JOURNAL OF INFORMATICS DEVELOPMENT

E-ISSN : 2963-0568, P-ISSN : 2963-055X
Available online at:
https://ejournal.itbwigalumajang.ac.id/index.php/jid

Sentiment Analysis of Ijen Crater Reviews using Decision Tree Classification and Oversampling Optimization

Fadhel Akhmad Hizham[1], Hasyim Asy'ari[2], Maysas Yafi Urrochman[3]

Informatics Department, Institut Teknologi dan Bisnis Widya Gama Lumajang, Indonesia[1,2,3]

Corresponding Author: Fadhel Akhmad Hizham (hizhamfadhel@gmail.com)

ARTICLE INFO

Date of entry:
02 January 2024
Revision Date:
16 April 2024
Date Received:
31 October 2024

ABSTRACT

Sentiment analysis is a text mining technique that classifies content as positive, negative, or neutral polarity in each sentence or document. These lines or papers may be user reviews assessing the quality of a product or material supplied to them. The purpose of this study is to better understand the function of sentiment analysis in assessing evaluations of the Ijen Crater tourist destination based on Google Maps user comments. This study is conducted in four steps, beginning with data gathering in the form of Google Maps evaluations obtained by data scraping. Following data collection, text preparation includes case folding, tokenization, stopword elimination, and stemming. Following text preprocessing, the next stage is imbalaced data optimization, which involves modifying the minority class samples to be nearly equal to the majority class by randomly duplicating minority class samples. Then, each review is categorized according to sentiment using the Decision Tree (DT) method. Testing has done by comparing DT without optimization and DT with SMOTE-ENN and ADASYN optimization. The result shown DT with SMOTE-ENN optimization has the best accuracy improvement with 1.62%, from 96.94% to 98.56%.

Keywords: Ijen Creater, Sentiment Analysis, Decision Tree. SMOTE-ENN, ADASYN.

Cite this as: Hizham, F. A., Asyari, H., & Urrochman, M. Y. (2024). Sentiment Analysis of Ijen Crater Reviews using Decision Tree Classification and Oversampling Optimization. *Journal of Informatics Development*, *3*(1), 1–10. https://doi.org/10.30741/jid.v3i1.1399

INTRODUCTION

User reviews on platforms like Google Maps have a significant impact on tourists' perceptions (Bahri & Suadaa, 2023), (Wulandari et al., 2023), (Leiras & Eusébio, 2023), (De Boeck et al., 2022). This review serves as evaluation material for travel purposes and can shape a person's behavior when planning a tour, traveling, and after traveling (Ghaly, 2023). Tourists rely on these reviews to make decisions about visiting tourist attractions. This review, including aspects such as attractions, facilities, access, and prices, can be analyzed to understand visitor sentiment and satisfaction levels. The availability of parking spaces, adaptations for people with disabilities, and the provision of information are common concerns raised by tourists in their reviews. In addition, user-generated content and the credibility of social media travel influencers play a significant role in influencing the visit intentions of Generation Z tourists. Overall, user reviews on platforms like Google Maps have a substantial impact on tourists' perceptions and decision-making processes.

Sentiment analysis of reviews for tourist attractions, such as Kawah Ijen, is important because it helps in understanding the opinions and feelings of visitors towards the tourist site. This analysis can provide valuable insights for tourism management, enabling organizations to identify customer opinions and make informed decisions to enhance their services and facilities. This action also helps in identifying the strengths and weaknesses of tourist destinations, allowing for targeted improvements to boost customer satisfaction. Furthermore, sentiment analysis can assist in identifying potential issues or areas for improvement, enabling proactive measures to be taken (Sari et al., 2023), (Haris et al., 2023).

The Decision Tree method was chosen as the main focus of this research because it is a machine learning algorithm that can be used for sentiment analysis. The Decision Tree algorithm is effective for sentiment analysis because it can classify data based on different attributes and make decisions based on a set of rules. This algorithm can analyze the sentiment of text data by considering various features and patterns within the data. Several studies include the application of Shopee Food, where the C4.5 Decision Tree is used to analyze public sentiment based on Twitter users' opinions about the application, achieving an accuracy of 88% (Fersellia et al., 2023). The next study categorizes customer comments for the Bank of Khartoum in Sudan. The Decision Tree classifier is employed to classify comments based on their polarity, with an accuracy rate of 91% (Modwey & Elsamani, 2022). Another study focuses on sentiment analysis regarding smoking perceptions, where the Decision Tree method performs better with single-word search terms (Anwar et al., 2022). Additionally, there is research on sentiment regarding Telkom University on social media Twitter. The application of Decision Tree for the research resulted in an accuracy of 86.73% (Ryanto et al., 2022). Therefore, the Decision Tree method is closely related to sentiment analysis and can be used effectively.

Class imbalance in sentiment data sets can significantly impact the performance of sentiment analysis models. Imbalanced data, where one class dominates the other, can lead to models that have high accuracy on the majority class but are inversely related to the minority class (Achmad & Haris, 2023). This imbalance can result in misclassification of the minority class, affecting the overall classification performance (Moore et al., 2023). Various approaches have been proposed to address class imbalance, including sampling methods such as ADASYN and SMOTE, as well as algorithmic-level approaches and cost-sensitive learning (Kaope & Pristyanto, 2023). These techniques aim to balance the dataset and improve classification performance. However, the benefits of dataset balancing techniques can be fragile and depend on the evaluation set used(Wen & Zhao, 2023). Therefore, caution should be exercised when applying balancing techniques, and minor improvements to public evaluation sets should not be overly emphasized (Af'Idah et al., 2023).

The ADASYN oversampling technique was selected to enhance the performance of the Decision Tree algorithm in addressing class imbalance in datasets, particularly in loan status prediction. This integration aims to improve classification accuracy and model reliability. The combination of ADASYN with Decision Tree algorithms has demonstrated significant improvements in predictive accuracy, making it a robust choice for classification tasks in imbalanced scenarios (Naf'an et al., 2023). This integration is particularly beneficial in fields like credit risk assessment, where accurate predictions are crucial for financial decision-making (Vebriyanti et al., 2024). ADASYN (Adaptive Synthetic Sampling) generates synthetic samples for the minority class, effectively balancing the dataset. This method was shown to increase prediction accuracy by 12.22%, from 73.91% to 85.22% in loan status predictions (Ami Rahmawati et al., 2024). Studies indicate that ADASYN outperforms other oversampling methods, such as SMOTE, in certain contexts, particularly in enhancing supervised learning performance for imbalanced datasets (Masruriyah et al., 2023)

The SMOTE-ENN (Synthetic Minority Over-sampling Technique combined with Edited Nearest Neighbors) technique offers significant advantages when used with Decision Trees for handling imbalanced datasets. This hybrid approach not only generates synthetic samples to balance class distributions but also refines the dataset by removing noisy instances, leading to improved model performance. While SMOTE-ENN provides substantial benefits, it is essential to consider that the effectiveness of this technique can vary based on the dataset's characteristics and the specific application context. Some studies suggest that alternative methods or combinations may yield better results in certain scenarios (Li et al., 2024). The use of SMOTE-ENN helps in creating a more representative training set, which allows Decision Trees to generalize better on unseen data, thus reducing the risk of overfitting (Azhar et al., 2024). SMOTE-ENN effectively increases the number of minority class instances, which helps in reducing bias towards the majority class. This results in higher accuracy rates for classifiers like Decision Trees, as demonstrated by a study where accuracy improved from 17% to 86% after applying SMOTE (Rahayu et al., 2024). The combination of SMOTE and ENN has shown to enhance predictive capabilities, achieving an impressive accuracy of 95% in fraud detection applications (Bounab et al., 2024).

From the description, the researcher analyzes the sentiment of reviews for the Kawah Ijen tourist site using the Decision Tree classification method and undersampling optimization to address the imbalanced data in the dataset. The problem formulation in this study is how sentiment analysis plays a role in analyzing reviews of the Kawah Ijen tourist site based on user comments on Google Maps.

METHOD

Collecting Data

This research begins by collecting sample data obtained from reviews of Kawah Ijen found on the Google Maps API. The data collection was carried out by scraping review data from the Google Maps API, capturing review scores and comments from application users.

Preprocessing

After the data is obtained, the next stage is data preprocessing. Data preprocessing for sentiment analysis is referred to as text preprocessing. This stage begins with data cleaning, which involves the removal of data in the form of empty reviews that consist only of ratings without any comments. Then, case folding is performed to remove punctuation, eliminate non-alphabetic characters, and convert all sentences to lower case. After that, a tokenization process is carried out to break the sentence down into word by word. Then, a stopwords process is carried out, which involves extracting important words and removing overly common ones. After the stopwords process, stemming is performed, which involves converting words with affixes into their root forms. The stopwords and stemming processes in this research use the WordNetLemmatizer, PorterStemmer, and LancasterStemmer libraries in Python.

Word Weighting

Following the text preparation phase, word weighting is used. This stage uses the Process Document from Data operator and the term frequency - inverse document frequency (TF-IDF) technique to calculate scores based on word occurrence (Ginantra et al., 2022). The frequency with which a word appears in a single text is quantified using term frequency (TF). Meanwhile, the word's significance is assessed using the Inverse Document Frequency (IDF) (Manning et al., 2008). Equation 1 displays the formula for TF-IDF calculation.

$$tf.idf\ (t, d, D) = \left(1 + \log\left(f_{t,d}\right)\right)\left(log\,\frac{N}{df_t}\right) \qquad (1)$$

Note that $\left(f_{t,d}\right)$ is the world of world t in document d, N is the total number of documents in a collection and df_t is the number of documents that include the word t, if the word value does not exist in all documents (0) then the value is 1.

E-ISSN : 2963-0568, P-ISSN : 2963-055X
Available online at:
https://ejournal.itbwigalumajang.ac.id/index.php/jid

Optimization and Classification

After the word weighting procedure is completed, the processed data is optimized using SMOTE Oversampling, which includes randomly replicating minority class samples to make them roughly comparable to the majority class (He et al., 2018). Next, we divide each review into good and negative sentiments. The categorization is generated manually using review scores obtained from the Google Maps API. Review scores of three to five indicate good sentiment, while scores of one or two indicate negative emotion.

In this study, classification is performed using the Decision Tree approach. A decision tree using the C4.5 algorithm method is a classification strategy for extracting meaningful associations from data. This method separates the training data based on information gain. High-frequency attributes are used to distinguish the data from the information in the dataset (Hardiani, 2021). The formula for Decision Tree may be defined as follows (Hozairi et al., 2021):

$$Entropy(S) = \sum_{i=1}^{n} pi * log_2 pi \qquad (2)$$

Note that *S* is the case set, *n* is the number of *S* partitions, and *pi* is proportion from *Si* on *S*. After calculating a value of entropy, the next step is counting Information Gain using the formula:

$$Gain\ (S, A) = Entropy(S) - \sum_{i=1}^{n} \frac{|S_1|}{|S|} * Entropy(S_1) \qquad (3)$$

Note that *A* is attribute, |*Si*| is number of case at i-th partition, and |*S*| is number of case at S.

Evaluating Classification

The Decision Tree approach was used to carry out the classification tests, and a confusion matrix was used to calculate the classification performance. Accuracy, precision, and recall measurement results are derived from the confusion matrix. Accuracy involves comparing all data with correctly classified positive and negative data. An evaluation of the data's relevance to the required information is called precision. Recall measures how well the system is able to retrieve data. In Table 1, the confusion matrix is displayed.

Table 1. Confusion Matrix

		Actual Class	
		True	**False**
Prediction Class	**True**	TP (*True Positive*)	FP (*False Positive*)
	False	FN (*False Negative*)	TN (*True Negative*)

Source : (Saputra et al., 2018).

True Positive (TP) indicates that the anticipated data is positive and corresponds to the real (positive) value. False Positive (FP) indicates that the expected data does not match the actual value. False Negative (FN) indicates that the projected value is negative while the actual value is positive. True Negative (TN) indicates if the forecast is negative and the actual negative is true. Equations 4–7 describe how to quantify accuracy, precision, recall, and F-measure values using the confusion matrix:

$$\text{Akurasi} = \frac{TP + TN}{TP + FN + FP + TN} \qquad (4)$$

Presisi $= \frac{TP}{TP + FN}$ (5)

Recall $= \frac{TP}{TP + FP}$ (6)

F-Measure $= \frac{2 \times TP}{2 \times TP + FP + FN}$ (7)

RESULTS AND DISCUSSION

Data Collection Result

The first step before developing the approach is to collect review data about Kawah Ijen using the Google Maps API. Data is collected via scraping data from the Outscrapper website. As a consequence, 3,063 reviews were gathered, with ratings ranging from one to five stars. The review score breakdown includes 35 one-star reviews, 17 two-star reviews, 64 three-star reviews, 342 four-star reviews, and 2,605 five-star reviews. In this study, review ratings are classified into two categories: positive sentiment for three to five stars, and negative emotion for one to two stars.

Text Preprocessing

Following data collection, the next stage is text preparation. Text preparation occurs in four processes at this stage: case folding, tokenizing, stopwords, and stemming. Python was used for all of the text preparation. In this study, the pandas library was used to import the dataset, which was then preprocessed through a number of processes.

After text preprocessing, weights are assigned to each word in the dataset using TF-IDF. There are 7 empty review items in the dataset that underwent text preprocessing owing to one of the preparation processes, as well as 2 reviews that had phone numbers, which were deleted to protect privacy. The overall data to be used is 3,054 reviews, which comprise a total of 58,791 words acquired up to the stemming step, with 5,411 unique terms once duplicates are removed. The TF-IDF weighting is performed by computing the TF value based on the frequency of word occurrences in each review. The results of the TF value calculation are shown in Table 2.

Table 2. TF Calculation

Data	TF(blue)	TF(crater)	TF(fire)	TF(beautiful)	TF(view)
1	1	2	0	1	0
2	1	2	1	0	2
3	0	0	0	0	0
4	1	2	0	0	1
5	0	0	0	0	0
6	0	0	0	0	0
7	2	0	2	0	0
8	0	0	0	1	0
9	0	0	0	0	0
10	1	4	0	0	0
⋮	⋮	⋮	⋮	⋮	⋮
3054	0	0	0	0	0

Source: Processed Data (2024)

Following the calculation of the TF value, the DF value is determined. The DF value is calculated by counting how many instances of each word in each dataset that are greater than zero. Table 3 shows the DF values.

E-ISSN : 2963-0568, P-ISSN : 2963-055X
Available online at:
https://ejournal.itbwigalumajang.ac.id/index.php/jid

Table 3. DF Calculation

DF(blue)	DF(crater)	DF(fire)	DF(beautiful)	DF(view)
804	663	640	606	604

Source: Processed Data (2024)

After obtaining the DF value, proceed to determine the IDF value for each word in the keyword. The IDF value is obtained by dividing the total number of datasets by their DF value. This value is then used to balance phrases that appear overly often across all datasets. The IDF value falls when DF increases, and vice versa. Table 4 shows the IDF values based on the DF values from Table 3.

Table 4. IDF Calculation

IDF(blue)	IDF(crater)	IDF(fire)	IDF(beautiful)	IDF(view)
0,5796	0,6634	0,6787	0,7024	0,7038

Source: Processed Data (2024)

Following the determination of the IDF value, the TF-IDF value is calculated. To get the TF-IDF value, multiply the TF and IDF values together. For example, in dataset 10, the word "crater" has a TF value of 4 and an IDF value of 0.6634. As a consequence, the TF-IDF value is 4 multiplied by 0.6634, which is 2.6536. Table 5 shows the results from the TF-IDF computation.

Table 5. TF-IDF Calculation

Dataset	TF-IDF (blue)	TF-IDF (crater)	TF-IDF (fire)	TF-IDF (beautiful)	TF-IDF (view)
1	0,5796	1,3268	0	0,7024	0
2	0,5796	1,3268	0,6787	0	1,4076
3	0	0	0	0	0
4	0,5796	1,3268	0	0	0,7038
5	0	0	0	0	0
6	0	0	0	0	0
7	1,1592	0	1,3374	0	0
8	0	0	0	0,7024	0
9	0	0	0	0	0
10	0,5796	2,6536	0	0	0
⋮	⋮	⋮	⋮	⋮	⋮
3054	0	0	0	0	0

Source: Processed Data (2024)

Classification Method Implementation

The dataset used for classification implementation consists of 5,411 attributes comprising words that have been text preprocessed, with each attribute's value matching to the word weighting applied using TF-IDF. Meanwhile, the categorization is separated into two categories: favorable reviews with three to five stars and bad evaluations with one to two stars. The survey includes 51 negative ratings and 3,003 good reviews.

In this study, an optimization procedure was also used to address the disparity between the majority and minority data. Out of 3,054 evaluations, 3,003 are classed as "positive sentiment" and 51 as "negative sentiment." The amount is extremely imbalanced, hence optimization is required. This study employed the Synthetic Minority Oversampling Technique Edited Nearest Neighbor (SMOTE-ENN) and Adaptive Synthetic Sampling (ADASYN) optimization techniques

In addition to augmenting the dataset for the minority class, SMOTE optimization uses synthetic samples that are misclassified or considered noisy by ENN. ENN eliminates some of these fake examples, resulting in a decrease in the number of occurrences in both classes. The results reveal that there are 2,547 data points in the "positive sentiment" class and 2,974 in the "negative sentiment" class. SMOTE-ENN optimization resulted in a total of 5,521 data. Meanwhile, in ADASYN optimization, the process is more focused on the weight distribution for data in the minority class, resulting in a higher number of "negative sentiment" data points in this study compared to the "positive sentiment" class, totaling 3,009 data. Therefore, a total of 6,012 data were obtained after ADASYN optimization.

Evaluating Classification

Performance testing is used to evaluate the results of the Decision Tree-implemented classification by mapping the confusion matrix. The confusion matrix may be used to calculate accuracy, precision, recall, and the F1-score. In this study, performance testing was conducted using a dataset divided into three equal parts: 40:60 (60% training data and 40% test data), 30:70 (70% training data and 30% test data), and 20:80 (80% training data and 20% test data). Tables 6–9 demonstrate the accuracy, precision, recall, and F1-score for each test set using the Decision Tree technique (without optimization), Decision Tree and SMOTE-ENN optimization, and Decision Tree with ADASYN optimization.

Table 6. Accuration Result

Data Test Percentage	Classification Method		
	DT	DT + SMOTE-ENN	DT + ADASYN
40%	97,46%	98,73%	98,50%
30%	96,95%	98,49%	98,28%
20%	96,40%	98,46%	98,00%
Average	96,94%	98,56%	98,26%

Source: Processed Data (2024)

Table 7. Precision Result

Data Test Percentage	Classification Method		
	DT	DT + SMOTE-ENN	DT + ADASYN
40%	49,50%	98,67%	98,51%
30%	49,22%	98,44%	98,28%
20%	54,25%	98,41%	98,00%
Average	50,99%	98,51%	98,26%

Source: Processed Data (2024)

Table 8. Recall Result

Data Test Percentage	Classification Method		
	DT	DT + SMOTE-ENN	DT + ADASYN
40%	49,21%	98,77%	98,50%
30%	49,22%	98,53%	98,28%
20%	52,49%	98,49%	98,01%
Average	50,31%	98,60%	98,26%

Source: Processed Data (2024)

Table 9. F1-Score Result

Data Test Percentage	Classification Method		
	DT	DT + SMOTE-ENN	DT + ADASYN
40%	49,36%	98,76%	98,50%
30%	49,22%	98,48%	98,28%
20%	53,24%	98,45%	98,00%
Average	50,61%	98,56%	98,26%

Source: Processed Data (2024)

Based on Table 6 to Table 9, the results show that the Decision Tree method experienced a significant performance increase after optimization to overcome data imbalance. In the accuracy metric, the Decision Tree optimized with SMOTE-ENN experienced an increase of 1.62%, from 96.94% to 98.56%, while ADASYN provided an increase of 1.32%. Likewise, the precision, recall, and F1-Score metrics experienced consistent improvements after optimization. Without optimization, Decision Tree had lower results due to data imbalance, which caused bias towards the minority class. SMOTE-ENN showed the best results among the two optimization methods, with the highest average values for all metrics, namely 98.56% for accuracy, 98.51% for precision, 98.60% for recall, and 98.56% for F1-Score. This shows that SMOTE-ENN not only effectively balances the data but also improves predictions on the minority class and reduces existing bias. In contrast, although ADASYN also showed improvement, its results were not as good as SMOTE-ENN. This result can be interpreted that SMOTE-ENN is more suitable for data with a small minority class compared to ADASYN in this context. Overall, this study shows that using optimization to address data imbalance has a positive impact on model accuracy, and SMOTE-ENN is proven to be a more effective optimization method in this data context.

CONCLUSION

This study analyzed 3,054 Google Maps reviews of Kawah Ijen to classify user sentiment, where scores from 1 to 2 indicated "negative sentiment" and scores from 3 to 5 represented "positive sentiment." The data showed a significant class imbalance, with 3,003 entries as "positive" and 51 as "negative." To address this, the Decision Tree classifier was used along with SMOTE-ENN and ADASYN optimization. The SMOTE-ENN optimization yielded the best accuracy improvement, increasing from 96.94% to 98.56%, effectively enhancing classification accuracy in the presence of imbalanced data.

REFERENCES

Achmad, R. R., & Haris, M. (2023). Hyperparameter Tuning Deep Learning for Imbalanced Data. TEPIAN, 4(2). https://doi.org/10.51967/tepian.v4i2.2216

Af'Idah, D. I., Anggraeni, P. D., Handayani, S. F., & Dairoh. (2023). Imbalanced Classes Treatment in Deep Learning Multi-label Aspect Classification using Oversampling and Under-sampling. ICCoSITE 2023 - International Conference on Computer Science, Information Technology and Engineering: Digital Transformation Strategy in Facing the VUCA and TUNA Era. https://doi.org/10.1109/ICCoSITE57641.2023.10127671

Ami Rahmawati, Yulianti, I., Mardiana, T., & Pribadi, D. (2024). Integration of Adasyn Method with Decision Tree Algorithm in Handling Imbalance Class for Loan Status Prediction. Jurnal Riset Informatika, 6(3), 131–140. https://doi.org/10.34288/jri.v6i3.299

Azhar, N. A., Mohd Pozi, M. S., Din, A. M., & Jatowt, A. (2024). An Investigation of SMOTE Based Methods for Imbalanced Datasets with Data Complexity Analysis (Extended Abstract). 2024 IEEE 40th International Conference on Data Engineering (ICDE), 5735–5736. https://doi.org/10.1109/ICDE60146.2024.00499

Bahri, C. A., & Suadaa, L. H. (2023). Aspect-based sentiment analysis in bromo tengger semeru national park indonesia based on google maps user reviews. IJCCS (Indonesian Journal of Computing and Cybernetics Systems), 17(1), 79–90.

Bounab, R., Guelib, B., & Zarour, K. (2024). A Novel Machine Learning Approach For handling Imbalanced Data: Leveraging SMOTE-ENN and XGBoost. 2024 6th International Conference on Pattern Analysis and Intelligent Systems (PAIS), 1–7. https://doi.org/10.1109/PAIS62114.2024.10541220

De Boeck, K., Verdonck, J., Willocx, M., Lapon, J., & Naessens, V. (2022). Reviewing review platforms: a privacy perspective. Proceedings of the 17th International Conference on Availability, Reliability and Security, 1–10.

Fersellia, F., Utami, E., & Yaqin, A. (2023). Sentiment Analysis of Shopee Food Application User Satisfaction Using the C4.5 Decision Tree Method. Sinkron, 8(3). https://doi.org/10.33395/sinkron.v8i3.12531

Ghaly, M. I. (2023). The influence of user-generated content and social media travel influencers credibility on the visit intention of Generation Z. Journal of Association of Arab Universities for Tourism and Hospitality, 24(2), 367–382.

Ginantra, N. L. W. S. R., Yanti, C. P., Prasetya, G. D., Sarasvananda, I. B. G., & Wiguna, I. K. A. G. (2022). Analisis Sentimen Ulasan Villa di Ubud Menggunakan Metode Naive Bayes, Decision Tree, dan K-NN. Jurnal Nasional Pendidikan Teknik Informatika (JANAPATI), 11(3), 205–215. https://doi.org/10.23887/janapati.v11i3.49450

Hardiani, T. (2021). Comparison of Naive Bayes Method, K-NN (K-Nearest Neighbor) and Decision Tree for Predicting the Graduation of 'Aisyiyah University Students of Yogyakarta. International Journal of Health Science and Technology, 2(1). https://doi.org/10.31101/ijhst.v2i1.1829

Haris, N. A. K. M., Mutalib, S., Ab Malik, A. M., Abdul-Rahman, S., & Kamarudin, S. N. K. (2023). Sentiment classification from reviews for tourism analytics. International Journal of Advances in Intelligent Informatics, 9(1), 108–120.

He, H., Zhang, W., & Zhang, S. (2018). A Novel Ensemble Method for Credit Scoring: Adaption of Different Imbalance Ratios. Expert Systems with Applications, 98, 105–117. https://doi.org/10.1016/j.eswa.2018.01.012

Hozairi, H., Anwari, A., & Alim, S. (2021). IMPLEMENTASI ORANGE DATA MINING UNTUK KLASIFIKASI KELULUSAN MAHASISWA DENGAN MODEL K-NEAREST NEIGHBOR, DECISION TREE SERTA NAIVE BAYES. Network Engineering Research Operation, 6(2). https://doi.org/10.21107/nero.v6i2.237

Kaope, C., & Pristyanto, Y. (2023). The Effect of Class Imbalance Handling on Datasets Toward Classification Algorithm Performance. MATRIK : Jurnal Manajemen, Teknik Informatika Dan Rekayasa Komputer, 22(2). https://doi.org/10.30812/matrik.v22i2.2515

Leiras, A., & Eusébio, C. (2023). Perceived image of accessible tourism destinations: a data mining analysis of Google Maps reviews. Current Issues in Tourism, 1–19.

Li, H., Wang, S., Jiang, J., Deng, C., Ou, J., Zhou, Z., & Yu, D. (2024). Augmenting the diversity of imbalanced datasets via multi-vector stochastic exploration oversampling. Neurocomputing, 583. https://doi.org/10.1016/j.neucom.2024.127600

Manning, C. D., Raghavan, P., & Schutze, H. (2008). Scoring, Term Weighting, and The Vector Space Model. Cambridge University Press.

Masruriyah, A. F. N., Novita, H. Y., Sukmawati, C. E., Fauzi, A., Wahiddin, D., & Handayani, H. H. (2023). Thorough Evaluation of the Effectiveness of SMOTE and ADASYN Oversampling Methods in Enhancing Supervised Learning Performance for Imbalanced Heart Disease Datasets. 2023 8th International Conference on Informatics and Computing, ICIC 2023. https://doi.org/10.1109/ICIC60109.2023.10382105

Mizan Khairul Anwar, M. K., Yusoff, M., & Kassim, M. (2022). Decision Tree and Naïve Bayes for Sentiment Analysis in Smoking Perception. 2022 12th IEEE Symposium on Computer Applications and Industrial Electronics, ISCAIE 2022. https://doi.org/10.1109/ISCAIE54458.2022.9794558

Modwey, H. H. F., & Elsamani, E. E. A. E. (2022). Sentiment Analysis Bank of Khartoum Customers' comments Using a Decision Tree Classifier. Humanitarian and Natural Sciences Journal, 3(10). https://doi.org/10.53796/hnsj31028

Moore, R. C., Ellis, D. P. W., Fonseca, E., Hershey, S., Jansen, A., & Plakal, M. (2023). Dataset Balancing Can Hurt Model Performance. ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings, 2023-June. https://doi.org/10.1109/ICASSP49357.2023.10095255

E-ISSN : 2963-0568, P-ISSN : 2963-055X
Available online at:
https://ejournal.itbwigalumajang.ac.id/index.php/jid

Naf'an, S. M., Meiska, I., Kallista, M., Wibawa, I. P. D., & Aina, B. F. (2023). Improving Decision Tree Accuracy through AdaBoost Ensemble with SMOTE Oversampling and ExtraTreeClassifier Feature Selection. International Conference on Electrical Engineering, Computer Science and Informatics (EECSI). https://doi.org/10.1109/EECSI59885.2023.10295750

Rahayu, W., Jollyta, D., Hajjah, A., Nora Marlim, Y., & Desnelita, Y. (2024). Journal of Artificial Intelligence and Engineering Applications Synthetic Minority Oversampling Technique (SMOTE) for Boosting the Accuracy of C4.5 Algorithm Model (Vol. 3, Issue 3). https://ioinformatic.org/

Ryanto, S. A., Richasdy, D., & Astuti, W. (2022). Partner Sentiment Analysis for Telkom University on Twitter Social Media Using Decision Tree (CART) Algorithm. JURNAL MEDIA INFORMATIKA BUDIDARMA, 6(4). https://doi.org/10.30865/mib.v6i4.4533

Saputra, D. D., Pratama, B., Akbar, Y., & Gata, W. (2018). Penerapan Text Mining untuk Assignment Complaint Handling Customer Terhadap Divisi Tterkait menggunakan Metode Decision Tree Algoritma C4.5 (Studi Case: PT. XL AXIATA, TBK). Journal CKI On SPOT, 11(2), 207–216.

Sari, A. W., Hermanto, T. I., & Defriani, M. (2023). Sentiment Analysis Of Tourist Reviews Using K-Nearest Neighbors Algorithm And Support Vector Machine. Sinkron: Jurnal Dan Penelitian Teknik Informatika, 7(3), 1366–1378.

Vebriyanti, L. M. L., Martha, S., Andani, W., & Rizki, S. W. (2024). Analisis Kelayakan Kredit Menggunakan Classification Tree dengan Teknik Random Oversampling. Euler : Jurnal Ilmiah Matematika, Sains Dan Teknologi, 12(1), 1–8. https://doi.org/10.37905/euler.v12i1.24182

Wen, H., & Zhao, J. (2023). Sentiment Analysis of Imbalanced Comment Texts under the Framework of BiLSTM. 2023 6th International Conference on Artificial Intelligence and Big Data, ICAIBD 2023. https://doi.org/10.1109/ICAIBD57115.2023.10206154

Wulandari, W., Sianturi, A., Rahmadiani, A., Nurinto, B., Raudhatul, K. J., Marsha, A., Rizqy, M., & Yulia, S. M. (2023). Electronic Word Of Mouth On Visiting Decisions: Case Study On Google Review Lokawisata Baturraden. Journal of Tourism, Hospitality and Travel Management, 1(1), 17–22.