Journal of Artificial Intelligence and Engineering Applications

Website: https://ioinformatic.org/

15th February 2026. Vol. 5. No. 2; e-ISSN: 2808-4519

Sentiment Analysis of Honda Esaf Frame Quality Based on Reviews on Platform X Using Support Vector Machine Algorithm

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Abstract

This study analyzes public sentiment towards Honda's eSAF frame through 1513 reviews on Platform X during the period of January 2023-October 2025, which was triggered by crucial issues related to the potential for rust, corrosion, and fracture in motorcycle frames. Using a quantitative method with a computational approach, this study applies the Support Vector Machine (SVM) Algorithm with data preprocessing (Case Folding, Cleaning, Tokenizing, Stopword Removal, Stemming), TF-IDF weighting, and Lexicon-based sentiment labeling to classify positive and negative perceptions. The evaluation results show that the SVM-TF-IDF model achieved 98% accuracy on the test data, with negative sentiment dominated by the keywords "rust" and "damaged", while positive sentiment centered on "strong" and "safe", providing an objective picture of public perception as a basis for evaluating product quality and improving corporate communication strategies.

Keywords: *Analisis Sentimen, Rangka eSAF Honda, Support Vector Machine, TF-IDF, Lexicon-Based*

1. Introduction

Social media is a platform that allows users to interact, share, and build social bonds online [1]. These social media platforms provide a space for the public to openly express opinions, including complaints about the quality of Honda's eSAF frame, which has been widely discussed since 2023 due to its potential for rust, corrosion, and damage. As a key component of a motorcycle, the frame supports various components, requiring careful strength calculations for rider safety [2]. The numerous complaints, particularly regarding Platform X, have led to a lack of trust in some models, such as the Vario 160.

Sentiment analysis is a method for identifying public opinion by classifying text into positive and negative categories [3]. In this study, this technique was used to evaluate public perception of Honda's eSAF chassis based on reviews on Platform X. The SVM method was chosen because of its ability to find the optimal hyperplane to separate sentiment classes and handle non-linear data through kernels [4]

Platform X has a large automotive community, where posts about the eSAF chassis, often accompanied by photos or videos of damage, generate intense discussion. This phenomenon underscores Platform X's relevance as a significant data source, in line with its nature as a medium for conveying ideas and expressing individual sentiments [5]. Through sentiment analysis, dominant complaint patterns can be identified, allowing the company to gain a better understanding of aspects that require improvement.

The use of SVM is further enhanced by its ability to process large amounts of text data, especially when combined with the TF-IDF technique, which assigns weights based on the frequency of term occurrence [6]. By analyzing comments from Platform X, this study provides an objective picture of public perception of the eSAF framework, which can serve as a basis for Honda's evaluation to improve product quality and communication strategies. This approach also contributes to academic studies on the application of sentiment analysis in the context of social and technological issues.

2. Main Body

This research is quantitative with a computational experimental approach, which focuses on analyzing and measuring the performance of the Support Vector Machine (SVM) algorithm in classifying sentiments related to eSAF frames on Honda motorcycles using data from

Platform X. The SVM algorithm functions to determine the optimal separator function to separate two groups of objects, and in the context of sentiment analysis, this method has proven effective due to its ability to optimally group text data into specified categories. Thus, the entire classification process in this study relies entirely on the application of the SVM algorithm [7]. The following stages of the research method are shown in Figure 1.

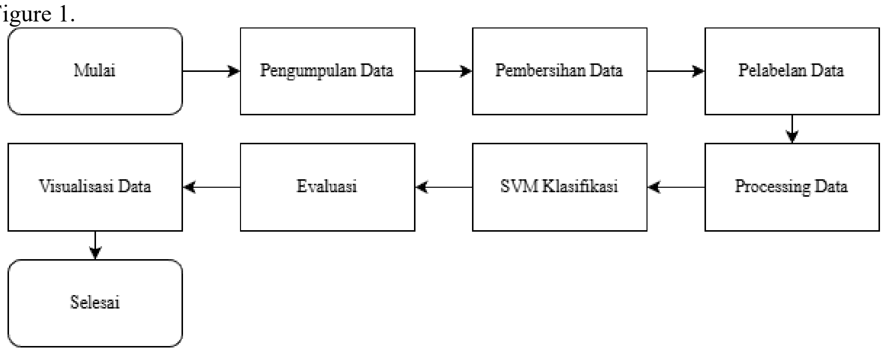

Fig. 1: Stages of Research Methods

Figure 1 illustrates the flow of the research method used. The initial stage began with data collection through Google Colab connected to social media X using the keyword 'esaf' to collect a collection of reviews. After that, the data cleaning stage was carried out, namely removing irrelevant elements through several steps such as removing URLs, account tags (@username), various symbols, and adjusting spacing (trimming). Next, the data was labeled with sentiment as the basis for machine learning for the classification process. The cleaned data was then further processed through the stages of case folding, tokenizing, stopword removal, and token filtering, then divided into training data and test data. In the classification stage, the Support Vector Machine (SVM) algorithm was used with TF-IDF-based feature representation to separate positive and negative reviews. The final step was evaluation and visualization, where model performance was measured by metrics such as accuracy, precision, and recall, while also displaying the most frequently appearing words in the Honda eSAF frame review dataset.

2.1. Research Object

The main object of this research is the sentiment analysis of reviews and public opinions regarding the eSAF frame on Honda motorcycles, which are systematically collected through Platform X. The data used include comments, reviews, and posts that represent positive and negative perceptions of the eSAF frame.

2.2. Preprocessing

Data preprocessing is a crucial initial stage in machine learning and data analysis workflows, involving processing raw data to improve its quality to meet the requirements of machine learning models [8]. The sequential steps implemented in this study include

2.2.1. Case Folding

In the case folding stage, all characters in the tweet data are converted to lowercase. This formatting standardization is implemented to ensure more consistent classification and simplify subsequent text processing [9].

2.2.2. Cleaning

Cleaning is the step of cleaning a data set by searching for, then correcting or deleting entries that are incorrect, incomplete, or no longer needed so that only valid data is kept for analysis [10].

2.2.3. Tokenizing

Tokenization refers to the process of breaking text into smaller pieces, such as words or phrases. These smaller units are then used as the basis for various subsequent stages of text analysis [11].

2.2.4. Stopword Removal

Stopwords are words with very little information value related to the research problem, usually functional words such as prepositions or conjunctions. Therefore, a specific stopword list has been compiled that can be tailored to the characteristics of the data. Examples of stopwords in English include "the," "a," "when," "is," and so on [12].

2.2.5. Stemming

Stemming is done by removing word forms that do not contribute to important meaning and returning them to their basic form, for example removing common words such as "dan", "yang", or "di" in Indonesian texts [13]

2.3. Labeling

The labeling stage involves assigning class labels to each piece of data based on the intrinsic characteristics of the sentences in the dataset. A lexicon-based approach is applied, where preprocessed data is classified as positive or negative based on the polarity scores of the lexicon used [14].

2.4. Term Frequency-Inverse Document Frequency

Term weighting is a crucial process for optimizing sentiment analysis capabilities in text mining. This study adopted the Term Frequency-Inverse Document Frequency (TF-IDF) method. Term Frequency (TF) represents the proportion of word relevance based on its frequency of occurrence in documents, while Inverse Document Frequency (IDF) monitors the distribution of tokens across a text corpus [15].

2.5. Evaluation

Model evaluation is a fundamental step in the data analysis cycle, evaluating model performance using standard metrics to ensure high accuracy and reliable predictions on previously unseen data [2]. This process allows for the identification of model strengths and weaknesses, while supporting decision-making for iterative improvement. This study applied three main metrics: Precision, Recall, and Accuracy, with the following calculation formula:

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

2.6. Results and Discussion

The results and discussion represent the solutions and outcomes obtained from the research. This study used crawled data from a social media platform named "X," which generated 1,513 tweets with the keyword "eSAF Framework" from January 1, 2023, to October 31, 2025. The data was processed to form public sentiment towards the eSAF framework using the following steps.

2.6.1. Data collection

Data collection is the process of gathering or searching for data. The data collection technique used in this study is crawling using the Python library tweet-harvest. The brief flow is as follows:

Fig. 2: Data Crawling Flow

Figure 2 illustrates that data collection through crawling aims to obtain a Twitter Authorization Token (the token must not be shared). This process uses Google Colab with the Python library. The crawl results are then generated in a CSV file as shown below.

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	conversation_id_	created_at	favorite_	full_text	id_str	image_url	in_reply_	lang	quote_co	reply_cou	retweet_c	tweet_url	user_id_s
2	1,98E+18	Thu Oct 30 0	156	Tangki bensin motor Yamaha dan SuzukiÂ bisa tahan etanol hingga 10% (E10) Hati-l	1,98E+18	https://pbs.twimg.c		in	3	7	59	https://x.	7,95E+17
3	1,98E+18	Wed Oct 22 1	0	@kaambing Sama aja bang mereka kan kartelan tapi kalau mau Honda jangan beli y	1,98E+18		kaambin	in	0	1	0	https://x.	3,8E+09
4	1,98E+18	Sun Oct 12 1	2	@SammiSoh Yamaha lah ketiban rezeki dari longornya rangka eSAF Honda beat	1,98E+18		SammiS	in	0	0	0	https://x.	1,71E+18
5	1,98E+18	Sat Oct 11 12	86	Pembeli cerdas tidak akan membeli lagi motor merk Honda Pengkhianatan Honda	1,98E+18	https://pbs.twimg.c		in	3	11	26	https://x.	7,95E+17
6	1,98E+18	Thu Oct 09 0	6	@meutiafaradilla Rangka esaf Honda sama BBM oplosan Pertamina juga awalnya c	1,98E+18		meutiaf	in	0	1	1	https://x.	1,65E+08
7	1,98E+18	Tue Oct 07 0	0	@tanyakanrl Buat gen sekarang gw ngindarin Honda rangka eSaf sih jujur-jujuran w	1,98E+18		tanyakar	in	0	0	0	https://x.	8,74E+17
8	1,98E+18	Mon Oct 06 0	0	@Sigiter @innovacommunity Semoga aja hoax pertamina kan penggunaannya pul	1,98E+18		Sigiter	in	0	0	0	https://x.	1,92E+18
9	1,97E+18	Thu Oct 02 0	0	@Big_Edik @Ary_PrasKe2 Gugat Pertamina? kasus Honda rangka ESAF aja apa ada y	1,97E+18		Big_Edik	in	0	0	0	https://x.	1,05E+18
10	1,97E+18	Tue Sep 30 1	0	@febrisc rangka esaf noh kaya produk honda	1,97E+18		febrisc	in	0	0	0	https://x.	1,34E+18
11	1,97E+18	Tue Sep 30 0	0	@haawtmilf Gini saja. Kalau km beli baru untuk Honda yg make rangka ESAF sebaik	1,97E+18		haawtmi	in	0	1	0	https://x.	1,25E+18
12	1,97E+18	Mon Sep 22	0	Minggu lalu temen sekolah nawarin service motor honda gratis dari Ahas dan dape	1,97E+18	https://pbs.twimg.c		in	0	0	0	https://x.	2,13E+08
13	1,97E+18	Sat Sep 13 0	0	@tralaw666 Rangka esaf honda inovatif memang	1,97E+18		tralaw66	in	0	0	0	https://x.	9,37E+17
14	1,97E+18	Sat Sep 13 0	0	@SosmedAnu Kasihan Honda kena serang mulu. Rangka eSAF udah bagus loh lur	1,97E+18		Sosmed/	in	0	0	0	https://x.	1,71E+18
15	1,97E+18	Tue Sep 09 1	1	@icantikmu Honda 160 sampah semua apalagi pake rangka esaf	1,97E+18		icantikm	in	0	0	0	https://x.	1,72E+18
16	1,96E+18	Sat Sep 06 1	1	@SajakNaira @UHarahap4 @pale_arte @tanyakanrl Motor honda keluaran 2019 ke	1,96E+18		SajakNai	in	0	2	0	https://x.	1,39E+18
17	1,96E+18	Sat Sep 06 14	3	@pale_arte @tanyakanrl Kalau metic baru jgn beli yg rangka esaf(beat Scoopy yg h	1,96E+18		pale_art	in	0	1	0	https://x.	1,75E+18
18	1,96E+18	Mon Aug 18	0	@sbyfess Jangan yang rangka esaf yang penting nder. Ya nek honda paling opsinya	1,96E+18		sbyfess	in	0	0	0	https://x.	4,37E+08
19	1,96E+18	Fri Aug 15 12	0	REVIEW Foto Honda Stylo 160 ABS Warna Biru Doff Terbaru 2025 Rangka Unde... htt	1,96E+18			in	0	0	0	https://x.	1E+08
20	1,96E+18	Thu Aug 14 1	1	seorang sales gak akan ngomong hal2 negatif tentang produk yang lagi dia jual! bay	1,96E+18			in	0	2	2	https://x.	2,34E+09
21	1,96E+18	Thu Aug 14 0	0	@haawtmilf Kalau km tipe yg malas merawat hindari Yamaha. Bukan mudah rewel	1,96E+18		haawtmi	in	0	0	0	https://x.	1,25E+18
22	1,96E+18	Wed Aug 13	0	@haawtmilf Honda lebih tahan disiksa. Kalo gak telaten ganti oli better pilih Hond	1,96E+18		haawtmi	in	0	0	0	https://x.	4,41E+08
23	1,96E+18	Wed Aug 13	0	@haawtmilf Honda beat Scoopy Genio Vario yg pake rangka esaf rawan patah tiba	1,96E+18		haawtmi	in	0	0	0	https://	3,26E+09

Fig. 3: Crawling Results

2.6.2. Preprocessing

Preprocessing is the initial stage of data processing, including letter folding, cleaning, tokenization, keyword removal, and stemming. Here's an example sentence that has gone through these initial stages.

Table 1: Preprocessing example in the form of case folding

Before	After

@kaambing Sama aja bang mereka kan kartelan tapi kalau mau Honda jangan beli yang rangka esaf	@kaambing sama aja bang mereka kan kartelan tapi kalau mau honda jangan beli yang rangka esaf

Table 1 is a folding case where all capital letters will be made into lower case.

Table 2: Preprocessing example in the form of cleaning

Before	**After**
@kaambing sama aja bang mereka kan kartelan tapi kalau mau honda jangan beli yang rangka esaf	sama aja bang mereka kan kartelan tapi kalau mau honda jangan beli yang rangka esaf

Table 2 is data cleaning, namely removing symbols such as @, URLs, and irrelevant characters.

Table 3: Preprocessing example in the form of tokenizing

Before	After
sama aja bang mereka kan kartelan tapi kalau mau honda jangan beli yang rangka esaf	"sama, aja, bang, mereka, kan, kartelan, tapi, kalau, mau, honda, jangan, beli, yang, rangka, esaf"

Table 3 is the stage of separating words one by one.

Table 4: Preprocessing example in the form of stopwords removal

Before	After
"sama, aja, bang, mereka, kan, kartelan, tapi, kalau, mau, honda, jangan, beli, yang, rangka, esaf"	"sama, aja, bang, mereka, kartel, tapi, kalau, mau, honda, jangan, beli, yang, rangka, esaf"

Table 4. is a removal of stopwords or prepositions or irrelevant words.

Table 5: Preprocessing example in the form of stemming

Before	**After**
"sama, aja, bang, mereka, kartel, tapi, kalau, mau, honda, jangan, beli, yang, rangka, esaf"	"bang, kartel, beli"

Table 5 is the result of the final stage of preprocessing, namely stemming or removing words that have unimportant meaning.

2.6.3. Labeling

Data obtained from crawling is unlabeled, so this study labeled the data using lexicon-based labeling. Lexicon-based labeling separates negative and positive words, with results influenced by the number of positive and negative words in a sentence.

Table 6: Labeling Example

Full_Text	**Label**
@babegini @kegblgnunfaedh Ettdah kena air laut?? Org gila mana yg bawa motor masuk berendem ke laut???? Kena angin laut terus2an emangnya satu kota gak ada yg kena angin laut?! Kenapa cm honda doank dgn rangka esaf nya yg keropos&amp	Negatif
@SosmedAnu Kasihan Honda kena serang mulu. Rangka eSAF udah bagus loh lur	Positif

Table 6 is an example of negative and positive labeling. This labeling uses simple logic: if a word is positive, it adds 1 point, and if it is negative, it subtracts 1 point. This calculation uses scores: if the score is greater than 0, it is positive, and if it is less than 0, it is negative. The code example is shown in the figure below.

```python
positive_words = set(open("positif.txt").read().split())
negative_words = set(open("negatif.txt").read().split())

def lexicon_label(text):
    score = 0
    for word in text.split():
        if word in positive_words:
            score += 1
        elif word in negative_words:
            score -= 1

    if score > 0:
        return "positif"
    else:
        return "negatif"

df["label"] = df["clean"].apply(lexicon_label)
df.head()
```

Fig. 4: Simple Logic of Labeling

2.6.4. TF-IDF

Term Frequency-Inverse Document Frequency is a weighting method in the Support Vector Machine algorithm. Processing results using the Support Vector Machine algorithm and weighting using TF-IDF produce good accuracy, precision, recall, and F1 scores.

```
Accuracy : 0.9802631578947368
Precision: 0.9798088972431078
Recall   : 0.9802631578947368
F1-Score : 0.9799037917374079
```

Fig. 5: Processing results using TF-IDF

Figure 5, gives satisfactory results because it gets above 95% for all of them.

2.6.5. Evaluation

After processing the data using the Support Vector Machine algorithm and weighting with TF-IDF, the advantages and disadvantages of this processing can be identified.

```
Classification Report:
              precision    recall  f1-score   support

     negatif       0.99      0.99      0.99       139
     positif       0.92      0.85      0.88        13

    accuracy                           0.98       152
   macro avg       0.95      0.92      0.93       152
weighted avg       0.98      0.98      0.98       152
```

Fig. 6: SVM Classification Results

Figure 5 shows that classification using the SVM algorithm yielded satisfactory results with 98% accuracy on 152 test datasets. However, this classification showed a significant imbalance between negative and positive labels, with only 13 positive labels.

2.6.6 Visualization

Visualization is a place to see data more easily by visualizing it in the form of images like image 7 below.

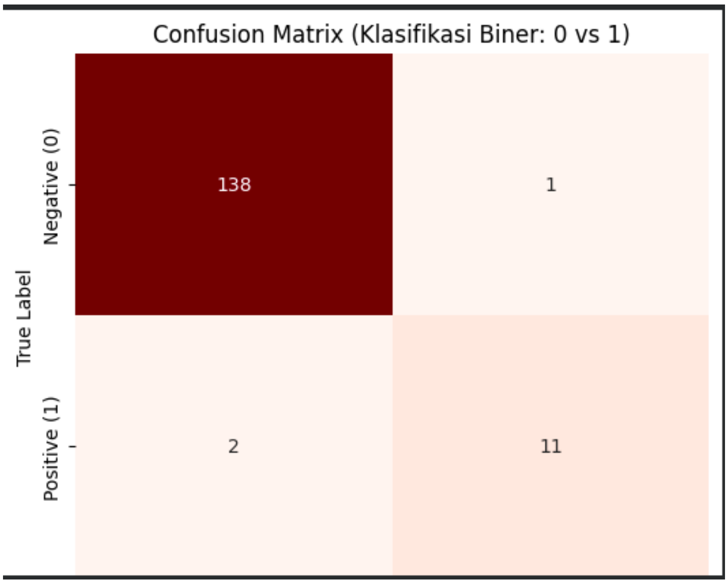

Fig. 7: Confusion Matrix Classification

Figure 7 shows that the following results provide good accuracy because the prediction and actual are the same while the error in prediction is only 1 or 2 data.

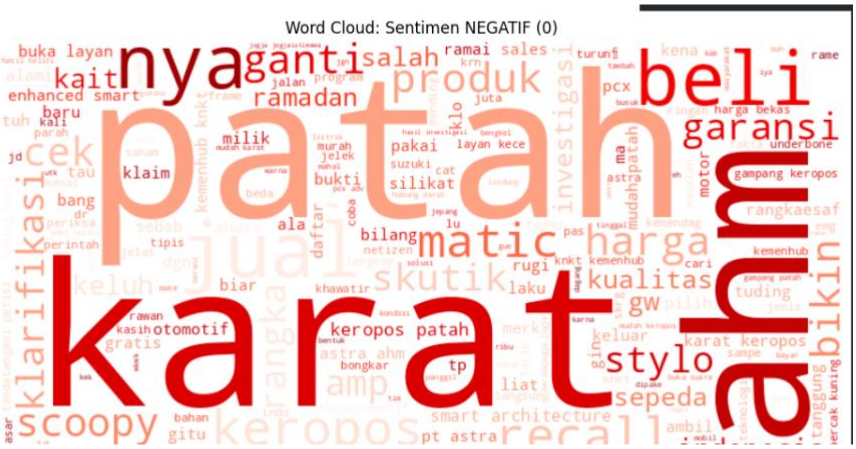

Fig. 8: Negative sentiment word cloud

Figure 7 shows the negative words that frequently appear in the data set. As can be seen, the most common negative words are “karat” and “patut,” as both words were popular during the study.

Fig. 9: Positive Word Cloud

Figure 9 shows the results of the emergence of positive words such as strong and safe which are very prominent in the positive Word Cloud.

3. Conclusions

3.1. Conclusions

Based on the results of sentiment analysis conducted on 1513 reviews regarding the quality of Honda's eSAF frame on Platform X, it can be concluded that the application of the Support Vector Machine (SVM) Algorithm combined with Term Frequency-Inverse Document Frequency (TF-IDF) weighting is an effective method for sentiment classification, as evidenced by the high model accuracy reaching 98% on test data. Substantively, this study identified that the dominant negative sentiment in the community was driven by concerns about problems such as rust and damage, while positive sentiment tended to be connected to the perception that the frame was strong and safe. This study makes a significant practical contribution, providing objective data on public perception that can be used as a basis for in-depth evaluation by manufacturers to improve product quality, as well as planning more appropriate and targeted communication strategies to restore consumer confidence.

3.2. Suggestions

Although this study achieved high accuracy in sentiment classification, there are several areas for future research to improve. First, further exploration of the data imbalance identified in the classification results, where positive labels account for only 13 of the 152 test datasets, is needed. Resampling techniques such as SMOTE (Synthetic Minority Oversampling Technique) or ensemble learning methods could be considered to address classification bias. Second, future research could compare the performance of SVM with other machine learning algorithms such as Random Forest, Naive Bayes, or Deep Learning (LSTM, BERT) to evaluate which method is most optimal in the context of automotive product sentiment analysis. Third, this analysis could be extended by adding neutral sentiment classification to provide a more comprehensive picture of public perception. Fourth, the application of aspect-based sentiment analysis is recommended to specifically identify which components or features of the eSAF framework are most problematic or most appreciated by consumers. Finally, longitudinal research with a longer and continuous data collection period could be conducted to monitor changes in public sentiment as companies improve their products, allowing for empirical evaluation of the effectiveness of improvement strategies.

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