ANALYSIS OF PUBLIC SENTIMENT RELATED TO THE FAILURE OF INDONESIA TO HOST U-20 USING MULTINOMIAL NAÏVE BAYES CLASSIFIER

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(Article received: July 12, 2023; Revision: November 07, 2023; published: Desember 23, 2023)

Abstract

The case of Indonesia's failure to host the U-20 World Cup in 2023 has become a hot topic of discussion in Indonesia. The rejection of the Israel U-20 national team and security factors by FIFA are considered the main reasons for the cancellation. This raises many issues and controversies from various parties. In this study, sentiment analysis using the Naive Bayes algorithm was conducted. Researchers use the naive bayes algorithm because this algorithm has high accuracy with simple calculations. The data obtained in this study came from 250 tweets of Twitter data with a ratio of training and test data of 7:3. The results showed good data classification with 97.26% accuracy, 93.33% precision, and 100% recall. In conclusion, the classification model developed can describe public sentiment related to Indonesia's failure in the U-20 World Cup well.

Keywords: *naive bayes, sentiment analysis, world cup u-20.*

1. INTRODUCTION

In the current era of technological advancement, social media has become one of the main platforms for people to interact and communicate quickly and easily. One of the popular social media platforms that is often used to express opinions freely is Twitter [1]. Twitter is a social media platform that has the largest number of users among several other social media with a total of 328 million users in the world [2][3].

Twitter is considered as a platform that allows users to express their thoughts and opinions more freely, easily due to its accessibility, unlimited number of followers and character limit of only 280 characters [4]. This allows users to convey their messages clearly, concisely and effectively [3]. As one of the most popular social media platforms, Twitter gives users the ability to express their objective opinions on various topics. So from this, there are many studies on sentiment analysis using Twitter data to find out a person's opinion or reaction to a phenomenon both negatively and positively.

Currently, an event that is being discussed by many people in Indonesia is the case of Indonesia's failure to host the U-20 world cup in 2023. According to PSSI Chairman Erick Thohir, the reason why FIFA canceled Indonesia as the host of the 2023 U-20 World Cup was because there were intervention factors, namely the rejection of the Israeli U-20 national team and security factors. The rejection is considered a paradox because previously Indonesia volunteered as the host and was successfully selected by FIFA [5]. Issues eventually developed in the community that blamed Ganjar Pranowo as the person who caused the failure of the U-20 world cup in Indonesia because of his statement that refused the Israeli national team to compete. Another issue was the Kanjuruhan tragedy that resulted in the death of several people[6].

The topic was discussed by many people through social media that people have. Where many also provide opinions, criticisms and suggestions on Twitter social media ranging from positive responses and negative responses. The response data on Twitter social media regarding Indonesia's failure to host the world cup can be used as a valuable source of information in understanding people's opinions and reactions to the event.

Response data or opinions written by people on Twitter social media can be classified using sentiment analysis [7]. Sentiment analysis is a technique used to analyze the viewpoints, emotions, and attitudes expressed by the public on a topic [8]. In the case of Indonesia's failure to host the world cup, it is quite difficult to determine the negative, positive, or neutral sentiment of tweets manually because it will take a lot of time and effort considering the large amount of Twitter. Therefore, a machine is needed that can automatically analyze tweets and classify the sentiment of the tweet to be negative, positive, or neutral. Text classification can be a solution to the problem so that sentiment determination can be faster [3].

One classification algorithm that is often used is the naïve bayes algorithm. Naïve Bayes algorithm is an algorithm for classifying data in a very simple way in assuming attribute classification [9]. This algorithm is often used in solving problems in the machine learning process and is also known to have a high level of accuracy with simple calculations [10], [11]. Multinomial Naive Bayes is one of the variations of the Naive Bayes algorithm used in data classification. The use of Multinomial Naive Bayes aims to classify data by utilizing probability information from various features or attributes in the data. This method is suitable for overcoming problems in text processing such as document classification or sentiment analysis [12]. So in this study, the naïve bayes algorithm will be used in the text classification process because the Multinomial Naive Bayes algorithm has the speed and simplicity needed in text processing [13].

Some previous research on sentiment analysis is research by Afandi who conducted research on analyzing public sentiment regarding opinions related to the implementation of electronic systems using the logistic regression method. The results of this study indicate that of the 1,074 sentiments collected there are 126 sentiments that are negative, 657 sentiments that are neutral, and 291 sentiments that are positive. The Logistic Regression algorithm managed to produce an accuracy value of 79.07%. This shows that most Indonesians agree with the PSE policy implemented but there are still some people who have not accepted the policy [8]. Then research by Hasan who conducted research to find out the number of positive and negative sentiment results from the Grab Indonesia service opinion dataset and find out the results of the algorithm testing process and the accuracy value of the evaluation test using the naïve bayes method. The results of this study show that there are 911 positive sentiments and 89 negative sentiments. In addition, the results of evaluation testing show that for negative sentiment the precision value is 57%, recall 67%, and f1-score 62%. As for positive sentiments, the precision value is 97%, recall 95%, and f1-score 96%. From these results it can be concluded that most customers are satisfied with Grab Indonesia's services [1].

From the problems previously described, this research will analyze the sentiment of the community on Twitter towards the failure of the U-20 world cup in Indonesia using the naïve bayes algorithm. The results of this research are expected to provide an overview of public responses to the failure of the Indonesian U-20 soccer team in the World Cup and are also expected to be useful in making decisions regarding communication strategies and actions that can be taken by related parties in dealing with similar situations in the future. This research has urgency in providing in-depth insight into the views and feelings of the public towards the failure of the Indonesian U-20 football team in the World Cup.

2. METHODOLOGY

In this study, data processing was carried out with several processes that must be passed, which can be seen in Figure 1:



Further explanation of Figure 1 is as follows: Data collection

- In this study, researchers collected data from Twitter using keywords related to the failure of the Indonesian U-20 World Cup. The data taken are tweets posted within a certain period of time.
- 2. Preprocessing is the initial stage in data processing where raw or unstructured data is converted into data that is more structured and ready to be used for further analysis [14]. In this study, six Preprocessing stages were carried out in this study including
- A. Dataset labeling is the process of labeling or determining the class of Twitter responses.
- B. Cleansing

1

The process of cleaning documents from unnecessary words or also known as the cleaning stage. The goal is that the documents to be processed become cleaner and more relevant. One way to clean documents is to remove tweet entities such as mentions, retweets, hashtags and URL links that do not contribute to text analysis [15].

C. Transform case

Transform case is a process in text analysis that aims to change the letters on words in documents to lowercase or uppercase [16].

D. Tokenize

Tokenization is the process of converting a text document into a series of tokens or units, such as words or phrases, which are easier for computers to process [17].

E. Stem

The stemming process is done by removing affixes or prefixes in words so that it only leaves the basic word [3].

F. Stopword filter

Stopword filter is a process in text analysis that aims to eliminate words that do not make an important contribution to understanding the content of the document. These words are called stopwords or conjunctions [18].

- G. Filter tokens by length Filter tokens by length is a process in text analysis that aims to eliminate words that have a certain number of letters [19].
- At the implementation stage, text classification 3. modeling is carried out using data that can already be processed. Before modeling the data that has been preprocessed will go through the TF-IDF weighting stage, which is a weighting method used in text analysis to evaluate how important a word or phrase is in a document [20]. Then after that, data balancing is carried out using the smote up sampling technique. SMOTE technique is a technique to balance the amount of sample data distribution in the minority class by selecting the sample data until the amount of sample data becomes balanced with the number of samples in the majority class [21]. Then the data is divided into testing data and training data. Then after that, modeling is done using the naïve bayes algorithm.
- 4. Testing at this stage is testing the model performance of the model that has been generated using the confusion matrix. Confusion matrix is a calculation that compares the dataset with the Classification results according to the actual data with the total amount of data. The final result of this matrix is the level of accuracy in units of percent (%) [22].

3. RESULTS AND DISCUSSION

1. Data collection

At this stage the researcher collects datasets on the Twitter application which contains opinions, suggestions and criticisms through tweets. The opinion or keyword that is searched to find data is the keyword "U-20 world cup". Illustrations of Twitter data collection in this study are as follows.



Figure 2. Data Retrieval Process from Twitter Using Rapidminer

Figure 2 shows the process of pulling data from the rapidminer tool. It can be seen that the withdrawal process starts from connecting rapidminer with Twitter using the token key and Twitter access key. After connecting, just enter the keyword "U-20 world cup" in the query parameter. Later rapidminer will pull tweet data that has the word U-20 world cup. After the withdrawal process is complete, the researcher exports the data into an excel file. The data taken from March 27 to April 1, 2023. The data obtained from the withdrawal of the data is 250 Indonesian-language tweet data.

| No | Tweet |
|----|---|
| 1 | Pernyataan Sekjen @PDI. Perjuangan tentang "potensi" pemakzulan Presiden Ri jika tak menolak israel dim Drawing Piala Dunia U20 di Bali, yg saya tafsirka |
| 5 | Tentang https://t.co/GcvStrqoLe https://t.co/Shpn2llklE |
| 6 | Namanya juga Hasto, panik dihajar fans bola malah nyeret2 orang yang nga bersuara ??https://t.co/IWhi@rukxZ |
| 7 | YAHANA - YAHANU • MAK INI MAK ITU "KHAS" BANGSAWAN POLITIK" @PDI_Perjuangan |
| 10 | Dalihnya selalu berubah - ubah sejak dibatalkannya Drawing Piala Dunia U20 di Bali, selalu menempatkan diri sebagai pihak YANG MAHA BENAR & pihak lain |
| 13 | Atau mungkin tabiathttps://t.co/qLOLVCqNra https://t.co/c0p1ZeiCII |
| 14 | RT @otnayram_me: Ganjar dengan jelas, tegas, artikulatif, dan tidak emosional kembali menegaskan betapa pentingnya sikap utk menolak kehadi |
| 15 | @ganjarpranowo Gimana pak rasanya blunder? Terima kasih Iho pak, telah membunuh mimpi anak-anak muda Indonesia untuk berlaga membela Merah Pu |
| 16 | Øyunartowijaya Same energy dgn sekjen partai banteng yg minta tanggapannya ttg kasus pembatalan piala dunia u20 ? |
| 17 | |
| 18 | Waktu awal2 tampil di tv, analisanya keren bgt mas karena berimbang, skrg kok Ibh nyerang pihak lain yah #justsaying |
| 19 | RT @otnayram me: Ganjar dengan jelas, tegas, artikulatif, dan tidak emosional kembali menegaskan betapa pentingnya sikap utk menolak kehadi |
| 20 | Ganjar dukung adanya pengganti event piala dunia U20 di Solo |
| 21 | #KekuatanGanjarMajukanRI https://t.co/AlleopggMx |
| 22 | RT @bamantara00: Ya, Indonesia memang terancam sanksi dari FIFA ketika gagal menyelenggarakan Piala Dunia U20. |
| | |

Figure 3. Partial Result of Tweet Data

Figure 3 shows the results of some of the tweet data that has been drawn relating to the opinions, suggestions and criticisms of the public through Twitter on the failure of the Indonesian U-20 football team in the World Cup.

2. Preprocessing

After collecting the tweet data, the next step is to do the preprocessing stage. In this study, six stages of Preprocessing were carried out in this study including:

A. Dataset labeling

The next stage is to perform the data labeling process on the tweet data manually by the researcher using the help of the Microsoft Excel application as shown in the figure below.



After the data labeling process and cleaning duplicate data, the overall result of the total data is 214 data with the highest number of tweet categories is negative tweet data as much as 121 data. Then the amount of positive category tweet data is 93 data.

B. Cleansing

After the data labeling process is carried out, the next is the process of cleaning the document from unnecessary words or also known as the cleaning stage. The cleaning process in this study uses the rapidminer tool. This stage will remove tweets such as mentions, retweets, hashtags and URL links that do not contribute to text analysis.



Figure 5. Cleansing Process Using rapidminer Tool

Figure 5 shows the cleansing process using the rapidminer tool. The operator used is the community sentiment data operator associated with the replace operator. The replace operator is used to replace certain values in the data with new values. As for this cleansing process, there are 5 replace operators that have different regular expressions, namely Replace remove RT @, remove URL, remove hashtag, remove mention and remove symbol. Table 1 shows the results of the results of the cleansing process using the rapidminer tool

Table 1. Partial Data Cleansing Result

| into lo | Categories | After | Before |
|---|------------|--|--|
| | Negatif | Namanya juga Hasto panik dihajar fans bola | Namanya juga Hasto, panik dihajar fans bola malah nyeret2 orang yang |
| Nama panik malah yang i | | malah nyeret2 orang yang nga bersuara | nga bersuara ?? |
| Dalihi beruba dibata Piala Bali mener sebag MAH lain pa laaah lagi u aj ma | Negatif | Dalihnya selalu berubah ubah sejak dibatalkannya Drawing Piala Dunia U-20 di Bali selalu menempatkan diri sebagai pihak YANG MAHA BENAR pihak lain pasti salah | Dalihnya selalu berubah - ubah sejak dibatalkannya Drawing Piala Dunia U- 20 di Bali, selalu menempatkan diri sebagai pihak YANG MAHA BENAR & pihak lain pasti salah. |
| nginej 20 ga di sa partai: Islam nolak bung nolak | Positif | laaah udh lah pildun lagi udh basibersyukur aj masih ad yg mo nginepkalo pildun U-20 gagal harusnya yg di salahin Ganjar n partainyakalo orang Islam mah udh lama nolak | @tempodotco laaah udh lah pildun lagi udh basibersyukur aj masih ad yg mo nginepkalo pildun U-20 gagal harusnya yg di salahin Ganjar n partainyakalo orang Islam mah udh lama nolak Israel dari zaman bung Karnoga ujug2 nolak |
| Gimar blund lho memb | | Israel dari zaman bung Karnoga ujug2 nolak | |
| anaka Indon berlag Merał Dunia KARI DIPO TAM SEMO KEGO BAPA | Negatif | Gimana pak rasanya blunder Terima kasih lho pak telah membunuh mimpi anakanak muda Indonesia untuk berlaga membela Merah Putih di Piala Dunia U-20 | @ganjarpranowo Gimana pak rasanya blunder? Terima kasih lho pak, telah membunuh mimpi anak-anak muda Indonesia untuk berlaga membela Merah Putih di Piala Dunia U-20. SEMOGA KARIR BAPAK DIPOLITIK SEGERA TAMAT |

| JUGA. SEMOGA | SEMOGA |
|-------------------------|--------------------|
| KEGOBLOKAN | KARIR BAPAK |
| BAPAK BISA JADI | DIPOLITIK |
| CONTOH AGAR | SEGERA |
| TIDAK DITIRU YANG | TAMAT JUGA |
| LAIN. | SEMOGA |
| | KEGOBLOKAN |
| | BAPAK BISA |
| | JADI CONTOH |
| | AGAR TIDAK |
| | DITIRU YANG |
| | LAIN |
| Kita Semua Harus | Kita Semua Negatif |
| Introspeksi Terkait | Harus |
| Kegagalan Jadi Tuan | Introspeksi |
| Rumah Piala Dunia U-20 | Terkait |
| https://t.co/HvovOX4bnR | Kegagalan Jadi |
| | Tuan Rumah |
| | Piala Dunia U-20 |

C. Transform case

The next stage is to transform the case to change the letters in the words in the document to lowercase or uppercase [19]. In this study, it will be converted into lowercase letters.

| Table 2 shows the results of the Transform case | s the results of the Transform case |
|---|-------------------------------------|
|---|-------------------------------------|

| Before | After | Categories |
|--|---|------------|
| Namanya juga Hasto panik dihajar fans bola malah nyeret2 orang yang nga bersuara | namanya juga hasto panik dihajar fans bola malah nyeret2 orang yang nga bersuara | Negatif |
| Dalihnya selalu berubah ubah sejak dibatalkannya Drawing Piala Dunia U-20 di Bali selalu menempatkan diri sebagai pihak YANG MAHA BENAR pihak lain pasti salah | dalihnya selalu berubah ubah sejak dibatalkannya drawing piala dunia u-20 di bali selalu menempatkan diri sebagai pihak yang maha benar pihak lain pasti salah | Negatif |
| laaah udh lah pildun lagi udh basibersyukur aj masih ad yg mo nginepkalo pildun U- 20 gagal harusnya yg di salahin Ganjar n partainyakalo orang Islam mah udh lama nolak Israel dari zaman bung Karnoga ujug2 nolak | laaah udh lah pildun lagi udh basibersyukur aj masih ad yg mo nginepkalo pildun u-20 gagal harusnya yg di salahin ganjar n partainyakalo orang islam mah udh lama nolak israel dari zaman bung karnoga ujug2 nolak | Positif |
| Gimana pak rasanya blunder Terima kasih lho pak telah membunuh mimpi anakanak muda Indonesia untuk berlaga membela Merah Putih di Piala Dunia U-20 SEMOGA KARIR BAPAK DIPOLITIK SEGERA TAMAT JUGA SEMOGA KEGOBLOKAN | gimana pak rasanya blunder terima kasih lho pak telah membunuh mimpi anakanak muda indonesia untuk berlaga membela merah putih di piala dunia u-20 semoga karir bapak dipolitik segera tamat juga semoga kegoblokan bapak bisa jadi contoh | Negatif |

| CONTOH TIDAK YANG LAIN | AGAR DITIRU | agar tidak ditiru yang lain |
|--|---|---|
| Kita Semua Introspeksi Kegagalan Ja Rumah Piala 1 20 | Harus Terkait di Tuan Dunia U- | kita semua harus Negatif introspeksi terkait kegagalan jadi tuan rumah piala dunia u-20 |

D. Tokenize

Next is to perform a tokenization process to convert text documents into a series of tokens or units, such as words or phrases. The results of the tokenization process can be seen in Table 3

Table 3. Partial Tokenization Results

| Before | After | Categories |
|--|---|------------|
| namanya juga hasto panik dihajar fans bola malah nyeret2 orang yang nga bersuara | namanya, juga, hasto, panik, dihajar, fans, bola, malah, nyeret, orang, yang, nga, bersuara | Negatif |
| dalihnya selalu berubah ubah sejak dibatalkannya drawing piala dunia u-20 di bali selalu menempatkan diri sebagai pihak yang maha benar pihak lain pasti salah | dalihnya, selalu, berubah, ubah, sejak, dibatalkannya, drawing, piala, dunia, u, di, bali, selalu, menempatkan, diri, sebagai, pihak, yang, maha, benar, pihak, lain, pasti, salah | Negatif |
| laaah udh lah pildun lagi udh basibersyukur aj masih ad yg mo nginepkalo pildun u- 20 gagal harusnya yg di salahin ganjar n partainyakalo orang islam mah udh lama nolak israel dari zaman bung karnoga ujug2 nolak | laaah, udh, lah, pildun, lagi, udh, basibersyukur, aj, masih, ad, yg, mo, nginepkalo, pildun, u-20, gagal, harusnya, yg, di, salahin, ganjar, n, partainya, jika, orang, islam, mah, udh, lama, nolak, israel, dari, zaman, bung, karnoga, ujug2, nolak | Positif |
| gimana pak rasanya blunder terima kasih lho pak telah membunuh mimpi anakanak muda indonesia untuk berlaga membela merah putih di piala dunia u-20 semoga karir bapak dipolitik segera tamat juga semoga kegoblokan bapak bisa jadi contoh agar tidak ditiru yang lain | gimana, pak, rasanya, blunder, terima, kasih, lho, pak, telah, membunuh, mimpi, anakanak, muda, indonesia, untuk, berlaga, membela, merah, putih, di, piala, dunia, u-20, semoga, karir, bapak, di, politik, segera, tamat, juga, semoga, kegoblokan, bapak, bisa, jadi, contoh, agar, tidak, ditiru, yang, lain | Negatif |
| kita semua harus introspeksi terkait kegagalan jadi tuan rumah piala dunia u- 20 | kita, semua, harus, introspeksi, terkait, kegagalan, jadi, tuan, rumah, piala, dunia, u-20 | Negatif |

E. Stem

Then after the tokenization process, the stemming process will be carried out, namely removing affixes or prefixes in words so that it only leaves the basic word [3]. The results of the stem process can be seen in Table 4.

| Table | | |
|--|--|------------|
| Before | After | Categories |
| namanya, juga, hasto, panik, dihajar, fans, bola, malah, nyeret, orang, yang, nga, bersuara | nama, juga, hasto, panik, hajar, fans, bola, malah, seret, orang, yang, tidak, suara. | Negatif |
| dalihnya, selalu, berubah, ubah, sejak, dibatalkannya, drawing, piala, dunia, u, di, bali, selalu, menempatkan, diri, sebagai, pihak, yang, maha, benar, pihak, lain, pasti, salah | dalih, selalu, ubah, ubah, sejak, batal, drawing, piala, dunia, u, di, bali, selalu, tempat, diri, sebagai, pihak, yang, maha, benar, pihak, lain, pasti, salah | Negatif |
| laaah, udh, lah, pildun, lagi, udh, basibersyukur, aj, masih, ad, yg, mo, nginepkalo, pildun, u-20, gagal, harusnya, yg, di, salahin, ganjar, n, partainya, jika, orang, islam, mah, udh, lama, nolak, israel, dari, zaman, bung, karnoga, ujug2, nolak | lah, pildun, lagi, basibersyukur, aj, masih, ad, yg, mo, nginep, pildun, u-20, gagal, harus, yg, di, salah, ganjar, n, partai, jika, orang, islam, mah, udah, lama, tolak, israel, dari, zaman, bung, karnoga, ujug, nolak. | Positif |
| gimana, pak, rasanya, blunder, terima, kasih, lho, pak, telah, membunuh, mimpi, anakanak, muda, indonesia, untuk, berlaga, membela, merah, putih, di, piala, dunia, u-20, semoga, karir, bapak, di, politik, segera, tamat, juga, semoga, kegoblokan, bapak, bisa, jadi, contoh, agar, tidak, ditiru, yang, lain | gimana, pak, rasa, blunder, terima, kasih, lho, pak, telah, bunuh, mimpi, anak, muda, indonesia, untuk, laga, bela, merah, putih, di, piala, dunia, u-20, moga, karir, bapak, di, politik, segera, tamat, juga, moga, goblok, bapak, bisa, jadi, contoh, agar, tidak, tiru, yang, lain. | Negatif |
| kita, semua, harus, introspeksi, terkait, kegagalan, jadi, tuan, rumah, piala, dunia, u-20 | kita, semua, harus, introspeksi, terkait, gagal, jadi, tuan, rumah, piala, dunia, u-20 | Negatif |

F. Stopword filter

After the stem process is complete, the next step is to filter stopwords, removing words that do not make an important contribution to understanding the content of the document. These words are called stopwords or conjunctions [19]. The results of the Stopword Filter process can be seen in Table 5.

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|------|---------------------------|---------|-----------------|------------|-----------|-----------|
|------|---------------------------|---------|-----------------|------------|-----------|-----------|

| Table 5. Part | ial Stopword Filter Re | sults | pihak, vang. | | |
|---|--|------------|--|--|---------------|
| Before | After | Categories | maha, benar, | | |
| nama, juga, hasto, panik, hajar, fans, bola, malah, seret, | nama,hasto,panik, hajar, fans, bola,seret, orang, | Negatif | pihak, lain, pasti, salah | | |
| orang, yang, tidak, suara. | suara. | | lah, pildun, lagi, basibersyukur, aj, masih, ad, yg, mo, | pildun, basibersyukur, masih, nginep, pildun, gagal, salah, ganjar, | Positif |
| dalih, selalu, ubah, ubah, sejak, batal, drawing, piala, dunia, u, di, bali, selalu, tempat, diri, sebagai, pihak, yang, maha, benar, pihak, lain, pasti, salah | dalih, ubah, batal, drawing, piala, dunia, bali, tempat, diri, pihak, maha, benar, pihak, salah. | Negatif | nginep, pildun, u- 20, gagal, harus, yg, di, salah, ganjar, n, partai, jika, orang, islam, mah, udah, lama, tolak, israel, dari, zaman, bung, karnoga, ujug, | partai, orang, islam, udah, lama, tolak, israel, zaman, bung, karnoga, ujug, nolak. | |
| lah, pildun, lagi, | lah, pildun, | Positif | nolak. | | |
| basibersyukur, aj, masih, ad, yg, mo, nginep, pildun, u-20, gagal, harus, yg, di, salah, ganjar, n, partai, jika, orang, islam, mah, udah, lama, tolak, israel, dari, zaman, bung, karnoga, ujug, nolak. | basibersyukur, aj, masih, ad, yg, mo, nginep, pildun, u- 20, gagal, yg, salah, ganjar, n, partai, orang, islam, mah, udah, lama, tolak, israel, zaman, bung, karnoga, ujug, nolak. | | gimana, pak, rasa, blunder, terima, kasih, lho, pak, telah, bunuh, mimpi, anak, muda, indonesia, untuk, laga, bela, merah, putih, di, piala, dunia, u-20, moga, karir, bapak, di, politik, | gimana, rasanya, blunder, terima, kasih, bunuh, mimpi, anak, muda, indonesia, laga, bela, merah, putih, piala, dunia, moga, karir, bapak, politik, tamat, moga, goblok, bapak, contoh, tiru. | Negatif |
| gimana, pak, rasa, blunder, terima, kasih, lho, pak, telah, bunuh, mimpi, anak, muda, indonesia, untuk, laga, bela, merah, putih, di, piala, dunia, u-20, | gimana, pak, rasanya, blunder, terima, kasih, lho, pak, bunuh, mimpi, anak, muda, indonesia, laga, bela, merah, | Negatif | segera, tamat, juga, moga, goblok, bapak, bisa, jadi, contoh, agar, tidak, tiru, yang, lain. | | |
| moga, karir, bapak, di, politik, segera, tamat, juga, moga, goblok, bapak, bisa, jadi, contoh, agar, tidak, tiru, yang, lain. | putih, piala, dunia, u-20, moga, karir, bapak, politik, tamat, moga, goblok, bapak, contoh, tiru. | | kita, semua, harus, introspeksi, terkait, gagal, jadi, tuan, rumah, piala, dunia, u-20 As for help | semua, introspeksi, terkait, gagal, tuan, rumah, piala, dunia | Negatif |
| kita, semua, harus, | semua, | Negatif | starting from the | transform case stage, to | okenize, ster |

As for helping the data preprocessing process starting from the transform case stage, tokenize, stem, Stopword Filter to filter tokens by length, researchers will use the rapidminer tool. Figure 6 shows the process of advanced preprocessing starting from the transform case stage, tokenize, stem, Stopword Filter to filter tokens by length.



Figure 6. Preprocessing using rapidminer tool

As for the Stem and Stopword Filter process, researchers first looked for a stem dictionary containing words based on KBBI and an Indonesian stopword dictionary containing conjunctions. Researchers managed to find both dictionaries via the internet, namely https://www.kaggle.com/oswinrh/indonesian-stoplist (Indonesian Stopword Dictionary) and https://github.com/sastrawi/sastrawi/tree/master/data (Indonesian Stem Dictionary). After that, the two dictionaries are included in the stem dictionary parameters and stopwords filter. The result of this process is data that is ready to be modeled.

G. Filter tokens by length

terkait,

tuan.

introspeksi,

20

gagal, jadi,

rumah, piala, dunia, u-

The last step in the preprocessing process is Filter tokens by length which is to eliminate words that have a certain number of letters [19]. The results of the Filter tokens by length process with letter parameters of 4-15 letters per word can be seen in Table 6.

introspeksi, terkait,

piala, dunia, u-20.

tuan,

gagal,

rumah,

| Table 6. | Partial | results | of filtering | tokens | by length | |
|----------|---------|----------|--------------|--------|----------------|--|
| 14010 0 | | reserves | 01 111001111 | , | o ji i o ingun | |

| Before | After | Categories |
|--|--|------------|
| nama, juga, hasto, panik, hajar, fans, bola, malah, seret, orang, yang, tidak, suara. | nama,hasto,panik, hajar, fans, bola,seret, orang, suara. | Negatif |
| dalih, selalu, ubah, ubah, sejak, batal, drawing, piala, dunia, u, di, bali, selalu, tempat, diri, sebagai, | dalih, ubah, batal, drawing, piala, dunia, bali, tempat, diri, pihak, maha, benar, pihak, salah. | Negatif |

- 3. Implementation
- A. TF-IDF Weighting

In the first step of the implementation process, TF-IDF weighting is carried out first to determine the weight of words in the document. One way to do TF-IDF weighting is to use the Process Documents from Data operator on the RapidMiner platform. As for the operator, the researcher includes the stages of the transform case, tokenize, stem, Stopword Filter to filter tokens by length. Figure 7 showed the process in TF-IDF weighting using the rapidminer tool.

| । 🕞 🖪 🔜 🖉 | Parameters | ents from Data | |
|-----------------------------|---------------------|----------------|---|
| Process Documents from Data | create word vector | | Ø |
| | vector creation 💙 | TF-IDF • | 0 |
| | ✓ add meta informat | tion | ٢ |
| | 🗌 keep text 💙 | | 0 |
| | prune method 💙 | none | 0 |
| | data management | auto | 0 |
| | select attributes a | nd weights | ٢ |

Figure 7. TF-IDF Weighting Process Using Rapidminer Tool

The results of the TF-IDF weighting process which shows the number of times the word appears in the dataset can be seen in Figure 8.

| Word | Attribute Name | Total Occurences 4 | Document Occurences | Negatif | Positif |
|-----------|----------------|--------------------|---------------------|---------|---------|
| dunia | dunia | 96 | 89 | 58 | 38 |
| piala | piala | 88 | 82 | 52 | 36 |
| indonesia | indonesia | 85 | 69 | 64 | 31 |
| pildun | pildun | 61 | 50 | 39 | 22 |
| gagal | gagal | 60 | 58 | 38 | 22 |
| ganjar | ganjar | 53 | 41 | 33 | 20 |
| israel | israel | 51 | 40 | 22 | 29 |
| kecewa | kecewa | 40 | 39 | 22 | 18 |
| timnas | timnas | 40 | 37 | 20 | 20 |
| rumah | rumah | 36 | 35 | 24 | 12 |
| tuan | tuan | 35 | 34 | 23 | 12 |
| palestina | palestina | 25 | 20 | 14 | 11 |

Figure 8. Preprocessing Process Using rapidminer Tool

Based on Figure 8. Shows that the 7 words that appear most often are the word world by 96 words, trophy by 88 words, indonesia by 85 words, pildun by 61 words, failure by 60 words and ganjar by 53 words.

B. Data Visualization

After the previous stages are completed, the next step is to connect the Process Documents from Data operator to the WordList to Data operator. This operator is tasked with calculating the weight value and frequency of occurrence of each word in the dataset that has gone through the stages of transform case, tokenize, stem, stopword filter, and token by length filter. Figure 9 shows the data visualization process with WordCloud.



Figure 9. Data Visualization Process with WordCloud

The operator used is the community sentiment data operator which is connected to the replace operator previously described in cleansing. Then the operator is connected to the nominal to text operator to convert the input data into text form. Then it is connected again with the Process Documents from Data operator which collects transform case, tokenize, stem, Filter Stopword to filter tokens by length operators. Then it is connected to the WordList to Data operator which is used to convert the word list into a data format that can be used for further analysis. This operator needs to be connected again with the sort operator and Filter Example Range to be able to visualize the result data from the wordcloud.

After this process, the next step is to visualize wordcloud on the results that have been obtained to be able to more easily understand the information produced that can be seen in Figure 10. These results show that the greater the total words in the document, the greater the words displayed. As for this study, it can be seen that 8 words that often appear in sentiment data regarding the failure of the U-20 world cup in Indonesia are the words world, cup, indonesia, pildun, failed, ganjar, israel and disappointed.



Figure 10. Data Visualization Results with WordCloud

The words that appear can be concluded that the public sentiment towards the failure of the 2023 U-20 world cup is negative. People feel disappointed regarding the failure of the event. Then there are the words "Ganjar" and "Israel" which refer to Ganjar Pranowo, the Governor of Central Java, who the public considers as the person who thwarted the event because of his statement that refused the Israeli national team to compete.

C. Classification using Multinomial Naïve Bayes algorithm

In the implementation stage, text classification modeling is carried out using the multinomial naïve bayes algorithm. The algorithm process starts by calculating the probability of words in the text to determine which category is most likely. This algorithm uses smoothing to overcome words that may not be in the training sample [23]. However, before the modeling process is carried out, a data balancing process will first be carried out using the SMOTE technique due to data imbalance between positive and negative sentiment data. After that, the data is divided into test data and training data using split data with a ratio of 3: 7. The ratio comparison used in this study is 3: 7 because based on research [24] states that the greater the percentage difference or ratio between training data and testing data, the higher the accuracy obtained. So in this study, a ratio comparison of 3: 7 ratio between test data and training data to determine the accuracy that will be generated. So if in the division of the 3: 7 ratio, modeling is found that has a good performance model, it can be concluded that the accuracy value at a ratio of 1: 9 between test data and training data will produce a better performance model.



Figure 11 shows the process of the modeling stage in this study using the naïve bayes algorithm

The operators used include the Process Documents from Data operator which collects transform case operators, tokenize, stem, Stopword Filter to filter tokens by length. Then connected with the SMOTE Upsampling operator which is used to balance negative and positive data. Then for the modeling process, it is necessary to divide the data between testing data and training data using the split data operator. Then the operator is connected to the naïve bayes operator as a classification algorithm. Then it is connected to the apply model operator to apply the model to the testing data to generate sentiment predictions. And finally connected with the performance operator to provide a metric for evaluating the performance of the model in this study, namely accuracy, precission and recall.

As for using the SMOTE Upsampling operator, it makes the data balanced where the overall total data after balancing the data is 242 data with the number of classes between positive and negative sentiments as much as 121 data.

D. Testing

At this stage, model performance testing is carried out from the model that has been generated using the confusion matrix. This test is carried out to measure the accuracy of the model in classifying data. As in Figure 11, it can be seen that there is a split data operator that is used to divide the data into test data and training data. Then the operator is reconnected with the naïve bayes operator and apply model for the modeling process. After that, it is finally connected with the performance operator to determine the performance of the model using the confusion matrix.

Figure 12 shows the results of the accuracy of the modeling results. The results of the classification of public sentiment about Indonesia's U-20 world cup failure using the naïve bayes classifier obtained an accuracy of 97.26% which shows that the model built

has a good ability to classify public sentiment. This shows that the Multinomial naïve bayes classifier model is able to recognize well whether a text contains positive or negative sentiment regarding Indonesia's failure in the tournament.

| accuracy: 91.20% | | | | |
|------------------|--------------|--------------|-----------------|--|
| | true Negatif | true Positif | class precision | |
| pred. Negatif | 43 | 0 | 100.00% | |
| pred. Positif | 2 | 28 | 93.33% | |
| class recall | 95.56% | 100.00% | | |
| | | | | |

Figure 12. Accuracy Results

Figure 13 shows the results of the precission on the modeling results. The results of the classification of public sentiment about the failure of the Indonesian U-20 world cup using the naïve bayes classifier obtained a precission of 93.33% which shows that of all the positive classification results, 93.33% of them are truly positive.

| precision: 93.33% (positive class: Positif) | | | | |
|---|--------------|--------------|-----------------|--|
| | true Negatif | true Positif | class precision | |
| pred. Negatif | 43 | 0 | 100.00% | |
| pred. Positif | 2 | 28 | 93.33% | |
| class recall | 95.56% | 100.00% | | |
| | | | | |

Figure 13. Precission result

Figure 14 shows the results of recall on the modeling results. The results of the classification of public sentiment about the failure of the Indonesian U-20 world cup using the naïve bayes classifier obtained a Recall of 100% which shows that the model is able to recognize negative sentiment well with the model's ability to recognize negative sentiment by 100%.

| recall: 100.00% (positive class: Positif) | | | | |
|---|--------------|--------------|-----------------|--|
| | true Negatif | true Positif | class precision | |
| pred. Negatif | 43 | 0 | 100.00% | |
| pred. Positif | 2 | 28 | 93.33% | |
| class recall | 95.56% | 100.00% | | |
| Figure 14. Recall Results | | | | |

4. DISCUSSION

The difference between this journal [1] and other journals is the specific focus and research topic. This journal focuses on sentiment analysis in the context of community reviews and responses to certain events or applications, such as the failure of the Indonesian U-20 soccer team in the World Cup and the PeduliLindungi application. The research in this journal specifically compares the performance and accuracy of Multinomial Naive Bayes and decision tree algorithms with the application of AdaBoost in sentiment analysis [1].

On the other hand, other journals may have different topics and research methodologies. For example, another journal [13] focuses on sentiment analysis on hotel reviews using Multinomial Naive Bayes classifier. The research in this journal specifically analyzed sentiment in the context of hotel reviews, rather than public responses to specific events or applications. Therefore, the difference between this journal and other journals lies in the research focus, topic, and methodology used in each study.

5. CONCLUSION

Based on the results of data collection, 214 tweet data were obtained regarding public responses to the failure of the Indonesian U-20 football team in the World Cup from March 27 to April 1, 2023. From the results of data analysis obtained information that there are more negative sentiments than positive sentiments which indicate that public responses regarding the failure of the Indonesian U-20 soccer team in the World Cup tend to be negative seen from the large amount of negative sentiment data in the data. As for the research conducted, it was also obtained information that some people were disappointed with Indonesia's failure to host the U-20 World Cup which the community believed was caused by Ganjar Pranowo's response who refused the State of Israel to compete in the match. This can be seen from the 8 words that often appear in sentiment data regarding the failure of the U-20 world cup in Indonesia, namely the words world, cup, indonesia, pildun, failed, ganjar, israel and disappointed. Then the results of data classification using naïve bayes show good results, namely accuracy of 97.26%, precission of 93.33% and Recall of 100% so it can be concluded that the classification model obtained can classify well the public sentiment related to Indonesia's failure in the U-20 World Cup. The results of this study are expected to be useful in regarding making decisions communication strategies and actions that can be taken by related parties in dealing with similar situations in the future.

Suggestions for this research for the development of this research are to use other techniques or methods besides Multinomial naïve bayes classifier to compare the performance and accuracy between different models. In addition, future research can expand the range of sentiment analysis on other topics by using a larger dataset.

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