A Comparative Study of Embedding Techniques and Classifiers for Aspect-Based Sentiment Analysis of Shopee Reviews

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Abstract - E-commerce platforms like Shopee generate massive volumes of user reviews that contain valuable insights about products, services, and user experiences. Aspect-Based Sentiment Analysis (ABSA) enables fine-grained sentiment classification by identifying sentiment polarity toward specific aspects such as product quality, pricing, delivery, and application performance. This study presents a comprehensive comparative analysis of different embedding techniques and classification models for ABSA on Indonesian Shopee reviews. We evaluate three embedding approaches: FastText, GloVe, and BERT embeddings, combined with four classification models: Support Vector Machine (SVM), Convolutional Neural Network (CNN), BERT, and IndoBERT. Our experiments focus on five key aspects: product, price, delivery, application, and general sentiment. The results demonstrate that FastText embeddings combined with IndoBERT classifier achieves the highest accuracy of 91.59%, while BERT embeddings show more balanced performance across different classifiers. The findings provide valuable insights for e-commerce platforms seeking to implement effective sentiment analysis systems for Indonesian market understanding.

Keywords - Aspect-Based Sentiment Analysis, FastText, GloVe, BERT, IndoBERT

1. INTRODUCTION

The rapid growth of e-commerce platforms in Indonesia has transformed consumer shopping behaviors, with Shopee emerging as one of the leading platforms in the Southeast Asian market. User-generated reviews on these platforms contain rich information about customer experiences, product quality, service satisfaction, and overall sentiment toward various aspects of the shopping experience [1]. However, the vast volume of unstructured review data presents challenges for manual analysis, necessitating automated sentiment analysis approaches.

Traditional sentiment analysis techniques focus on determining overall polarity (positive, negative, or neutral) of entire documents or sentences. However, this approach fails to capture nuanced opinions about specific aspects of products or services. Aspect-Based Sentiment Analysis (ABSA) addresses this limitation by identifying sentiment polarity toward specific aspects or features mentioned in reviews [2]. For instance, a customer might express positive sentiment about product quality while simultaneously showing negative sentiment about delivery speed.

The Indonesian language presents unique challenges for natural language processing tasks, including rich morphology, flexible word order, and the prevalence of mixed languages (Indonesian and regional languages) in informal text such as e-commerce reviews [3]. These characteristics necessitate specialized approaches for effective sentiment analysis in Indonesian e-commerce contexts. Recent advances in deep learning and transformer-based models have significantly improved the performance of sentiment analysis tasks. Models like BERT and its Indonesian variant IndoBERT have shown promising results in various NLP tasks [4]. However,

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the effectiveness of these models often depends on the quality of input representations and the compatibility between embedding techniques and classification architectures.

This study aims to address the research gap in comparative evaluation of embedding techniques and classifiers for Indonesian ABSA in e-commerce contexts. We systematically compare three popular embedding approaches (FastText, GloVe, and BERT embeddings) with four classification models (SVM, CNN, BERT, and IndoBERT) using a dataset of Indonesian Shopee reviews labeled across five aspects: product, price, delivery, application, and general sentiment [5], [6].

The main contributions of this research are:

1. A comprehensive comparison of embedding techniques for Indonesian ABSA in e-commerce domain
2. Systematic evaluation of traditional and deep learning classifiers with different embedding approaches
3. Performance analysis across multiple aspects relevant to e-commerce platforms
4. Recommendations for optimal model configurations for Indonesian e-commerce sentiment analysis

2. RELATED WORKS

2.1. Sentiment Analysis in E-commerce

E-commerce sentiment analysis has gained significant attention due to its practical applications in understanding customer satisfaction and improving business operations. Agustina et al. [1] implemented Naive Bayes algorithm for sentiment analysis of Shopee reviews on Google Play Store, demonstrating the feasibility of automated sentiment classification for Indonesian e-commerce platforms. Their work highlighted the importance of preprocessing techniques in handling noisy user-generated content.

Simanungkalit et al. [2] conducted aspect-based sentiment analysis on Shopee application reviews using Naive Bayes algorithm, focusing on specific aspects of the mobile application experience. Their study revealed the importance of aspect-level analysis in understanding user satisfaction with different components of e-commerce applications.

2.2. Aspect-Based Sentiment Analysis

The development of ABSA techniques has evolved from rule-based approaches to sophisticated deep learning models. Suchrady and Purwarianti [3] introduced Indo LEGO-ABSA, a multitask generative approach for Indonesian ABSA that addresses multiple subtasks simultaneously. Their work demonstrated the potential of generative models in handling complex aspect-sentiment relationships in Indonesian text.

Cahyani [5] conducted aspect-based sentiment analysis specifically on Shopee marketplace platform, focusing on user-generated content analysis. The study emphasized the importance of domain-specific preprocessing and feature engineering for effective sentiment classification in e-commerce contexts.

2.3. Embedding Techniques for Indonesian NLP

Various embedding techniques have been applied to Indonesian NLP tasks with varying degrees of success [7] . FastText embeddings, trained on large corpora, have shown effectiveness in capturing morphological variations common in Indonesian text. GloVe embeddings provide global statistical information about word co-occurrences, while BERT embeddings offer contextualized representations that consider surrounding words and sentence structure [8] [9].

2.4. Cross-platform E-commerce Analysis

Yusuf et al. [10] compared sentiment analysis across multiple Indonesian e-commerce platforms including Shopee, Tokopedia, Lazada, and Blibli using lexicon-based approaches

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combined with Random Forest classifier. Their comparative analysis provided insights into platform-specific sentiment patterns and user behavior differences.

3. METHODOLOGY

The methodology that will be used in carrying out the introduction and classification of Aspect-Based Sentiment Analysis in this paper are Deep Learning (BERT, indoBERT, CNN) and Machine Learning (SVM). The process of introduction and classification can be seen in Figure 1 as follows:

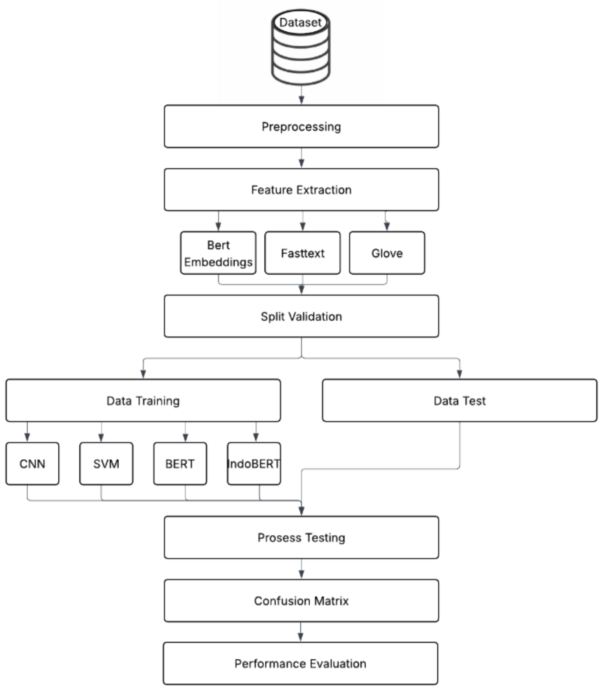

Figure 1. Concept Methodology

This experiment was conducted to compare the performance of three feature extraction methods: BERT Embeddings, FastText, and GloVe across four machine learning algorithms: CNN, SVM, BERT, and IndoBERT. The process began with a preprocessing stage to clean and prepare the text data. Subsequently, feature extraction was performed using the three embedding methods. After the data were divided through split validation, each combination of features and algorithms was applied during the training and testing phases. The test results were analyzed using a confusion matrix to evaluate model performance and determine the feature–algorithm combination that achieved the highest accuracy.

3.1 Dataset

The dataset consists of Indonesian Shopee reviews collected from various product categories. The reviews are manually annotated for five key aspects relevant to e-commerce experience:

1. Product: Sentiment toward product quality, features, and specifications
2. Price: Sentiment toward pricing, value for money, and cost-effectiveness
3. Delivery: Sentiment toward shipping speed, packaging, and delivery service

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4. Application: Sentiment toward Shopee mobile application performance and usability
5. General: Overall sentiment toward the shopping experience

Each review is labeled with sentiment polarity (positive, negative, neutral) for applicable aspects. The dataset underwent stratified sampling to ensure balanced representation across different aspects and sentiment categories.

3.2 Preprocessing Pipeline

To ensure optimal model performance and consistent input format, we implemented a comprehensive preprocessing pipeline:

1. Data Cleansing
   a. Case Folding: Converting all text to lowercase to reduce vocabulary size and improve consistency
   b. Normalization: Standardizing informal Indonesian text, including common abbreviations and slang terms frequently used in e-commerce reviews
   c. Punctuation Removal: Eliminating punctuation marks that do not contribute to sentiment information
   d. Emoji Removal: Removing emoji characters while preserving their potential sentiment information through preprocessing logs
   e. Number Removal: Eliminating numeric values that do not contribute to aspect-based sentiment
   f. Whitespace Removal: Normalizing spacing and removing excessive whitespace characters
   g. Stopword Removal: Eliminating common Indonesian stopwords that do not carry sentiment information
2. Tokenization
   Text segmentation into individual tokens (words or subwords) using Indonesian-specific tokenization rules that account for the language's morphological characteristics.
3. Stemming
   Reducing words to their root forms using Indonesian stemming algorithms to handle the language's complex affixation system and improve vocabulary consolidation.

3.3 Feature Extraction

We evaluate three different embedding approaches to capture semantic and syntactic information from preprocessed text:

1. FastText Embeddings
   FastText represents words as bags of character n-grams, making it particularly effective for morphologically rich languages like Indonesian. The model can generate embeddings for out-of-vocabulary words by combining subword information, which is crucial for handling informal e-commerce review text.
2. GloVe Embeddings
   Global Vectors for Word Representation (GloVe) captures global statistical information from word co-occurrence matrices. We utilize pre-trained GloVe embeddings adapted for Indonesian text, providing dense vector representations that capture semantic relationships between words.
3. BERT Embeddings
   Bidirectional Encoder Representations from Transformers (BERT) provides contextualized word embeddings that consider the surrounding context of each word. We extract embeddings from pre-trained BERT models, including both multilingual BERT and Indonesian-specific variants.

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3.4 Classification Models

We compare four different classification approaches, ranging from traditional machine learning to state-of-the-art transformer models:

1. Support Vector Machine (SVM)
   A traditional machine learning classifier that finds optimal hyperplanes for separating different sentiment classes. SVM has shown robust performance in text classification tasks and serves as a strong baseline for comparison.
2. Convolutional Neural Network (CNN)
   A deep learning architecture that applies convolutional filters to capture local patterns in text. CNNs are effective at identifying important phrases and patterns relevant to sentiment classification.
3. BERT
   Fine-tuned BERT model for sentiment classification, leveraging the pre-trained transformer architecture's ability to understand complex linguistic patterns and contextual relationships.
4. IndoBERT
   An Indonesian-specific variant of BERT trained on Indonesian corpora, designed to better capture language-specific patterns and cultural nuances in Indonesian text processing.

3.5 Evaluation Metrics

To evaluate and compare the performance of models and feature representation combinations used in Aspect-Based Sentiment Analysis (ABSA) tasks, this research adopts standard evaluation metrics commonly used in sentiment classification [11] [12] :

- Accuracy: Measures the proportion of correctly classified data against the total data.

$$Accuracy = TP+TN / (TP+TN+FP+FN) \qquad (1)$$

- Precision: Measures the proportion of true positive predictions.

$$Precision = TP / (TP\ FP) \qquad (2)$$

- Recall (Sensitivity): Measures the proportion of positive data that has been correctly predicted.

$$Recall = TP / (TP+FN) \qquad (3)$$

- F1-Score: The harmonic mean of precision and recall.

$$F1 - Score = \frac{2*Precision*Recall}{(Precision+Recall)} \qquad (4)$$

4. RESULT AND DISCUSSION

4.1 Overall Performance Comparison

Our experimental evaluation reveals significant performance variations across different embedding-classifier combinations. The results demonstrate the critical importance of matching appropriate embedding techniques with compatible classification architectures.

4.2 FastText Embeddings Performance

FastText embeddings combined with various classifiers showed the most promising results overall:

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Table 1. Comparison of FastText-Based Models

Model	Acc.	Prec.	Recall	Macro F1
FastText + CNN	84.00%	79.00%	80.00%	0.79
FastText + SVM	89.00%	86.00%	84.00%	0.85
FastText + BERT	79.50%	73.70%	79.00%	0.74
FastText + IndoBERT	91.59%	86.00%	91.00%	0.88

The Table 1 above compares the performance of four FastText-based models FastText + CNN, FastText + SVM, FastText + BERT, and FastText + IndoBERT—on the Shopee Aspect-Based Sentiment Analysis (ABSA) dataset using Accuracy, Precision, Recall, and Macro F1-score metrics. Among these models, FastText + IndoBERT achieved the best results with 91.59% accuracy, 86% precision, 91% recall, and a Macro F1-score of 0.88, indicating that the integration of FastText embeddings with IndoBERT's contextual representation provides superior performance in aspect-based sentiment classification.

FastText + SVM also showed strong results with 89% accuracy and a Macro F1-score of 0.85, proving its effectiveness despite being a simpler model. In contrast, FastText + CNN obtained 84% accuracy and a Macro F1 of 0.79, performing moderately well, while FastText + BERT recorded the lowest accuracy at 79.5% and Macro F1 of 0.74, possibly due to limited compatibility between static and contextual embeddings. Overall, the findings suggest that combining FastText with IndoBERT produces the most accurate and balanced model for analyzing multi-aspect sentiment in Shopee reviews.

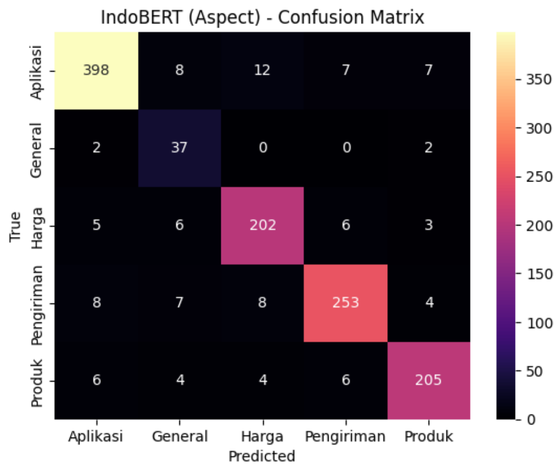

Figure 2. Confusion Matrix IndoBERT with FastText

In Figure 2 The confusion matrix for IndoBERT with FastText embeddings reveals exceptional classification performance across all five aspects. The model demonstrates particularly strong performance in aspect classification with high diagonal values indicating correct predictions.

The classification performance across different aspects demonstrates consistently high accuracy levels, indicating that the model performs well in identifying sentiment for each category. The Application aspect achieved the highest accuracy, correctly classifying 398 out of 432 instances (92.1%), showing that user feedback related to the app's functionality and usability was captured effectively. The Product aspect followed closely with 91.1% accuracy (205 out of 225 instances), suggesting that the model can accurately interpret opinions about product quality. Similarly, the Price and Delivery aspects showed strong performance with 91.0% (202/222) and

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90.4% (253/280) accuracy, respectively, reflecting the model's capability to distinguish sentiment related to cost and shipping experience. Lastly, the General aspect also yielded a solid 90.2% accuracy (37/41), indicating overall robustness of the model across all sentiment categories. These results collectively demonstrate that the model is reliable and effective in handling multi-aspect sentiment classification on Shopee reviews.

The confusion matrix shows minimal cross-aspect misclassification, with most errors occurring between semantically related aspects. For instance, some product-related sentiments are occasionally misclassified as application-related, which is understandable given the overlap between product features and application functionality in e-commerce contexts. The model's ability to distinguish between different aspects while maintaining high accuracy demonstrates the effectiveness of combining FastText's subword-level representations with IndoBERT's contextual understanding capabilities.

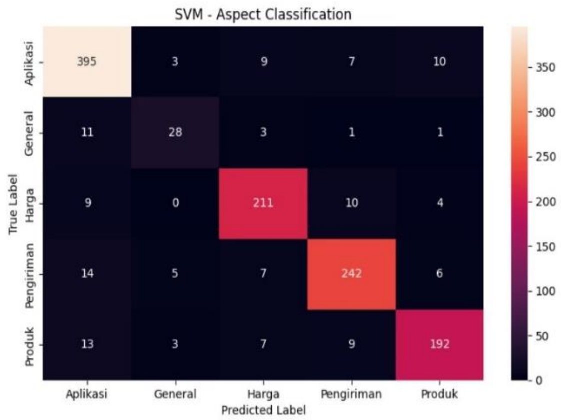

Figure 3. Confusion Matrix-SVM with FastText

In Figure 3 The SVM classifier with FastText embeddings shows robust performance across all aspects with strong diagonal dominance in the confusion matrix. The classification results show varying levels of accuracy across different aspects, indicating that the model performs strongly in some categories but struggles in others. The Application aspect achieved the highest accuracy, correctly classifying 395 out of 424 instances (93.2%), demonstrating excellent performance in capturing sentiments related to the functionality and usability of the Shopee application. The Price aspect also performed well with 90.2% accuracy (211 out of 234 instances), showing that the model can effectively interpret opinions related to product pricing. Meanwhile, the Delivery and Product aspects achieved moderate accuracy levels of 88.3% (242/274) and 85.7% (192/224), respectively, indicating that the model can reasonably identify sentiments about shipping and product quality, though with some misclassifications. In contrast, the General aspect recorded the lowest performance at 63.6% accuracy (28/44), suggesting difficulties in distinguishing more generic or mixed sentiments. Overall, the model demonstrates strong performance in most specific aspects but requires further improvement in handling generalized sentiment expressions.

The SVM model shows particularly strong performance in application and price-related aspects, achieving over 90% accuracy in these categories. However, the model struggles more with the general sentiment category, likely due to the broader and more ambiguous nature of general sentiments compared to specific aspects. The relatively higher misclassification between product and delivery aspects suggests some semantic overlap in how users express sentiments about these related e-commerce components.

Despite being a traditional machine learning approach, SVM's performance with FastText embeddings demonstrates that linear classifiers can effectively leverage rich semantic

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representations when the feature space adequately captures the underlying sentiment patterns. The strong performance validates that computational efficiency and interpretability of SVM remain valuable in practical applications.

The combination of FastText embeddings with IndoBERT achieved the highest accuracy of 91.59%, demonstrating the effectiveness of combining subword-level information from FastText with the contextual understanding capabilities of IndoBERT. This result aligns with findings from previous studies on Indonesian NLP tasks [13].

The strong performance of FastText + SVM (89.00% accuracy) indicates that traditional machine learning approaches can still compete effectively when paired with appropriate embedding techniques. FastText's ability to handle out-of-vocabulary words and morphological variations appears particularly beneficial for processing informal Indonesian e-commerce reviews.

Figure 4 illustrates the comprehensive performance comparison of all FastText embedding combinations across four key metrics: accuracy, precision, recall, and macro F1-score. The visualization reveals several important patterns in model performance:

The performance gap between IndoBERT and BERT when using FastText embeddings (91.59% vs 79.50%) highlights the importance of language-specific pre-training for Indonesian text processing. IndoBERT's superior performance can be attributed to its Indonesian-specific training corpus, which better captures the linguistic patterns and cultural nuances present in Indonesian e-commerce reviews.

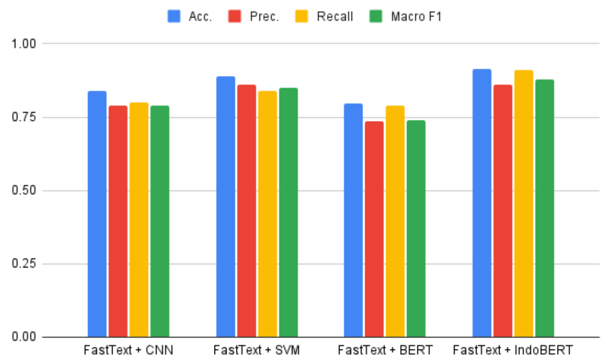

Figure 4. Comparative Results

4.3 GloVe Embeddings Performance

GloVe embeddings showed moderate performance across different classifiers:

Table 2. Comparison of Glove-Based Models on Shopee ABSA Dataset

Model	Acc.	Prec.	Recall	Macro F1
GloVe + CNN	79.00%	74.00%	67.00%	0.69
GloVe + SVM	75.00%	59.00%	61.00%	0.60

The Table 2 presents the performance comparison of two GloVe-based models GloVe + CNN and GloVe + SVM evaluated on the Aspect-Based Sentiment Analysis (ABSA) task using Accuracy, Precision, Recall, and Macro F1-score as performance metrics. The results show that GloVe + CNN achieved better overall performance with 79% accuracy, 74% precision, 67% recall, and a Macro F1-score of 0.69, indicating that the convolutional architecture was more effective in capturing semantic patterns and contextual relationships within the data. Meanwhile, GloVe + SVM produced lower results, with 75% accuracy, 59% precision, 61% recall, and a

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Macro F1-score of 0.60, suggesting that while SVM can perform basic classification, it is less capable of modeling complex linguistic features compared to CNN. Overall, these results highlight that combining GloVe embeddings with CNN yields superior performance for sentiment classification tasks compared to the traditional SVM approach.

The relatively lower performance of GloVe embeddings compared to FastText reveals fundamental incompatibilities between static global embeddings and the requirements of modern sentiment analysis tasks. GloVe embeddings demonstrate particular incompatibility with transformer-based models like BERT and IndoBERT, which is why these combinations were excluded from our final evaluation.

The fundamental architectural mismatch between GloVe embeddings and transformer-based classifiers arises from several key factors. GloVe produces fixed vector representations for each word regardless of its context, while models like BERT and IndoBERT are designed to capture contextual information through self-attention mechanisms. This leads to a representational gap, as transformers expect dynamic, context-aware inputs but instead receive static embeddings.

Additionally, GloVe typically uses 100–300-dimensional vectors derived from global co-occurrence statistics, whereas BERT-based models operate with much higher embedding dimensions (e.g., 768 for BERT-base), requiring projection layers that may cause information loss. Furthermore, the training objectives differ significantly BERT and IndoBERT are pre-trained using masked language modeling and next sentence prediction to enhance contextual understanding, while GloVe is optimized on co-occurrence matrices emphasizing global statistical relationships.

Tokenization methods also diverge: GloVe functions at the word level, whereas transformers employ subword tokenization such as WordPiece or BPE, creating integration challenges without extensive preprocessing. Finally, BERT's self-attention mechanism is designed to learn relationships among contextualized embeddings, which becomes ineffective when static embeddings like GloVe are used, as they lack the dynamic semantic variations that attention mechanisms rely on.

These architectural incompatibilities result in suboptimal performance and training instability, making GloVe embeddings unsuitable for transformer-based classifiers in our experimental setup. The static nature of GloVe embeddings fundamentally conflicts with the dynamic, context-dependent processing paradigm of modern transformer architectures.

4.4 BERT Embeddings Performance

BERT embeddings demonstrated consistent but not optimal performance:

Table 3. Comparison of BERT Embeddings-Based

Model	Acc.	Prec.	Recall	Macro F1
BERT Embeddings + CNN	87.00%	86.50%	86.50%	0.86
BERT Embeddings + SVM	83.00%	87.50%	68.50%	0.68
BERT Embeddings + BERT	85.00%	84.50%	79.00%	0.80
BERT Embeddings + IndoBERT	84.00%	83.00%	78.00%	0.80

In Table 3 BERT embeddings achieved the best results when combined with CNN classifier (87.00% accuracy), suggesting that convolutional architectures can effectively process contextualized embeddings for sentiment classification. The moderate performance of BERT embeddings with BERT classifier (85.00%) indicates potential redundancy or overfitting when using the same model architecture for both embedding generation and classification.

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4.5 Error Analysis and Limitations

Several factors contribute to classification errors in sentiment analysis. One major challenge is language mixing, as Indonesian reviews often contain a blend of languages and informal expressions that standard embeddings struggle to interpret accurately [14], [15]. Additionally, implicit sentiments where opinions are expressed indirectly rather than through explicit statements make it difficult for models to detect the underlying sentiment. Another issue arises from aspect ambiguity, where overlapping or closely related aspects lead to confusion during classification. Finally, data imbalance across sentiment categories and aspects can bias the model toward majority classes, reducing its ability to generalize effectively across diverse sentiment expressions.

4.6 Computational Considerations

The performance analysis also considers computational efficiency as an important factor. Among the models, FastText + IndoBERT delivers the highest accuracy but demands substantial computational resources, making it suitable for high-performance environments. In contrast, FastText + SVM offers a balanced trade-off between performance and efficiency, making it ideal for systems with limited computational capacity. GloVe + CNN demonstrates moderate performance while maintaining reasonable resource requirements, providing a practical option for mid-range applications. Meanwhile, models utilizing BERT embeddings generally consume more memory and processing power due to their complex architecture, which can limit their feasibility in resource-constrained settings despite their strong contextual understanding.

5. CONCLUSION

This comparative study provides comprehensive insights into the effectiveness of different embedding techniques and classifiers for aspect-based sentiment analysis of Indonesian Shopee reviews. The experimental results demonstrate that FastText embeddings combined with IndoBERT classifier achieves the highest accuracy of 91.59%, establishing a new benchmark for Indonesian e-commerce sentiment analysis. FastText embeddings consistently outperform other embedding techniques across different classifiers, with traditional SVM achieving competitive 89.00% accuracy, highlighting the importance of subword-level representations for handling morphological variations and informal language patterns in Indonesian e-commerce reviews. The study reveals fundamental incompatibilities between static embeddings like GloVe and transformer-based architectures, explaining why architectural alignment between embedding techniques and classification models significantly impacts performance.

The findings have substantial practical implications for e-commerce platforms and businesses operating in the Indonesian market. The superior performance of language-specific models like IndoBERT over general multilingual BERT (91.59% vs 79.50% with FastText) underscores the critical importance of Indonesian-specific pre-training for capturing cultural and linguistic nuances in user-generated content. For organizations with computational constraints, the FastText + SVM combination offers an optimal balance between performance and efficiency, making aspect-based sentiment analysis accessible for real-time applications. Future research should explore hybrid embedding approaches, automatic aspect extraction, and the transferability of these findings to other Southeast Asian e-commerce platforms to further advance the field of multilingual sentiment analysis in digital commerce contexts.

REFERENCES

[1] N. Agustina, D. H. Citra, W. Purnama, C. Nisa, and A. R. Kurnia, “Implementasi Algoritma Naive Bayes untuk Analisis Sentimen Ulasan Shopee pada Google Play Store,” *MALCOM*

Indones. J. Mach. Learn. Comput. Sci., vol. 2, no. 1, pp. 47–54, 2022, doi: doi: 10.57152/malcom.v2i1.195.

[2] A. Simanungkalit, J. P. P. Naibaho, and A. De Kweldju, "Analisis Sentimen Berbasis Aspek Pada Ulasan Aplikasi Shopee Menggunakan Algoritma Naïve Bayes," *Jutisi J. Ilm. Tek. Inform. dan Sist. Inf.*, vol. 13, no. 1, p. 659, 2024, doi: doi: 10.35889/jutisi.v13i1.1826.

[3] R. Z. Suchrady and A. Purwarianti, "Indo LEGO-ABSA: A Multitask Generative Aspect Based Sentiment Analysis for Indonesian Language," *Proc. Int. Conf. Electr. Eng. Informatics*, 2023, doi: doi: 10.1109/ICEEI59426.2023.10346852.

[4] A. Syah, F. Nurdiyansyah, and A. Y. Rahman, "Analisis Sentimen Aplikasi Shopee, Tokopedia, Lazada Dan Blibli Menggunakan Leksikon Dan Random Forest," *J. Inform. dan Tek. Elektro Ter.*, vol. 12, no. 3S1, 2024, doi: doi: 10.23960/jitet.v12i3s1.5155.

[5] A. D. Cahyani, "Aspect-Based Sentiment Analysis from User-Generated Content in Shopee Marketplace Platform," *J. Ilm. Tek. Elektro Komput. dan Inform.*, vol. 9, no. 2, 2023, doi: doi: 10.26555/jiteki.v9i2.26367.

[6] A. F. Wicaksono and N. S. Murni, "Analisis Sentimen Terhadap Ulasan Penggunaan Shopee Melalui Tweet Pada Twitter Menggunakan Algoritma Naïve Bayes," *J. RESTI (Rekayasa Sist. dan Teknol. Informasi)*, vol. 2, no. 2, pp. 67–74, 2023, doi: doi: 10.22236/jutikom.v2i2.12199.

[7] H. Z. Muflih, H. D. Al Assyam, F. A. Pangestu, and M. Kamayani, "Analisis Sentimen Terhadap Ulasan Penggunaan Shopee Melalui Tweet Pada Twitter Menggunakan Algoritma Naïve Bayes," *J. Tek. Inform. dan Komput.*, vol. 2, no. 2, pp. 67–74, 2023, doi: doi: 10.22236/jutikom.v2i2.12199.

[8] S. Ali, G. Wang, and S. Riaz, "Aspect based sentiment analysis of ridesharing platform reviews for kansei engineering," *IEEE Access*, vol. 8, pp. 173186–173196, 2020, doi: doi: 10.1109/ACCESS.2020.3025823.

[9] A. Jazuli, Widowati, and R. Kusumaningrum, "Optimizing Aspect-Based Sentiment Analysis Using BERT for Comprehensive Analysis of Indonesian Student Feedback," *Appl. Sci.*, vol. 15, no. 1, doi: doi: 10.3390/app15010172.

[10] K. K. Yusuf, E. Ogbuju, T. Abiodun, and F. Oladipo, "A Technical Review of the State-of-the-Art Methods in Aspect-Based Sentiment Analysis," *J. Comput. Theor. Appl.*, vol. 1, no. 3, pp. 287–298, doi: doi: 10.62411/jcta.9999.

[11] A. Angdresey, L. Sitanayah, and I. L. H. Tangka, "Sentiment Analysis for Political Debates on YouTube Comments using BERT Labeling, Random Oversampling, and Multinomial Naïve Bayes," *J. Comput. Theor. Appl.*, vol. 2, no. 3, pp. 342–354, doi: doi: 10.62411/jcta.11668.

[12] H. V. Gandhi and V. Z. Attar, "Polarity Detection and Feature-Based Summarization for Aspect Based Sentiment Analysis Dataset," *Int. J. Intell. Eng. Syst.*, vol. 15, no. 4, pp. 11–19, 2022, doi: doi: 10.22266/ijies2022.0831.02.

[13] J. A. J. Limbong, I. Sembiring, and K. D. Hartomo, "Analisis Klasifikasi Sentimen Ulasan Pada E-Commerce Shopee Berbasis Word Cloud Dengan Metode Naive Bayes Dan K-Nearest Neighbor Analysis of Review Sentiment Classification on E-Commerce Shopee Word Cloud Based With Naïve Bayes and K-Nearest Neighbor Meth," *J. Teknol. Inf. dan Ilmu Komput*, vol. 9, no. 2, pp. 347–356, 2021, doi: doi: 10.25126/jtiik.202294960.

[14] Q. Zhang, S. Wang, and J. Li, "A Contrastive Learning Framework with Tree-LSTMs for Aspect-Based Sentiment Analysis," *Neural Process Lett*, vol. 55, no. 7, pp. 8869–8886, doi: doi: 10.1007/s11063-023-11181-9.

[15] H. Benarafa, M. Benkhalifa, and M. Akhloufi, "An Enhanced SVM Model for Implicit Aspect Identification in Sentiment Analysis," *Int. J. Adv. Comput. Sci. Appl.*, vol. 14, no. 5, pp. 42–53, 2023, doi: 10.14569/IJACSA.2023.0140505.

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