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Improving Sentiment Analysis in Digital Marketplaces through SVM Kernel Fine-Tuning

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Abstract: The rapid growth of the online market, particularly in the digital realm, has spurred the need for in-depth studies regarding marketing strategies through public opinion, especially on platforms like Twitter. The sentiments expressed in customer tweets hold significant insights into their satisfaction or dissatisfaction levels with a service. Therefore, the use of ML algorithms in sentiment analysis is imperative to detect whether such comments lean towards positivity or negativity regarding a service. This research focuses on sentiment analysis towards three major e-commerce platforms in Indonesia: Tokopedia, Shopee, and Lazada, through the utilization of Twitter. The classification process involves various stages, including preprocessing, feature extraction and selection, data splitting for classification, and evaluation. The selection of both linear and non-linear SVM models as the focus of this research is based on their ability to handle large and complex datasets. The linear kernel is chosen for its proficiency in cases with a linear relationship between features and class labels, while the non-linear SVM provides flexibility in dealing with complex and non-linear relationships. Based on the evaluation results of the SVM model on the dataset, it is found that the polynomial kernel provides the highest accuracy value of 93%, with a training data share of 85%. This model features strong prediction capabilities with a precision of 93% for negative and 93% for positive labels. Although the linear kernel and other kernels showed solid performance, the polynomial kernel provided the most optimal results in the context of online marketplace sentiment analysis using data from Twitter

Keywords: SVM, Machine Learning, Marketplace Online, Indonesia

1. INTRODUCTION

Online marketplaces have become a significant force in the global market, especially in Indonesia. They provide various opportunities for businesses to promote their products and interact with potential customers. Through Twitter features such as tweets, retweets, and hashtags, sellers can build brand awareness, monitor market trends in real time, and gather feedback from customers. Despite challenges such as reputation management and privacy regulations, Twitter remains an effective tool for supporting growth and success in the online market. Indonesia is a country known for its vast maritime territory, thousands of islands, and vast land mass. It is also known for its rich cultural heritage, diverse languages, and vibrant traditions. E-commerce has emerged as an important driver in the country's economic growth, connecting millions of customers across the country, even in remote areas. Giants such as Tokopedia, Shopee, and Lazada play an important role in this process. Through technological advancements and strong logistics networks, these platforms have driven wider access to products [1].

A. Problem Statement

Indonesia's diversity includes not only its geographical and cultural landscape, but also its linguistic diversity. With more than 700 regional languages spoken by various ethnic groups and communities, Indonesia has an incredible wealth of languages. While not all of these languages have official recognition or are widely accepted, Bahasa Indonesia is the official language of the country, used widely in official proceedings, government, education, and media dissemination. Broadly speaking, languages in Indonesia can be categorized into two main streams: standard languages, which are subject to government regulations, and nonstandard languages, which are characterized by the existence of unofficial varieties in terms of grammar, spelling, and pronunciation. Although everyday language use can vary depending on the context, Indonesian remains the most widely used language in daily communication [2] [3].

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B. Proposed Solution

The solution offered in the research is how ML can help give weight to words found on Twitter social media. method for improving word selection in documents in order to achieve effectiveness and time efficiency in data analysis when reading service comments whether they are classified as good or bad. This approach will help in selecting linguistic diversity in words in Indonesia.

C. Related Work

the relationship with previous research on ML is related In the field of network security, machine learning (ML) has been utilized to help detect SQL injection security attacks. Several ML methods including KNN and NB have been used for this purpose [4][5].

In addition to security attacks, ML can also be used to detect the Cavendish, Mas and Horn varieties of bananas using the SVM method [6].

research explores the power of ML in various areas such as analyzing Tokopedia's Twitter service using Naive Bayes [7], reviewing Gojek's app with KNN and SVM [8], improving B2C E-Commerce experience with K-Means and SVM [9], and analyzing Twitter user sentiment through SVM [10].

In the healthcare industry, ML has the ability to detect disease models such as diabetes, using the Decision Tree and NB algorithms [11], and standing diseases using the NB algorithm and KNN classification. It can also predict heart failure [12] and classify malnourished toddlers using the K-Nearest Neighbor algorithm [13] [14]. Tumor disease detection using the CNN algorithm[15]

For indoor security, ML combined with Facial Recognition Verification using the CNN method can work effectively [16].

The next area of research is the ability of ML to detect Javanese text characters in the context of Hanacaraka writing using the CNN method which is known to carry out classification well [17].

Based on previous research data, researchers have gained a deep understanding of the ML context. Therefore, we are interested in studying ML in service problems that are often complained about on Twitter in Indonesia, with a special focus on Tokopedia, Shopee, and Lazada. The diversity of language variations in Indonesia means that each word has a different meaning. To overcome these challenges, researchers used the SVM classification method to analyze and classify sentiment patterns from the collected data.

2. RESEARCH METHODOLOGY

The Research Framework is a structure or plan of steps that a researcher wants to apply in carrying out a study. The Research Framework helps researchers to organize and plan all the stages needed in the research process, from problem formulation to data analysis and conclusion making. The research framework can be seen in Figure 1

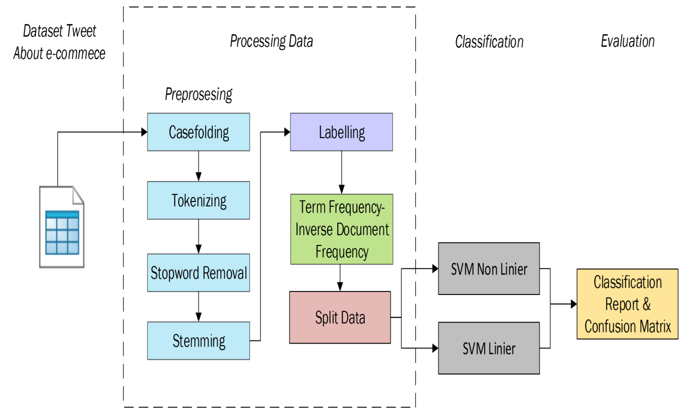

Figure 1. Research Flowchart

A. Dataset Tweet Collection

At this crucial stage of our research, we explored Indonesia's vast world of online marketplaces, looking for insights and sentiments expressed through reviews and comments. Our focus revolved around keywords such as ”service,” ”promo,” ”cashback,” and ”Indonesian online marketplace.” These carefully selected keywords aim to capture a comprehensive understanding of user experience, promotional activities, and the overall landscape of the online marketplace ecosystem in Indonesia [18] [19]

The dataset for our analysis covers the period from 20 December 2022 to 30 June 2023, and consists of 2,176 datasets. There are many user opinion vocabularies based on which we got including Indonesian language diversity. This language diversity is very unique to describe positive and negative opinions. To collect this information, we used Twitter API as a technique to collect twitter conversation data. During the research, we processed to get the result using jupyter notebook device with phyton programming language.

B. Processing Data

1) Preprocessing

Preprocessing is an important part of data analysis, which includes a series of important steps such as casefolding, tokenization, stopword removal, and stemming. Preprocessing functionally aims to improve the quality and relevance of a collection of datasets.

The following is an explanation of the steps in preprocessing:

1) Case folding is the step of changing all the text in a sentence to lowercase with the aim of ensuring uniformity and consistency in problems related to letter variations.

2) Tokenization is the arrangement of text or sentences into small individual units, often words or phrases.
3) Stopword removal is another important preprocessing step that involves removing common words (e.g., “and,” “it,” ”is”) that do not add significance to the analysis, simplifying the data set, and reducing confusion.
4) Stemming is a step used to reduce words to their basic form or base word by removing the ending of the word. The purpose of stemming is to combine words that have the same root so that it can increase consistency in text analysis.

The main processes of preprocessing include removing irrelevant words, handling duplicates to ensure data integrity, normalizing data to a consistent format, handling outliers to prevent skewed analysis, and performing feature extraction to reveal underlying patterns in the dataset [20] [21] [22]. By performing these preprocessing steps, researchers create a cleaner, more standardized dataset that becomes the basis for accurate and in-depth data analysis. This preprocessing preparation can increase the effectiveness of the subsequent analysis process to produce better, more reliable, and implementable insights.

2) Labelling

Labeling in sentiment analysis is an important process in ML, as a process for distinguishing and categorizing sentiment expressions in sentence text. This step involves assigning categories or labels to the text based on the general sentiment being analyzed. Primarily used to decipher the emotional tone of content, sentiment labeling typically classifies text as positive, negative, or neutral. By utilizing techniques ranging from traditional text analysis to ML methods [23].

The main goal of sentiment labeling is to process raw text data so that it can be understood more broadly, including understanding the feelings contained in user-generated content. These labeled data sets become a valuable source of information for understanding patterns, trends, and general attitudes that emerge from user responses to various topics, products, or events [24].

Equipped with sentiment labels, this dataset plays a crucial role in various fields, with applications including social media analysis, market research, and customer perspective understanding. In social media, labeled sentiment data allows for the exploration of user sentiments, providing insights into the mood and collective opinions circulating within online communities. Market researchers use labeled sentiment data to measure consumer reactions and sentiments towards products and services, thus providing information for strategic decision-making and marketing campaigns.

The steps involved in the labeling process are elaborated in depth in the illustration or Figure 2.

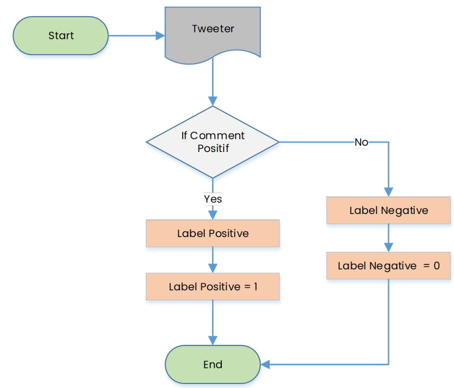

Figure 2. Steps for Determining Label Classification

3) Term Frequency-Inverse Document Frequency

Term weighting is an important process in text processing that gives weight or importance to words or terms that appear in text based on their relevance or occurrence in context. The main purpose of term weighting is to measure how words or terms affect their meaning or contribution to a document or document collection [25] [26]

In text analysis, term weighting is usually done using techniques such as Term Frequency-Inverse Document Frequency (TF-IDF). In this method, words that appear frequently in a document but rarely appear throughout the document collection are given a higher weight, as they are considered more unique and informative. Conversely, words that appear frequently in the entire document collection but rarely appear in a single document are given a lower weight [27] [28].

Here is the form of the mathematical equation:

1) Term Frequency (TF) The Term Frequency (TF) value is obtained from the frequency of occurrence of feature t in document d.

$$TF_{t,d} = \frac{t}{d} \quad (1)$$

2) Inverst Document Frequency The Inverse Document Frequency value is obtained from the logarithm of the number of documents n divided by df documents containing feature t.

$$IDF_{t,d} = log\frac{t}{D} \quad (2)$$

3) TF.IDF The Term Frequency Inverse Document Frequency (Wt) value is obtained by switching the TF value with IDF.

$$TF.IDF_{t,d,D} = TF_{t,d}.IDF_{t,D} \quad (3)$$

4) Split Data

Splitting data is the process of dividing a dataset into different subsets for the purpose of model development and evaluation. The most important stage in creating an ML model aims to avoid overfitting and validate the model performance [29] [30].

In the context of machine learning, data division is generally done into two parts:

- **Training Set :** This subset is used to train the model. The model uses this data to adjust its internal parameters during the training process.
- **Testing Set :** This subset is used to finally evaluate the model performance, after the training process is complete. This is an independent dataset that is not used during the training or validation process, providing a more accurate picture of the model's real-world performance.

This data distribution can be done randomly or based on certain criteria such as time, location, or other characteristics of the data. It is important to ensure that each subset reflects the same distribution of relevant classes or features to ensure the trained model performs well on new data [31].

C. Classification

1) SVM Linier

Linear SVM is a powerful and effective machine learning algorithm for data classification. The main goal is to find the optimal hyperplane to clearly separate two classes of data in the feature space. This hyperplane has a maximum margin, which is the shortest distance between the hyperplane and the closest points of both data classes. Linear SVMs are particularly useful when data is inherently separable by a line, plane, or hyperplane.

The learning process of a linear SVM involves the optimization of an objective function that aims to maximize the margin and, at the same time, minimize the norm or quadratic norm of the model's weight vector. Once the optimal hyperplane is found, the model can be used to predict new classes of data by projecting the data into feature space and measuring its distance from the hyperplane.

2) SVM Non Linier

Non-linear SVM is a variation of the SVM algorithm that allows complex, non-linear separation between data classes. In contrast to linear SVM which is only able to find a linear hyperplane, non-linear SVM uses non-linear transformation of the data into a higher dimensional feature space. This allows SVM to find the optimal non-linear hyperplane to clearly separate data classes.

The non-linear SVM learning process involves mapping data into a higher feature space using kernel functions. This kernel allows the SVM to compute dot products in a higher feature space without explicitly computing data transformations into that space. Thus, non-linear SVMs can handle more complex separation between data classes.

SVM is a machine learning algorithm used for sentiment analysis in tweet data. The model is trained with labeled training data and used to classify tweets not seen in the test data. The results can be sentiment analysis, tweet categorization, or tasks according to research needs [7] [32]. The following are the formulas in the non-linear SVM vector space in Table I.

TABLE I. Formulas In The SVM Vector Space

Kernel	Function
Linear	$k(x, y) = (x \cdot y)^1$
Polynomial	$k(x, y) = (x \cdot y + c)^d$
RBF	$K(x, y) = \exp(-\gamma \cdot (x - y)^2)$
Sigmoid	$K(x, y) = \tanh(\gamma \cdot (x \cdot y) + c)$

The accuracy of kernel SVM models is influenced by hyperparameters, which project the two input vectors 'x' and 'y' into a higher dimensional feature space. These hyperparameters are crucial in determining the model's ability to separate and classify data correctly.

D. Evaluation

researchers measure the accuracy and effectiveness of the classification models used. For example, in medical research, studies may classify patients as positive or negative for a condition based on test results. The confusion matrix will help in measuring the extent to which the model can identify positive patients (True Positive) or negative (True Negative), as well as the extent to which the model can make mistakes by classifying positive patients as unfavorable (False Negative) or vice versa (False Positive). Confusion Matrix is also used to calculate other evaluation metrics such as accuracy, precision, recall, and F1-score, all of which provide deeper insight into the performance of the classification model in the research study. Using the Confusion Matrix, researchers can measure and make more accurate and reliable decisions on research results in various fields [33] An example of a Confusion Matrix is presented in Figure 3

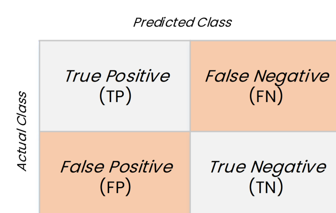

Figure 3. Confusion Matrix

The evaluation of sentiment analysis models relies on critical metrics such as Accuracy, Precision, Recall, and F1 Score, each offering unique insights into the model's performance. Accuracy is a holistic measure of overall correctness, representing the ratio of correctly classified tweets to the total number of tweets. A higher accuracy score indicates the model's proficiency in making accurate predictions across the entire dataset [34].

On the other hand, precision delves into the model's accuracy in identifying positive sentiments. percentage of tweets correctly classified as containing a positive response to the total tweets predicted to have positive emotions. A higher precision score signifies the model's ability to identify and classify positive sentiments accurately. The Recall metric focuses on the model's capability to capture all positive sentiments within the dataset. It calculates the ratio of correctly classified tweets containing positive responses to the total tweets that contain positive emotions. A higher recall score indicates the model's effectiveness in identifying a substantial portion of positive sentiments present in the dataset. The F1 Score plays a crucial role by balancing precision and Recall. As a harmonic mean of precision and Recall, this metric provides a consolidated evaluation of the model's performance, especially when there is a need to weigh the trade-off between accuracy and Recall. In sentiment analysis on Indonesian online marketplace reviews, these metrics serve as valuable benchmarks, guiding practitioners in fine-tuning their models to achieve a harmonious balance between accurate classification and comprehensive coverage of positive sentiments. This nuanced evaluation ensures that sentiment analysis models meet the specific demands of analyzing sentiment in the context of online marketplace reviews in Indonesia.

Accuracy is the percentage of total correct predictions from the model.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{4}$$

Precision is the proportion of correctly predicted positives out of all positive predictions made by the model

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

Recall (Sensitivity) is the proportion of true positives correctly predicted by the model out of all true positive instances

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

F1-Score is the harmonic mean of precision and recall, providing a balance between the two metrics.

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

3. RESULT AND DISCUSSION

A. Dataset Tweet Collection

In this research study, the primary objective was to analyze and mitigate positive and negative responses within Indonesian online marketplace reviews. The dataset, comprising 1276 instances, was sourced from Twitter and consisted of 538 positive and 738 negative responses.

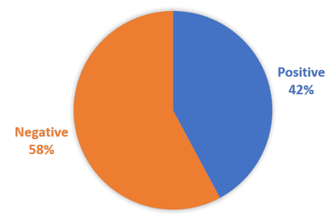

Figure 4. Pie Diagram Analysis

Seen in Figure 4, the results of e-commerce sentiment in Indonesia, especially on the Tokopedia, Shopee, and Lazada platforms, show that negative sentiment reaches 58%, while positive sentiment is 42%. This indicates a decline in the level of public trust in e-commerce services. This decline can be caused by a variety of factors, including changes in service policies, a decline in service levels, and a lack of effective service promotion [35] [36].

The next process is feature extraction using the TF-IDF method to represent textual information numerically. The classification model utilized in the study was the SVM, employing both linear and non-linear kernels. To comprehensively evaluate the model's performance, the researchers implemented eight different scenarios for splitting the data, encompassing ratios of [0.6, 0.65, 0.7, 0.75, 0.8, 0.85, 0.9, 0.95]. The grid search was conducted over a range of parameters, including the degree parameter [2, 3, 4, 5, 6], C values [0.1, 1, 10, 100, 1000], and coef0 values [0.0, 0.1, 0.5, 1.0].The evaluation of the model's performance was conducted through various metrics, including confusion matrix metrics such as precision (Pre), recall (Rec), F1-score (F1-scr), and accuracy (Acc). These metrics are based on the outcomes of TP, TN, FP, and FN.In summary, the study encompasses a comprehensive analysis of sentiment classification in Indonesian online marketplace reviews, considering different data split scenarios and employing SVM with linear and non-linear kernels. The evaluation metrics provided a nuanced understanding of the model's effectiveness in capturing positive and negative sentiments within the dataset.

B. Spliting Data

In Table II , we can see the percentage of data sharing between the training set and the testing set. The percentage varies from 60% to 95%. The training data set consists of a larger number than the testing data set, with the number increasing as the percentage of data sharing increases. For example, with a 60% data split, there are 1264 data in the training set and 844 data in the testing set. Meanwhile, with a data distribution of 95%, there are 2002 data in the training set and 106 data in the testing set. This shows that the greater the percentage of data allocated for training, the greater the amount of data used to train the model.

TABLE II. Training and Testing Data

Set (%)	60	65	70	75	80	85	90	95
Training	1264	1370	1475	1581	1686	1791	1897	2002
Testing	844	738	633	527	422	317	211	106

C. Model SVM Linier

Exploring linear SVM kernels is foundational in understanding their unique attributes and applications in machine learning. Linear SVM is a versatile and widely utilized algorithm known for its efficacy in scenarios where the underlying data exhibits a linearly separable pattern. This distinctive quality makes it particularly valuable in tasks requiring a clear boundary to segregate different classes within the dataset. One of the critical strengths of linear SVM lies in its simplicity and computational efficiency. The algorithm excels when the relationship between input features and target variables follows a linear trajectory. The linear decision boundary, often a hyperplane, enables the algorithm to efficiently classify data points, making it well-suited for high-dimensional datasets [37].

This research uses the SVM kernel as a comparison test using eight split training data scenarios namely 60%, 65%, 70%, 75%, 80%, 85%, 90%, 95%. The results of the linear SVM kernel performance evaluation can be shown in Table III.

TABLE III. Performance of SVM Linear

Kernel	Persen %							
	Split	a	b	c	d	e	f	Acc.
Linier	60	82	91	86	87	73	79	83
	65	88	92	90	89	83	86	88
	70	87	92	90	89	83	86	88
	75	88	93	81	90	84	87	89
	80	88	95	91	93	83	87	90
	85	92	95	94	92	88	90	92
	90	92	96	94	94	89	92	93
	95	88	95	91	91	81	86	89

where the explanation :

a : Precision Negative Label
b : Recall Negative Label
c : f1-Score Negative Label
d : Precision Positive Label
e : Recall Positive Label
f : f1-Score Positive Label

The evaluation results on SVM with linear kernel showed excellent performance, especially on split data of 90%, with the highest accuracy. The model could predict negative labels with 92% precision and 96% recall and positive labels with 94% precision and 94% recall. This indicates that the model can correctly identify instances that should belong to both categories, giving high f1-score values for negative labels of 0.94 and positive labels of 0.92. This performance can be interpreted as a good balance between precision and recall, resulting in a reliable and effective classification model on the tested dataset.

In the context of sentiment analysis on online marketplaces in Indonesia, the prowess of SVM with a linear kernel at 90% training data share produced very impressive results. The model's high performance in classifying customer reviews or comments can have a positive impact in the context of e-commerce business. A precision of 92% in predicting negative labels demonstrates the model's ability to reduce the risk of providing inaccurate or harmful information to consumers. On the other hand, the recall of 96% on negative labels indicates the model's ability to detect and respond to the majority of reviews that may be negative, enabling quick handling of issues or complaints.

The prediction of positive labels characterized by 94% precision and 94% recall indicates that the model is very good at identifying and highlighting positive customer reviews. In the context of online marketplaces, this can provide valuable insights related to product or service elements that consumers favor. The high balance between precision and recall, reflected in the high f1-score (0.94 for negative labels and 0.92 for positive labels), indicates that the linear SVM model has the potential to provide accurate and valuable sentiment insights in an online marketplace environment in Indonesia. A visualization of the Linear kernel SVM performance using eight split data scenarios specifically focusing on the classification report is presented in Figure 5.

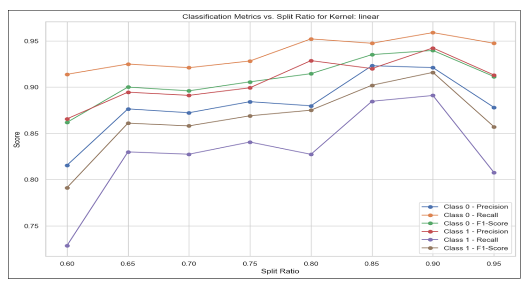

Figure 5. Performance of Precision, Recall, and F1-Score Linear SVM

The model demonstrates high precision for negative (92%) and positive (94%) labels, indicating its ability to predict negative and positive reviews accurately. Additionally, the model exhibits high recall for negative (96%) and positive (94%) labels, showcasing its capability to capture the majority of tweets that should be identified in both categories. With high f1 scores for both labels (0.94 for negative and 0.92 for positive), the model successfully achieves an optimal balance between precision and recall, providing reliable and effective sentiment predictions for online marketplace reviews in the Indonesian context. Visualization of the performance of Linear kernel SVM using eight split data scenarios specifically focusing on accuracy values is presented in Figure 6

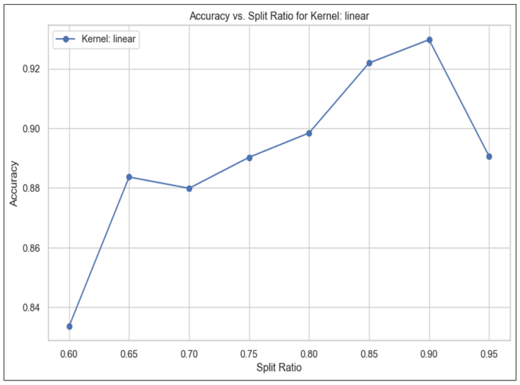

Figure 6. Performance of Accuracy Score Linear SVM

The evaluation of the linear kernel SVM on a 90% data split reveals its outstanding performance, achieving the highest accuracy. Linear SVM proficiency in handling high-dimensional datasets is particularly advantageous in scenarios where the number of features is substantial. Its ability to discern linear patterns in such datasets contributes to its widespread adoption in various domains, including text classification, image recognition, and bioinformatics [38] [39].

Visualization of Linear kernel SVM performance using eight split data scenarios, specifically focusing on the confusion matrix report, is presented in Figure 7

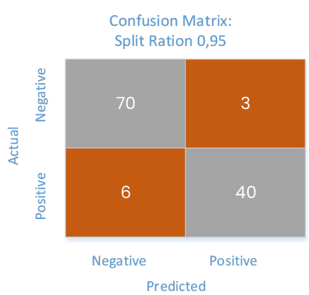

Figure 7. Confution Matrix Linear SVM

Assessing the linear kernel SVM model's performance in a particular data split scenario provides insights into its effectiveness in categorizing sentiments in online reviews. These findings include 70 instances of accurately identifying positive reviews TP and 49 cases correctly classifying negative reviews TN. However, the model also exhibited 6 instances of mistakenly labelling reviews as positive when they were negative FP and 3 instances of misclassifying reviews as negative when they were positive FN. These results shed light on how the linear SVM model handles sentiment analysis in the context of online reviews on the Indonesian online marketplace platform.

D. Model SVM Non-Linier

On the other hand, non-linear SVM kernels, such as polynomial, radial basis function (RBF), and sigmoid, extend the model's ability to handle non-linear and complex relationships in the data. These kernels provide the flexibility to capture intricate patterns, allowing SVM to excel in scenarios where decision boundaries are more complex or exhibit non-linear behaviour. This comparison is critical as it guides practitioners in choosing the appropriate kernel based on the nature of the dataset and the underlying patterns.

The advantage of non-linear SVM lies in its ability to handle data with more complex structures and non-linear relationships. Kernels such as polynomials can capture interaction patterns between features, while RBF kernels can manage highly non-linear relationships [40] [41]

It is important to note that kernel selection should be based on the characteristics of the data. A linear kernel may be more appropriate if the data has a clear linear relationship. In contrast, a non-linear kernel may provide better performance if the relationship between features is complex and non-linear. In addition, sigmoid kernels can be used to handle data that has rapid changes in growth rate, and RBF kernels are generally very effective in managing unstructured data with a lot of variation. This research uses the SVM kernel as a comparison test using eight split training data scenarios namely 60%, 65%, 70%, 75%, 80%, 85%, 90%, 95%. . The results of the Non-linear SVM kernel performance evaluation can be shown in Table IV

TABLE IV. Performance of SVM Non-Linier

Kernel	**Persen %**							
	Split	**a**	**b**	**c**	**d**	**e**	**f**	**Acc.**
Polynomial	60	86	92	89	88	80	84	87
	65	87	92	89	89	82	85	88
	70	87	94	90	91	82	87	89
	75	87	92	90	89	82	85	88
	80	88	86	92	94	82	88	90
	85	93	96	94	93	90	92	93
	90	92	96	94	94	89	92	93
	95	90	95	92	91	85	88	91
Rbf	60	82	92	87	88	73	80	84
	65	84	92	87	88	73	80	84
	70	84	93	89	90	77	83	86
	75	86	94	90	91	80	85	88
	80	86	96	91	94	79	86	89
	85	92	96	94	93	87	90	92
	85	92	96	94	93	87	90	92
	90	89	96	92	94	84	88	91
	95	86	95	90	91	77	83	88
Sigmoid	60	81	91	86	86	72	79	83
	65	86	91	88	87	81	84	86
	70	85	92	88	89	79	83	86
	75	88	82	90	89	83	86	88
	80	87	95	91	93	82	87	89
	85	89	91	90	87	83	85	88
	90	89	93	91	90	85	88	90
	95	88	97	93	95	81	88	91

Performance evaluation of SVM with non-linear kernels showed performance variation depending on the kernel type. In the polynomial kernel, the model achieved the highest accuracy of 93% at 85% training data split, with 93% precision for negative and positive labels, 96% recall for negative labels and 90% for positive labels. The high f1-score values at 94% and 92% indicate a good balance between recall and precision. Meanwhile, the RBF kernel gives an accuracy of 92%, with a precision of 92% and 93% for negative and positive labels, respectively. Recall of negative labels is 96%, while recall of positive labels is 87%. This kernel gives an f1-score of 0.94 for negative and 0.90 for positive labels, indicating good performance, albeit with a decrease in recall on positive labels. Although giving 90% accuracy, the sigmoid kernel showed good precision of 89% for negative and 90% for positive labels but lower recall of 93% for negative and 85% for positive labels. The F1-score obtained was 0.91 for negative labels and 0.88 for positive labels. In conclusion, kernel selection significantly impacts model performance, and it is necessary to consider the trade-off between precision and recall depending on the application needs.

The Non-Linear Polynomial kernel SVM performance across diverse split data scenarios is visually represented in Figure 8, with a specific focus on the classification report. This detailed illustration offers an in-depth exploration of how the SVM navigates through the intricacies introduced by varied training and testing data ratios, providing valuable insights into its classification capabilities

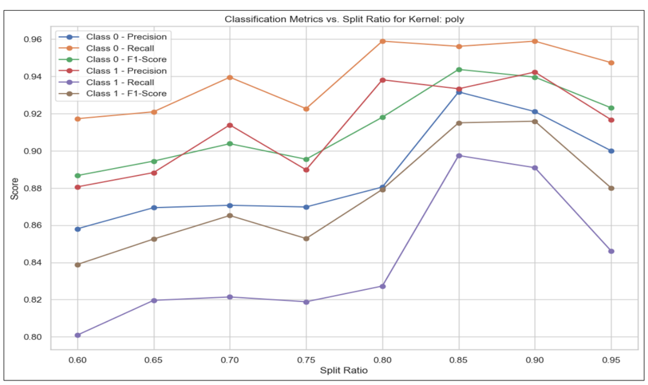

Figure 8. Performance of Precision, Recall, and F1-Score Non Linear SVM Polynomial

Trained with an 85% split of the training data, the polynomial kernel achieved remarkable precision rates of 93% for both negative and positive labels, highlighting its accuracy in classifying instances in both categories. Additionally, the model demonstrated outstanding recall rates, reaching 96% for negative labels and 90% for positive labels. The noteworthy f1-score values, standing at 0.94 and 0.92, underscore the model's proficiency in striking a fine balance between recall and precision, solidifying its robust performance in sentiment analysis tasks.

Visualization of the SVM performance of the non-linear rbf kernel using eight split data scenarios specifically focusing on the classification report is presented in Figure 9

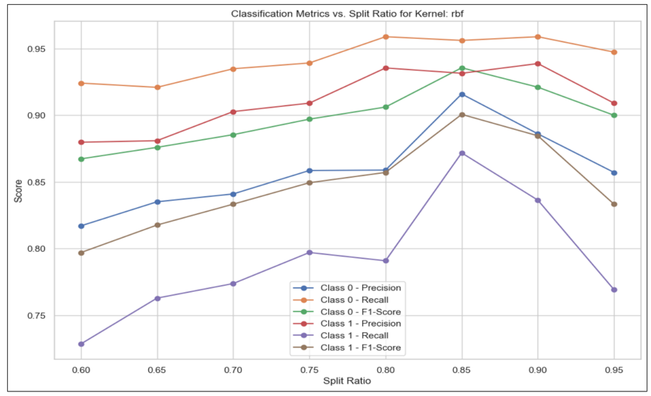

Figure 9. Performance of Precision, Recall, and F1-Score Non Linear SVM Rbf

Exhibiting precise predictions, the RBF kernel achieves an impressive 92% precision for negative labels and 93% for positive labels. Notably, it demonstrates robust recall rates, especially for negative labels at 96% and positive labels at 87%. The balanced performance is evident in the f1-scores, with 0.94 for negative labels and 0.90 for positive labels, underscoring the kernel's effectiveness in maintaining accuracy and equilibrium between precision and recall in sentiment analysis tasks.

A visualization of the performance of the non-linear sigmoid kernel SVM using eight split data scenarios specifically focusing on the classification report is presented in Figure 10

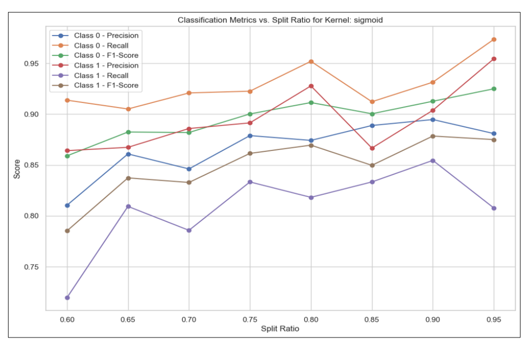

Figure 10. Performance of Precision, Recall, and F1-Score Non Linear SVM Sigmoid

On the contrary, the sigmoid kernel demonstrates commendable precision levels, reaching 89% for negative labels and 90% for positive labels. Despite this strength, it presents a trade-off, as the recall values are comparatively lower, standing at 93% for negative labels and 85% for positive labels. The associated f1-scores reveal a balanced performance, with 0.91 for negative labels and 0.88 for positive labels. This suggests that while the sigmoid kernel excels in precision, it somewhat compromises recall, emphasizing the importance of considering the specific requirements of the classification task.

The visual representation of the optimal accuracy outcomes within the eight split data scenarios, meticulously explored by the researchers, is vividly depicted in Figure 11. This graphical illustration provides a compelling insight into the nuanced variations and performance nuances across different data splits. It serves as a valuable visual aid, offering a comprehensive overview of how the SVM model's accuracy responds to diverse training data proportions. Such visualizations play a pivotal role in unraveling the intricate dynamics of model performance and contribute significantly to the comprehensive understanding of sentiment analysis in the context of Indonesian online marketplace reviews.

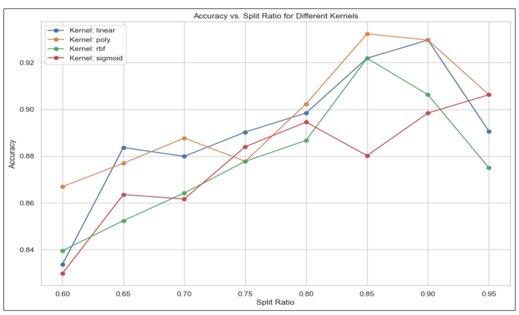

Figure 11. Accuration of Svm Linier and Non Linier (Polynomial, Rbf And Sigmoid)

In summary, the non-linear polynomial kernel emerges as the top performer, boasting an outstanding accuracy result of 93%. This conclusion underscores the pivotal role of kernel selection in influencing the overall accuracy of the Support Vector Machine model.

Visualization of non-linear kernel SVM performance using eight split data scenarios that specifically focus on the confusion matrix report is presented in Figure 12

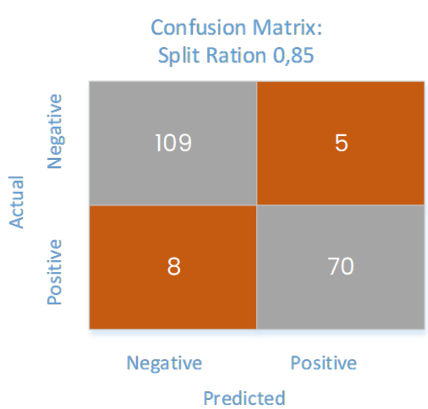

Figure 12. Confution Matrix Non Linear SVM (polynomial)

In the evaluation results, 109 positive reviews were correctly predicted TP, 70 truly negative reviews were also correctly predicted TN, 8 reviews that were negative but predicted as positive FN, and 5 reviews that were positive but predicted as negative FN. The TP value reflects the number of positive reviews accurately predicted by the model, while TN reflects the number of negative reviews successfully predicted. FP indicates reviews that were negative but predicted as positive, while FN includes positive but negative reviews.

Visualization of non-linear kernel SVM performance using eight split data scenarios that specifically focus on the confusion matrix report is presented in Figure 13

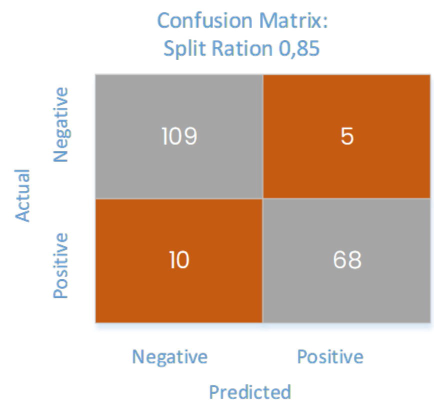

Figure 13. Confution Matrix Non Linear SVM (RBF)

In the context of evaluating the linear kernel SVM model in one of the data split scenarios, the following evaluation results were obtained: TP of 109, TN of 68, FP of 10, and FN of 5. The TP value reflects the number of truly positive reviews correctly predicted by the model. On the other hand, TN indicates the number of truly negative reviews correctly predicted. FP reflects the number of reviews that should be negative but are predicted as positive by the model. Meanwhile, FN reflects the number of reviews that should be positive but are predicted as negative by the model.

Visualization of non-linear kernel SVM performance using eight split data scenarios that specifically focus on the confusion matrix report is presented in Figure 14

In the evaluation results of the linear kernel SVM model, we obtained a total of 37 TP, 21 TN, 5 FP and 1 FN. The TP value reflects the number of reviews correctly classified as positive, TN indicates the number of reviews correctly classified as negative, FP represents the number of reviews incorrectly classified as positive, and FN is the number of reviews incorrectly classified as negative.

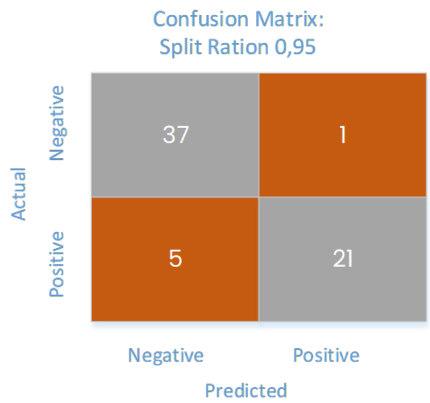

Figure 14. Confution Matrix Non Linear SVM (Sigmoid)

E. Comparasion Model SVM Linier and Non Linier

Understanding the advantages and limitations of linear and non-linear SVM is important for effective model selection. While linear SVM can be advantageous in scenarios with clear linear separability and computational efficiency, non-linear kernels offer the flexibility to address complicated real-world data relationships. The choice between linear and non-linear SVM depends on the specific characteristics of the dataset and the complexity of the underlying patterns, emphasizing the importance of a comprehensive comparison to make informed decisions in machine learning applications. As seen in the table, the comparative results of linear and non-linear kernel svm. The results of the best performance comparison for linear and non-linear svm kernels can be seen in Table V.

TABLE V. Comparison of Best Performance of SVM Linear and Non-Linear

Kernel	**Persen %**							
	Split	**a**	**b**	**c**	**d**	**e**	**f**	**Acc.**
Linear	60	92	95	94	92	88	90	92
Polynomial	85	93	96	94	93	90	92	93
rbf	85	92	96	94	93	87	90	92
sigmoid	95	88	97	93	95	81	88	91

Analysis of the performance of the Support Vector Machine (SVM) model with various kernel types on this dataset provides valuable insights. In the linear kernel with a 60% data split, the model showed a good precision level for both negative (0.92) and positive (0.92) labels. Although it had a slightly lower recall for positive labels (0.88), the balanced f1-score (0.94 for negative labels and 0.90 for positive labels) indicates the model's ability to provide reliable predictions with an accuracy of 92%. With an 85% data split, the polynomial kernel demonstrated outstanding performance with precision of 0.93 for both labels, recall of 0.96 for negative labels, and recall of 0.90 for positive labels. High f1-score values (0.94 for negative and 0.92 for positive labels) and an accuracy of 93% indicate the model's ability to deliver consistent and reliable results.With an 85% data split, the RBF kernel showed strong performance with precision of 0.92 for both labels, recall of 0.96 for negative labels, and recall of 0.87 for positive labels. With high f1-score values (0.94 for negative labels and 0.90 for positive labels) and an accuracy of 92%, this model can provide balanced and reliable predictions.

However, in the sigmoid kernel with a 95% data split, the model exhibited low precision for negative (0.88) and positive (0.95) labels. Although it had high recall for negative labels (0.97), lower recall for positive labels (0.81) resulted in lower f1-score values (0.93 for negative labels and 0.88 for positive labels), with an accuracy of 91%. In conclusion, the choice of kernel significantly impacts the model's performance, and a thorough understanding of application needs is required to select a model that aligns with the data characteristics.

From all linear and non-linear SVM kernels, it can be seen that the best accuracy value is in the non-linear kernel (Polynomial) at a split number of 85% training data. With a prediction of negative label and positive label 0.93. recall value of negative label 0.96 and Positive label 0.90. f1-score balance value on Negative label 0.94 and Positive label 0.90. Visualization of the SVM performance of comparation svm kernel linier dan non linier specifically focusing on the classification report is presented in Figure 15

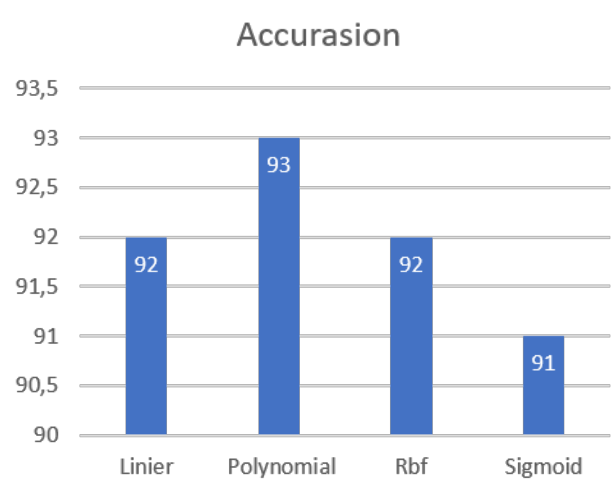

Figure 15. Comparasion Best Performace of Kernel Linier and Non Linier

The assessment of kernel performance reveals distinct accuracy values across the different types. The Polynomial kernel emerges as the frontrunner with an impressive accuracy of 0.93, showcasing its proficiency in accurately classifying data instances. Following closely, both the RBF and Linear kernels demonstrate commendable accuracy, recording values of 0.92 each. Meanwhile, the Sigmoid kernel exhibits a slightly lower accuracy of 0.91. These accuracy metrics offer valuable insights into the respective strengths and capabilities of each kernel, underscoring the nuanced impact that kernel selection can have on the overall performance of Support Vector Machine models.

4. CONCLUSION

Optimizing services to increase the number of visits and positive comments on an online marketplace in Indonesia is very important for companies and the user community. some obstacles are indirectly difficult to achieve through the application. such as which parts need improvement. Researchers found an increase in negative sentiment (58%) coupled with a decrease in positive sentiment (42%) on the customer service side, which indicates a shift in public perception which is most likely influenced by policy adjustments, decreased service quality, and inconsistent promotional strategies. effective.

In the context of machine learning models, based on the results of evaluating the Support Vector Machine (SVM) model on the dataset, it was found that the polynomial kernel provided the highest accuracy value of 93%, with training data sharing of 85%. This model has strong predictive ability with a precision of 93% for negative labels and 93% for positive labels. In general, SVM is able to provide a high accuracy value of 93%, giving an idea that the analysis results are appropriate and correct for online marketplace services

for future research suggestions from this research, the research focus can be expanded to compare various machine learning models, including Decision Trees, Random Forests, Neural Networks, etc., to evaluate their effectiveness in improving e-commerce services, customer satisfaction or promotion satisfaction overall. whole.

References

[1] L. Wang and C. A. Alexander, "Machine learning in big data," *Int. J. Math. Eng. Manag. Sci.*, vol. 1, no. 2, pp. 52–61, 2016. [Online]. Available: https://doi.org/10.33889/ijmems.2016.1.2-006

[2] M. I. Al-Mashhadani, K. M. Hussein, E. T. Khudir, and M. Ilyas, "Sentiment analysis using optimised feature sets in different facebook/twitter dataset domains with big data," *Iraqi J. Comput. Sci. Math.*, vol. 3, no. 1, pp. 64–70, 2022. [Online]. Available: https://doi.org/10.52866/ijcsm.2022.01.01.007

[3] A. Z. Praghakusma and N. Charibaldi, "Comparison of kernel functions in support vector machine method for sentiment analysis on instagram and twitter (case study: Corruption eradication commission)," *JSTIE (Jurnal Sarj. Tek. Inform.)*, vol. 9, no. 2, pp. 33–42, 2021. [Online]. Available: https://doi.org/10.12928/jstie.v9i2.20181

[4] V. N. Kristanto, I. Riadi, and Y. Prayudi, "Forensic analysis of faces on low-quality images using detection and recognition methods," *J. RESTI (Rekayasa Sist. dan Teknol. Informasi)*, vol. 7, no. 2, pp. 218–225, 2023.

[5] Herman, I. Riadi, and Y. Kurniawan, "Vulnerability detection with k-nearest neighbor and naïve bayes method using machine learning," *Int. J. Artif. Intell. Res.*, vol. 7, no. 1, p. 10, 2023.

[6] A. Pamungkas and A. Fadlil, "Optimizing banana type identification: An support vector machine classification-based approach for cavendish , mas , and tanduk varieties microscopic camera," *BISTE*, vol. 5, no. 4, pp. 539–551, 2023.

[7] R. Kusumawati, A. D'Arofah, and P. A. Pramana, "Comparison performance of naive bayes classifier and support vector machine algorithm for twitter's classification of tokopedia services," in *Journal of Physics: Conference Series*, vol. 1320, 2019, p. 012016.

[8] M. N. Muttaqin and I. Kharisudin, "Sentiment analysis on gojek application reviews using support vector machine and k nearest neighbor method," *UNNES J. Math.*, vol. 10, no. 2, pp. 22–27, 2021. [Online]. Available: https://doi.org/10.22146/jk.v9i1.60426

[9] X. Xiahou and Y. Harada, "B2c e-commerce customer churn prediction based on k-means and svm," *J. Theor. Appl. Electron. Commer. Res.*, vol. 17, pp. 458–475, 2022. [Online]. Available: https://doi.org/10.3390/jtaer17020024

[10] Z. Alhaq, A. Mustopa, S. Mulyatun, and J. D. Santoso, "Application of the support vector machine method for twitter user sentiment analysis," *J. Inf. Syst. Manag.*, vol. 3, no. 2, pp. 44–49, 2021. [Online]. Available: https://doi.org/10.24076/joism.2021v3i2.558

[11] M. M. S. Jogo, M. K. Biddinika, and A. Fadlil, "Diabetes disease classification with decision tree and naïve bayes algorithms," *Resist. (Elektronika Kendali Telekomun. Tenaga List. Komputer) Vol.*, vol. 6, no. 2, pp. 113–118, 2013. [Online]. Available: https://jurnal.umj.ac.id/index.php/resistor/article/view/14571/9628

[12] A. Masitha, M. K. Biddinika, and Herman, "Preparing dual data normalization for knn classfication in prediction of heart failure," *Klik - Kumpul. J. Ilmu Komput.*, vol. 4, no. 3, pp. 1227–1234, 2023.

[13] S. Lonang, A. Yudhana, and M. K. Biddinika, "Comparative analysis of machine learning algorithm performance for stunting detection," *J. Media Inform. Budidarma*, vol. 7, no. 4, pp. 2109–2117, 2023. [Online]. Available: https://ejurnal.stmik-budidarma.ac.id/index.php/mib

[14] M. Yunus, M. K. Biddinika, and A. Fadlil, "Optimization of naïve bayes algorithm using backward elimination feature selection for stunting prevalence classification," *Decod. J. Pendidik. Teknol. Inf.*, vol. 3, no. 2, pp. 278–285, 2023.

[15] A. Muis, S. Sunardi, and A. Yudhana, "Cnn-based approach for enhancing brain tumor image classification accuracy," *Int. J. Eng. Trans. B Appl.*, vol. 37, no. 5, pp. 984–996, 2024.

[16] Sunardi, A. Fadlil, and D. Prayogi, "Room security system using machine learning with face recognition verification," *Rev. d'Intelligence Artif.*, vol. 37, no. 5, pp. 1187–1196, 2023.

[17] E. Dio, B. Sudewo, M. K. Biddinika, A. Fadlil, M. Informatika, and U. A. Dahlan, "Javanese script hanacaraka character prediction with resnet-18 architecture," *JURTEKSI*, vol. 10, no. 2, pp. 401–408, 2024. [Online]. Available: http://jurnal.stmikroyal.ac.id/index.php/jurteksiJAVANESE

[18] H. Syahputra, "Sentiment analysis of community opinion on online store in indonesia on twitter using support vector machine algorithm (svm)," in *Journal of Physics: Conference Series*, vol. 1819, 2021, p. 012030.

[19] A. N. Rohman, R. L. Musyarofah, E. Utami, and S. Raharjo, "Natural language processing on marketplace product review

sentiment analysis," 2020. [Online]. Available: https://doi.org/10.1109/ICORIS50180.2020.9320827

[20] A. B. Osmond and F. Hidayat, "Electronic commerce product recommendation using enhanced conjoint analysis," *Int. J. Adv. Comput. Sci. Appl.*, vol. 12, no. 11, pp. 666–673, 2021. [Online]. Available: https://doi.org/10.14569/IJACSA.2021.0121176

[21] F. E. Barakaz, O. Boutkhoum, and A. E. Moutaouakkil, "A new preprocessing method to reduce dimensionality in classification models," *ACM Int. Conf. Proceeding Ser.*, 2019. [Online]. Available: https://doi.org/10.1145/3372938.3373005

[22] E. R. Kaburuan, Y. S. Sari, and I. Agustina, "Sentiment analysis on product reviews from shopee marketplace using the naïve bayes classifier," *Lontar Komput. J. Ilm. Teknol. Inf.*, vol. 13, no. 3, p. 150, 2022. [Online]. Available: https://doi.org/10.24843/lkjiti.2022.v13.i03.p02

[23] T. T. Widowati and M. Sadikin, "Twitter sentiment analysis of public figures with the naive bayes algorithm and support vector machine," *Simetris J. Tek. Mesin, Elektro dan Ilmu Komput.*, vol. 11, no. 2, pp. 626–636, 2021. [Online]. Available: https://doi.org/10.24176/simet.v11i2.4568

[24] L. Ardiyani and H. Sujaini, "Implementation of sentiment analysis on public responses to development in pontianak city," *Jurnal Sistem dan Teknologi Informasi*, vol. 8, no. 2, pp. 183–190, 2020. [Online]. Available: https://doi.org/10.26418/justin.v8i2.36776

[25] A. A. Jalal and B. H. Ali, "Text documents clustering using data mining techniques," *Int. J. Electr. Comput. Eng.*, vol. 11, no. 1, pp. 664–670, 2021. [Online]. Available: https://doi.org/10.11591/ijece.v11i1.pp664-670

[26] S. W. Kim and J. M. Gil, "Research paper classification systems based on tf-idf and lda schemes," *Human-centric Comput. Inf. Sci.*, vol. 9, no. 1, 2019. [Online]. Available: https://doi.org/10.1186/s13673-019-0192-7

[27] R. C. Chen and H. L. Lin, "Application of support vector machines in predicting repeat visitation," in *Int. Conf. Comput. Intell. Man-Machine Syst. Cybern. - Proc.*, vol. 1, 2006, pp. 152–157.

[28] A. R. Lubis, M. K. M. Nasution, O. S. Sitompul, and E. M. Zamzami, "The effect of the tf-idf algorithm in time series forecasting of words on social media," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 22, no. 2, pp. 976–984, 2021. [Online]. Available: https://doi.org/10.11591/ijeecs.v22.i2.pp976-984

[29] H. Zhou, "Research of text classification based on tf-idf and cnn-lstm," *J. Phys. Conf. Ser.*, vol. 2171, no. 1, 2022. [Online]. Available: https://doi.org/10.1088/1742-6596/2171/1/012021

[30] L. Zhang, "Research on case reasoning method based on tf-idf," *Int. J. Syst. Assur. Eng. Manag.*, vol. 12, no. 3, pp. 608–615, 2021. [Online]. Available: https://doi.org/10.1007/s13198-021-01135-6

[31] M. S. Reza, U. Hafsha, R. Amin, R. Yasmin, and S. Ruhi, "Improving svm performance for type ii diabetes prediction with an improved non-linear kernel: Insights from the pima dataset," *Comput. Methods Programs Biomed. Updat.*, vol. 4, p. 100118, 2023. [Online]. Available: https://doi.org/10.1016/j.cmpbup.2023.100118

[32] N. Nandal, R. Tanwar, T. Choudhury, and S. C. Satapathy, "Context-driven bipolar adjustment for optimized aspect-level sentiment analysis," *J. Sci. Ind. Res. (India).*, vol. 79, no. 2, pp. 122–127, 2020. [Online]. Available: https://doi.org/10.56042/jsir.v79i2.68447

[33] M. Desai and M. A. Mehta, "Techniques for sentiment analysis of twitter data: A comprehensive survey," in *Proceeding - IEEE Int. Conf. Comput. Commun. Autom. ICCCA 2016*, 2017, pp. 149–154.

[34] R. Ahuja, A. Chug, S. Kohli, S. Gupta, and P. Ahuja, "The impact of feature extraction on sentiment analysis," *Procedia Comput. Sci.*, vol. 152, pp. 341–348, 2019. [Online]. Available: https://doi.org/10.1016/j.procs.2019.05.008

[35] S. N. Alsubari, S. N. Deshmukh, A. A. Alqarni, N. Alsharif, T. H. H. Aldhyani, F. W. Alsaade, and O. I. Khalaf, "Data analytics for the identification of fake reviews using supervised learning," *Computers, Materials and Continua*, vol. 70, no. 2, pp. 3189–3204, 2022. [Online]. Available: https://doi.org/10.32604/cmc.2022.019625

[36] M. I. Alfarizi, L. Syafaah, and M. Lestandy, "Emotional text classification using tf-idf (term frequency-inverse document frequency) and lstm (long short-term memory)," *JUITA: Jurnal Informatika*, vol. 10, no. 2, pp. 225–232, 2022. [Online]. Available: https://doi.org/10.30595/juita.v10i2.13262

[37] M. A. Virgananda, I. Budi, Kamrozi, and R. R. Suryono, "Purchase intention and sentiment analysis on twitter related to social commerce," *Int. J. Adv. Comput. Sci. Appl.*, vol. 14, no. 7, pp. 543–550, 2023. [Online]. Available: https://doi.org/10.14569/IJACSA.2023.0140760

[38] K. S. Manoj and S. Smita, "Support vector machine and random forest machine learning algorithms for sentiment analysis on tourism reviews: a performance analysis," *i-manager's J. Comput. Sci.*, vol. 9, no. 3, pp. 1–9, 2021. [Online]. Available: https://doi.org/10.26634/jcom.9.3.18479

[39] R. H. Muhammadi, T. G. Laksana, and A. B. Arifa, "Combination of support vector machine and lexicon-based algorithm in twitter sentiment analysis," *Khazanah Inform. J. Ilmu Komput. dan Inform.*, vol. 8, no. 1, pp. 59–71, 2022. [Online]. Available: https://doi.org/10.23917/khif.v8i1.15213

[40] A. Z. Arifin and I. Lestari, "Sentiment analysis of political comments on twitter social media," *Jurnal Sistem Informasi Bisnis*, vol. 9, no. 2, pp. 153–160, 2019. [Online]. Available: https://doi.org/10.33633/jsib.v9i2.2256

[41] P. Arsi and R. Waluyo, "Sentiment analysis of discourse on the relocation of the capital city of indonesia using support vector machine algorithm," *Jurnal Ilmiah Teknologi Informasi Asia*, vol. 15, no. 2, pp. 132–142, 2021. [Online]. Available: https://doi.org/10.29036/jitia.v15i2.188

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