Journal of Information Systems and Informatics
Vol. 6, No. 4, December 2024 e-ISSN: 2656-4882 p-ISSN: 2656-5935
DOI: 10.51519/journalisi.v6i4.930 Published By DRPM-UBD

Optimizing Aspect-Based Sentiment Analysis for Kyai Langgeng Park Using PSO and SVM

Dio Raka Venda Saputra[1], Maimunah[2], Endah Ratna Arumi[3]

[1,2,3]Informatics Engineering, Muhammadiyah University of Magelang, Magelang City, Central Java, Indonesia
Email: [1]rakadio666@gmail.com, [2]maimunah@unimma.ac.id, [3]arumi@unimma.ac.id

Abstract

This study aims to analyze aspect-based sentiment on Taman Kyai Langgeng tourism reviews, focusing on three main aspects: price, service, and facilities. This study combines Particle Swarm Optimization (PSO) method for feature selection and Synthetic Minority Over-sampling Technique (SMOTE) to handle data imbalance, which is a novel approach in aspect-based sentiment analysis. A total of 827 review data were retrieved from the Google Maps platform and manually labeled. This method resulted in significantly improved sentiment classification accuracy over the model without optimization. After the application of PSO and SMOTE, the model accuracy for the price aspect increased from 91.56% to 94.28%, the service aspect from 89.75% to 92.85%, and the facility aspect from 79.51% to 88.88%. The results of this study show that the combined PSO and SMOTE approach not only improves the accuracy, but also the consistency of sentiment classification on various aspects. These findings provide deep insights for tourism managers in identifying strengths and weaknesses based on visitor reviews.

Keywords: Aspect-based Sentiment Analysis, PSO, SMOTE, SVM

1. INTRODUCTION

Tourism is a key driver in enhancing regional and national economic growth. It plays a vital role in creating employment and fostering business opportunities for local communities. Therefore, every region must prioritize the development of its tourism sector to maximize its potential benefits. Kyai Langgeng Park, one of Magelang City's notable tourist destinations, offers a range of attractions that draw visitors. To further promote tourism, the Magelang City Government has implemented a program that emphasizes planning and enhancing tourist attractions to attract more visitors and improve existing facilities [1]. As tourism develops, it is essential to evaluate how the number of tourists increases and understand the factors influencing their satisfaction. This necessitates research to analyze visitor reviews and gain actionable insights [2].

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

Tourism managers often face challenges in identifying the strengths and weaknesses of different aspects of tourist attractions. Reviews left by visitors, though abundant, often remain unprocessed, resulting in a loss of valuable insights. Sentiment analysis provides a solution by extracting and processing textual data to determine the sentiments expressed in reviews, whether positive or negative [3], [4]. This approach enables tourism managers to uncover critical information from unstructured data, helping them better understand visitor perceptions.

Previous research has applied sentiment analysis to reviews of tourist attractions, categorizing sentiments into positive, negative, and neutral categories [5]. For instance, one study classified sentiments in online reviews, while another analyzed reviews on TripAdvisor to identify causal factors influencing user satisfaction to provide positive or negative feedback [6]. However, these studies only quantified positive and negative reviews without delving into specific aspects. Another study expanded sentiment analysis by offering recommendations for tourist attractions based on reviews, but the insights remained generalized, providing little actionable value for managers seeking to improve specific elements of their offerings [7].

The gap in these studies lies in their inability to perform aspect-based sentiment analysis, which could provide a more granular understanding of visitor feedback. For example, a study on the MyPertamina application conducted sentiment analysis on specific aspects such as bugs, usability, and payment. This approach revealed that negative reviews were concentrated on certain aspects, providing managers with precise information on areas that required improvement [8]. Such targeted insights are essential for formulating effective strategies to enhance user satisfaction.

Sentiment analysis issues can be addressed using advanced techniques such as deep learning and machine learning. For instance, research conducted by [9] employed machine learning methods, using the K-Nearest Neighbor algorithm and feature extraction techniques, achieving an accuracy of 98.6% on sentiment testing for packaging aspects. Similarly, another study compared classification methods such as NB, SVM, K-NN, and PSO feature selection, with results showing that combining PSO feature selection with SVM algorithms produced superior accuracy and performance [10].

Addressing the identified gaps, this research focuses on optimizing sentiment analysis by applying Particle Swarm Optimization (PSO) for feature selection and Synthetic Minority Over-sampling Technique (SMOTE) to address data imbalances. Unlike previous studies, this research performs aspect-based sentiment analysis on Taman Kyai Langgeng reviews, focusing on three critical aspects: price, service, and facilities. The aim is to evaluate the effectiveness of

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

PSO in improving the accuracy of sentiment analysis and to use SMOTE to handle imbalanced datasets, providing detailed insights for actionable management strategies.

This research makes a practical contribution by offering precise and accurate information that supports operational decision-making in the management of Taman Kyai Langgeng. By applying PSO and SMOTE, the analysis provides detailed insights into specific aspects, such as price, service, and facilities, enabling managers to identify strengths and weaknesses. These findings allow managers to implement effective strategies, such as adjusting pricing policies, improving service quality, and upgrading facilities, ultimately enhancing tourist satisfaction and loyalty.

2. METHODS

In completing research on sentiment analysis based on aspects of Kyai Langgeng Park tourist reviews, the particle swam optimization feature selection method and Support Vector Machine (SVM) machine learning are used as described in Figure 1.

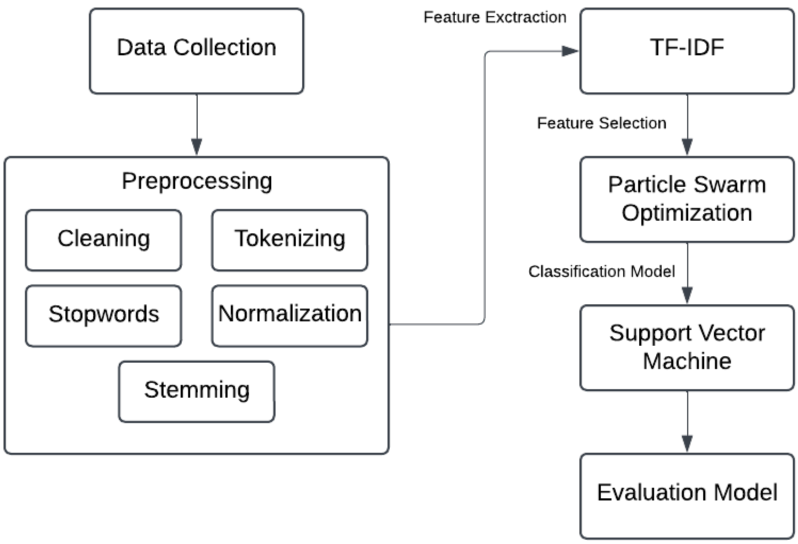

Figure 1. Research Flow

2.1. Data Collection

The data in this study were taken from the results of cawling tourist reviews of Kyai Langgeng Park through the Google Maps platform using the Botsol Crawler application. The data amounted to 827 reviews that were manually labeled. The

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

selection of Google Maps is based on the popularity of this platform as a source of tourist reviews that reflect visitor satisfaction. All data is divided into three aspects, namely price, service, and facilities. Each review in the dataset has a positive sentiment value of "1", negative "0", and has no sentiment based on the "-" aspect. The data obtained is unbalanced and more focused on certain aspects, so special techniques are needed to handle this imbalance.

2.2. Preprocessing

The labeled review data is then processed to the preprocessing stage because the data is still unstructured. The preprocessing stage is very important because it has an impact on the accuracy of the classification model. Here are some of the preprocessing stages:

1. Cleaning: At this stage, characters in the review sentences such as symbols, punctuation marks, numbers, and links are removed [11]. Making all of the letters in the review lowercase for consistency is the last step in the cleaning procedure.
2. Tokenizing: This stage separates the review sentence into chunks per word using the NLTK library, so that the review becomes more structured for analysis.
3. Stopwords: Following word separation, frequent words that don't affect sentiment classification are eliminated.
4. Normalization: Normalization unifies word variations into one standard form, e.g. "not" becomes "not," making the analysis more accurate.
5. Stemming: This stage involves taking each word from the previous stage into a base word by using the library Sastrawi [11].

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

TF-IDF is used as a feature extraction method to calculate word weights in travel reviews. TF-IDF was chosen for its ability to highlight words that are relevant to a particular document, while reducing the influence of common words that appear frequently across documents [12]. This is important in the context of aspect-based sentiment analysis, where words such as 'price', 'service', or 'facilities' can provide significant information about the review [13] according to formula (1).

$$tf\text{-}idf(t,d,D) = tf_d^t * log\frac{N}{df^t} \quad (1)$$

Where tf_d^t frequency of occurrence of word t in document d. The value N is the total number of documents in the corpus, and for df^t is the document frequency, i.e. the number of documents containing word t.

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

2.4. Imbalanced Data

Data imbalance occurs when the amount of data from one class has a significant difference with another class. The majority class has more objects than the minority class. So it is necessary to balance the class using SMOTE [14]. The SMOTE method works by randomly taking a number of nearby instances of the minority class, then creating a new instance between that instance and its randomly selected nearest neighbor [15]. This method is prioritized to overcome data imbalance effectively without reducing information from the majority class.

2.5. Feature Selection

Feature selection is an important stage in sentiment analysis to identify the most relevant features. In this research, PSO feature selection is chosen as the feature selection approach, as PSO is able to explore the solution space effectively to find the optimal combination of features. PSO mimics the social behavior of a flock of birds in solution search, where each candidate solution, or particle, will seek the best position based on individual experience (pbest) and group experience (gbest) [16] as follows (2).

$$V_{n,d}^{t+1} = \omega V_{n,d}^{t} + C_1 r_1 \left(X_{n,d}^{Pbest,t} - X_{n,d}^{t} \right) + C_2 r_2 \left(G_d^{best,t} - X_{n,d}^{t} \right) \quad (2)$$

Where the corresponding dimensional components of the group's best position $G_d^{best,t}$ i.e. social component and the individual's best position $X_{n,d}^{Pbest,t}$ i.e. cognitive self-component are used to modify the new velocity $V_{n,d}^{t+1}$ of every nth particle on the n dimension during the d iteration of the search process [17].

2.6. SVM

SVM is used as a classification algorithm because it has a good ability in handling high-dimensional data, such as text feature extraction results from TF-IDF. Compared to other algorithms such as Naive Bayes and K-Nearest Neighbor (KNN), SVM offers the advantage of separating classes with maximum margin, which is important for improving classification accuracy [18]. In addition, SVM also has the flexibility to handle non-linear data through the use of kernels, making it suitable for aspect-based sentiment analysis involving complex text reviews [19]. The SVM formula in this case can be seen as follows (3).

$$f(x) = sign\ (w.x + b) \quad (3)$$

Where $f(x)$ is the prediction function, w is the weight vector, x is the input feature vector, and b is a constant. Hyperparameter optimization in SVM is performed using grid search to find the best combination of C and gamma parameters. The

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

C parameter controls the misclassification rate on the training data and decision margin, while gamma affects the extent of influence of each data point in the model. The grid search process involves systematically exploring various parameter values, and the performance of each combination is evaluated using validation data. The best parameters are selected based on the combination that provides the highest accuracy [20].

2.7. Model Evaluation

Testing and evaluation is the last step after the model is completed. Confusion matrix is used to compare the original categories with the predicted categories, which includes accuracy, precision, recall, and f1-score measurements. Accuracy (4) shows the percentage of correct predictions from all test data. Precision (5) measures the accuracy of the model in providing the correct result for the data of interest. Recall (6) assesses the extent to which the model successfully identifies data that fits the category it is supposed to. F1-Score (7) is useful when there is an imbalance between positive and negative classes, as F1-Score combines precision and recall in one value [21].

$$accuracy = \frac{TP+TN}{(TP+FP+FN+TN)} \tag{4}$$

$$precision = \frac{\sum_{l=1}^{L} TP_l}{\sum_{l=1}^{L} TP_l+FP_l} \tag{5}$$

$$recall = \frac{\sum_{l=1}^{L} TP_l}{\sum_{l=1}^{L} TP_l+FN_l} \tag{6}$$

$$F1\text{-}Score = 2\frac{precision \times recall}{precision+recall} \tag{7}$$

This evaluation was conducted to determine the accuracy of the model and help select the best model for aspect-based sentiment analysis on Taman Kyai Langgeng tourism reviews.

3. RESULTS AND DISCUSSION

This study uses 827 review data divided into positive and negative sentiments. Because there is an unbalanced composition in the dataset, the dataset is distributed into 3 aspects along with the sentiment class.

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

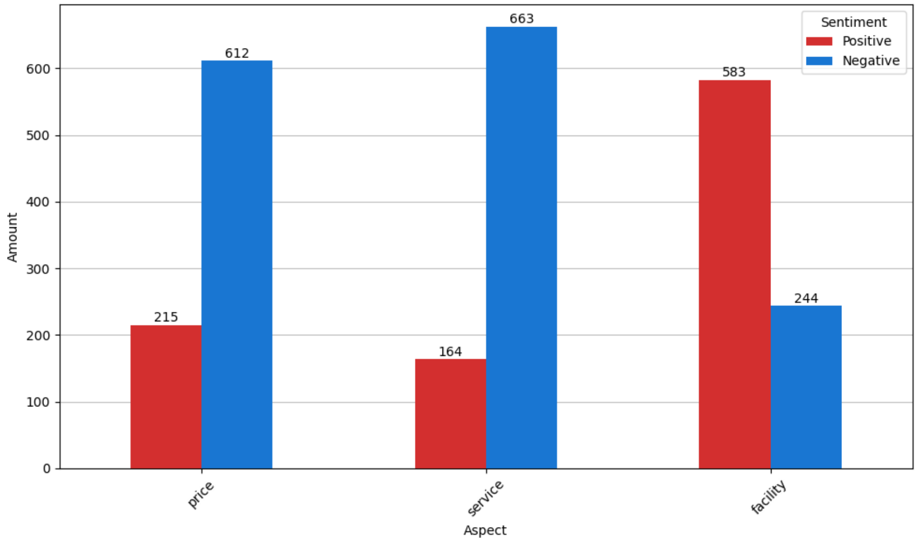

Figure 2. Sentiment Classification

Figure 2 shows that the sentiment data is unbalanced, with the dominance of positive sentiment on the facility aspect. Conversely, there is a dominance of negative sentiment in the price and service aspects. From the results of the sentiment distribution of each aspect, the facility aspect gets the best results with a high number of positive sentiments and a minimum of negative sentiments.

3.1. Preprocessing

Preprocessing was performed on the review data in 5 stages, as mentioned in the methodology, Tables 1 to 4 show examples of preprocessing results.

Table 1. Cleaning and Case Folding Results

Review	Review Clean
Ngikutin maps, nggak sampai ke lokasi parkir mobil lho.. entah gimana, tapi tiba disana sepi sekali. Bisa lihat dari luar, cuma kok minim petunjuk harus parkir dimana. Pintu pejalan kaki kebuka, tapi sepi banget. Wahana juga nggak pada beroperasi. Apa pas tutup ya... waktu itu hari rabu jam 1.30 siang. 2x muter tetep nggak nemu. Next bakal dicoba kesana lagi, mudah2an ketemu tuh dimana central parkirnya.	*ngikutin maps nggak sampai ke lokasi parkir mobil lho entah gimana tapi tiba disana sepi sekali bisa lihat dari luar cuma kok minim petunjuk harus parkir dimana pintu pejalan kaki kebuka tapi sepi banget wahana juga nggak pada beroperasi apa pas tutup ya waktu itu hari rabu jam siang x muter tetep nggak nemu next bakal dicoba kesana lagi mudahan ketemu tuh dimana central parkirnya*

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

Tahun lalu kesini sekarang kesini lagi. Saya pikir tiket bakal naik ternyata sama masih terjangkau. Wahananya juga sama masih berkualitas	*tahun lalu kesini sekarang kesini lagi saya pikir tiket bakal naik ternyata sama masih terjangkau wahananya juga sama masih berkualitas*

Table 2. Tokenization

Review Clean	Review Token
tahun lalu kesini sekarang kesini lagi saya pikir tiket bakal naik ternyata sama masih terjangkau wahananya juga sama masih berkualitas	*tahun, lalu, kesini, sekarang, kesini, lagi, saya, piker, tiket, bakal, naik, ternyata, sama, masih, terjangkau, wahananya, juga, sama, masih, berkualitas*

Table 3. Normalization

Review Token	Review Normalized
wahana, rekreasi, keluarga, yg, tiketnya, terjangkau, tempat, nyaman, luas, pas, untuk, memanjakan, mata	*wahana, rekreasi, keluarga, yang, tiketnya, terjangkau, tempat, nyaman, luas, cocok, untuk, memanjakan, mata*

Table 4. Stopword

Review Normalized	Review Stopwords
hari, sabtu, yang, ramai, kolam, renang, agak, sepi	*ramai, kolam, renang, sepi*

3.2. Model Performance Testing

This stage is the stage of testing the unbalanced data carried out on each aspect, following the test results in Table 5.

Table 5. Model Classification Results

Aspect	Model	Accuracy	Precision	Recall	F1-Score
Price	SVM	91.56%	91.2%	87.88%	89.32%
Facility	SVM	89.75%	90.4%	78.39%	82.47%
Service	SVM	79.51%	80.3%	69.33%	71.51%

Table 5 shows the test results performed by SVM on the three aspects without using PSO feature selection. The SVM classification results without the application of PSO and SMOTE show an accuracy of 91.56% on price, 89.75% on service, and 79.51% on facilities. The lower performance on the facility aspect suggests that the model struggles to recognize sentiment patterns in facility-related reviews. This challenge could stem from the variation in reviews or the data imbalance, as evidenced by a precision of 80.3% but a recall of only 69.33%, resulting in an F1-score of 71.51%.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

In a management context, these results highlight the need for greater attention to facility-related reviews. For example, analyzing negative reviews in this aspect could reveal specific complaints, such as the quality of amenities or the availability of attractions, which can then inform targeted improvements. While the price and service aspects performed well with accuracies of 91.56% and 89.75% respectively, ongoing efforts are needed to ensure the model captures sentiment patterns more effectively, especially in aspects with lower performance.

3.3. Effect of PSO and SMOTE on Model Performance

In this case, PSO feature selection and SMOTE approaches are used to test the SVM algorithm. By selecting the best feature from 50 iterations, the confusion matrix is used to evaluate the accuracy result of the SVM algorithm optimized with PSO and SMOTE.

Table 6. Classification Results of PSO and SMOTE Models

Aspect	Model	Accuracy	Precision	Recall	F1-Score
Price	SVM+PSO+SMOTE	94.28%	94.23%	94.36%	94.27%
Facility	SVM+PSO+SMOTE	92.85%	92.86%	92.83%	92.84%
Service	SVM+PSO+SMOTE	88.88%	89.19%	88.85%	88.85%

Table 6 shows that the application of PSO and SMOTE provides a significant increase in accuracy, demonstrating the effectiveness of these methods in enhancing sentiment analysis performance. The accuracy of the price aspect increased to 94.28%, service to 92.85%, and facilities to 88.88%. This improvement highlights the ability of PSO to select relevant features and SMOTE to address data imbalance, ensuring that the model can perform consistently across all aspects.

From a management perspective, these results offer actionable insights. On the pricing aspect, the improved accuracy can assist in setting a more competitive pricing policy based on visitor sentiment, potentially increasing visitor satisfaction and retention. For the service aspect, the enhanced accuracy (F1-Score: 92.84%) points to specific areas for improvement, such as staff responsiveness or overall convenience during a visit. The facility aspect, with an accuracy of 88.88% and an F1-Score of 88.85%, underscores the need to address recurring complaints about amenities or infrastructure, which could include maintenance or accessibility issues.

Overall, the optimization using PSO and SMOTE successfully addressed data imbalance and improved the model's ability to recognize sentiment patterns in each aspect. This approach not only improves the analytical accuracy but also equips

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

management with clearer insights to prioritize and strategize improvements that directly impact visitor satisfaction.

While this approach has yielded positive results, it also presents some challenges in real-world implementation. First, the scalability of the system needs to be considered as the number of reviews on platforms like Google Maps continues to grow. Processing large amounts of data requires adequate computing infrastructure. Second, the approach needs to be tested on data from other platforms, such as TripAdvisor or TikTok, to ensure the generalizability of the model. Finally, review data is often biased as more highly satisfied or highly dissatisfied visitors tend to leave reviews. This can affect sentiment analysis results if not addressed with specialized techniques such as bias analysis.

4. CONCLUSION

The results of the analysis of visitor reviews of Kyai Langgeng Park indicate that the facility is generally well-received, as evidenced by the predominance of positive reviews, particularly in the facility aspect. However, the price and service aspects require greater attention due to the higher proportion of negative reviews. This research employs an SVM model optimized with PSO for feature selection and SMOTE to handle data imbalance, achieving a significant accuracy improvement, with the highest score of 94.28% on the price aspect. The combination of these methods also enhanced precision, recall, and F1-score values across all aspects, demonstrating the model's robustness. These findings highlight the effectiveness of this method in aspect-based sentiment analysis, offering actionable insights for tourism management. For example, managers can use these results to identify specific areas requiring improvement, such as price adjustments or enhancing customer service quality. Future research can explore extending this approach to other aspects, integrating data from multiple review platforms, and testing advanced methods such as deep learning to further improve model performance and applicability in larger datasets.

REFERENCES

[1] B. Prasetyo, W. Hidayat, and N. Ngatno, "Pengaruh Fasilitas dan Electronic Word Of Mouth terhadap Keputusan Berkunjung Wisatawan di Objek Wisata Taman Kyai Langgeng Kota Magelang," *J. Ilmu Adm. Bisnis*, vol. 11, no. 2, pp. 134–141, 2022, doi: 10.14710/jiab.2022.34132.
[2] M. R. A. Yudianto, P. Sukmasetya, R. A. Hasani, and Maimunah, "Aspect-Based Sentiment Analysis of Borobudur Temple Reviews Use Support Vector Machine Algorithm," *E3S Web Conf.*, vol. 500, pp. 1–9, 2024, doi: 10.1051/e3sconf/202450001005.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[3] R. Naquitasia, D. H. Fudholi, and L. Iswari, "Analisis Sentimen Berbasis Aspek pada Wisata Halal dengan Metode Deep Learning," *J. Teknoinfo*, vol. 16, no. 2, p. 156, 2022, doi: 10.33365/jti.v16i2.1516.
[4] A. R. Makhtum and M. Muhajir, "Sentiment Analysis of Omnibus Law Using Support Vector Machine (Svm) With Linear Kernel," *BAREKENG J. Ilmu Mat. dan Terap.*, vol. 17, no. 4, pp. 2197–2206, 2023, doi: 10.30598/barekengvol17iss4pp2197-2206.
[5] J. Ipmawati, S. Saifulloh, and K. Kusnawi, "Analisis Sentimen Tempat Wisata Berdasarkan Ulasan pada Google Maps Menggunakan Algoritma Support Vector Machine," *MALCOM Indones. J. Mach. Learn. Comput. Sci.*, vol. 4, no. 1, pp. 247–256, 2024, doi: 10.57152/malcom.v4i1.1066.
[6] A. M. Ndapamuri, D. Manongga, and A. Iriani, "Analisis Sentimen Ulasan Aplikasi Tripadvisor Dengan Metode Support Vector Machine, K-Nearest Neighbor, Dan Naive Bayes," *INOVTEK Polbeng - Seri Inform.*, vol. 8, no. 1, p. 127, 2023, doi: 10.35314/isi.v8i1.3260.
[7] I. W. B. Suryawan, N. W. Utami, and K. Q. Fredlina, "Analisis Sentimen Review Wisatawan pada Objek Wisata Ubud Menggunakan Algoritma Support Vector Machine," *J. Inform. Teknol. dan Sains*, vol. 5, no. 1, pp. 133–140, 2023.
[8] I. Maulana, W. Apriandari, and A. Pambudi, "Analisis Sentimen Berbasis Aspek Terhadap Ulasan Aplikasi Mypertamina Menggunakan Support Vector Machine," *IDEALIS Indones. J. Inf. Syst.*, vol. 6, no. 2, pp. 172–181, 2023, doi: 10.36080/idealis.v6i2.3022.
[9] R. Nurhidayat and K. E. Dewi, "Penerapan Algoritma K-Nearest Neighbor Dan Fitur Ekstraksi N-Gram Dalam Analisis Sentimen Berbasis Aspek," *Komputa J. Ilm. Komput. dan Inform.*, vol. 12, no. 1, pp. 91–100, 2023, doi: 10.34010/komputa.v12i1.9458.
[10] A. P. Giovani, A. Ardiansyah, T. Haryanti, L. Kurniawati, and W. Gata, "Analisis Sentimen Aplikasi Ruang Guru Di Twitter Menggunakan Algoritma Klasifikasi," *J. Teknoinfo*, vol. 14, no. 2, p. 115, 2020, doi: 10.33365/jti.v14i2.679.
[11] M. H. Wicaksono, M. D. Purbolaksono, and S. Al Faraby, "Perbandingan Algoritma Machine Learning untuk Analisis Sentimen Berbasis Aspek pada Review Female Daily," *eProceedings Eng.*, vol. 10, no. 3, pp. 3591–3600, 2023.
[12] S. A. Pratomo, S. Al Faraby, and M. D. Purbolaksono, "Analisis Sentimen Pengaruh Kombinasi Ekstraksi Fitur TF-IDF dan Lexicon Pada Ulasan Film Menggunakan Metode KNN," *e-Proceeding Eng.*, vol. 8, no. 5, pp. 10116–10126, 2021.
[13] D. A. Fatah, E. M. S. Rochman, W. Setiawan, A. R. Aulia, F. I. Kamil, and A. Su'ud, "Sentiment Analysis of Public Opinion Towards Tourism in Bangkalan Regency Using Naïve Bayes Method," *E3S Web Conf.*, vol. 499, pp. 1–8, 2024, doi: 10.1051/e3sconf/202449901016.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[14] Muhammad Daffa Al Fahreza, Ardytha Luthfiarta, Muhammad Rafid, and Michael Indrawan, "Analisis Sentimen: Pengaruh Jam Kerja Terhadap Kesehatan Mental Generasi Z," *J. Appl. Comput. Sci. Technol.*, vol. 5, no. 1, pp. 16–25, 2024, doi: 10.52158/jacost.v5i1.715.

[15] Y. A. Sir and A. H. H. Soepranoto, "Pendekatan Resampling Data Untuk Menangani Masalah Ketidakseimbangan Kelas," *J. Komput. dan Inform.*, vol. 10, no. 1, pp. 31–38, 2022, doi: 10.35508/jicon.v10i1.6554.

[16] N. Sholihah, F. Fauzi Abdulloh, and M. Rahardi, "Optimasi Analisis Sentimen terhadap Kinerja Direktorat Jenderal Pajak Indonesia Melalui Teknik Oversampling dan Seleksi Fitur Particle Swarm Optimization," *Smart Comp Jurnalnya Orang Pint. Komput.*, vol. 12, no. 4, 2023, doi: 10.30591/smartcomp.v12i4.5814.

[17] K. M. Ang *et al.*, "A Modified Particle Swarm Optimization Algorithm for Optimizing Artificial Neural Network in Classification Tasks," *Processes*, vol. 10, no. 12, pp. 1–35, 2022, doi: 10.3390/pr10122579.

[18] M. Isnan, G. N. Elwirehardja, and B. Pardamean, "Sentiment Analysis for TikTok Review Using VADER Sentiment and SVM Model," *Procedia Comput. Sci.*, vol. 227, pp. 168–175, 2023, doi: 10.1016/j.procs.2023.10.514.

[19] S. Rabbani, D. Safitri, N. Rahmadhani, A. A. F. Sani, and M. K. Anam, "Perbandingan Evaluasi Kernel SVM untuk Klasifikasi Sentimen dalam Analisis Kenaikan Harga BBM," *MALCOM Indones. J. Mach. Learn. Comput. Sci.*, vol. 3, no. 2, pp. 153–160, 2023, doi: 10.57152/malcom.v3i2.897.

[20] A. H. Ali and M. Z. Abdullah, "A parallel grid optimization of SVM hyperparameter for big data classification using spark radoop," *Karbala Int. J. Mod. Sci.*, vol. 6, no. 1, 2020, doi: 10.33640/2405-609X.1270.

[21] N. Hafidz and D. Yanti Liliana, "Klasifikasi Sentimen pada Twitter Terhadap WHO Terkait Covid-19 Menggunakan SVM, N-Gram, PSO," *J. RESTI (Rekayasa Sist. dan Teknol. Informasi)*, vol. 5, no. 2, pp. 213–219, 2021, doi: 10.29207/resti.v5i2.2960.