

## 1. Introduction

Social media has become the main platform for sharing activities and expressions in daily life. One of the most popular social media, Twitter, now called X, is often used to discuss current issues. The conversations made by X users when giving a review or opinion have various emotions, such as anger, sadness, fear, or joy [1]. Identifying emotions on social media is critical to understanding user interactions, improving user experience, shaping public policy and refining business strategies [2].

Emotions have an essential role in understanding human expression. In the context of sentiment analysis, the feelings felt at that moment can also be one of the indicators to measure people's response to an issue [3]. These feelings appear in different conditions, such as happy, fear, anger, and sadness. The conditions experienced affect how people think and act, resulting in certain expressions [4]. This shows how important it is to accurately detect and classify such expressions in texts, especially in social media [5]. Emotions coming from texts are difficult to understand. So, further text processing techniques are needed, namely text mining methods, to extract unstructured words and create machine learning models that can classify emotions more quickly [6]. The selection of the right algorithm will significantly affect the results of sentiment analysis, especially in the context of complex text. Besides the algorithm, preprocessing and selection of extraction features also greatly affect the classification results [7].

Preprocessing cleans the raw text by handling informal language, misspellings and removing irrelevant symbols that are often found in posts [8]. For example, in the context of Bahasa Indonesia, preprocessing must handle the diversity of languages and informal expressions that often appear in social media data. Feature extraction techniques, such as Bag of Word (BoW), term frequency-inverse document frequency (TF-IDF), and Word2Vec, transform textual data into numerical representations that machine learning algorithms can process. While BoW captures word frequency [9], TF-IDF emphasizes word importance in the dataset (Haya et al., 2024) [10], and Word2Vec provides semantic relationships between words [11]. These steps significantly impact model performance by enhancing the quality of the input data [12].

Naive Bayes is a popular algorithm due to its simplicity and speed in processing text data. However, this algorithm is less effective when dealing with datasets that have too many features, which can cause its accuracy to decrease [3]. Compared to Naive Bayes, SVM often provides better accuracy in processing text data because SVM can analyze patterns well, so SVM is effective in analyzing sentiment [13]. Although SVM excels in accuracy, Naive Bayes also has the advantage of coping with large datasets with independent features, where Naive Bayes efficiently enables fast processing without requiring large resources [14]. Naive Bayes is often used for simple text analysis such as spam email classification, where the features are independent and the complexity is low [15].

In a study conducted by Sarimole & Kudrat, 2024 [16] who compared the performance of SVM and Naive Bayes. Their research resulted in SVM accuracy of 87.95% and Naive Bayes of 65% on 1081 total data and using TF-IDF extraction features. The results of their study indicate that SVM has superior performance compared to Naive Bayes. Then in research conducted by Supian et al., 2024 [17], SVM is also superior to 94% compared to Naive Bayes which is only 91% in analyzing sentiment about the National Capital on twitter which has 2,130 total datasets. In their study using TF-IDF for feature extraction. Datasets in their study go through several preprocessing stages, namely cleansing, case folding, tokenizing, stopword removal, stemming, and normalization. Both studies used the TF-IDF feature because of its ability to emphasize words that are relevant in a particular context, reduce the influence of common words, and provide a more informative representation of the text to improve the model's ability to detect emotional patterns.

This research was conducted to overcome the shortcomings of previous research. As in the research conducted by Supian et al., 2024 [17] where their research only focuses on TF-IDF extraction features so that it is less illustrated if using other extraction features. Then in the research conducted by Sarimole & Kudrat, 2024 [16] which is less than optimal in handling the complexity of social media text, such as slang, hashtags, or emojis, which can affect sentiment classification accuracy. Both studies also did not discuss what parameters and kernels were used. This research aims to explore some important aspects that were not discussed previously, namely the effect of preprocessing on the final result, the performance of various feature extraction methods and the impact of parameters on the performance of classification models. In addition, this research will also compare the performance of Naïve Bayes and SVM algorithms in classifying emotions into four classes using the most optimal parameters. The findings of this research are expected to provide insights for building optimal models in analyzing emotions, and checking mental health through posts.