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Sentiment Analysis of Suicide on X Using Support Vector Machine and Naive Bayes Classifier Algorithms

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Abstract—Background: The World Health Organization (WHO) defines health as a state of physical, mental, and social well-being, not just the absence of disease. Mental health, essential for overall well-being, is often neglected, leading to disorders like depression, a major cause of suicide. In Indonesia, suicide cases have surged, with 971 reported from January to October 2023. **Objective**: This study aims to analyze public sentiment regarding the rise in suicide cases in Indonesia using sentiment analysis methods, specifically Support Vector Machine (SVM) and Naive Bayes Classifier (NBC). The findings are expected to raise public awareness and provide policy recommendations to support mental health initiatives. **Methods**: One method used to understand public perception regarding the issue of suicide is text mining. This research employs text mining techniques with the Support Vector Machine (SVM) and Naive Bayes Classifier algorithms to analyze public sentiment related to suicide cases in Indonesia. Data was collected from tweets on social media platform X using crawling methods with snscrape and Python, totaling 1,175 tweets. **Results**: The results indicate that the Linear SVM model achieved higher accuracy than Naive Bayes in classifying tweet sentiments, with an accuracy rate of 80%. **Conclusion**: The SVM algorithm with a linear kernel achieved 80% accuracy and an identical ROC-AUC score. Word cloud visualization highlighted terms like "kill," "self," "depression," and "stress" as key negative sentiments. This study aims to raise public awareness and support better mental health policies in Indonesia.

Keywords—Suicide Awareness; Sentiment Analysis; Text Mining; Support Vector Machine; Naive Bayes Classifier

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I. INTRODUCTION

The World Health Organization (WHO) states that health is the well-being of the body, mind, and social aspects, which goes beyond merely the absence of illness or physical weakness [1]. Health is defined not only as physical health but also encompasses psychological health. Mental health refers to a state where a person enhances their ability to interact with their environment and is able to fully develop their physical, mental, and emotional aspects in harmony with their surroundings [2], [3]. To create a harmonious balance that is free from anxiety, fear, restlessness, and inner conflict (self-confrontation), all elements of human psychology, such as thoughts, feelings, desires, attitudes, perceptions, visions, and beliefs, must be aligned with one another [4].

Mental health is an important aspect of a person's well-being, yet it is often neglected or underestimated. Research shows that excessive stress and chronic anxiety can lead to mental disorders such as depression and generalized anxiety disorder [5]. A number of scientific publications indicate that mental illness or depression is a contributing factor to suicide, with one of the reasons for suicide being severe depression. However, few studies have explored public sentiment regarding suicide cases in Indonesia, particularly through text mining techniques like SVM and NBC. A distorted self-concept that makes a person feel unloved, unwanted, and worthless is the root cause of depression [6]. Someone with depression may experience long-term discomfort, emotional instability, hopelessness, and altered mental processes that affect all aspects of thinking, feeling, and acting. Suicide is one of the possible outcomes of these unpleasant feelings and potentially harmful thoughts [7].

Based on information from the National Criminal Information Center (PUSIKNAS) of the Indonesian National Police (POLRI), a total of 971 suicide cases were recorded in Indonesia between January and October 2023. This figure has surpassed the 900 cases recorded in 2022. Statistics from the Indonesian National Police also show an increase in suicide cases from December 2018 to July 2023, as shown in Figure 1. The number of suicide cases increased by 31.7% between January to July 2023 in comparison to the same timeframe last year, with 640 cases recorded from January to July 2023, compared to 486 cases in 2022 [8].

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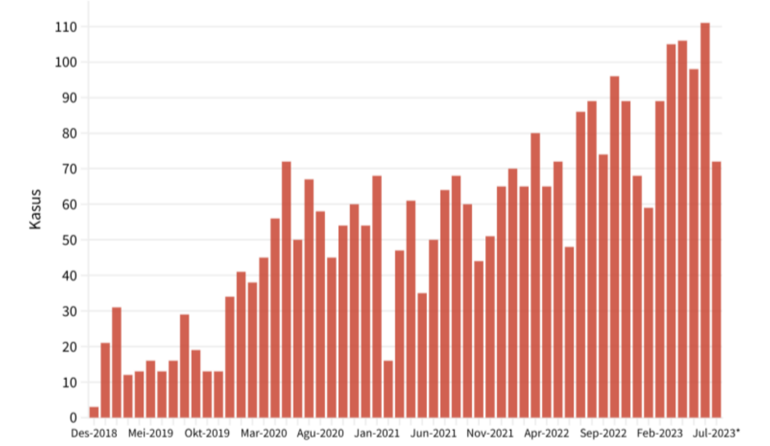

Fig 1. The Number of Suicide Cases in Indonesia from December 2018 to July 2023

According to a news article from CNN Indonesia on June 18, 2024, numerous suicide incidents have occurred in Indonesia since the beginning of 2024. One such case took place on April 27, 2024, when Brigadier RA allegedly committed suicide by crashing his car into another vehicle in the Mampang area, South Jakarta. This case adds to the growing list of suicide incidents among police officers, highlighting the importance of psychological support for those in service. Additionally, there was a tragic family suicide in North Jakarta on March 9, 2024. This incident involved four family members who jumped from the 22nd floor of the Teluk Intan Apartment. The case drew attention as it was seen to reflect the state's neglect of its citizens' welfare and mental health issues.

To analyze public perception regarding the rise of suicide cases in Indonesia, one of the methods that can be used is text mining. Text mining is one of the methods used for handling classification, clustering, information extraction, and information retrieval. The difference from data mining is that text mining derives patterns from unstructured natural language data, while data mining derives patterns from structured databases [9], [10], [11]. Sentiment analysis is a computational study to analyze emotions expressed in written text and opinions [12]. Its goal is to identify whether a person’s opinion or sentiment toward a certain issue or object is positive or negative [13].

Previous research has laid the groundwork for further analysis. For example, studies on mental health issues have been conducted by Aulia [14] and Pangestu [15]. [14] classified tweet data regarding the stigma surrounding health issues in society, using the Naive Bayes Classifier to categorize sentiments and emotions. The results of the experiment showed that positive sentiment dominated. Furthermore, [15] conducted a study was carried out to analyze public sentiment about mental health during the COVID-19 pandemic, focusing on posts from the social media platform X. Results indicated that the SVM using a polynomial kernel outperformed the Naive Bayes, achieving an accuracy rate of 80.81%. Research on community sentiment on social media X on

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mental health has also been conducted by Yan [16] It was concluded that the accuracy of the naïve bayes method was 79% with a negative classification of 50.8%. Then, research on the relationship between depression levels and risk factors for suicidal ideation has also been conducted using correlation and regression analysis. The study found that there is significant relationship between depression levels and risk factors for suicidal ideation or there is a positive correlation between the two [17].

The difference between this research and previous studies is the focus on analyzing public perceptions of suicides in Indonesia using SVM and NBC, while previous studies have focused on global mental health issues or pandemic-related contexts. In contrast to these studies, this research examines real-world data on suicides in Indonesia, incorporating sentiment analysis to gain actionable insights. In addition, the novelty of this research can also be seen from the method that uses text mining. The purpose of this research is to analyze public sentiment regarding the increase in suicides in Indonesia using sentiment analysis methods, specifically Support Vector Machine (SVM) and Naive Bayes Classifier (NBC). The findings of this research are expected to increase public awareness and provide policy recommendations to support mental health initiatives.

Building on insights from past research and current trends, the researcher aims to explore sentiment analysis of suicide cases in Indonesia by employing Support Vector Machine (SVM) and Naive Bayes Classifier (NBC) techniques. The findings from this analysis are anticipated to provide valuable guidance for future improvements and policy-making to raise public awareness about suicide cases in Indonesia.

II. RESEARCH METHOD

A. Data

Text mining using the SVM and NBC algorithms was applied to analyze the sentiments of Indonesian society, with secondary data sourced from social media platform X, consisting of user tweets about the issue of suicide cases in Indonesia. Data collection was performed using the data crawling technique with the help of Python software and tools such as snscrape and Node.js to extract 1.175 tweets based on the keyword 'suicide' at the beginning of 2024.

B. Research Variables

This study has two variables: predictor variables and response variables. The predictor variable consists of user tweets from social media platform X regarding suicide cases in Indonesia, while the response variable involves classifying the tweet data into positive and negative sentiments. The classification process involves two steps: learning and classification. In the learning or training phase, training data is analyzed to establish rules for classification. Then, in

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the classification phase, testing data is used to estimate the accuracy of the model [18], [19]. Therefore, the tweet data is divided into training and testing sets of data. The proportion used is 85% for training and 15% for testing [20].

C. Data Collection Techniques

1. Data Source

The data to be collected is secondary tweets from the social media platform X. This data source is used because it contains direct public opinions or sentiments, which are relevant for analyzing sensitive issues like suicide. A total of 1.175 tweets with the keyword "suicide" were collected using snscrape. The extracted data includes tweet text, posting time, location (if available), and user information.

2. Data Collection Method

Tweets were collected using the data crawling technique, an automated method for gathering information from the internet. In this case, the data collected consists of tweets containing the keyword "suicide." The tools used were Python and snscrape. The collected data is stored in formats like CSV or JSON to facilitate further analysis.

D. Data Analysis Steps

1. Collect data using web scraping techniques to gather information related to the topic of suicide. The data collected may include comments, posts, or tweets containing keywords such as "suicide," "depression," or "loneliness." The data is then stored in a suitable format such as CSV or JSON, including important attributes like text, date, user, and others.
2. Preprocess the collected data, including data normalization, stop word removal, tokenization, and stemming.
3. Manually or automatically label the data to categorize the text into two sentiment classes:

a. Positive: Comments expressing support, encouragement, or empathy.

b. Negative: Comments that contain suicidal thoughts, depression, or other negative elements.

4. Extract features from the data using Term Frequency Inverse Document Frequency (TF-IDF), which converts the text into numerical values based on word frequency in the text and overall document, giving higher weight to more important words [21].
5. Apply the Synthetic Minority Oversampling Technique (SMOTE) algorithm to address data imbalance.
6. Split the dataset into training and testing data, for example, with a proportion of 85% for training data and 15% for testing data.
7. Implement the SVM algorithm on the same dataset by identifying the optimal hyperplane that distinguishes between the sentiment classes (positive and negative) in a multidimensional

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space. Then, the performance of SVM will be evaluated using metrics like precision, recall, F1-score, and accuracy.

8. Use the NBC on the preprocessed dataset by determining the likelihood of each word for both positive and negative classes. Next, assess the model's performance by calculating precision, recall, F1-score, and accuracy.
9. Compare the performance of the SVM and NBC algorithms based on the evaluation metrics produced, such as precision, recall, F1-score, and accuracy, to determine which model provides the best results in sentiment analysis of suicide-related tweets on social media platform X.
10. Visualize the results using a Confusion Matrix to observe correct and incorrect classifications for each model, a Bar Chart to show the sentiment distribution, and a Word Cloud to display the most frequently occurring words in each sentiment category.

The stages of the analysis are presented in the following operational framework diagram. The bolded diagram is the novelty of this research.

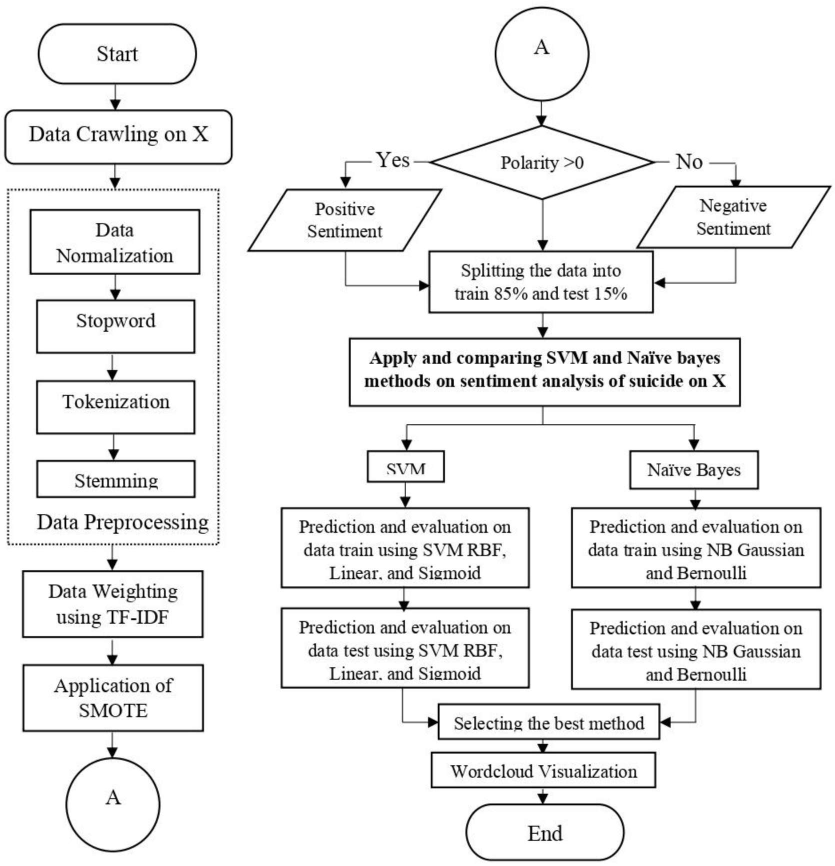

Fig 2. Operational Framework

III. RESULT AND DISCUSSION

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Sentiment analysis on social media X regarding the phenomenon of suicide cases uses a comparison of the SVM and NBC. The following are the result through several stages.

A. Data Crawling

In this research, the data used comes from social media X with the keyword 'Suicide'. This data retrieval process uses the python programming language with the help of tools called Tweet Harvest and the snscrapes library. The advantage of Tweet Harvest is that it can be run through the Command Line Interface (CLI), such as Command Prompt or Terminal, and only requires a valid user author token that exists on the X account platform. This user author token is unique and varies from user to user [22]. This crawling produces a total of 1175 tweets. Here is an example of the results of crawling data that has been done.

created_at	favorite_c	full_text	username
Sun Sep 08 11:0	108	Keliatan sepele denger atau baca kalimat Laki-laki nggak boleh cengeng. Gara-gara mental model gitu ada p	emeliney31
Sat Aug 24 14:03	32468	Kamu self-harm atau percobaan bunuh diri ga dicover oleh BPJS Kamu berduka tapi dikejar2 kerjaan cuma d	bennysiauw89
Mon Aug 19 04:	229	Bisa ngomong gini kalo stigma terkait kesehatan mental &amp	
Sun Aug 18 05:5	7060	Pun jangan lupa beberapa muslim terlalu fokus sama dosa bunuh diri sampai lupa gimana cara mencegah o	maculosus_
Sat Aug 17 12:36	420	Ada Seorang Sahabat Rasulullah yang bunuh diri karena tekanan Mental yang parah karena depresi parah. I	el_ambatukam
Sat Aug 17 05:40	5783	@sunwookimz Menurutku bisa jadi bukan karena diancam tapi emang bunuh diri di Indonesia kesannya jad	yeongijalhae
Fri Aug 16 03:20	427	Survei di kalangan residen ini pernah dilakukan jg di AS. Di sana residensi bebas bullying dibayar jam kerja d	lutfithe13th
Tue Aug 13 09:5	634	Mahasiswa UGM angkatan 2021 ditemukan meninggal dunia di kamar kosnya di Pogung Sleman. Diduga korban bunuh diri. UG	
Thu Jul 25 07:10	1399	Persoalan kesehatan mental belum menjadi isu seksi dalam kebijakan pemerintah. Padahal problem keseha	ganjarpranowo
Wed Jul 24 07:2	1267	Maraknya kasus bunuh diri di kalangan anak muda membuat miris kita semua. Ternyata salah satu penyeb	ganjarpranowo
Sat Jul 20 06:57:	886	@ARSIPAJA Solusi yang tidak solutif. Dikiranya orang bunuh diri karena gangguan jin. Padahal alasan seben	faraahax
Tue Jun 04 01:41	2316	Self-harm percobaan bunuh diri dan kekerasan dalam rumah tangga tidak bisa di-cover oleh BJPS. Jadi g her	AmirahWahdi
Fri Mar 15 02:14	1971	Dalam The Boy Crisis menyatakan antara krisis lelaki di zaman moden ialah mereka telah hilang tujuan hidu	zamirmohyedin
Thu Feb 08 10:4	579	9000 Tentara IDF Kena Ganguan Mental (Gila) Ada Yg Bunuh Diri Dengan Cara Membakar Diri Sendiri... Cum	_jacobson91
Wed Jan 31 13:4	4284	Ya Allah. I terfikir. Aku punyalah nak mati. Nak bunuh diri. Tapi badan aku berjuang nak rescue aku. Badan a	eddthinksdesign
Fri Jan 19 14:36:	434	@mynewshub UPDATE!!!! Ni bukan kes tembakannn. Ni kes suami dia ada sakit mental &amp	
Wed Jan 10 17:4	589	Sy saat ini adalah sy yang berkali-kali membatalkan niat bunuh diri merakit mental yg hancur lebur dan men	birokayumanis
Tue Jan 09 13:06	773	Kita ni mental health advocates bila ada orang bunuh diri je. Selain dari tu jauh lagi perjalanan kita sebagai s	malissaali
Sun Jan 07 06:51	736	@tamawijaaya @Koreaboo @daeri_hrb @daeri2019daeri kalau mental warga kalian masih banyak yang bu	diyasmovic
Sun Jan 07 02:10	3888	sekarang aku tau knp banyak orang memilih untuk bunuh diri rasa cape yang tidak bisa di ungkapkan memb	jankasikendor
Thu Dec 07 07:0	610	wahai orang melayu dan malaysians amnya. hitler bukan saja bunuh orang yahudi orang romani pun dia bu	gnarliith

Fig 3. Data Crawling Results

B. Data Preprocessing

This stage aims to remove distractions or irrelevant elements in tweets, making it easier to calculate weights and analyze in the next stage. Thus, it is expected that the classification results will be more precise and accurate [23]. The steps to perform data preprocessing are as follows [24], [25]:

1. Case Folding: converting capital letters (upper case) to lower case.
2. Data Cleaning: removing hashtags, emojis, mentions, usernames, and URLs from the tweet content.
3. Tokenization: separating sentences into a list of single words.
4. Normalization: restores nonstandard words to their base words.
5. Stopword: removes unimportant words using a stoplist algorithm.
6. Stemming: reduces words to their basic form by removing affixes.

Table 1. Data Preprocessing Results

Tweet-	Before Data Preprocessing	After Data Preprocessing

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38	ï¸• PENCEGAHAN BUNUH DIRI Bunuh diri adalah tindakan seseorang yang dengan sengaja mengakhiri hidupnya sendiri. Kondisi ini sangat serius dan pikiran bunuh diri bisa timbul pada siapa pun tanpa memandang usia jenis kelamin atau latar belakang sosial. https://t.co/eefBxF0FRx	cegah bunuh diri bunuh diri tindak orang dengan sengaja mengakhiri hidup sendiri kondisi sangat serius pikir bunuh diri timbul siapa tanpa pandang usia jenis kelamin latar belakang sosial
73	@kegblgnunfaedh Hidup udah susah jgnlah ditambah tambah lagi kesusahannya angka bunuh diri karna kemiskinan aja udah tinggi lho sebelum adanya ini apa ga dipertimbangkan sampe kesitu???	hidup udah susah jgnlah tambah tambah susah angka bunuh diri karna miskin aja udah tinggi lho ada apa ga timbang sampe kesitu
128	@ScaraSkripsi ABANG JANGAN BUNUH DIRI kamu bisa jadi anak ayah dan papa ku juga kok...	abang jangan bunuh diri kamu jadi anak ayah papa ku kok

Coloumn “Before Data Preprocessing” is the original data from social media X which includes symbols, punctuation, mentions, and other unique characters.

C. Labeling

Labeling is a stage to determine whether the tweet includes in positive or negative sentiment which will later be tested [26]. The labeling done in this research is manual labeling through one's own opinion. Manual labeling is done because it can minimize the possibility of errors in automatic labeling and is also proven to increase accuracy optimally [27].

Table 2. Labeling Results

Tweet	Classification
ikhtiar ga putus dari kemarin tapi gak ada juga solusi bunuh diri adalah jalan ninjaku	Negative
aku mau diem aja tentang semua deh tekan trauma takut bilang caper lebay diem aja tau tau mati bunuh diri wowkwk dah ya bye	Negative
gw tau masalah lu lewatin cukup berat gw benci banget sama orang suka mau bunuh diri kek gini	Positive
pikir bunuh diri aku lihat digrub wa teman tinggal usia muda aku kata hati kok kasihan aku sadar aku kasihan diri sendiri moga aku nikmat hidup dengan baik bisa dapat bahagia	Positive
udah gak ada yang menarik saran bunuh diri dong	Negative

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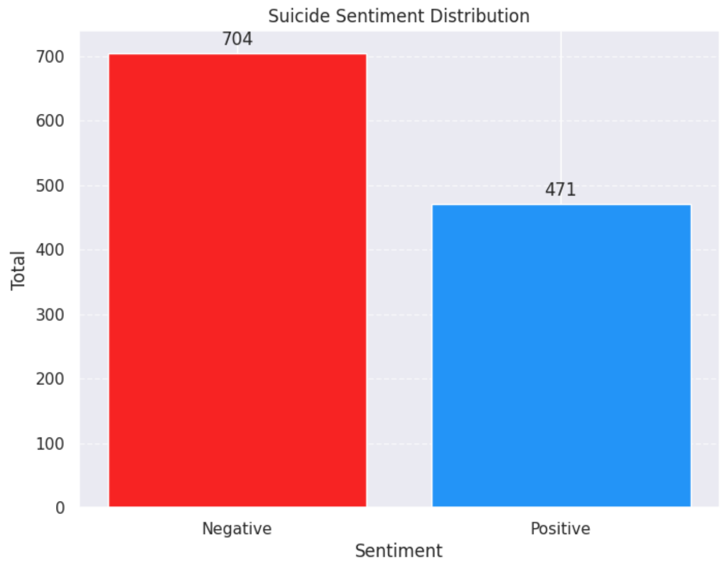

Fig 4. Data Crawling Results

The labeling process resulted in 471 data classified as positive tweets and 704 data classified as negative tweets. It can be seen that positive tweets are more directed towards regretting suicide because there are so many negative impacts that harm yourself and others and empathy for the victim's family.

D. Wordcloud

After that, the tweets are visualized using wordcloud to find out what words often appear in the data used. The size of the word shows how much the word appears, the larger the size, the word appears frequently [28].

Fig 5. Positive Sentiment Wordcloud

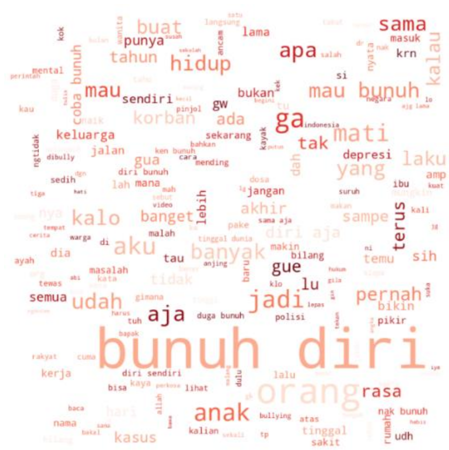

Fig 6. Negative Sentiment Wordcloud

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The figure above presents a wordcloud showing the most frequently occurring words in positive and negative sentiments regarding suicides on social media X. The most frequent words in the wordcloud for positive sentiment are kill, self, don't, live, make, me, and good. This suggests positive encouragement to people who may be experiencing mental health issues. The use of words such as “don't” and “live” signify an invitation to prevent suicide and provide support. These words reflect care and an attempt to convey a message of hope, encouragement, and encouragement to seek help. In contrast, in the negative sentiment wordcloud, frequent words include kill, self, die, want, ga, problem, and live. These words tend to indicate a sense of hopelessness and stress that individuals are facing. The use of words such as “die”, “problem”, and “want” signify a feeling of being trapped in a difficult situation, reflecting negative emotions or an inability to get out of trouble.

E. Suicide Sentiment Classification with Support Vector Machine and Naïve Bayes Methods

Before dividing the data into train and test, weighting is done with the TF-IDF method to convert text data into numeric. TF or Term Frequency itself is the number of times a word of a term appears in the document in question, IDF or Inverse Document Frequency, measures how widely a term is distributed across a collection of documents. This process is run automatically using the TF-IDF Vectorizer library [29], [30].

Then, there is one more step that must be done before dividing the data into training and testing, namely data balancing. It can be seen in the previous labeling results, there is an imbalance of data between positive sentiment and negative sentiment. The purpose of balanced data is so that the model can recognize data patterns better and avoid anomalies in the dataset [31]. One way of balancing is with the SMOTE algorithm. This method generates synthetic data for the minority class by utilizing the closest distance between data points [32], [33]. After SMOTE, 704 positive and negative sentiment data were obtained for further testing.

After the data has been balanced, train and test data are divided with the most optimal proportion being 85% training data and 15% testing data. Then, classification is carried out based on positive sentiment and negative sentiment using the SVM and NBC methods. In the SVM method, a comparison is made on 3 types of kernels, namely linear, Radial Basis Function (RBF), and sigmoid.

Table 3. Classification with SVM Method

	Output	Linear		RBF		Sigmoid	
		Training	Testing	Training	Testing	Training	Testing
Precision	0	0.98	0.82	1.00	0.74	0.94	0.80
	1	0.97	0.79	1.00	0.85	0.94	0.78

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Recall	0	0.97	0.77	1.00	0.88	0.94	0.77
	1	0.98	0.83	1.00	0.70	0.93	0.80
F1-Score	0	0.98	0.80	1.00	0.81	0.94	0.78
	1	0.98	0.81	1.00	0.77	0.94	0.79
Support	0	598	106	598	106	598	106
	1	598	106	598	106	598	106
Accuracy		0.98	0.80	1.00	0.79	0.94	0.79
ROC-AUC Score		0.98	0.80	1.00	0.79	0.94	0.79

Based on accuracy and ROC-AUC Score, the best model obtained is the Linear SVM. This model shows varying performance in classifying Negative Sentiment (0) and Positive Sentiment (1) classes on training and testing data. In the Negative Sentiment (0) class, the model achieved a precision of 0.98 and recall of 0.97 in the training data, while in the testing data, the precision moderately decreased to 0.82 and recall was also 0.77. In contrast, in the Positive Sentiment class (1), the model produced a precision of 0.97 and recall of 0.98 in the training data, but in the testing data, the precision decreased to 0.79 with recall also 0.83. The accuracy and ROC-AUC Score of the testing data are also quite good at 0.80. The F1-Score for both classes in the testing data, 0.80 and 0.81 respectively, confirmed that the model was able to combine precision and recall well, making it effective in identifying positive and negative instances in both classes.

Furthermore, classification is carried out with the NBC method to compare with the results that have been obtained with the SVM method. In the NBC method, a comparison is made on 2 types, namely Naive Bayes Gaussian and Naive Bayes Bernoulli, shown in Table 3.

Table 4. Classification with Naïve Bayes Method

	Output	Gaussian		Bernoulli	
		Training	Testing	Training	Testing
Precision	0	1.00	0.81	0.84	0.72
	1	0.89	0.62	0.99	0.82
Recall	0	0.88	0.45	0.99	0.85
	1	1.00	0.90	0.81	0.67
F1-Score	0	0.93	0.58	0.1	0.78
	1	0.94	0.73	0.89	0.74
Support	0	598	106	598	106
	1	598	106	598	106
Accuracy		0.94	0.67	0.90	0.76
ROC-AUC Score		0.94	0.67	0.90	0.76

Based on accuracy and ROC-AUC Score, the best model obtained is Naive Bayes Bernoulli. This model shows varying performance in classifying Negative Sentiment (0) and Positive Sentiment (1) classes on training and testing data. On the Negative Sentiment (0) class, the model achieved a precision of 0.84 and recall of 0.99 on the training data, while on the testing data, the

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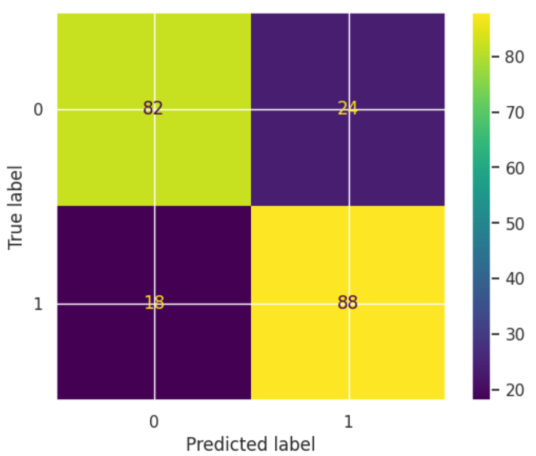
precision moderately decreased to 0.72 and recall was also 0.85. In contrast, for the Positive Sentiment class (1), the model achieved a precision of 0.99 and a recall of 0.81 in the training data, but in the testing data, the precision decreased to 0.82 with a recall of 0.67. The accuracy and ROC-AUC Score of the testing data are also quite good at 0.76. F1-Score for both classes in the testing data, 0.78 and 0.74 respectively.

Then the best method will be found by comparing the two methods that have been obtained previously. The performance comparison of the two methods can be reviewed based on the level of accuracy and the resulting ROC-AUC Score. The performance comparison of the analysis results can be identified in the following table.

Table 5. Comparison of SVM and NBC Methods

Model	Data	Accuracy	ROC-AUC Score
SVM Linear	Training	0.98	0.98
	Testing	0.80	0.80
Naïve Bayes Bernoulli	Training	0.90	0.90
	Testing	0.76	0.76



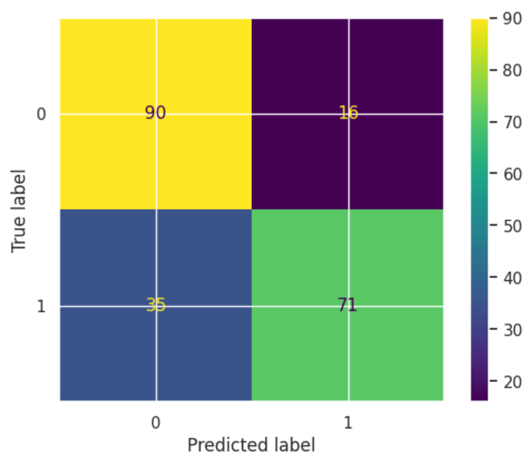


Fig 7. Confusion Matrix SVM Linear **Fig 8.** Confusion Matrix NB Bernoulli

Based on Table 5, the model generated by applying the Linear SVM method is proven to have a higher accuracy of testing data compared to applying the Naive Bayes Bernoulli method with a fairly close difference of 4%. It can be said that the Linear SVM method is good enough to classify the tweet into positive sentiment or negative sentiment with an accuracy of 80%. The findings of this research are that the Linear SVM method outperforms the Naive Bayes Bernoulli method in classifying sentiments on suicide-related tweets on social media X, achieving a higher accuracy of 80% and better ROC-AUC scores, making it a reliable approach for sentiment analysis in this context.

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The results of this research are in line with studies by [15], which also found that SVM performs better than NBC in text classification tasks due to its ability to handle high-dimensional data and find optimal hyperplanes for classification. However, this research further demonstrates the effectiveness of SVM in a specific context, namely sentiment analysis of suicide-related tweets in Indonesia.

IV. CONCLUSION

This research conducts sentiment analysis of suicides in Indonesia using SVM and NBC algorithms on data obtained from tweets on X social media. By collecting 1175 tweets, the classification process uses text mining methods through the steps of data crawling, preprocessing, labeling, and data weighting using TF-IDF. As a result, SVM algorithm with Linear kernel showed the best performance compared to NBC, with 80% accuracy rate and the same ROC-AUC Score on the test data.

In addition, from the word cloud visualization, it was found that related words such as “kill”, “self”, “depression”, and “stress” appeared frequently, suggesting that negative sentiments related to suicide are commonly associated with depression and stress. This study is anticipated to offer further insights to encourage increased public awareness on the issue of suicide and support better policies related to mental health in Indonesia.

Based on the sentiment analysis, efforts to reduce suicide rates in Indonesia should focus on addressing depression and stress, the key factors linked to suicide-related discussions. This includes expanding mental health services, improving access to counseling, and promoting stress-reduction programs in schools and workplaces. Public awareness campaigns should target destigmatizing mental health and encouraging early intervention, particularly through social media. Additionally, ongoing sentiment analysis using text mining can provide real-time insights to support quicker responses to emerging mental health crises.

This study highlights the potential of sentiment analysis to enhance mental health awareness but faces limitations, including a small dataset of 1175 tweets, potential bias in manual labeling, and a focus solely on Indonesian-language text without multimodal analysis. Future research should address these gaps by expanding datasets, using automated labeling, and incorporating multilingual and multimodal approaches to capture diverse suicide-related discussions. Developing predictive models for early mental health crisis detection and promoting public awareness campaigns, counseling access, and destigmatization initiatives can further support efforts to reduce suicide rates and foster a more supportive society.

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