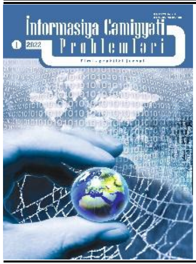

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Machine learning-based sentiment analysis of Twitter data

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ABSTRACT

The paper analyzes the views of Twitter users on the COVID-19 corona virus pandemic based on machine learning algorithms. The role of sentiment analysis increased with the advent of the social network era and the rapid spread of microblogging applications and forums. Social networks are the main sources for gathering information about users' thoughts on various themes. People spend more time on social media to share their thoughts with others. One of the themes discussed on social networking platforms Twitter is the COVID-19 corona virus pandemic. In the paper, machine learning methods as Naive Bayes, Support Vector Machine, Random Forest, Neural Network are used to analyze the emotional "color" (positive, negative, and neutral) of tweets related to the COVID-19 corona virus pandemic. The experiments are conducted in Python programming using the scikit-learn library. A tweet database related to the COVID-19 corona virus pandemic from the Kaggle website is used for experiments. The RF classifier shows the highest performance in the experiments.

1. Introduction

Sentiment analysis (SA) has recently become a very popular research topic with the rapid development of social networking sites. SA is a field of research that examines people's opinions on various issues (products, events, organizations, etc.) [1, 2]. The role of SA has significantly increased in the wide discussions on social networks, forums, blogs, microblogging. Today, almost every website has a section for users to post comments about products or services and share them with their friends on Facebook or Twitter. The collection of these ideas provides information to perceive people's collective behavior and has a valuable commercial interest. Thus, an ever-increasing data collection shows that by analyzing content on social media, it is possible to predict opinions about COVID-19 or the unemployment rate from time to time.

The world's most used Twitter microblogging has become a place where many users: students, professionals, celebrities, companies and politicians share their thoughts in recent years due to its short and simple expression style. The opinion of others has always been important to mankind. Whether it's a policy or a simple choice, such as choosing a product in a market, we always care what others are going to think about our choices. From this point of view, Twitter has quickly become one of the most powerful social media platforms for influencing opinions [3].

Owing to sites such as Twitter, sentiment or opinion analysis has become one of the most researched and discussed themes in the Natural Language Processing (NLP), text mining [4] and etc. However, collecting opinions or analyzing sentiments is not an easy task. Due to the recent increase in the availability of data, companies around the world are trying to get insights from data to solve real problems or achieve business goals. The volume, velocity and variety of data generated have reached unprecedented level. This requires not only new platforms such as Hadoop for Big data processing, but also new machine learning methods and algorithms for extracting information from the data [3].

The whole world is currently experiencing the

COVID-19 pandemic. During this period, many people lost their lives, and many successfully overcame the disease. COVID-19, first known as coronavirus disease in 2019, was declared a pandemic by the World Health Organization on March 11, 2020. The COVID-19 pandemic has become a major discussion topic on social networks. People all over the world began to express their views on the COVID-19 pandemic on social networks, including Twitter. Based on these collected tweets, people's behavior and moods related to the disease are analyzed.

This study can be useful for a variety of stakeholders. For example, the government observes how people react to this new tension, such as malnutrition, lack of masks, etc. and can use this information for political purposes. Various commercial organizations can start producing the necessary products, and thus make a profit by analyzing different opinions from the tweets about the above-mentioned difficulties. Non-governmental organizations can decide how to use facts and information in accordance with their rehabilitation strategy and so forth [5-9].

Many studies on the Sentiment analysis of Twitter data present different approaches. Lexicon-based, rule-based, hybrid approaches and machine learning algorithms are used to identify opinion words in tweets [10-13]. The disadvantage of the lexicon-based approach is that the sentiment polarity of the words included in the dictionary depends on the subject area and context. This requires each area to create its own dictionary. The disadvantage of the rule-based approach is that a large number of rules need to be described in order to achieve high accuracy in the analysis of emotionality. This is a time-consuming and complex process.

This article aims to conduct a SA based on the data from Twitter users from different countries related to the COVID-19 pandemic using machine learning algorithms.

The following part of the article is organized as follows. Section 2 summarizes the related works. Section 3 presents classifiers used. Section 4 offers described the methodology of the proposed approach. Section 5 presents experimental trials of the proposed approach and discusses the results of the experiment. Conclusion of the study is introduced in Section 6. The final section includes a list of references.

2. Related studies

There has recently been a lot of research in the field of SA on various topics discussed on Twitter microblogging.

[11] offers a new hybrid approach using both corpus-based and lexicon-based methods to determine the semantic orientation of opinion words in tweets. Opinion words (combinations of adjectives with verbs and adverbs) in tweets are extracted to detect sentiment. The corpus-based method is used to find the semantic orientation of adjectives, and the lexicon-based method is used to find the semantic orientation of verbs and adverbs.

Another study suggests two approaches for SA: lexicon-based and machine learning method. It describes several methods to implement these approaches and how they can be used for sentiment classification of Twitter messages. The article provides a comparative analysis of different lexicon combinations. The authors show that by enhancing sentiment lexicons with emoticons, abbreviations and slang expressions, the accuracy of lexicon-based classification for Twitter can be improved. They analyze the importance of feature generation and feature selection processes for sentiment classification. Algorithms are tested on Twitter data from the SemEval 2013 (Semantic Evaluation Workshop) competition to evaluate the effectiveness of SA methods. The results indicate that machine learning methods based on the Support Vector Machine (SVM) and Naive Bayes (NB) classifiers outweigh the lexicon method [12].

[14] presents a web tool called Sentimentor for SA of Twitter data. The tool uses the Naive Bayes classifier to classify Twitter data in real time as positive, negative and neutral.

In [15], the authors view the application of various sentiment analyzers with machine learning algorithms to determine the most accurate approach to the study of sentiment in elections. In lexicon-based SA, semantic direction is expressed in words, expressions or sentences calculated in the text. The polarity in the lexicon-based method is calculated on the basis of a dictionary consisting of a semantic score of a particular word. Naive Bayes and SVM algorithms are used to classify the text. A lot of work has been done in the field of SA, using both sentiment lexicons and machine learning approaches. However, this study aims to compare three- dimensional dictionaries such as W-WSD (Word Sequence Disambiguation), SentiWordNet, and TextBlob. These three sentiment analyzers are tested using two machine learning algorithms. As a result, feedback is calculated by three analyzers. Moreover, the results are tested with two controlled machine-learning classifiers, Naive Bayes and SVM. Although the results are relatively better based on the TextBlob dictionary, the best performance when analyzing tweets is achieved with W-WSD.

Detection and analysis of sarcasm on Twitter provides public opinion on recent trends and events. Through sarcasm detection, companies can analyze perceptions of users about their products. TextBlob is used for the preprocessing of data. TextBlob is a package installed in NLTK (Natural Language Toolkit). TextBlob is used to find confidence in polarity and subjectivity. RapidMiner is used to determine the polarity and subjectivity of tweets. The Weka platform is used to calculate the accuracy based on SVM classifier and the Naive Bayes classifier. A total of 2250 tweets are used. The accuracy of Naive Bayes classifier is 65.2% and the accuracy of SVM is 60.1%. This indicates that Naive Bayes classifier performs more accuracy compared to SVM classifier [16].

SA or opinion mining has recently become the focus of many researchers. Thus, the analysis of online texts is useful for market research, scientific surveys from a psychological and sociological point of view, political polls, business intelligence, enhancement of online shopping infrastructure, etc. [17]. An innovative solution is introduced for the SA of Twitter messages. The hybrid method uses a sentiment Lexicon (SentiStrenght) to create a new set of features for the development of a linear SVM classifier. It is shown that hybrid method outperforms unigram baseline.

Twitter is one of the most popular social networking sites where people can freely express their views, opinions and emotions. These tweets are analyzed to reveal the emotions associated with the terrorist attack (Uri attack) on security forces near the Indian city of Uri. Intellectual text analysis techniques are used to identify emotions and polarity in the tweets. Approximately 5,000 tweets are re-encoded and pre-processed to generate a data set of frequently used words. The programming language R is used for mining emotions and polarity. Experiments show that 94.3% of people despise the Uri attack [18].

E. Evirgen proposes a structure in the programming language R that acts as a gateway for the tweets' analysis that express emotions in a short and concise format. [3]. The target tweets include a brief emotion description and words used in the wrong format or grammatical structure. Five different machine learning methods are compared: SVM, Random Forest (RF), Boosting, Maximum Entropy, and Artificial Neural Networks.

[19] proposes a reputation model using SA methods to extract sentiments on product features. This model provides more realistic reputation about product features for customers. The model uses sentiments provided by users. Then a method is presented to generate a more realistic reputation value for each feature of the product and product itself. When calculating the product's reputation, not all of its features are treated equally, because some features are more important to customers than others, and as a result can have a greater impact on customer decisions.

[20] offers an ensemble classifier by combining base learning classifier to improve the efficiency and accuracy of sentiment classification. The proposed ensemble classifier outperforms the individual classifier.

[21] uses SA-assisted machine learning methods to classify opinions from Twitter. The main goal is to process a large number of opinions with a multi-class classification. The multi-class SVM algorithm can classify different classes such as positive, negative, happy, love and fun. The proposed algorithm performs better results than those of Naive Bayes and SVM algorithms in terms of the F-measure's obtained value.

In [22], the authors propose a mechanism for predicting sentiment on Turkish tweets by using two methods based on Polarity Lexicon (PL) and Artificial Intelligence (AI). The PL method provides a dictionary of words and tweets are matched with them. Tweets are classified to be either positive, negative or neutral based on the result obtained after matching the words in the dictionary. The AI method uses a SVM and RF classifiers to classify tweets as either positive, negative or neutral. Experimental results indicate that SVM demonstrates an accuracy of 76% on the stemmed data. Whereas, RF performs better results on raw data with an accuracy of 88%. The performance of PL method has consistently increased from 45% to 57% as a raw data is replaced by a stemmed data.

Apparently, the number of researches is constantly increasing due to the SA of social networking data, especially Twitter data [5, 6, 8, 9]. One of the main topics discussed on social networks recently is the COVID-19 pandemic. [5] analyzes the sentiments on the COVID-19 pandemic. Coronavirus-related tweets are extracted using the Twitter API to analyze the sentiments of people's opinion about the disease and these tweets are analyzed as positive, negative, and neutral by using machine learning methods and tools. Experiments are performed on various tweets using the NLTK library used for the pre-processing of tweets in the Python programming environment. The tweets dataset is then analyzed by using the Textblob package and positive, negative and neutral sentiments are presented through various visualizations.

[6] presents a data set of 19298967 tweets about COVID-19 collected from 5977653 individuals. These tweets were collected between March 2020 and July 2020 using the query terms 'coronavirus', 'COVID' and 'mask'. The authors used topic modeling, SA, and descriptive statistics to describe the collected tweets related to COVID-19 and the geographical location of the tweets.

[7] offers an approach to detect COVID-19 patients using Twitter messages without requiring medical records. An intelligent model using machine learning based approaches, such as support vector machine, logistic regression, Naive Bayes, random forest and decision tree with the help of TF-IDF- frequency inverse document frequency is proposed to detect the COVID-19 in Twitter messages. The proposed intelligent model classifies Twitter messages into three categories: death, recovered, and suspected ones. For the experimental analysis, tweets related to the COVID-19 pandemic are analyzed to evaluate the results of machine learning approaches. Experiments show the accuracy of the COVID-19 pandemic in Twitter messages to vary between 70-80%. The performance of the proposed approach is evaluated by precision, recall, F-measure criteria and confusion matrix methods.

COVID-19 preventive measures interfere with the day-to-day activities of millions of people, also affect their mental health. One of such preventive measures is social distancing. Users are free to express their opinions through the social media platforms like Twitter. [8] The main objective is to analyze the public sentiments on social distancing. The SentiStrength tool is used to increase the sentiment polarity of Twitter data specific to Canada and the SVM algorithm is applied for sentiment classification. Evaluation of performance is measured with a confusion matrix, precision, recall and F-measure. As a result, a total of 629 tweets are extracted. 40% of tweets are neutral, 35% of tweets are negative and only 25% of tweets are positive about social distancing. The SVM algorithm is applied by dividing the data set into 80% training and 20% test data. Performance evaluation resulted in an accuracy of 71%. While using Twitter texts with only positive and negative sentiment polarity, the accuracy increased to 81%. The accuracy of the test data is observed to increase to 87% with a 10% reduction. The results indicate that an increase in training data improved the performance of the algorithm.

[9] develops a model to extract topics related to the coronavirus pandemic and then implement SA on these topics in two different periods of 2020: March-April and September-October. In terms of the study, a dataset of English tweets related to COVID-19 is extracted 567064 tweets are extracted and analyzed. The work is carried out in several stages, from initial processing to obtaining the optimal model. This work performs the stemming and lemmatization (obtaining the basic or lexical form of a word using vocabulary and morphological analysis) to achieve the best results. In addition, the LDA (The Latent Dirichlet Allocation) model for topic extraction is used and the eight most important coronavirus-related topics are identified. This model is based on NLP, and 80% of the data set is training data and 20% is test data.

Moreover, based on most of the topics covered in this article, SA of collected tweets is presented using lexical-based approaches to classify people's feelings.

As a part of this research, experiments are conducted on the Spark platform in the Python programming language to improve the analysis and processing of large-scale tweets.

3. Proposed approach

The proposed approach consists of the following steps.

Step 1. Data collection. Data collection is the first step in SA. The Twitter dataset is taken from Kaggle (https://www.kaggle.com) website. The work is implemented in a Python environment. This dataset consists of 6 attributes (UserName, ScreenName, Location, TweetAt, OriginalTweet, Sentiment). For analysis, we classify them into three classes (positive, negative, neutral) using only 12,726 records and two attributes (OriginalTweet, Sentiment). 10180 tweet training data and 2546 tweet test data are used for the experiments.

Step 2. Data pre-processing. This step is the most important stage of the SA process. Twitter data includes words, symbols, emotion icons, URLs, usernames beginning with the @ symbol, hashtags and user references. The words may also include a mixture of words made up of misspelled words, many dots, and many repetitive letters. Therefore, in order to bring the data into a standard form, the pre-processing is essential. Data pre-processing is the process of cleaning up a database of insignificant and unnecessary data to reduce noise and improve machine learning algorithms. Raw data from various sources often requires pre-processing before analysis. Online texts often consist of a large number of noises and parts such as HTML tags, scripts, and ads. Raw tweets taken from Twitter are often a noisy data collection. There are special signs of Tweets like user references, emotional expressions, etc. Raw Twitter data should be normalized to create a data set that can be easily learned through various classifiers. There are a number of pre-processing steps that need to be taken to standardize tweet data and reduce its size. The pre-processing includes the following stages [10, 23, 24]:

- Tweets become lowercase.
- 2 or more points are replaced by an empty field.
- Punctuation marks, numbers and special characters are removed at the end of tweets.
- 2 or more empty fields are replaced by one empty field.
- All URLs, hashtags (#topic), usernames (@username) on the tweet are deleted.
- Retweets starting with RT are deleted.
- Short words are deleted.
- Stop words or unnecessary words are removed from the tweet.
- Stemming, i.e., the root of the word is retained and the suffixes are discarded.
- The tokenization process is implemented.

The code of the pre-processing stages is given below:

```
#new column with removed @user
import re
df['Tweet'] =
np.vectorize(remove_pattern)(df['OriginalTweet'
], '@[\w]*')
df.head(2)
import re
df['Tweet'] = df['Tweet'].apply(lambda x:
re.split('https:\/\/.*', str(x))[0])
df.head(3)
# remove special characters, numbers,
punctuations
df['Tweet'] = df['Tweet'].str.replace('[^a-zA-Z#]+','
')
df.head(5)
# remove short words
df['Tweet'] = df['Tweet'].apply(lambda x: '
'.join([w for w in x.split() if len(w) > 2]))
df.head(2)
# create new variable tokenized tweet
tokenized_tweet = df['Tweet'].apply(lambda x:
x.split())
df.head(2)
from nltk.stem.porter import *
stemmer = PorterStemmer()
   # apply stemmer for tokenized_tweet
tokenized_tweet =
tokenized_tweet.apply(lambda x:
[stemmer.stem(i) for i in x])
df.head(2)
# join tokens into one sentence
for i in range(len(tokenized_tweet)):
  tokenized_tweet[i] = ' '.join(tokenized_tweet[i])
# change df['Tweet'] to tokenized_tweet
df['Tweet'] = tokenized_tweet
df.head(2)
def hashtag_extract(x):
  hashtags = []
for i in x: ht = re.findall(r'#(\w+)', i)
```

Information on some commonly used tools for pre-processing can be found in [25].

4. Classifiers used

Naive Bayes, SVM, RF and NN machine learning algorithms are used to conduct multi-grade classification in the article.

Naive Bayes. The Naive Bayes classifier is based on Bayes theorem. Naive Bayes is the simplest model that can be used to classify texts. The algorithm is used to determine the sentiment "shade" of the texts. Using Bayes' theorem, the conditional probability for classes is calculated as follows:

$$P(c|t) = \frac{P(c)P(t|c)}{P(t)} \quad (1)$$

$$c = \underset{c}{\operatorname{argmax}} P(c|t) \quad (2)$$

$$P(c|t) \propto P(c) \prod_{i=1}^{n} P(f_i|c) \quad (3)$$

In the above formula, f_i denotes the i-th sign from the sign n. $P(c)$ and $P(f_i|c)$ are calculated with maximum true similarity values [25, 26].

Support vector machine. The support vector machine is a controlled learning algorithm that uses a hyperplane to classify data. The hyperplane is constructed by finding areas that separate adjacent points of different classes. Points outside the boundary form support vectors. Hyperplane easily distinguishes the classes for simple tasks. Hyperplane is defined as follows [24, 27-30]:

$$h(x) = w^T x \quad (4)$$

Here, w is the weight vector of the points on the hyperplane along h (x) = 0.

Assume that the training data set for two-class classification problems is $(x_i,\ y_i)$. Here, $x_i \in R$-is a vector of signs and y_i is the corresponding class sign, $y_i \in \{+1, -1\}$. We have to find such a hyperplane that separates the points o $y_i = 1$ and $y_i = -1$, passing through the maximum distance from the nearest points of the training set. The equation of the hyperplane is expressed as $w \cdot x - b = 0$. If the scalar product of the vector w with x_i is greater than the admissible value of b, then the new point refers to the first category, if less, $w \cdot x_i > b \Rightarrow y_i = 1$, $w \cdot x_i < b \Rightarrow y_i = -1$, to the second.

Random Forest. A Random Forest algorithm is a machine learning algorithm that uses a decision tree ensemble. RF provides a single decision tree of numerous classifications and regressions. The algorithm is based on the Bagging approach and the selection of a random set of characters. Assume that $x_1, x_2, \dots, x_n$ are the set of tweets, $y_1, y_2, \dots, y_n$ are their corresponding sentiment signs. A random (X_i, Y_i) pair is selected by substitution by applying bagging. Each classification tree is taught using f_k random (X_k, Y_k). Here $k \in \{-1, K\}$. The algorithm achieves high accuracy of classification. The decision ensemble is formed independently of each other. In the end, the final decision of the K decision tree is determined by a majority voting [23, 25].

Neural network. A neural network is a mathematical model based on the principle of organization and operation of biological neural networks, i.e., the networks of nerve cells of a living organism, as well as its software or hardware. The connections of biological neurons are modeled as the weights between nodes in artificial neural networks. A positive weight represents an exciting connection, while a negative weight represents a delay. All receipts are modified and aggregated by weight. This action is called a linear combination. Consequently, the activation function controls the amplitude of the output signal. For example, the acceptable output range is often from 0 to 1 or from 1 to 1 [31].

$$\vec{h_i} = f(W_x \vec{x_i} + b_x) \tag{5}$$

Here, $\vec{h}_i$ denotes the hidden features; $f(z)$ - activation function; $W_x, \vec{b}_x$ - weight and inclination parameters; x_i - the input vector.

5. Experiments and discussion

The various classifiers described above are implemented in a Python environment using a scikit-learn library, and experiments are performed on data taken from https://www.kaggle.com website. Figure 1 illustrates the reaction of Twitter users from several countries to the COVID-19 pandemic. Selected (Naive Bayes, SVM, RF and NN) algorithms are trained on the received training data. The experiments are then performed on test data. The results of each classifier used in the experiment on the test data are presented in Table 1.

The results of the classifiers on the Precision, Recall, F-measure criteria are identified. The sentiment polarity of tweets is classified as neutral, negative, and positive.

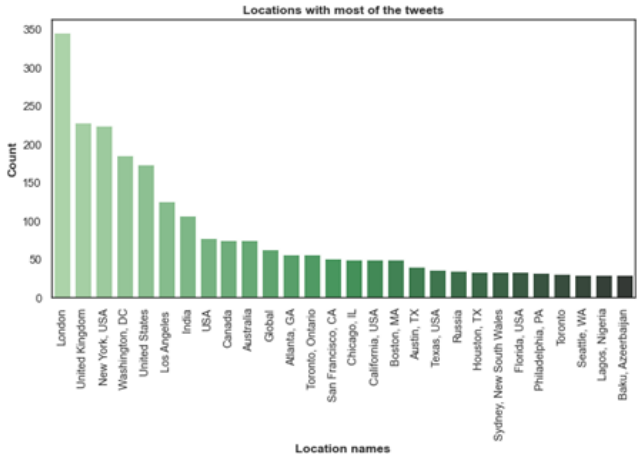

Figure 1. Distribution of COVID-19 related tweets across countries.

Table 1. Results of classifiers on criteria.

Sentiment	Precision				Recall				F-measure			
	NB	SVM	RF	NN	NB	SVM	RF	NN	NB	SVM	RF	NN
Negative	0.76	0.77	0.79	**0.79**	0.71	0.80	**0.83**	0.79	0.73	0. 78	**0.81**	0.79
Neutral	0.27	0.72	0.77	0.68	0.70	0.68	0.71	0.66	0.39	0.70	0.74	0.67
Positive	0.80	0.80	**0.81**	0.79	0.67	0.80	0.80	0.80	0.73	0.80	**0.81**	0.79

As Table 1 shows, for the neutral mood according to the Precision criterion, the NB classifier performed the lowest result, while the RF classifier performed the highest result. According to the negative mood, the NB classifier performs the lowest result, while the RF classifier performs the highest result. According to the positive mood, the NN classifier performed the lowest result, while the RF classifier performed the highest result. According to the neutral mood on the Recall criterion, the NN classifier performed the lowest result, while the RF classifier performed the highest result. According to the negative mood, the NB classifier performed the lowest result, while the RF classifier performed the highest result. The NB classifier performed the lowest result with the positive mood, while the SVM, RF and NN classifiers performed the highest result. According to the F-measure criterion, the NB classifier performed the lowest result, while the RF classifier performed the highest result with the neutral mood. According to the negative mood, the NB classifier performed the lowest result, while the RF classifier performed the highest result. According to the positive mood, the NB classifier performed the lowest result, while the RF classifier performed the highest result.

Figure 2 illustrates a visual representation of the results of the classifiers on the criteria in the tests conducted on the test data and Figure 3 displays the distribution of the sentiment polarity of the tweets based on the test data.

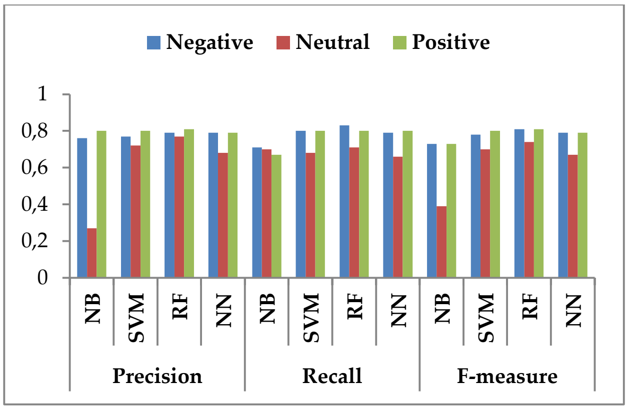

Figure 2. Classifiers performances on criteria.

As seen from the graph in Figure 2, the NB classifier performed the lowest result for the neutral mood on the criteria, and the RF classifier performed the highest result for the positive and negative moods.

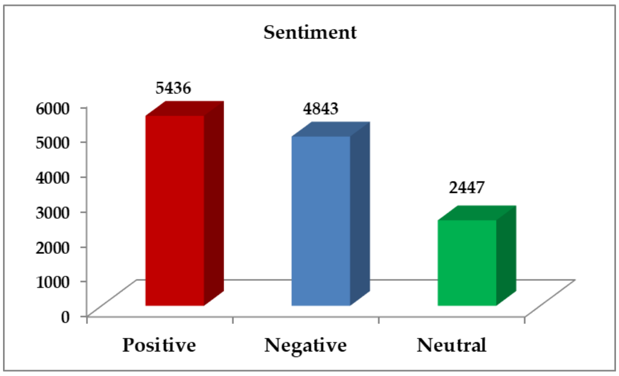

Figure 3. Distribution of tweets by sentiment polarity.

According to the bar chart in Figure 3, there are 5436 positive mood tweets, 4843 negative mood tweets and 2447 neutral mood tweets.

The metrics used to evaluate the effectiveness of the algorithms are expressed by the following formulas [32, 33]:

$$Precision = \frac{TP}{TP + FP} \quad (6)$$

$$Recall = \frac{TP}{TP + FN} \quad (7)$$

$$F - measure = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (8)$$

$$Accuracy = \frac{TP + NN}{TP + FP + FN + TN} \quad (9)$$

The accuracy test of classifiers is presented in Table 2 and the schedule of the accuracy test is displayed in Figure 4.

Table 2. Accuracy test of classifiers.

Classifiers	Accuracy test (%)
Naive Bayes	68.69
Random Forest	79.37
Support Vector Machine	77.37
Neural Network	76.63

As seen from Table 2, the RF classifier performed the highest accuracy.

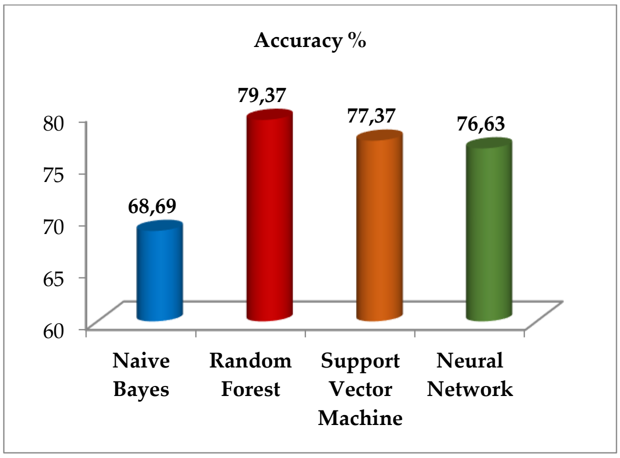

Figure 4. Schedule of accuracy test of classifiers on criteria.

As seen from Figure 4, the NB classifier performed the lowest accuracy, while the RF classifier performed the highest accuracy. The SVM and NN classifiers performed the same accuracy.

6. Conclusion

As COVID-19 spreads rapidly around the world and affects the lives of millions of people, a number of countries have declared quarantine to test its severity. During the quarantine period, Twitter played an important role in spreading information about the COVID-19 pandemic around the world as people expressed their feelings through social media. Given this catastrophic situation, an approach was offered to analyze people's attitudes to the pandemic on Twitter. This article highlighted the SA of tweets related to the Coronavirus or COVID-19 pandemic. The article analyzed the data of Twitter users from different countries related to the COVID-19 pandemic using machine learning methods (Naive Bayes, Support Vector Machine, Neural Network and Random Forest) and its classification as neutral, positive and negative. Four classifiers were used in the study. Of the classifiers, the Random Forest classifier performed the highest accuracy.

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