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IMPLEMENTATION OF NATURAL LANGUAGE PROCESSING (NLP) IN CONSUMER SENTIMENT ANALYSIS OF PRODUCT COMMENTS ON THE MARKETPLACE

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Abstract

Market product reviews are invaluable information if processed carefully. The process of analyzing product reviews is more than just considering star ratings; Comprehensive examination of the overall content of review comments is essential to extracting the nuances of meaning conveyed by the reviewer. The problem currently occurring in analyzing reviews of product purchases in the marketplace is the large number of abbreviations and non-standard language used by commenters, making it difficult for the system to understand. Therefore, a Natural Language Processing (NLP) approach is needed to improve the language in the content of review comments so as to achieve maximum performance in sentiment analysis. This research utilizes the KNN and TF-IDF algorithms, coupled with NLP techniques, to categorize Muslim fashion product reviews into two different groups that is positive and negative. The NLP-enhanced classification achieved 76.92% accuracy, 80.00% precision, and 74.07% recall, surpassing the results obtained without NLP, which had 69.23% accuracy, 80.00% precision, and 64.52 recall. %. Frequently appearing words in reviews serve as a description of collective buyer sentiment regarding the product. Positive reviews indicate customer satisfaction with the quality, speed of delivery, and price of the goods, while negative reviews indicate dissatisfaction with factors such as color differences and differences in the number of items received.

Keywords: *consumer sentiment analysis, marketplace, natural language processing (NLP), product comment.*

1. INTRODUCTION

A marketplace represents the evolutionary progression of e-commerce, manifesting as an internet-based platform facilitating business operations and transactions between customers and sellers [1]–[5]. Within this virtual domain, buyers can peruse a myriad of offerings from various sellers and establishments. According to data sourced from iPrice's Indonesian Ecommerce Map, Tokopedia emerged as the second-most-visited marketplace in Indonesia during the first quarter of 2023, garnering 55 million visitors monthly, trailing behind Shopee. This platform provides an avenue for producers, Small and Medium Industries (IKM), Micro, Small and Medium Enterprises (MSME), suppliers, and distributors to connect with potential buyers seeking their products [6]–[10]. Notably, Muslim fashion products hold a prominent position among the popular items on Tokopedia. Beyond the visual assessment facilitated by photographs and product descriptions, the inclusion of product reviews from past purchasers enhances the consumer's ability to gauge the quality of Muslim fashion products . These reviews stand as a valuable source of information, exerting a substantial influence on consumer perceptions of product quality [11]–[14].

Buyers engaging in marketplace transactions have the opportunity to furnish reviews subsequent to receiving their purchased items [15]–[18]. These product reviews encapsulate both ratings and commentary, encompassing responses, commendations, critiques, and overall feedback regarding the acquired product. The accumulation of stars in these reviews is indicative of the product's standing and reputation; a higher number of stars correlates with an elevated product reputation. These reviews wield significant influence over the purchasing decisions of potential buyers.

Sellers, recognizing the pivotal role of customer satisfaction, can leverage product reviews to garner insights for enhancing products and services, thereby augmenting customer contentment [19]–[23]. Customer contentment stands as a paramount objective for any company. While star ratings offer a concise metric for review analysis, they inherently lack the depth to encapsulate the entirety of a review's contents. A comprehensive understanding of the review's primary intent necessitates a thorough examination of the entire review commentary. Manual review evaluation, while feasible for a limited number of reviews, becomes impractical with a large volume, prompting the adoption of sentiment analysis systems for expeditious processing.

Researchers in this study conducted sentiment analysis on product reviews within the Tokopedia marketplace. The product review section encompasses both free-text comments and a star rating system ranging from 1 to 5. The content of these review comments serves as the basis for discerning the specific aspects that consumers emphasize when composing reviews. The limitation arises from the fact that each review is accompanied by a single-star rating, which, in isolation, cannot comprehensively represent the nuanced evaluations of various product features by customers.

Buyers provide diverse information in their reviews, covering product attributes such as price, quality, materials, color, shape, size, taste, and quantity. Additionally, service-related aspects, including packaging, delivery time, and seller responsiveness, are also frequently included.

Extensive prior research has highlighted the positive impact of product reviews on purchase intentions, with potential buyers relying on reviews to ascertain the anticipated quality of their prospective purchases [24]. Noteworthy studies by Lutfi and Permatasari [25] on the Bukalapak marketplace and Muljono and Dian on Twitter opinion data [26] related to Indonesian marketplace services underscore the efficacy of sentiment analysis methodologies, achieving high accuracy rates using Support Vector Machine and Naive Bayes techniques, respectively. Further contributions by Norman Kendal [27] have demonstrated the efficiency of Natural Language Processing (NLP) in predicting product categories from online fashion product titles.

The problem currently occurring in analyzing reviews of product purchases in the marketplace is the large number of abbreviations and non-standard language used by commenters, making it difficult for the system to understand. The primary objective of this study is to assess the sentiment of product purchase reviews for "Muslim fashion products" items on Tokopedia, employing the KNN algorithm with TF-IDF weighting to categorize reviews into positive and negative groups. The success rate of categorization is then compared between data pre-processed with and without the NLP technique. Another aim is to identify specific characteristics of "Muslim fashion products" products that are focal points in both favorable and negative evaluations. This insight is crucial for sellers seeking to make informed modifications and enhancements to product and service quality.

The challenge in assessing product purchase feedback lies in the prevalence of acronyms and non-standard language within the marketplace, making interpretation challenging. Consequently, a Natural Language Processing (NLP) approach is imperative to enhance the linguistic understanding of review comments, thereby maximizing the performance of sentiment analysis. It is emphasized that meaningful progress in Machine Learning is contingent on the integration of NLP methodologies.

2. METHODOLOGY

Figure 1 illustrates the research flow in the sentiment analysis of product purchase reviews on Tokopedia, employing the Natural Language Processing (NLP) approach. The initial phase of the research entails the identification of the target product for study, followed by the systematic collection of product review data. Subsequently, a pre-processing stage is implemented on the gathered reviews, considering both datasets with and without the NLP approach [28]–[31]. This results in the creation of two distinct datasets—one with the integration of the NLP approach and the other without.

Each dataset is then partitioned into training and test data subsets. Following the partitioning, TF-IDF weighting computations are executed on both datasets, enabling a comparative analysis of the outcomes. This approach facilitates a comprehensive examination of the impact of the NLP methodology on the sentiment analysis of product purchase reviews within the Tokopedia platform.

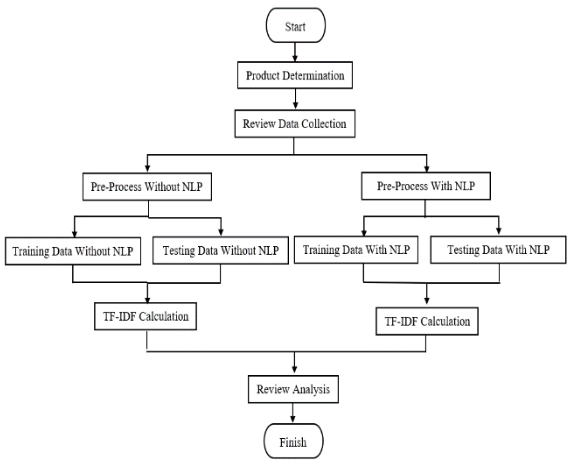

Figure 1. Framework Research

The items used in this research were the 150 best-selling products on Tokopedia based on product search results using the keyword "Baju Gamis Muslim" at the product determination stage. Products are chosen based on the order of product sales, without regard for the store of origin or the location of origin. The following are the grounds for selecting the keyword "Baju Gamis Muslim": 1) According to Google Trends, it has a higher number of searches than other types of Baju Gamis Muslim as of April 2023; 2) It has high sales on Tokopedia, with the highest sales reaching 40 thousand products per month from one product; and 3) The type of Baju Gamis Muslim has complex features ranging from model, material, color, size, cut, and stitching.

The Scraper application, which was independently developed using the Python language, was employed to collect review data. Each product received 6 ratings ranging from 1 to 5 stars on the first page, amounting to a total of 3,341 reviews.

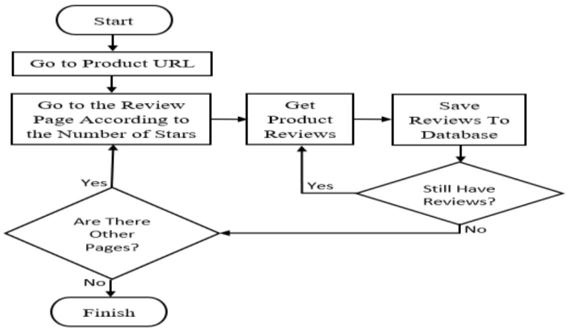

Figure 2. The Process of Taking Comments Uses the Scraper Application

Figure 2 illustrates the workflow of the Scraper application system. The process initiates by accessing the product URL and opening the review page with a one-star rating, subsequently downloading and saving the displayed product reviews individually to the database. Upon completing the download of all one-star reviews, the Scraper application proceeds to the review page with two stars, continuing in this manner until reaching the review page with a five-star rating.

For the sake of streamlined maintenance, product purchase reviews are systematically recorded in a MySQL database. The selection of reviews from the total of 3,250 received was based on the following criteria:

1. Each product is ordered based on the most recent reviews and receives a maximum of one review for each number of stars that match the criteria.
2. Reviews with fewer than 100 characters are not used.
3. The reviews used are only those with tags.
4. Reviews containing simply emoticons or symbols are not permitted.
5. Reviews that simply contain the same one word are not used, for example "mantul mantul mantul mantul mantul mantul mantul mantul".
6. Comments that are not in the Indonesian vocabulary are not used, for example "urkbroekheueofnfbsheowmshsodbaegaefeafaf afafafaadadada"

Following the review selection, 260 reviews were identified as potentially valuable for dataset creation. The dataset underwent manual tagging by five correspondents, consisting of three Tokopedia consumers with experience in purchasing on the platform and two Tokopedia sellers. Each product's positive and negative reviews were appropriately labeled in the dataset.

Subsequently, the dataset underwent a cleaning and preparation process for analysis through pre-processing. The initial stage involved pre-processing without the application of an NLP technique, encompassing the elimination of emoticons and symbols, lowercase folding, and tag handling. The subsequent step involved pre-processing with a Natural Language Processing (NLP) approach to enhance the wording in the reviews. This decision was influenced by the observation that the reviews contained numerous instances of non-standard vocabulary and abbreviations. Natural Language Processing (NLP) is a field of Artificial Intelligence dedicated to the comprehension and manipulation of natural language, addressing the challenges posed by everyday conversational language in computer systems.

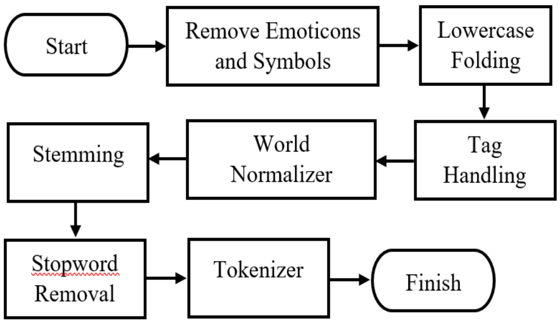

Figure 3. The pre-processing stage uses an NLP approach

Figure 3 illustrates the workflow of the pre-processing steps employing the NLP technique, with a detailed description of each stage as follows:

a. Emojis and Symbols Removal: Emojis and symbols were excluded from reviews as the study primarily focused on the language within them. Various symbols such as "", " "", "!", " $", "%", " ", " &", " *", " (", ")", " _", " - ", " +", " =", ":", "", " "", " ", " >", "comma", " period", "?", " /", "", " #", and " |" were removed. For instance, reviews containing symbols like "memuaskan banget kak :)" were processed to "memuaskan banget kak."
b. Lowercase Folding: Lowercase folding involved changing all letters to lowercase to ensure uniformity. For example, the comment "memuaskan banget kak" becomes "bagus banget sesuai pesanan" after the capital "B" is converted to lowercase "b."
c. Tag Handling: Review tags, provided by platforms like Tokopedia, were addressed. Reviews with tags had these tags added to become part of the review comment content. Examples of tags include "Kecepatan pengiriman sangat baik" and "Respon penjual sangat baik."
d. Word Normalizer: The Word Normalizer adjusted words in reviews to conform to Indonesian grammatical norms, enhancing clarity and meaning. For instance, "the item is really good" became "barangnya bagus banget" after the Word Normalizer process.
e. Word Normalizer (Enhanced): A repeated mention of the Word Normalizer, highlighting its role in adjusting words to generate

grammatically correct sentences based on Indonesian norms.

f. Stopword Elimination: Stopword removal involved deleting frequently occurring but unimportant words, such as "yang," "dan," "di," and "dari." This process ensured that only essential words remained. For example, "arang yang warna hijau dan biru bagus" was transformed to "barang warna hijau biru bagus."

g. Tokenizer: The tokenizer divided input text into an array of tokens, separating each token with a space. For instance, "barangnya bagus banget" became “barangnya,” “bagus,” “banget.”

The pre-processed dataset, both with and without the NLP technique, is partitioned into two segments, comprising 208 training data and 52 test data. Subsequently, the Term Frequency Inverse Document Frequency (TF-IDF) technique is applied for weighting. TF-IDF is employed to assess the significance of a word or term within the overall review. The frequency of a term's occurrence in a review indicates its importance in that particular review, aiding in the categorization of reviews into two groups, namely positive and negative reviews. The TF-IDF calculation is conducted using Equation 1.

$$w_{x,y} = tf_{x,y}\ x\ \log\left(\frac{N}{df_x}\right) \tag{1}$$

Where $w_{x,y}$ is the weight of the term (t_y) against the document (d_x). Meanwhile $tf_{x,y}$ is the number of occurrences of the term (t_y) in the document (d_x). N is the number of all documents in the dataset and dfx is the number of documents containing the term (t_y), at least one word, namely the term (t_y).

3. RESULT

3.1. List of Tokopedia Product Reviews

The reviews used were obtained from product review search activities in April 2023 on Tokopedia. Reviews are taken from best-selling products by searching using the keyword "Baju Gamis Muslim". Examples of reviews used are shown in Table 1.

Table 1. Example of a Product Review

No	Account	Review Contents	Review Tags	Star	Label
1	an***ow	Thank God the owner is kind, yes, even though I chatted for a while the reply took a while, I also understand because I wasn't the only one who bought it.	Product quality is very good.	5/5	Positive
2	na**ul	The sizes are not the same. Some are small, some are just right. Hmm, it's okay not to just give it 4 stars because the product is still not consistent.	Product quality is good.	4/5	Negative
3	gi***mi	It turns out to be really thin, huhuuu sad, but it's okay, it's okay for staying at home every day, I have to wear a lid that covers it if it's not transparent, maybe because of the price too...\n But the delivery is really fast..\n That's a plus or minus, guys..\n Happy shopping guys.	Standard product quality.	3/5	Negative

In Table 1, the anonymous account provided a review concerning the messaging service, expressing dissatisfaction with the number of items sent. However, the review tag indicated a very good product quality, accompanied by several 5/5 stars, resulting in a positive label. On the other hand, the named account wrote a review highlighting issues with the size, tagged the product quality as good with a rating of 4/5 stars, and received a negative label. This illustrates that the star rating alone does not consistently represent the comprehensive content of the review. A 5/5-star rating does not necessarily ensure complete satisfaction with all aspects of the received goods and services. The review tag feature offers buyers a more specific way to articulate the aspects they are evaluating. The insights gathered from these reviews can be utilized to implement improvements for the seller in subsequent transactions.

3.2. Review Analysis

The utilized dataset comprised 280 reviews, meticulously labeled by five correspondents, resulting in 135 positive reviews and 120 negative reviews. The dataset was structured with 200 training data and 55 test data, subsequently undergoing pre-processing through an NLP approach. During the pre-processing phase, word normalizer, stemming, and stopword removal features were implemented on each review. The word normalizer function addresses variations in written words that convey the same meaning, ensuring they are considered as a singular term. Examples of such variations are illustrated in Table 2.

Table 2. Variations in writing words in reviews that have the same meaning

No	Terms in Reviews	Word Normalizer	Number of Reviews
1	tidak	tidak	40
2	tdk	tidak	11
3	gak	tidak	33
4	g	tidak	7
5	tdak	tidak	1
6	ga	tidak	40
7	gk	tidak	10
8	banget	banget	28
9	bgt	banget	12
10	bget	banget	1

Table 2 presents word variations with identical meanings. Buyers employed the term "tidak" in 40 reviews and the word "gak" in 33 reviews as alternatives for "no." Furthermore, the term "bgt" appeared in 12 reviews, while "bget" emerged in 1 review, both instances where buyers substituted "banget" for "banget." A word normalizer is adept at handling diverse word forms within buyer reviews, unifying them into consistent terms. Subsequently, the dataset undergoes stemming to eliminate prefixes, insertions, and suffixes from words, ensuring they assume their base form for more efficient and effective information retrieval. Table 3 provides an illustration of stemming in action.

Table 3. Results of Applying Stemming

No	Terms In Reviews	Stemming	Number of Reviews
1	dikirim	kirim	24
2	dikirimkan	kirim	1
3	langganan	langgan	26
4	berlangganan	langgan	1
5	jahitannya	jahit	10
6	dijahit	jahit	2
7	penjahit	jahit	1
8	pesanan	pesan	23
9	memesan	pesan	1
10	dipesan	pesan	1

In Table 3, words in the review such as "dikirim" and "dikirimkan" are featured. Removal of prefixes, insertions, and suffixes reduces them to the base word "kirim". Similarly, words like "kahitannya," "dijahit," and "penjahit," after undergoing the stemming process, transform into the base word "jahit." Stemming standardizes the words in the review to their basic forms, ensuring consistency across terms. Subsequently, a stopword removal process eliminates stopwords from the review. The list of stop words used was compiled by me, considering the contextual usage of words in reviews and online buying and selling. An example of the stop words list is presented in Table 4.

Table 4. Example of a Stopword List

No	Stopword	Number of Occurrences
1	yang	214
2	di	104
3	tapi	92
4	dan	73
5	ya	62
6	juga	61
7	jadi	34
8	untuk	32
9	dengan	31
10	ke	22

Table 4 shows that the term "yang" is one of the most often occurring stopwords, appearing 214 times, and the word "di" appears 104 times. Numbers, in addition to words, are included in stop words. Numbers have no effect on sentiment analysis and can be eliminated, reducing noise and enhancing efficiency. Table 5 shows the total outcomes of the preprocessing process.

Table 5 displays product reviews subjected to pre-processing using an NLP approach with word normalization, stemming, and stopword removal features. One key metric for customer satisfaction is the product's performance meeting or exceeding customer expectations. This is gauged through reviews containing positively connotated words, as identified by correspondents labeling reviews with terms like "bagus" (good), "suka" (like), and "cepat" (fast).

Table 5. Pre-processing Results

No	Product Reviews	Pre-processing			Actual Label
		Word Normalizer	Stemming	Stopword Removal	
1	Thanks admin, the Muslim robe has arrived, it's nice even though it's a bit thin and a little see-through, but when you wear it it's not transparent at all.	Thank you admin, the Muslim robe has arrived, it's good, even though it's a bit thin and a little see-through, but if you wear it, I hope it won't be see-through	Thank you admin, the hijab has arrived, it's good, although it's a bit thin and a little revealing, but if you wear it, hopefully it won't show up.	Thank you admin, the Muslim gamis shirt arrived, nice and thin, worn transparently	Positive
2	The quality of the product is very good, the product is original, the speed of the product is very good, hopefully in the future it will be better and more trustworthy, good luck, amiiinnnn	product quality is very good, original product, product speed is very good, hopefully in the future it will be better and more trustworthy good luck amen	The product quality is very good, the original product is fast, the product is very good, hopefully the future will be better and trustworthy, God bless you, Amen	Good product quality, original product, fast, good product blessing trust	Positive
3	This is good, the brego is long at the front and back. Most annoyed, Brego is usually short in the back, I really like this one. The rope is thick. The stitching is good, but I still have to cut off the remaining threads.	This is good, the front and back are long, the most annoying bergo is usually short at the back, this one really likes the thick straps The stitching is good but I still have to cut off the remaining thread	This is good, the long front and back bergo is the most annoying, the regular bergo is short at the back, this one really likes the thick strap, the sewing is good, but I still have to cut off the remaining thread.	nice bergo sebel bergo like thick rope good sewing cut off excess thread	Positive

Conversely, dissatisfied customers express their discontent through reviews featuring negatively connotated words such as "tidak" (not), "kecewa" (disappointed), and "tipis" (thin). For instance, in review number 1, despite being labeled positive, the content criticizes the seller for describing the hijab material as "thin." This exemplifies that assigning a high star rating does not invariably capture the entirety of a buyer's sentiment. Some buyers may be dissatisfied with specific features while content with others, allowing room for improvement and still assigning a high star rating.

3.3. KNN Calculation Using TF-IDF

To classify reviews, the KNN algorithm with k=3 is employed in this study. The application of KNN to assess the weight or relevance level of a word in a review is substantiated by TF-IDF. TF-IDF calculations were executed on 208 training data and 52 test data in their raw form after pre-processing with and without the NLP technique. The number of matches in the labeling outcomes from the 52 test data predictions was subsequently computed and juxtaposed with manual labeling by the correspondent using a confusion matrix. The confusion matrix categorizes scenarios as follows: True Positive (TP) denotes the quantity of data with a positive class and correct prediction results; False Positive (FP) signifies the amount of data with a negative class and incorrect predictions; True Negative (TN) represents the amount of data with a negative class and correct prediction results; False Positive (FP) indicates the amount of data with a positive class but incorrect predictions; and False Negative (FN) illustrates the amount of data with a negative class but incorrect predictions. Table 6 displays the prediction outcomes.

Table 6. Confusion matrix results of test data with and without NLP pre-processing

Clarification Results	No Pre-processing	With Pre-processing
True Positif (TP)	20	20
True Negatif (TN)	16	20
False Positif (FP)	5	5
False Negatif (FN)	11	7

The confusion matrix findings are subsequently calculated to derive accuracy, precision, and recall levels. Accuracy is defined as the ratio of correctly identified samples to the total number of samples; accuracy is computed using Equation 2. Precision is defined as the proportion of correctly identified positive samples to the total number of positive samples anticipated. Precision is determined using Equation 3. The recall is defined as the proportion of positive samples properly identified to the total number of positive samples; recall is computed using Equation 4.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (4)$$

$$Precision = \frac{TP}{FP+TP} \quad (5)$$

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

Equations 2, 3 and 4 are applied to the test results of two test data conditions, namely without the NLP approach and with the NLP approach, the comparison results obtained are shown in Table 7.

Table 7. Test Results With and Without NLP Pre-processing

Test Result	Without Preprocessing	With Pre-processing
Accuracy	75,25%	80,92%
Precision	82,00%	85,00%
Recall	70,45%	78,00%

The test results in Table 7 demonstrate that classification through pre-processing without the NLP approach has an accuracy of 69.23%, but classification through pre-processing with the NLP technique has an accuracy of 76.92%. Both datasets have the same precision, which is 80.00%. The data recall value after pre-processing without NLP is 64.52%, but it increases to 74.07% after pre-processing with NLP. Overall, classification scores on data that has been pre-processed using the NLP approach have improved. The use of pre-processing with NLP allows for the conversion of non-standard terms and abbreviations into uniform ones, making the use of word weighting and computing the frequency of occurrence of words that are already uniform with TF-IDF more effective.

4. DISCUSSION

A previous study [32] explored sentiment analysis on Twitter, employing the K-Nearest Neighbors (KNN) algorithm and Term Frequency-Inverse Document Frequency (TF-IDF) technique, achieving a modest accuracy of 67.2%. In contrast, the current investigation significantly enhances this accuracy to 76.92%. The comparatively lower accuracy in the earlier research is attributed to the omission of a word normalizer. This oversight led to the inadequate handling of non-standard words, typographical errors, and the prevalent use of abbreviations in Twitter users' language, impacting the accuracy of sentiment classification. Meanwhile, another study [33] investigated the application of Deep Sentiment Analysis on open assessment questionnaires using KNN, recording a precision of 59.4%. However, in this current investigation, an impressive precision rate of 80% was attained. This was demonstrated through the system's ability to accurately predict the sentiment of 40 out of 52 reviews tested. These results underscore the importance of algorithmic refinement and context-specific adaptations in enhancing the precision of sentiment analysis tools.

In a notable study [34], text mining techniques were employed to gauge social media sentiment towards Hybrid Lectures. The findings revealed a diverse range of responses: 30% of sentiments expressed were positive, 20% neutral, and a significant 50% were negative. This data highlights varied public perceptions towards the concept of Hybrid Lectures. Additionally, another research endeavor [36] adopted the Term Frequency-Inverse Document Frequency (TF-IDF) method for feature extraction in tandem with the K-Nearest Neighbor (KNN) algorithm, using cosine similarity for calculating the nearest neighbor distance. This methodology was applied for the classification of text in applicant interviews. The outcome of this approach was noteworthy, as the KNN algorithm demonstrated considerable effectiveness, yielding an average accuracy of 65.2%. These results are indicative of the potential of KNN, especially in conjunction with TF-IDF, for nuanced text analysis tasks such as sentiment analysis and text classification in diverse contexts. This study not only underscores the versatility of KNN but also sheds light on the evolving landscape of sentiment analysis in educational and professional settings.

5. CONCLUSION

Sentiment analysis of product review content can unveil valuable insights into purchasers' opinions regarding products available on the Tokopedia marketplace. The application of Natural Language Processing (NLP) methods with KNN Calculation using TF-IDF in data pre-processing is pivotal to enhance classification accuracy. The Word Normalizer tool is instrumental in rectifying non-standard terminologies and abbreviations commonly employed in reviews, such as "tdk," “gak,” “g,” “tdak,” “ga,” dan “gk,” which might be erroneously interpreted as the word "no." Additionally, the utilization of Stemming and Stopword elimination features proves beneficial in further improving classification accuracy. Incorporating these three features yields accuracy values of 80.92%, precision values of 85.00%, and recall values of 78.00%, surpassing the results of the previous classification that did not involve NLP features, achieving only 75.25% accuracy, 82.00% precision, and 70.45% recall.

This study identified key terms in positive reviews such as "bagus,” “suka,” “cepat,” “banget,” “harga,” and “barang,” suggesting favorable feedback from purchasers on the quality of goods, prompt delivery, and pricing of the products. Conversely, dominant terms in negative reviews include "tidak,” “warna,” “kirim,” “kecewa,” and “pesan,” indicating unfavorable feedback on Muslim gamis clothing products, particularly concerning color discrepancies and issues related to quantity or specifications. The insights derived from this study can be integrated into marketing analysis systems, enabling the extraction of valuable information from marketplace reviews to assist sellers in enhancing their products and services.

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