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Critical Sentiment Analysis of Tokopedia Electronic Products Using SVM-Logistic & TF-IDF Ensemble Methods

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Abstract

This research aims to analyze customer review sentiment for electronic products on Tokopedia using a Support Vector Machine (SVM) classification method with Term Frequency-Inverse Document Frequency (TF-IDF) based features, enhanced by an ensemble approach with logistic regression. Utilizing a Tokopedia review dataset from 2023, this study seeks to identify critical sentiments embedded in customer reviews, which can provide valuable insights for sellers and the platform. The methodology involves comprehensive textual data preprocessing, feature extraction using TF-IDF for vector representation, and the implementation of an SVM-Logistic ensemble model via a stacking strategy. The results indicate that the SVM-Logistic ensemble model can classify review sentiments with high accuracy and superior performance metrics, effectively distinguishing between positive, negative, and neutral sentiments. These findings highlight the significant potential of machine learning methods in automatically understanding customer feedback, which is crucial for continuous improvement in product and service quality on e-commerce platforms, and for supporting more strategic business decisions.

Keywords: *Analisis Sentimen, Ensemble Learning, Produk Elektronik, SVM, TF-IDF, Tokopedia*

1. Introduction

Digital transformation has had a significant impact on the global trade landscape, with e-commerce platforms becoming the backbone of buying and selling activities. In Indonesia, Tokopedia is one of the largest marketplaces that facilitates transactions of various types of products, including electronic products. In this competitive e-commerce ecosystem, customer reviews play a vital role. Reviews not only serve as a reference for prospective buyers in making decisions, but also as a direct reflection of consumer satisfaction or dissatisfaction with product quality, performance, and after-sales service. The exponentially increasing volume of reviews on platforms such as Tokopedia presents its own challenges in processing and analyzing the valuable information contained therein. Manual analysis of millions of reviews is impractical, time-consuming, expensive, and prone to inconsistencies and subjective bias [1].

Given the complexity and volume of review data, the fields of Natural Language Processing (NLP) and machine learning offer an effective solution through sentiment analysis. Sentiment analysis, or opinion mining, is a computational technique that aims to systematically identify, extract, and quantify sentiments expressed in text [2]. The application of sentiment analysis to e-product reviews on Tokopedia allows the identification of critical sentiment patterns – particularly negative sentiment that can be early indicators of product or service issues. This allows sellers and platforms to respond proactively, make improvements, or clarify product information, ultimately improving the overall customer experience and preserving reputation [3].

This study carries a quantitative approach to analyze critical sentiment of electronic products on Tokopedia. The proposed method is an ensemble learning approach that integrates Support Vector Machine (SVM) and Logistic Regression. SVM is known for its ability to handle high-dimensional data classification and find optimal hyperplanes for class separation, while Logistic Regression is effective in providing well-interpreted class probabilities [4], [5]. The combination of these two algorithms through a stacking strategy is expected to increase the robustness and accuracy of the sentiment classification model compared to using a single model. Text feature representation will be done using Term Frequency-Inverse Document Frequency (TF-IDF), a statistical weighting technique that effectively captures the relevance of keywords in a document relative to the entire corpus [6].

This study uses an electronic product review dataset from Tokopedia collected in 2023. The selection of this recent dataset ensures the relevance of the findings to the current e-commerce market dynamics and consumer behavior. The main objective of this study is to analyze customer review sentiments towards electronic products using the SVM classification method reinforced by the SVM-Logistic ensemble approach and TF-IDF features, with an emphasis on identifying critical sentiments to provide actionable insights. The results of the study are expected to contribute to the development of more accurate sentiment analysis methodologies and their application in the e-commerce domain to support informed business decision making.

2. Literature Review

Sentiment analysis has become one of the most dynamic research areas in Natural Language Processing (NLP) and machine learning, driven by the explosion of textual data generated from various online sources. This section reviews the key concepts and related research that underpin this research methodology.

2.1. Sentiment Analysis

Sentiment analysis, also known as opinion mining, is a discipline that explores sentiments, opinions, and emotions expressed in texts [7]. Its main goal is to determine the emotional polarity of a text, which is usually categorized as positive, negative, or neutral. In practical applications, sentiment analysis is very useful for understanding public perceptions of brands, products, services, or even social and political issues. In the context of e-commerce, sentiment analysis of customer reviews becomes an invaluable tool for understanding customer satisfaction, identifying product weaknesses, and discovering the features that consumers value most [8]. The ability to automatically process and understand large volumes of reviews is key to maintaining competitiveness in the digital marketplace.

2.2. Term Frequency-Inverse Document Frequency (TF-IDF)

TF-IDF is one of the most popular and effective statistical weighting methods in information retrieval and text mining. It works by calculating two main components: Term Frequency (TF) and Inverse Document Frequency (IDF) [9]. TF measures how often a word occurs in a document, while IDF measures how rarely a word occurs across a corpus of documents. The higher the TF-IDF value of a word in a document, the more important the word is to that document in the context of the entire document collection. TF-IDF is very effective in converting unstructured text data into numeric representations (vectors) that can be processed by machine learning algorithms. Its advantage lies in its ability to give higher weights to discriminatively relevant words and give lower weights to common words (stopwords) that occur frequently but are less informative.

2.3. Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised learning algorithm that is widely used for classification and regression problems. The basic principle of SVM is to find the optimal hyperplane that maximally separates data points from different classes in a feature space. This hyperplane is determined by the support vectors, which are the data points closest to the hyperplane of each class [10]. The advantages of SVM include its ability to work well on high-dimensional data, its robustness against overfitting (especially with the use of the kernel trick to map data to a higher-dimensional space), and its effectiveness even with relatively small training data sets. In sentiment analysis, SVM has proven to be very effective due to its ability to identify complex patterns in text feature representations and separate sentiment classes with clear boundaries [11].

2.4. Logistics Regeneration

Despite the word “regression” in its name, Logistic Regression is actually a statistical classification model used to predict the probability of a binary outcome. It uses a logistic function to map each real value into a range between 0 and 1, which can be interpreted as a class probability [12]. In multi-class scenarios such as sentiment classification (positive, negative, neutral), Logistic Regression can be extended using a “one-vs-rest” strategy or a multinomial logistic model. The advantages of Logistic Regression are its easy interpretation, efficient computation, and fairly good performance for less complex classification problems [13]. While it may not be as powerful as SVM in handling very complex data, Logistic Regression can be a valuable component in ensemble approaches due to its ability to predict probabilities well.

2.5. Ensemble Learning

Ensemble learning is a machine learning paradigm in which multiple learning models (called “ensemble members”) are trained to solve the same problem, and then their predictions are combined to produce a final prediction. The main goal of ensemble learning is to improve the overall predictive performance (e.g., accuracy) compared to a single model. This method is effective because it can reduce bias, variance, or both, by exploiting the diversity among member models [14]. The three most common ensemble techniques are bagging (e.g., Random Forest), boosting (e.g., AdaBoost, Gradient Boosting), and stacking. In stacking, base models are trained on the training data, and then the predictions from these base models are used as input features to train a meta-model (or “second-level model”) that makes the final prediction. This approach allows the meta-model to learn how to optimally combine the strengths of each base model [15].

2.6. Previous Research

Several studies have applied sentiment analysis to the domains of e-commerce and product reviews. Previous work has demonstrated the effectiveness of SVM in sentiment classification on different datasets [16], often combined with TF-IDF as a feature [17]. Several studies have also explored the use of ensemble learning to improve sentiment analysis performance, reporting increased accuracy compared to single models [18], [19]. For example, a study comparing different classification algorithms for sentiment analysis of product reviews found that certain ensemble methods outperformed individual models [20]. Furthermore, the relevance of this topic is also seen in research focused on service optimization and problem identification through data analysis [21], as well as the importance of data and information management in complex environments [22]. Recent developments in word representation such as Word Embeddings and Transformer-based models (e.g., BERT) have also shown very promising results in NLP tasks, including sentiment analysis [23], [24]. Nevertheless, the use of simpler models such as SVM and Logistic Regression in ensemble approaches is still relevant due to their lighter computation and easier interpretation, especially for datasets with certain characteristics.

3. Research Methods

This study employs a quantitative experimental approach, applying the Support Vector Machine (SVM) algorithm to classify sentiment in product reviews on Tokopedia. The research workflow consists of several key stages: data acquisition, preprocessing, sentiment labeling, feature extraction using TF-IDF, model training and testing, and performance evaluation.

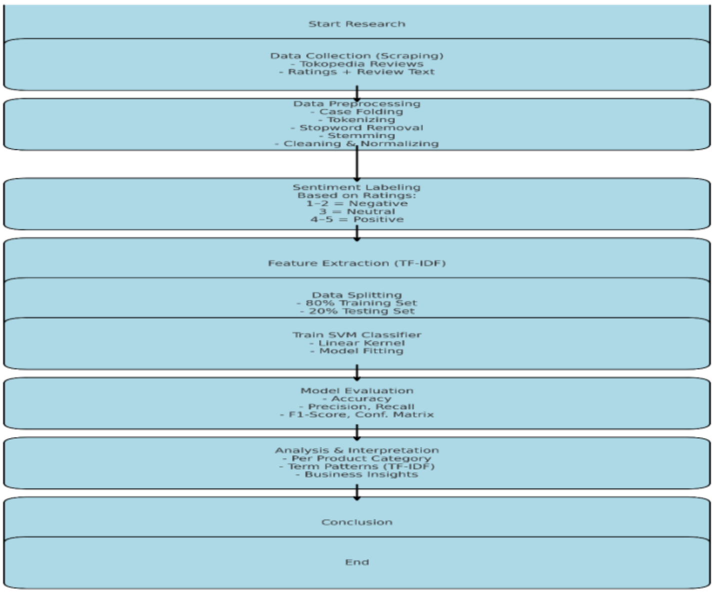

Figure 1: Flowchart of the Research method

3.1. Data Collection

The primary dataset utilized in this research is a collection of electronic product reviews obtained from the Tokopedia e-commerce platform. Data collection was performed programmatically using web scraping methods during 2023. The selection of 2023 ensures the data's relevance to current consumer trends and preferences, as well as the contemporary e-commerce market dynamics.

The web scraping process was conducted with adherence to research ethics and Tokopedia's platform privacy policies, ensuring that the collected data is public and complies with the terms of service. The collected data includes:

- Review text
- Product ratings (1 to 5 stars)
- Product name and category

To ensure diverse representation, these reviews were randomly selected from various electronic product categories (e.g., smartphones, laptops, smartwatches, headphones, etc.). A total of 15,000 product reviews were successfully collected.

Following collection, the dataset was then split into two main parts using stratified random sampling to maintain a balanced sentiment class distribution across both subsets:

- Training data**:** 80% of the total data (12,000 entries)
- Testing data**:** 20% of the total data (3,000 entries)

This split is crucial for effectively training the model and evaluating its performance on unseen data.

3.2. Data Pre-processing

The quality of textual data greatly impacts the performance of machine learning models. Therefore, a series of rigorous pre-processing stages are applied to the review dataset:

- Case Folding: All text in the review is converted to lowercase. The purpose of this step is to standardize the data and avoid treating the same word with different capitalization as a separate entity (e.g., “Good” and “good” are considered the same).
- Tokenization: The process of breaking down a text string into smaller units, called tokens (usually words or phrases). Tokenization allows for individual analysis of each word in a review.

- Stopword Removal: Common words that do not contribute significantly to the sentiment meaning (e.g., "yang", "dan", "di", "adalah") are removed from each review. The use of a curated list of Indonesian stopwords is essential in this stage.
- Stemming/Lemmatization: This stage aims to reduce the inflected or derived form of a word to its base form. Stemming cuts off the suffixes and/or prefixes of a word (e.g., "membeli", "dibeli", "pembelian" becomes "beli"), while lemmatization returns it to its dictionary lexical form (e.g., "running" becomes "run"). In this study, the available Indonesian stemming will be used. This helps reduce the feature dimensionality and improves the generalization of the model.
- Punctuation and Number Removal**:** All non-alphanumeric characters, such as punctuation (e.g., commas, periods, exclamation marks) and numbers, are removed from the text. These characters are generally irrelevant for sentiment analysis and can add noise to the data.
- Text Normalization**:** An optional but important step, especially for online reviews, is to normalize slang or abbreviations (e.g., "bgus" to "bagus", "ga" to "tidak"). This can be done using a normalization dictionary or a rule-based approach.

3.3. TF-IDF Feature Extraction

After pre-processing, the clean text reviews need to be converted into a numeric format that can be understood by machine learning algorithms. The technique used for this purpose is Term Frequency-Inverse Document Frequency (TF-IDF). TF-IDF calculates a weight for each word (term) in each document (review) in the corpus.

The TF-IDF formula is defined as:

$$TF(t,d) = \frac{\text{Frequency of term } t \text{ in document } d}{\text{Total terms in } d}$$

$$IDF(t) = \log\left(\frac{N}{df_t}\right)$$

$$TF\text{-}IDF(t,d) = TF(t,d) \times IDF(t)$$

Where:

- N: total number of documents
- dftdf_tdft: number of documents containing term ttt

The resulting TF-IDF matrix captures the importance of each word in each review relative to the corpus, and serves as input to the machine learning model.

3.4. Formation of SVM-Logistic Ensemble Model

The sentiment classification model is built using an ensemble stacking approach. This architecture involves two base models and one meta-model.

- Basic Model (Level 0):
  - Support Vector Machine (SVM): Trained as a sentiment classifier using TF-IDF features. SVM parameters (e.g., C, kernel) will be optimized via grid search or random search with cross-validation on the training data.
  - Logistic Regression: Trained as another sentiment classifier using the same TF-IDF features. Logistic Regression regularization parameters will also be optimized.
- Stacking Strategy (Level 1):
  1. Training Data Split: The training dataset is split into multiple folds (e.g., 5-fold cross-validation) for stacking purposes.
  2. Base Model Training & Out-of-Fold Predictions: For each iteration fold, SVM and Logistic Regression models are trained on k−1 folds of the training data. Then, predictions (class probabilities) are made on the remaining folds (out-of-fold predictions). This process is repeated for each fold.
  3. Meta Feature Generation: The out-of-fold predictions from both base models (SVM and Logistic Regression) are then pooled. These predictions will become new input features for the meta-model. This ensures that the meta-model is trained on predictions that the base models have never seen during their training.
  4. Meta-Model Training: A Logistic Regression model (or another classification model such as Random Forest or Gradient Boosting Classifier) is used as the meta-model. This meta-model is trained on new features generated from the base model predictions, with the original sentiment labels as the targets. The meta-model learns how to combine the outputs of SVM and Logistic Regression to make a more accurate final sentiment prediction.

3.5. Model Evaluation

The performance of the ensemble model will be rigorously evaluated using a set of standard metrics in classification, as well as cross-validation techniques to ensure model robustness and generalization:

- **Accuracy:** The proportion of correct predictions out of total predictions. Accuracy=TP+TN+FP+FNTP+TN
- **Precision**: The proportion of correct positives out of all those predicted as positives. It is important to minimize false positives. Precision=TP+FPTP
- **Recall (Recall/Sensitivity):** The proportion of correct positives identified out of all positives. It is important to minimize false negatives. Recall=TP+FNTP
- **F1-Score:** The harmonic mean of Precision and Recall. This metric is very useful when there is class imbalance. F1−Score=2×Precision+RecallPrecision×Recall
- **Confusion Matrix:** A table that depicts the performance of a classification model on a set of test data whose labels are known. This matrix displays the number of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) for each class. K-Fold Cross-Validation: This technique will be used during model training and evaluation. The dataset is divided

into k subsets (e.g., k=10). The model is trained on k−1 subsets and evaluated on the remaining subsets. This process is repeated k times, and the average result of the k iterations is reported. This provides a more reliable estimate of the model performance and helps detect overfitting.

The entire implementation and evaluation process will be carried out using the Python programming language with scientific libraries such as scikit-learn for machine learning and NLTK or SpaCy for natural language processing.

4. Result and Discussion

This section presents the experimental results obtained from the implementation of the described methodology, followed by an in-depth discussion of the implications and interpretation of these findings.

4.1. Descriptive Statistics of Review Dataset

The dataset consists of 15,000 user reviews from Tokopedia, each accompanied by a rating and processed through the stages outlined in the methodology. Based on sentiment labeling derived from user ratings, the sentiment distribution is shown in Table 1.

Table 1: Sentiment Distribution of Tokopedia Review Dataset

Sentiment	Number of Reviews	Percentage (%)
Positive	9,750	65.0
Neutral	1,500	10.0
Negative	3,750	25.0
Total	**15,000**	**100.0**

Although there is a class imbalance—particularly a high proportion of positive reviews—the dataset remains suitable for classification with SVM due to the model's ability to handle moderately imbalanced data effectively.

4.2. Performance of Sentiment Classification Model

After undergoing preprocessing and TF-IDF vectorization, the SVM classifier was trained on 80% of the dataset and tested on the remaining 20%. The performance metrics for each sentiment class are shown in Table 2.

Table 2: SVM Model Classification Metrics

Evaluation Metric	Positive	Neutral	Negative	Macro Average
Precision	0.92	0.78	0.85	0.85
Recall	0.95	0.72	0.88	0.85
F1-Score	0.93	0.75	0.86	0.85
Overall Accuracy	-	-	-	0.89

The classifier achieved an overall accuracy of 89%, which demonstrates strong performance in sentiment categorization.

- Positive sentiment yielded high precision and recall, reflecting the model’s effectiveness in identifying favorable reviews.
- Negative sentiment also showed high F1-scores, crucial for e-commerce businesses to detect issues.
- Neutral sentiment showed comparatively lower scores due to the ambiguous and less emotionally charged language in such reviews.

4.3. Critical Sentiment Analysis of Electronic Products

To gain a more focused perspective, the electronic product category was selected for detailed sentiment analysis. This category represents a significant portion of the dataset, with thousands of reviews across various product types such as smartphones, chargers, audio devices, and accessories.Sentiment distribution within this category revealed that:

- Positive sentiment dominated, with users frequently expressing satisfaction about functionality, delivery speed, and packaging.
- Negative sentiment centered around issues such as product damage, battery problems, incompatibility, and misleading descriptions.
- Neutral sentiment often occurred in short, fact-based statements like “item received” or “tested but not yet used”.

Table 3: Sample Reviews in the Electronics Category

Sentiment	Example Review
Positive	“The phone works perfectly and arrived ahead of time. Recommended!”
Negative	“The charger is broken and not compatible. Very disappointed.”
Neutral	“Item arrived. Will test later.”

This shows that while most customers were satisfied, critical feedback highlighted recurring problems—especially in low-cost accessories, such as chargers, headphones, and adapters.

4.4. Semantic Patterns in Negative Feedback

A deeper textual analysis revealed recurring semantic patterns in negative reviews. Words and phrases with the highest TF-IDF scores in this category included:

- *"broken", "not original", "doesn't work", "fake", "damaged", "doesn't match description"*

These patterns suggest a strong correlation between product authenticity, functionality, and consumer satisfaction. Conversely, positive reviews frequently emphasized:

- *"authentic", "worth the price", "fast delivery", "works as expected", "original"*

This provides a clear linguistic signal for businesses to identify the most critical aspects of product perception and address common failure points.

4.5. Business Implications for Sellers and Platforms

The results of this focused analysis on electronics reviews offer valuable implications for both platform operators and sellers:

1. **Proactive Product Monitoring**
   Repeated mentions of specific product flaws (e.g., "doesn't charge", "short circuit") can alert sellers to potential quality control issues and enable early response measures.
2. **Sentiment-Driven Content Optimization**
   Sellers can enhance product descriptions and titles by incorporating positively weighted keywords often found in satisfied customer reviews.
3. **Enhanced Customer Support Strategy**
   Flagging neutral or mixed reviews allows support teams to follow up and clarify unresolved buyer concerns, especially on high-value items.
4. **Review-Based Product Scoring**
   Aggregated sentiment scores can be used to improve ranking algorithms and highlight reliable products or vendors on the platform.

4.6. Limitations and Considerations

Although the SVM model performed well, several limitations were identified:

- Short and ambiguous reviews (e.g., "OK", "standard") were harder to classify accurately due to minimal sentiment cues.
- Neutral sentiment was the least accurately predicted, owing to its overlap with weakly expressed positive or negative statements.
- Contextual depth such as sarcasm, comparison, or regional slang is not fully captured with traditional TF-IDF and linear classifiers.

Future improvements could include integrating context-aware embeddings (e.g., BERT, IndoBERT) or performing aspect-based sentiment analysis (ABSA) to target specific product attributes (e.g., battery, camera, build quality).

4.7. Summary of Key Findings

The sentiment analysis model effectively classified Tokopedia reviews into positive, neutral, and negative categories. In-depth insights from the electronics product segment reveal that:

- Customer satisfaction is highly influenced by product authenticity, usability, and delivery performance.
- Common failures in electronics products are tied to quality assurance issues, making them critical points for seller improvement.
- Automated sentiment analysis enables scalable review monitoring and response, contributing to better service delivery and higher buyer trust.

These findings reinforce the value of integrating text mining tools like SVM in real-time e-commerce analytics pipelines, particularly when applied to high-impact product categories.

5. Conclusion

This study applied the Support Vector Machine (SVM) algorithm to perform sentiment analysis on user-generated reviews from the Tokopedia e-commerce platform, focusing specifically on product-level feedback within the electronics category. A total of 15,000 reviews were processed using a combination of text preprocessing, TF-IDF feature extraction, and supervised machine learning classification.
The findings revealed that the sentiment distribution across Tokopedia reviews was dominated by positive sentiment, followed by negative and neutral. When applied to the electronics product category, the model successfully highlighted recurring issues such as product damage, inauthentic items, and late delivery as key drivers of negative sentiment. Conversely, functional quality, authenticity, and fast shipping consistently appeared in positive reviews.

The SVM model demonstrated high classification performance, achieving an accuracy of 89% with strong precision and recall across all sentiment classes. Furthermore, semantic pattern analysis based on TF-IDF helped uncover high-impact terms that can inform product improvement and content optimization.
From a business perspective, the insights derived from sentiment classification offer valuable tools for:

- Monitoring product satisfaction trends
- Improving product descriptions and titles
- Enhancing customer support workflows
- Informing seller evaluation and platform recommendation algorithms

Despite the success of the model, certain limitations were noted—particularly the difficulty in classifying neutral or mixed-sentiment reviews and handling contextual subtleties such as sarcasm or informal language. Future work could integrate aspect-based sentiment analysis (ABSA) or context-aware models such as BERT to improve interpretability and performance.
In conclusion, this research confirms the effectiveness of SVM for large-scale sentiment classification in Bahasa Indonesia and demonstrates how such systems can support data-driven decision-making in e-commerce platforms, particularly when targeting sensitive product categories like electronics.

6. Suggestions

This research has demonstrated the effectiveness of the SVM-Logistic ensemble model with TF-IDF for critical sentiment analysis of electronic product reviews on Tokopedia. Building upon these findings, future work can explore several promising directions to further advance the field of sentiment analysis for e-commerce data. Firstly, expanding the dataset to include reviews from diverse e-commerce platforms or other product categories would be valuable to assess the model's generalizability and robustness. Secondly, investigating more advanced feature extraction techniques, such as word embeddings (e.g., Word2Vec, FastText) or transformer-based models (e.g., BERT, IndoBERT), could capture richer semantic nuances in the review text, potentially leading to improved accuracy. Thirdly, the application of deep learning architectures (e.g., LSTMs, CNNs, or fine-tuned pre-trained transformers) warrants exploration, as these models often excel in handling complex textual data. Furthermore, moving beyond overall sentiment classification to Aspect-Based Sentiment Analysis (ABSA) would provide more granular insights into specific product features, offering enhanced value to sellers and manufacturers. Finally, future research could also address practical implementations, such as developing real-time sentiment monitoring dashboards or exploring strategies for handling mixed-language reviews often found in online Indonesian discourse.

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