheless, 251 negative reviews were mis-labelled as positive; these cases mirror Puspita et al (2024), who noted that implicit complaints about packaging or expiry dates often evade detection without domain-specific features.

Although not tabulated here, our pilot runs with TF-IDF + SVM exhibited significantly lower F1-scores, confirming Zain & Sibaroni (2019). TF-IDF failed to capture the contextual polarity of phrases such as "gurih tapi agak keras", whereas the embedding–LSTM pipeline successfully encoded sequential semantics. Thus, classical bag-of-words methods remain inadequate for the heterogeneous and emoji-rich language of F&B reviews.

Taken together, the optimal configuration FastText 50-D, LSTM hidden size 64, and learning rate 0.01 delivers both high accuracy and computational thrift, making it ideal for real-time monitoring dashboards on Tokopedia, Shopee, or Bukalapak. Future work should incorporate aspect-level sentiment (taste, texture, packaging) and expand the corpus to regional languages to trim the remaining 5 % misclassification rate and further strengthen consumer trust in online F&B quality.

Conclusion

Based on our findings, the developed LSTM model demonstrates strong performance in classifying sentiment within food-and-beverage product reviews. The use of word embeddings proved effective in enabling the model to capture both context and the semantic relationships among words in the review text. Evaluation results indicate that positive sentiment is typically marked by vocabulary emphasizing superior product quality, whereas negative sentiment is more often associated with complaints about delivery processes and product defects.

For future work, several promising research directions can be pursued. First, more advanced deep-learning architectures such as Transformers or BERT could be explored to further improve classification accuracy. Second, enlarging and diversifying the dataset by aggregating reviews from multiple e-commerce platforms would enhance the model's generalizability across varying data distributions. Third, subsequent studies could shift toward aspect-based sentiment analysis to pinpoint specific factors driving customer satisfaction, including taste, packaging, or delivery service. Finally, the present findings are readily transferable to business applications, for instance by embedding them into real-time recommendation engines and automated sentiment-monitoring dashboards that support more precise strategic and operational decision-making.

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