Public Sentiment Analysis about Independent Curriculum with VADER Annotations using the Naive Bayes and K-Nearest Neighbor Methods

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Abstract:- The educational curriculum is a device or system of plans and arrangements regarding learning materials on teaching and learning activities. If the curriculum does not meet the requirements or facilitate teaching and learning activities, then the curriculum cannot be said to be good. The aim of this research is to filter and analyze sentiment from public opinion towards the newest curriculum in Indonesia, namely the independent curriculum, which will be made into the national curriculum in the upcoming 2024. The dataset used is tweets from Twitter as many as 667 lines of tweets labeled as positive and negative categories. The labeling process is done automatically using the VADER sentiment library. In sentiment analysis, one of the classification methods that is quite good in sentiment classification is Naive Bayes and K-Nearest Neighbor (KNN). The Naive Bayes method is fairly good in the data classification process that can study the training data provided to it properly, while KNN is a simple method that is quite easy to understand and is often used in the classification process which produces quite good accuracy compared to other methods. The stages in conducting sentiment analysis in this study are data collection, data preprocessing, labeling or annotation of data, data visualization, classification and evaluation. Based on the classification results using the Naive Bayes method, where the dataset is divided between training data and test data with a ratio of 80-20, an accuracy of 71% has been obtained . In addition, the results of sentiment tend to be negative, so it can be concluded that the independent curriculum which will be made into the national curriculum has not been well received by the public, so this can be taken into consideration for the Indonesian government to make the independent curriculum a national curriculum.

***Keywords**:- Sentiment Analysis, Independent Curriculum, Naive Bayes, KNN, VADER, Natural Language Processing.*

I. INTRODUCTION

Indonesia is a country that is very disciplined in education. Indonesia has an education level of twelve years divided into six years of elementary school, three years of junior high school, and three years of senior high school. Along with the times, Indonesia has implemented various educational curricula that have been practiced starting from the Education Level Unit Curriculum, Curriculum 13. In 2024 it will be replaced with a new curriculum, the Independent Curriculum. Many of the general public are pro and con against government policies in changing or developing the education curriculum in Indonesia. This is one of the problems that can impact education in Indonesia.

Along with the development of increasingly advanced internet technology, many social media or social networking services make it easy for users to post opinions in text, images or videos [1]. Social media has a two-way nature that can facilitate interaction among its users. In addition, social media can be used as a medium for researching public sentiment towards a policy issued by the government or a product from a company. In particular, the government can find out the public's sentiment towards a policy issued by the government through the opinions given by the public on social media. One social media or social networking service currently widely used worldwide is Twitter. Twitter is one of the social media or social networking services under the company Twitter Inc. Twitter provides social networking services in the form of microblogs that allow users to send and read messages in the form of *Tweets*. Opinions or opinions from the public on a policy are valuable for analysis. The results of an analysis of public opinion can be very valuable information in making decisions about related policies.

Sentiment analysis is a Natural Language Processing technique used to process data in text to obtain information from the text. Sentiment analysis is used to classify opinions in text form into 2 (two) sentiments: positive and negative. In the sentiment classification process, the first thing to do is to *clean* the data to change it into a structure for the classification process. After that, the data annotation process, namely the data annotation process based on sentiment from opinions. Data annotation is a process for assigning attributes, signs, or data labels to assist machine learning algorithms in understanding and classifying the information to be processed. After the data is annotated, *text preprocessing* or text pre-processing is performed. This process is carried out to select text data and change the data to be more structured with a series of stages, including *cleaning, case folding, tokenizing, filtering,* and *stemming,* so that the resulting data from *text preprocessing* can be used in the classification process [2].

Data annotation is crucial as an initial process in labeling a sentiment in a sentence. The annotation process requires experts who identify and label a sentence into groups of negative, positive, or negative sentiments. Manual annotations require much effort, time, and costs, so many studies should be addressed. This should be a concern

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because the more influential the time used in a study, the faster the research is completed. Currently, there are libraries in Natural Language Processing that can do annotations automatically, including VADER (Valence Aware Dictionary for Sentiment Reasoning).

VADER is a library often used to perform annotations and sentiment analysis automatically. According to the available lexicon data dictionary, this library is an English language data analysis dictionary with attention to emotional strength. VADER is a library for annotating text data using the English lexicon dictionary (en), where emotions are annotated using compound values [3]. In addition, VADER focuses on sentiment analysis from data on social media.

In this study, researchers hope to be able to analyze sentiments from public opinion so that the results of this analysis can be one of the inputs to the government in improving the national education curriculum and also in making a policy regarding the education curriculum which will be made into the national curriculum.

II. RESEARCH METHODS

A. Research Stages

The stages in research in making a forest fire disaster classification model are divided into several stages. These stages can be seen in chart Figure 1 .

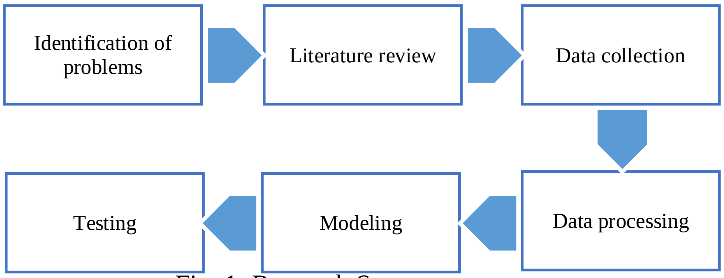

Fig. 1: Research Stages

Explanation of the research stages in Figure 1:

- Problem identification is a process and result of identifying problems in a study.
- Literature review is an analysis that aims to review previous studies in the form of constructive criticism or criticism of the research being carried out.
- Collection is an activity in searching data to achieve the research objectives.
- Pre-processing data is a technique in data mining to convert raw data into cleaner information that can be used in further data processing.
- Building is the stage of making a classification model to get good results in classification performance for predicting forest fire disasters.
- The testing phase is the stage of testing the model that has been built and analyzing the final results or outputs produced.

B. Literature review

The literature review is an analysis that aims to review previous studies in the form of constructive criticism or criticism of the research being carried out.

Research conducted by [4]using the lexicon library includes VADER, SentiWordNet, SentiStrength, Liu and Hu opinion, and AFINN-111. This study aimed to evaluate the most influential lexicon library-based automatic annotations in the field of sentiment analysis on Twitter data. The dataset used is divided into 2 (two) groups where the first group contains 1,600 comments, and the second group contains 4,000 comments on problems with the JIRA application tracking system. The results of the research that has been carried out yield accuracy for each lexicon: VADER of 72%, SentiWordNet 53%, SentiStrength of 67%, Liu and Hu opinion of 65%, and AFINN-111 of 65%. Research conducted by [5]aims to analyze the performance of 2 (two) lexicons, namely TextBlob and VADER. The dataset used is tweet data from Twitter by 1 (one) user from 2013 to 2019, totaling 7,997 lines of tweets. TextBlob and VADER were each used to label sentiments from 7,997 lines of data, and outside of these data, 300 tweet data were randomly selected to be labeled by 3 (three) psychologists manually. From this study, it was found that the two lexicons produced an acceptable level of accuracy, namely 79% for VADER and 73% for TextBlob.

Research conducted by [6] aims to analyze sentiment from public opinion towards administering the Sinovac vaccine during the COVID-19 pandemic. The dataset used is 2105 lines of tweets with the keyword '**Sinovac** 'without retweets. Library TextBlob is used as an automatic annotation, and the classification algorithms used to build the classification model are Support Vector Machine (SVM) and K-Nearest Neighbor (KNN). From this research, a sentiment accuracy value of 0.70 was obtained for the linear SVM kernel, 0.57 for the SVM polynomial kernel, 0.66 for the RBF SVM kernel, while for the KNN accuracy of 0.55 for n = 3, 0.55 for n =5 and 0.56 for n=7. In addition, research conducted by [7] uses the TextBlob library as a tool for automatic annotation and the Random Forest algorithm as a method used in building a text classification model. In this study, word weighting was carried out using TF-IDF to ensure machines understood it. From the results of this study, the accuracy of the model performance was obtained by 76%.

Research conducted by [8] classifies public opinion, especially service users of PT. Telkom Indonesia for the products offered, including indihome, myindihome, useetv, and wifi.id. The research assesses brand image, customer feedback, and marketing opportunities. The dataset used is from Twitter, as many as 3324 lines of tweets, and the

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annotation process is done automatically using the TextBlob library. The data preprocessing includes visualization in histograms, pie charts, and word clouds. The analysis results from 3324 tweets yielded 1590 neutral data, including 1266 valid and 324 invalid data, then 1082 positive data, including 858 valid and 224 invalid, besides 518 negative, of which 443 were valid, and 75 were invalid. From these results, the percentage of the analysis results is 34.4% positive tweets, 16.1% negative tweets, and 49.6% neutral tweets with an analysis accuracy of 77.2%.

The research conducted aims to analyze and validate the performance of 2 (two) [9] lexicon-based automatic annotations that are widely used, namely TextBlob and Valence Aware Dictionary and Sentiment Reasoner (VADER) by comparing the performance of the two libraries with manual annotations. The dataset from Twitter collected 25,800 tweets with keywords using Arabic language and writing. Of the 25,800 lines of text data, there are 3,124 positive tweets, 1,463 negative tweets, and 815 neutral tweets. The tweet is translated into English and automatically annotated using TextBlob and VADER. This study shows that automatic annotations are not standard in text data annotations. Many shortcomings and limitations are found in automatic annotations using lexicon-based algorithms. The highest level of accuracy obtained from a series of experiments is 75% for TextBlob and 70% for VADER. In this study, the author will investigate using automatic annotation, namely VADER, then compare the results with previous research results.

C. *Data collection*

In this study, the “Independence Curriculum” data set crawled from Twitter as many as 667 lines of tweets, with 261 positive and 406 negative tweets.

D. *Data Labeling*

Data labeling is done automatically using the VADER sentiment library. The labeling process is carried out after the data has been translated into English because the VADER library can only read English text.

E. *Preprocessing Data*

Text preprocessing is a series of gradual processes that aim to change the form of unstructured data into a more structured one according to the needs of the data mining process. The results are in the form of numeric data [10]. Text preprocessing is generally divided into several stages: cleaning (removing punctuation and symbols), case folding, tokenizing, normalization, and stemming.

F. *TF-IDF*

TF-IDF (Term Frequency Inverse Document Frequency) is a method used to determine the frequency value of a word in a document or article. Also, that frequency is in many documents. This calculation determines how relevant a word is in a document [11].

G. *Classification*

Classification of data of the same type into a class [12]. The results of the classification are the first step of prediction. Suppose the classification gets a high accuracy value. In that case, the prediction accuracy value will also be high, but conversely, if the classification accuracy value is below the target, the resulting prediction value will be increasingly inaccurate.

H. *VADER*

VADER is one of the lexicon-based sentiment analyzers and annotators with predefined rules for a word or lexicon. VADER labels that the lexicon is positive, neutral, or negative and also tells how positive, neutral, or negative a sentence is. The output from VADER on the Python dictionary is in the form of 4 (four) primary keys, namely 'pos', 'neg’, and 'compound.’ The compound is a compound score that is needed in the annotation of a sentence which is obtained by normalizing the scores of 'pos' and 'neg' and assigning values to numbers from -1 and +1. The more combined scores close to +1, the higher the positivity of a text.

```
print(sentiment.polarity_scores("This is a good car"))
{'neg': 0.0, 'neu': 0.508, 'pos': 0.492, 'compound': 0.4404}
```

Fig. 2: VADER Polarity Score

The advantages of using VADER in sentiment analysis are as follows:

- No training data is required
- VADER can understand text sentiment very well, including emoticons, slang, conjunctions, capital letters, punctuation marks, and more.
- VADER works very well with social media text analysis and can work with many domains.

I. *Naive Bayes*

Naive Bayes is a supervised learning algorithm used for the classification process through a probabilistic approach. The inventor of the Naive Bayes theory is an English scientist named Thomas Bayes, where theory predicts future opportunities based on previous experience, known as Bayes' Theorem. This method is widely used in various fields, especially in document classification [13]. The general equation of Bayes' predictions on the Bayes theorem is as follows:

$$P(Y|X) = \frac{P(X|Y) * P(Y)}{P(X)} \quad (1)$$

Table 1: Description of Bayes Equation Variables

Variable	***Information***
X	Data with an unknown class
Y	The data hypothesis X is a specific class
P(Y|X)	The final conditional probability or a hypothesis Y occurs if given evidence X (evidence) occurs.
P(X|Y)	The probability of a piece of evidence for X will influence the hypothesis
YP(Y)	The initial (priori) probability of hypothesis y occurring regardless of any evidence
P(X)	The initial (priori) probability that evidence X will occur regardless of any other evidence or hypothesis

Naive Bayes can be trained in supervised learning depending on probability models. The Naive Bayes model can be run without relying on Bayesian probabilities or using other Bayesian methods. The advantage of Naïve Bayes is that it only requires a small amount of training data to estimate the parameters needed for the classification process.

J. *K-Nearest Neighbor (KNN)*

K-Nearest Neighbor is the method used for decision-making that uses supervised learning where the results of the new input data are classified based on the nearest neighbors in the value data [14]. The KNN method is used to classify objects from learning data closest to the main object. KNN is a supervised learning algorithm in which the results of a new query instance are classified based on most of the categories in the KNN algorithm. The class that appears most frequently will later become the class resulting from the classification. Proximity is defined in metric distances, such as Euclidean distance.

III. RESULTS AND DISCUSSION

A. *Proposed Method*

In analyzing public opinion sentiment towards this independent curriculum, the proposed method is *Naive Bayes*. With this method, the machine can make intelligent decisions with limited assistance. The VADER library is used as an automatic annotation for the data annotation process.

B. *Data Visualization*

In data visualization, all data will be described in a visual form that can be seen and understood easily, such as graphs, maps, or charts. Data visualization is made to understand big or small data easily. To make it easier to understand the dataset's contents, the form of the data is made into visual data.

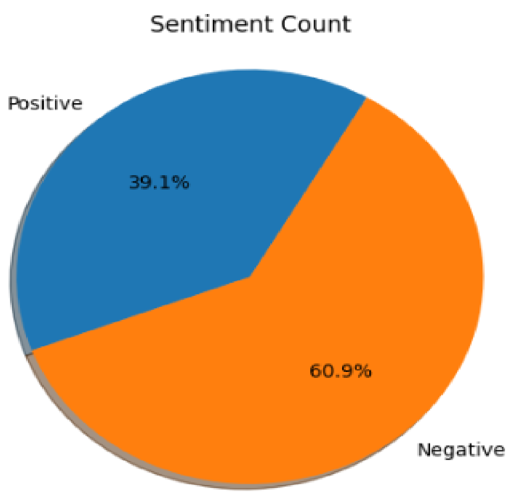

Fig. 3: Number of Sentiment Results of Labeling

From the comparison of data for each sentiment in Figure 6, it can be seen that the most common sentiment is negative sentiment, namely 60.9%, while positive sentiment is 39.1%.

C. *Preprocessing Data*

In data preprocessing, all data will be cleaned and returned to basic words for the data classification process.

- Cleaning (removing punctuation marks and symbols), At this stage, removing punctuation marks and symbols is the process of removing all punctuation marks and symbols from each line to not interfere with the data preprocessing process.

Clean	Text_Clean
KISI KISI Soal PAT Matematika Kelas 4 Semester...	KISI KISI Soal PAT Matematika Kelas Semester K...
mau tanya buat kakak kakak sma yang udah pake ...	mau tanya buat kakak kakak sma yang udah pake ...
: PDF Buku Paket SMA Kelas 10 Kurikulum Merdek...	PDF Buku Paket SMA Kelas Kurikulum Merdeka
: List materi & catatan kelas X (10) \nKur...	List materi amp catatan kelas Kurikulum Merd...
gue udh capek bgt sama kurikulum merdeka	gue udh capek bgt sama kurikulum merdeka

Fig. 4: Cleaning Process

* Data annotation (Labeling), At the data annotation or data labeling stage, it is done after the dataset has been translated into English. This is done because the VADER sentiment library can only process English text.

	Text_Clean	Tweets	Compund_Score
0	kisi kisi soal matematika kurikulum merdeka su...	grid pat math class semester independent curri...	0.0000
1	mau tanya buat kakak kakak sma yang udah pake ...	Senior high school brothers and sisters alread...	0.3182
2	pdf buku paket sma kelas kurikulum merdeka	pdf high school package book independent curri...	0.0000
3	list materi amp catatan kelas kurikulum merdek...	list of materials notes class curriculum merd...	0.0000
4	saya sudah capek sekali sama kurikulum merdeka	Im so tired of the independent curriculum	-0.4927
...	...	...	...
662	definitely fisika sama geo tapi sukanya bagian...	definitely geo physics likes earth free curric...	0.8316
663	baca aja kurikulum merdeka apa saja	read the independent curriculum	0.0000
664	gelar karya dan pentas seni penerapan projek p...	degree of work of performing arts strong proje...	0.5106
665	buku kurikulum merdeka sma kelas	Class High School Independent Curriculum Book	0.0000
666	buku kurikulum merdeka kelas smp	junior high school class independent curriculu...	0.0000

667 rows × 3 columns

Fig. 5: Dataset Labeling

* Casefolding, At the case folding stage, it is the process of converting all capital and lowercase letters from each row to a uniform form in lowercase. The purpose of case folding is to make the data used more structured.

Clean	Text_Clean
KISI KISI Soal PAT Matematika Kelas 4 Semester...	kisi kisi soal pat matematika kelas semester k...
mau tanya buat kakak kakak sma yang udah pake ...	mau tanya buat kakak kakak sma yang udah pake ...
: PDF Buku Paket SMA Kelas 10 Kurikulum Merdek...	pdf buku paket sma kelas kurikulum merdeka
: List materi & catatan kelas X (10) \nKur...	list materi amp catatan kelas kurikulum merd...
gue udh capek bgt sama kurikulum merdeka	gue udh capek bgt sama kurikulum merdeka

Fig. 6: Casefolding

- Tokenizing, at the tokenizing stage is the process of breaking sentences into words or called tokens to facilitate the process of data analysis. With tokenizing, word separators or not can be distinguished.

Text_Clean	Tweets
kisi kisi soal pat matematika kelas semester k...	[kisi, kisi, soal, pat, matematika, kelas, sem...
mau tanya buat kakak kakak sma yang udah pake ...	[mau, tanya, buat, kakak, kakak, sma, yang, ud...
pdf buku paket sma kelas kurikulum merdeka	[pdf, buku, paket, sma, kelas, kurikulum, merd...
list materi amp catatan kelas kurikulum merd...	[list, materi, amp, catatan, kelas, kurikulum,...
gue udh capek bgt sama kurikulum merdeka	[gue, udh, capek, bgt, sama, kurikulum, merdeka]

Fig. 7: Tokenizing

- Normalization, or normalization, is the process of returning non-standard words to the standard language in the Indonesian dictionary.

Text_Clean	Tweets
kisi kisi soal pat matematika kelas semester k...	[kisi, kisi, pat, matematika, kelas, semester,...
mau tanya buat kakak kakak sma yang udah pake ...	[kakak, kakak, sma, udah, pake, kurikulum, mer...
pdf buku paket sma kelas kurikulum merdeka	[pdf, buku, paket, sma, kelas, kurikulum, merd...
list materi amp catatan kelas kurikulum merd...	[list, materi, amp, catatan, kelas, kurikulum,...
gue udh capek bgt sama kurikulum merdeka	[gue, udh, capek, bgt, kurikulum, merdeka]

Fig. 8: Normalization

- Stemming is the stage where words/terms in each line of text that are not in the form of basic words (addition words or in irregular forms instead of roots) are changed into their basic form (stem).

```
2033
------------------------
kisi : kisi
pat : pat
matematika : matematika
kelas : kelas
semester : semester
kurikulum : kurikulum
merdeka : merdeka
dilengkapi : lengkap
kunci : kunci
pembahasan : bahas
kakak : kakak
sma : sma
udah : udah
pake : pake
```

Fig. 9: Stemming

D. Process Weighting (TF-IDF)

After the data preprocessing is done, the next process is weighting the words in each text. TF-IDF weighting process in the picture.

```
# proses TI - IDF
tf = TfidfVectorizer()
data = tf.fit_transform(df['Tweeter'].astype('U'))
#print(data)
#print('\n')
```

```
h_tfidf = TfidfTransformer()
x_tfidf = h_tfidf.fit_transform(data)
print('\n')
print(x_tfidf)
X = df.Tweeter
Y = df.Sentiment
```

```
  (0, 482)	0.45658670761467457
  (0, 905)	0.45658670761467457
  (0, 746)	0.3437870415055046
  (0, 202)	0.08213108102570549
```

Fig. 10: TF-IDF process

E. Dataset sharing

The division of dataset aims to divide the data into two parts, namely training data and test data, where the data distribution is training data by 80% while test data is 20%.

```
#splitting data
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(x_tfidf,df['Sentiment'],
                                                    test_size =0.2,
                                                    random_state=42)
```

Fig. 11: Tokenizing

F. Classification using Naive Bayes

Classification is done by building a model that has been previously trained, and then the model is used to analyze sentiment from the test data that has been divided before.

```
#klasifikasi
klas = MultinomialNB().fit(X_train, y_train)
predicted = klas.predict(X_test)
print("MultinomialNB Accuracy: ", accuracy_score(y_test,predicted))
print("MultinomialNB Precision: ",
      precision_score(y_test,predicted, average='weighted', pos_label="Positif"))
print("MultinomialNB Recall: ",
      recall_score(y_test,predicted, average='weighted', pos_label="Positif"))
print("MultinomialNB F1_Score: ",
      f1_score(y_test,predicted, average='weighted', pos_label="Positif"))

print(f'Confusion matrix:\n{confusion_matrix(y_test,predicted)}')
print('=====================================================\n')
print(classification_report(y_test,predicted,zero_division=0))
```

Fig. 12: Naive Bayes Classification

The classification results of the Naive Bayes model that has been built using test data can be seen in Figure 13 below.

```
MultinomialNB Accuracy:  0.7089552238805971
MultinomialNB Precision:  0.7856620786229037
MultinomialNB Recall:  0.7089552238805971
MultinomialNB F1_Score:  0.6650622534993426
Confusion matrix:
[[77  1]
 [38 18]]
=========================================================

              precision    recall  f1-score   support

     Negatif       0.67      0.99      0.80        78
     Positif       0.95      0.32      0.48        56

    accuracy                           0.71       134
   macro avg       0.81      0.65      0.64       134
weighted avg       0.79      0.71      0.67       134
```

Fig. 13: Results of the Naive Bayes Model

From Figure 13, sentiment classification using naive Bayes produces an accuracy of 71%, while Precision is 78%, Recall is 71%, and F1-Score is 66%.

G. Classification using K-Nearest Neighbor (KNN)

Classification using KNN is different from Naive Bayes. The classification process using KNN can be seen in Figure 14 below.

```
#KNN Model
x_train_cl = h_tfidf.fit_transform(X_train)
x_test_cl = h_tfidf.fit_transform(X_test)
```

```
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors=4)
classifier.fit(x_train_cl,y_train)
```

```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=4)
```

```
y_pred = classifier.predict(x_test_cl)
```

```
from sklearn.metrics import classification_report, confusion_matrix
cm = confusion_matrix(y_test, y_pred)
cr = classification_report(y_test, y_pred)
print(cm)
print(cr)
```

Fig. 14: KNN Classification

The classification results of the KNN model that has been built using test data can be seen in the following figure.

```
[[70  8]
 [31 25]]
              precision    recall  f1-score   support

     Negatif       0.69      0.90      0.78        78
     Positif       0.76      0.45      0.56        56

    accuracy                           0.71       134
   macro avg       0.73      0.67      0.67       134
weighted avg       0.72      0.71      0.69       134
```

Fig. 15: KNN Model Results

From Figure 15, sentiment classification using KNN produces an accuracy of 71%, Precision is 72%, Recall is 71%, and F1-Score is 69%.

H. Evaluation

The built model's testing and evaluation stages aim to test the model's performance that has been trained in classifying fire disasters. The prediction test was carried out using the test data used when testing the model as much as 20% of the 667 data lines and was carried out randomly. The results of the prediction test from the two sentiment classification models that have been built can be seen in Table 2.

Table 2: Outcome Evaluation

Method	Accuracy	Precision	Recall	F1-Score
Naive Bayes	71%	78%	71%	66%
KNN	71%	72%	71%	69%

Table 2 shows that the two methods produce similar results, and there are slight differences in the precision and F1-Score results. The two methods produce fairly good accuracy, so the models built from the two methods can be used to conduct research related to sentiment analysis.

IV. CONCLUSION

Based on the results of the research above, the researcher can conclude that the research This study has succeeded in analyzing the sentiments of the public about the independent curriculum by annotating VADER sentiment data using the Naive Byes and K-Nearest Neighbor (KNN) methods. The division of the dataset with a ratio of 80-20 between the training data and test data greatly affects the performance of the models made.

The results of research that has been done so performance value is obtained from the Naive Bayes method as follows; the accuracy value is 71 %, recall of 71 %, Precision of 78 %, and the F1-score is equal to 66 %. While the performance value of the KNN method produces an accuracy value of 71%, 71% recall, 72% precision, and 69% F1-Sore. The sentiment analysis using the Naive Bayes and KNN methods is quite good for the accuracy results obtained. Suggestions for future research are good for increasing the amount of data in the test and training data and conducting tests using higher data divisions, for example, 70:30 or 75:25.

REFERENCES

[1.] I. Ardiansah and A. Maharani, Optimalisasi Instagram Sebagai Media Marketing. 2020.

[2.] R. Ren, D. D. Wu, and D. D. Wu, "Forecasting stock market movement direction using sentiment analysis and support vector machine," IEEE Syst J, vol. 13, no. 1, 2019, doi: 10.1109/JSYST.2018.2794462.

[3.] D. Abimanyu, E. Budianita, E. Pandu Cynthia, F. Yanto, P. Studi Teknik Informatika, and F. Sains Dan Teknologi, "Analisis Sentimen Akun Twitter Apex Legends Menggunakan VADER," Jurnal Nasional Komputasi dan Teknologi Informasi, vol. 5, no. 3, 2022, [Online]. Available: https://techno.kompas.com

[4.] M. A. Al-Shabi, "Evaluating the performance of the most important Lexicons used to Sentiment analysis and opinions Mining," International Journal of Computer Science and Network Security, vol. 20, no. 1, 2020.

[5.] W. Nur Syahirah Wan Min, N. Zareen Zulkarnain, and F. Teknologi Maklumat Dan Komunikasi, "Comparative Evaluation of Lexicons in Performing Sentiment Analysis," 2020.

[6.] A. Baita and N. Cahyono, "Analisis Sentimen Mengenai Vaksin Sinovac Menggunakan Algoritma Support Vector Machine (SVM) dan K-Nearest NEighbor (KNN)," Information System Journal (INFOS), vol. 4, no. 2, pp. 42–46, Nov. 2021.

[7.] M. Irfan, P. S. Dewi, W. B. Zulfikar, C. Slamet, and I. Taufik, "Sentiment Analysis as Assessment of the COVID-19 Social Assistance Pollemic using Random Forest Algorithm," in Proceeding of 2022 8th International Conference on Wireless and Telematics, ICWT 2022, 2022. doi: 10.1109/ICWT55831.2022.9935483.

[8.] I. G. S. Mas Diyasa, N. M. I. Marini Mandenni, M. I. Fachrurrozi, S. I. Pradika, K. R. Nur Manab, and N. R. Sasmita, "Twitter Sentiment Analysis as an Evaluation and Service Base On Python Textblob," IOP Conf Ser Mater Sci Eng, vol. 1125, no. 1, 2021, doi: 10.1088/1757-899x/1125/1/012034.

[9.] B. M. Alenzi, M. B. Khan, M. H. A. Hasanat, A. K. J. Saudagar, M. Alkhathami, and A. Altameem, "Automatic Annotation Performance of TextBlob and VADER on Covid Vaccination Dataset," Intelligent Automation and Soft Computing, vol. 34, no. 2, 2022, doi: 10.32604/iasc.2022.025861.

[10.] H. Ashari, D. Afrianto, and H. A. Al Faruq, "Perbandingan Kinerja Algoritma Multinomial Naive Bayes (MNB), Multivariate Bernoulli dan Rocchio Algorithm Dalam Klasifikasi Konten Berita Hoax Berbahasa Indonesia Pada Media Sosial," Doctoral dissertation, Universitas Muhammadiyah Jember, 2020.

[11.] F. Hendy Evan and Y. W. Sigit Purnomo, "Pembangunan Perangkat Lunak Peringkas Dokumen dari Banyak Sumber Menggunakan Sentence Scoring dengan Metode TF-IDF," in Seminar Nasional Aplikasi Teknologi Informasi (SNATI) Yogyakarta, 2014, pp. G17–G22.

[12.] S. Bhardwaj, A. Ali Khan, M. Muzammil, and S. Mohd Khan, "ANN based classification of sit to stand transfer," Mater Today Proc, vol. 24, pp. 1029–1034, Jan. 2020, doi: 10.1016/J.MATPR.2020.04.416.

[13.] N. I. Pratiwi and Widodo, "Klasifikasi Dokumen Karya Akhir Mahasiswa Menggunakan NaÃ¯ve Bayes Classifier (NBC) Berdasarkan Abstrak Karya Akhir Di Jurusan Teknik Elektro Universitas Negeri Jakarta," PINTER : Jurnal Pendidikan Teknik Informatika dan Komputer, vol. 1, no. 1, pp. 31–38, Jun. 2017, doi: 10.21009/pinter.1.1.5.

[14.] IBM, "What is the k-nearest neighbors algorithm? | IBM," Https://Www.Ibm.Com/Topics/Knn. 2022.