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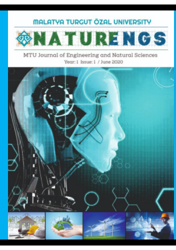

Research Article

Sarcasm Detection in Online Social Networks Using Machine Learning Methods

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ABSTRACT: Our lives have completely changed since the internet came into our lives. Role models for people are the people around them and people all over the world. Although there are positive aspects to this situation, we will deal with the negative aspects in this study. One of these negative aspects is that people share their ideas on social networks without supervision. In this way, people who use social networks are told offensive words by people they do not know in real life. Sometimes these words are not directly insulting, but they are expressed sarcastically and annoy the interlocutor. In this study, detecting sarcastic words in social networks is considered a classification problem. Since the data type used in the proposed method is text-based, both text mining and machine learning methods are used together. In this study, the sarcastic word classification process was carried out using a dataset obtained from the Twitter social network, which includes two public classes. The performance of the proposed method was obtained with the Random Forest algorithm with an accuracy of 94.9%.

Keywords: Social networks, Sarcasm detection, Text mining, Classification.

1. INTRODUCTION

Personal computers began to enter our lives in the 1980s. About 10 years later, in the 1990s, the use of the internet started to become widespread. The development of the internet is currently divided into three phases. Web 1.0, Web 2.0 and finally, Web 3.0 technologies. When Web 1.0 technology first entered our lives, people only existing accessed content, in other words, it is the most primitive internet technology. With the start of Web 2.0 technology in the 2000s, many applications were developed, from personal blog pages to social networks. The most popular social networks are Facebook, Twitter, Instagram and TikTok. Thanks to these technologies, people can comment on any photo, create their content and upload it to the internet, allowing all people to access this content.

In addition to facilitating access to information, this event also caused a parabolic increase in the amount of data on the internet. It also allowed people to increase their social interaction. Thanks to the internet, it has become effortless and ordinary to buy any product, share the negative aspects of this product, and influence other people. Even the fact that people who are far between continents and cannot see each other physically meet and marry thanks to this technology does not surprise anyone. Web 3.0 technology, on the other hand, can be described

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as the interpretation of data produced by Web 2.0 technology by computer systems. In this technology, also known as logical web technologies, it is possible to personalize people according to their frequency and internet use habits, thanks to algorithms developed using machine learning and artificial intelligence methods. The primary motivation for the progress of all these technologies is the need for access to information. Social networks that have entered our lives with Web 2.0 have made accessing information much easier. However, this situation also brought with it some undesirable negative aspects.

The first of these is the attack on personal rights. This is a crime. But people are not aware that they are committing a crime because they commit this crime on virtual platforms. Thinking that these crimes committed on online social networks will go unpunished, they continue their insults and humiliating innuendo without any boundaries. At the beginning of these crimes are insults, humiliation, swearing, phishing, fake news, mocking and sarcastic remarks. It is essential to prevent these undesirable situations [1]. The scientific world is constantly working to prevent crimes committed on the internet. If an intelligent system can be created, such attacks on personal rights can be prevented before they are transmitted to other people, thanks to artificial intelligence working in the background. Thus, a crime is prevented at the source before it is committed. Detecting the sarcastic word is a crucial step in sentiment analysis, considering the prevalence of sarcasm in emotional texts and the difficulties of detecting it [2]. This study used a dataset obtained from Kaggle [3], which was created using the online social networking platform Twitter data, to detect the sarcastic word. This dataset was first preprocessed by text mining and then classified by machine learning methods.

Many scientific studies continue to solve the problem of sarcastic word detection in social networks. The performances of the methods they have proposed in these scientific studies have been measured by many performance evaluation metrics [4]. The performance of the method we proposed in this study was evaluated using accuracy, precision, recall, and f_measure metrics.

The organization of this study is as follows: Chapter 2, scientific studies on the sarcastic word detection problem were examined. In Chapter 3, the proposed model for sarcastic word detection, text classification steps used during the experiments and machine learning methods are mentioned. In Chapter 4, the results of the experimental studies are given, and finally, the results and future work are shown in Chapter 5.

2. RELATED STUDIES

It is a fairly new problem that has attracted the attention of the scientific world. There are many studies on the detection of many sarcastic words in the literature. This section describes some of the research approaches and their results for detecting current sarcasm.

Campel and Katz state that sarcasm occurs in many different dimensions, such as unsuccessful expectations, pragmatic insincerity, negative tension, the presence of the victim, and along with stylistic components such as emotional words [5].

Joshi et al. presented a computational system that makes use of context incompatibility to detect sarcastic words. They classified two types of incompatible features as explicit and implicit. They also stated that they proposed a method that reveals the inconsistency between sentences. They said that a 10-20% F_measure value was obtained for the success of the method they offered in the study [6].

Riloff et al. developed a system to identify sarcastic words in tweets. They stated they developed a new pre-loaded algorithm that automatically learns positive and negative situations from sarcastic tweets [7].

Ghosh et al., by looking at a specific context type they have done, stated that they provided a complementary contribution to the modeling context studies available for the detection of sarcastic words. In their study, they sought answers to two questions. First, does modeling the speech context help with sarcasm detection? Second, can it be determined which part of the speech context triggers the sarcastic response? In response to the first question, they noted that Long Short-Term Memory (LSTM) networks, which can model both the context and the sarcastic response, outperform LSTM networks that only read the response. In response to the second question, they stated that an evaluation of the attention weights produced by the LSTM models was made. They emphasized that attention-based models can describe sarcastic speech characteristics [8].

Mishra et al., in their study, tried to observe the difference in the behavior of the eye when reading Sarcastic and Non-Sarcastic sentences. Starting from this observation, the cognitive features obtained from the eye movement data of the reader and the linguistic and stylistic features for the detection of sarcastic words were examined. They stated that they made statistical classification using the advanced feature set obtained. Augmented cognitive features improved their sarcastic remark detection (in terms of the F_measure metric) by 3.7% compared to the performance of the best-reported system [9].

3. SARCASM DETECTION MODEL

The representation of the data used in systems designed with artificial intelligence algorithms directly affects the stability of the system and the performance achieved. If the studied data is text-based, it must be converted to an appropriate representation. This is why basic text mining operations are so important. Since the tweets used in this study are text-based, text mining operations were carried out as preprocessing methods to extract useful information from the text. The flow chart for the proposed sarcastic word detection model is given in Figure 1.

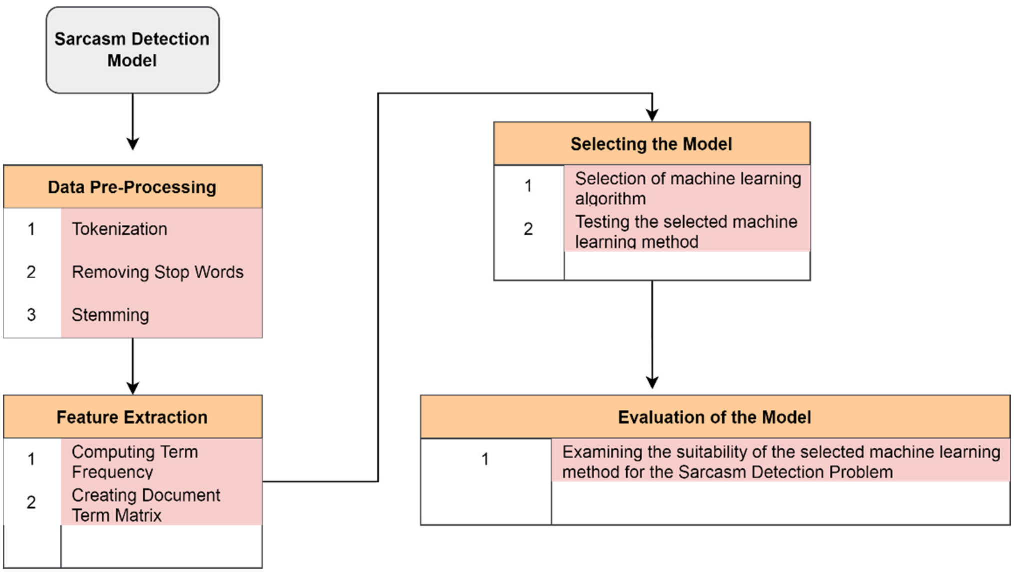

Figure 1. Flowchart of the sarcasm detection model

3.1. Data Preprocessing Steps

Text mining is a sub-branch of natural language processing. This application takes its place in natural language processing when viewed from the top. Like data mining, text mining is based on implementing some basic steps required to access information from raw data. Since the data type used during the experiments is text-based, text mining is done. The preprocessing applied to the raw tweet data during the experiments is shown in Table 1.

Table 1. Basic Preprocessing Steps.

Input: Entering textual data
Output: Preprocessed textual data
1. Extraction of numerical expressions from textual data
2. Removing punctuation marks from textual data
3. Removing texts with less than N characters
4. Applying the case converter to text
5. Removing stop words from the text
6. Rooting of textual data

3.1.1. Removing Numeric Expressions and Punctuation Marks

In this preprocessing step, numerical expressions, spaces and punctuation marks are removed from the text-based data and divided into small pieces called tokens. Here, the term token represents a useful semantic unit for processing data within a document [10]. It is the basic step for teaching words to machines.

3.1.2. N-Character Optimization and Case Conversion

Some words used in English are not keywords that help us solve the sarcastic word detection problem. These words need to be removed from the dataset. The number of N characters can be predetermined. In this study, N=3 was determined. In addition, integrity is important in the data to be analyzed, so all data is converted to uppercase or lowercase letters. In this study, all data has been converted to lowercase.

3.1.3. Removing Stop Words

Stop words are words that don't convey any information. Stop words include conjunctions and pronouns. In English, there are nearly 500 stop words. A the, by, of, while, did, that, on, afterward, once, and before are examples of these terms. [11].

3.1.4. Finding Root

In this process step, words are to reach their roots. It is the step of obtaining root states freed from their inflected state. The goal of rooting is to find the core forms of words with similar meanings but diverse word forms [11].

3.2. Feature Extraction, Selection, and Suggested Model

The common problem in data mining, text mining, image processing, and all other data analysis studies is the excess data size. When the data size is large, processing and storing this data takes a lot of time and requires the extra cost to store it. In addition, more processor and memory elements are required to process this data. For these reasons, it is important to remove residual and unnecessary features from the dataset that will not affect the model's accuracy. In this study, a feature selection method selects root terms whose frequency is greater than the predetermined threshold value in the datasets. Each document's terms in the dataset are weighted, and the document is turned into a vector of term weights. Vector Space Model is the name for this type of representation (VUM). Each word in VUM is represented with a value representing the word's weight in the document. In this study, Term Frequency (TF) method was used to calculate the weights [12].

Binary Vectors: Data containing text in the dataset are represented as 0's and 1's.

TF: It refers to the number of repetitions of word roots in the data as shown in Equation (1).

$$TF_{ij} = \frac{n_{ij}}{|d_i|} \tag{1}$$

di, i'. is the sum of all terms in the document. *nij* is *i'. j'* in the document. is the number of words. After calculating the TF value for each word of the document, a Document Term Matrix (DTM) is created using the weights of the words. This matrix is the m x n matrix. In DTM, each row represents the documents, each column indicates the term, and each cell shows the weight of the terms in the document [11]. The DTM used during the experiments is shown in Table 2.

Table 2. Document Term Matrix (DTM).

	T_1	T_2	…	T_n
D_1	W_{11}	W_{12}	…	W_{1n}
D_2	W_{21}	W_{22}	…	W_{2n}
…	…	…	…	…
D_m	W_{m1}	W_{m2}	…	W_{mn}

3.3. Machine Learning Algorithms Used in Experiments

The first of the machine learning algorithms used in the experiments is the J48 algorithm. This algorithm is the WEKA-edited version of the C4.5 decision tree algorithm. Decision trees are frequently used in regression and classification problems in the literature. A decision tree is one of the most preferred supervised learning methods. In this learning method, a learning set is first created. In this algorithm, rr is the label denoted by the name of an educational status class. Decision trees consist of roots, nodes and leaves [13].

Another of the machine learning methods we use in our experiments is Naive Bayes (NB), a statistical classification method. NB classification is based on Bayes' theorem in statistics. The probability that the available data belong to the determined classes is evaluated. It includes the logic of probabilistic calculation of the effect of each criterion of the data on the result. The NB method is frequently used in the literature due to its simplicity and simplicity compared to other classification algorithms [14].

Another regression analysis used in the study is logistic regression. It is one of the basic fields of statistics. Regression analysis can be defined as predicting the behavior of a random variable using a model. Here, the relationships between dependent and independent variables are examined. Thanks to this relationship between the variables, modeling or estimation are performed. There is more than one type of regression used in statistics. Logistic regression was used in this study [15].

Another machine learning method used in the study is the Random Forest (RF) method. The working logic of the RF method is similar to decision trees. As the name suggests, the random forest consists of a large number of individual decision trees that work as a community. In the RF method, the tree with the highest votes is used. In this way, it is possible to obtain high accuracy values in this method [16].

Yoav Freund and Robert Schapire developed the adaBoost algorithm, another machine learning method, [17]. An AdaBoost algorithm, one of the first applications of the Boosting method, is based on the ensemble learning technique [18]. Unlike other models, this method allows many models to be trained to solve the related problem. The results obtained in these models are then combined for classification or regression. It is possible to get more successful results as more than one model is trained.

4. DATASET, METRICS, AND EXPERIMENTAL RESULTS

This section gives the dataset used in the study, performance measurement metrics, and experimental results.

4.1. Dataset

The dataset used during the experiments is a publicly available two-class text-based dataset. The examples of sarcastic words used in the dataset were taken from www.theonion.com. Samples of non-sarcastic words are taken from www.huffpost.com, www.bbc.com, www.foxnews.com, www.aljazeera.com, and finally www.euronews.com. The original dataset used in the experiments contains 12506 data and 52% of this data is made up of sarcastic words and 48% of it is non-sarcastic [3]. However, 1475 pieces of data were randomly selected during the experiments. Of these chosen data, 722 were determined as sarcastic and 753 as non-sarcastic. A section from the dataset is shown in Figure 2.

Row ID	S Text	S State
1	CNN Triumphs (At Least in Most Demographic Categories)	Non Sarcastic
2	You Did The Best You Could Says Iron Man Action Figur…	Sarcastic
3	New Emails Reveal Warm Relationship Between Kamala …	Non Sarcastic
4	Donald Trump Jr. Gets Slammed Over Racist Birtherism …	Non Sarcastic
5	God Urges Rick Perry Not To Run For President	Sarcastic
6	Global Aid Pours into Haiti	Non Sarcastic
7	CNN Anchor Calls Obama Protester 'Rude' And 'Crazy'	Non Sarcastic
8	Federal Prisons Reinstitute Executions By Lethal Inflation	Sarcastic
9	Lou Dobbs Crumbles When Pressed On His 'NAFTA Sup…	Non Sarcastic
10	CNN Still Bent On Debating 'Two Sides' Of The Confeder…	Non Sarcastic
11	'Fox & Friends' Guest Says CNN Partly To Blame For Las…	Non Sarcastic
12	An Open Letter to CNN Regarding Nancy Grace	Non Sarcastic
13	Conservative Pundits: GOP Primary Lacks Foreign Policy…	Non Sarcastic
14	Soldier Back Home From Serving At Mexico Border Still H…	Sarcastic
15	Decades Of Breathing Really Starting To Catch Up With…	Sarcastic
16	U.S.â€"Cuba Relations End After Obama Hit By Foul Bal…	Sarcastic
17	Stanford Students Admit It Was Pretty Obvious Billionai…	Sarcastic
18	LA's Winners Of The Week June 11	Non Sarcastic
19	CNN's Ed Henry: McCain Playing Politics On Bailout	Non Sarcastic
20	Overwhelmed Archaeologists Struggling To Keep Pace …	Sarcastic
21	Study Finds Majority Of Accidental Heroin Overdoses C…	Sarcastic
22	Deli Worker Searches For Palest Mealiest Tomato To Pu…	Sarcastic
23	Cancer Researchers Develop Highly Promising New Pink…	Sarcastic
24	Kamala Harris Breaks Down Trump's â€˜Predatorâ€™ Pl…	Non Sarcastic
25	California's Death-Penalty Regime Ruled Unconstitution…	Non Sarcastic

Figure 2. A snippet of the sarcastic promise dataset.

4.2. Performance Evaluation Metrics

While detecting the proposed method for sarcasm detection in online social networks with machine learning algorithms, some metrics that are frequently used in the literature are used in this application to measure the proposed method's performance [19,20]. The metrics used in the needling word detection problem are shown in Table 3.

Table 3. Metrics

Performance Evaluation Metrics	Formulas
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{FN+TP}$
F-Measure	$\frac{2*\left(\frac{TP}{TP+FP}\right)*\left(\frac{TP}{TP+FN}\right)}{\left(\frac{TP}{TP+FP}\right)+\left(\frac{TP}{TP+FN}\right)}$

4.3. Experimental Results

In this study, the detection of sarcastic words is considered a classification problem. In this study, the sarcastic promise dataset was tested using different parameters on machine learning algorithms and their performances were compared.

The dataset was tested on seven different machine learning algorithms for sarcastic word detection. The entire dataset is set as training and tests on algorithms. Standard versions of machine learning algorithms were used during the experiments. The results obtained in this application are shown in Table 4. The graph of the values given in Table 4 is given in Figure 3.

Table 4. Performance values of machine learning algorithms (100% training).

	Machine Learning Algorithms						
	J48	Filtered Classifier	Naïve Bayes	Random Forest	Logistic Regression	JRip	AdaBoostM1
Accuracy	0.741	0.761	0.814	**0.949**	0.893	0.752	0.660
F-Measure	0.775	0.795	0.823	**0.947**	0.890	0.788	0.737
Recall	0.659	0.672	0.751	**0.937**	0.871	0.664	0.583
Precision	0.942	0.973	0.912	0.957	0.910	0.969	**0.998**

When Table 4 is examined, it is seen that the Random Forest algorithm gives the highest accuracy value with 94.9%. In addition, it has been determined that this algorithm has higher performance in F_measure and Sensitivity criteria than the other 6 machine learning methods. Only the precision metric is higher in the AdaBoostM1 algorithm than all other machine learning methods.

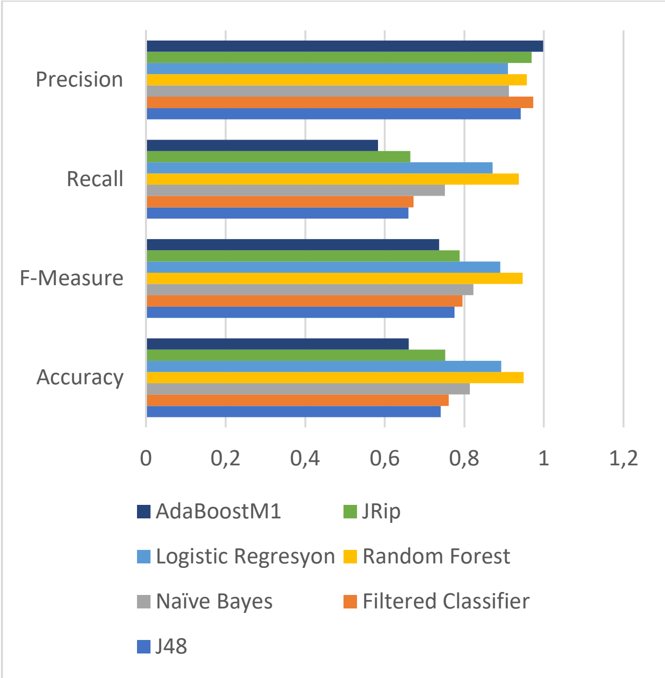

Figure 3. Performance results of algorithms (100% training)

The dataset was tested on seven different machine learning algorithms for sarcastic detection. The dataset is set as 70% training and 30% testing and tests on algorithms. Standard versions of machine learning algorithms were used during the experiments. The results of this application are shown in Table 5. The graph of the values given in Table 5 is given in Figure 4.

Table 5. Performance values of machine learning algorithms (70% training, 30% testing)

	Machine Learning Algorithms						
	J48	Filtered Classifier	Naïve Bayes	Random Forest	Logistic Regression	JRip	AdaBoostM1
Accuracy	0.695	0.727	0.787	**0.830**	0.735	0.690	0.654
F-Measure	0.748	0.772	0.803	**0.817**	0.773	0.749	0.731
Recall	0.613	0.638	0.712	**0.831**	0.650	0.606	0.578
Precision	0.960	0.977	0.920	0.806	0.954	0.983	**0.994**

When Table 5 is examined, it is seen that the Random Forest algorithm gives the highest accuracy value with 83%. In addition, it has been determined that this algorithm has higher performance in F_measure and Sensitivity criteria than the other 6 machine learning methods.

Only the precision metric is higher in the AdaBoostM1 algorithm than all other machine learning methods.

Figure 4. Performance results of algorithms (70% training, 30% testing)

The dataset was tested on seven different machine learning algorithms for sarcastic word detection. The dataset cross-validation is set as 5-fold cross-validation and tests on algorithms. Standard versions of machine learning algorithms were used during the experiments. The results of this application are shown in Table 6. The graph of the values given in Table 6 is given in Figure 5.

Table 6. Performance values of machine learning algorithms (5-fold Cross Validation).

	Machine Learning Algorithms						
	J48	Filtered Classifier	Naïve Bayes	Random Forest	Logistic Regression	JRip	AdaBoostM1
Accuracy	0.707	0.734	0.803	**0.817**	0.740	0.726	0.645
F-Measure	0.757	0.777	**0.815**	0.806	0.778	0.770	0.728
Recall	0.625	0.647	0.738	**0.815**	0.655	0.642	0.573
Precision	0.961	0.973	0.910	0.796	0.959	0.963	**0.998**

When Table 6 is examined, it is seen that the Random Forest algorithm gives the highest accuracy value with 81.7%. The Random Forest algorithm gave better results than other algorithms in terms of sensitivity metrics. In addition, the Naive Bayes algorithm showed the highest performance in terms of the F_measure metric. The precision metric is higher in the AdaBoostM1 algorithm than in all other machine learning methods.

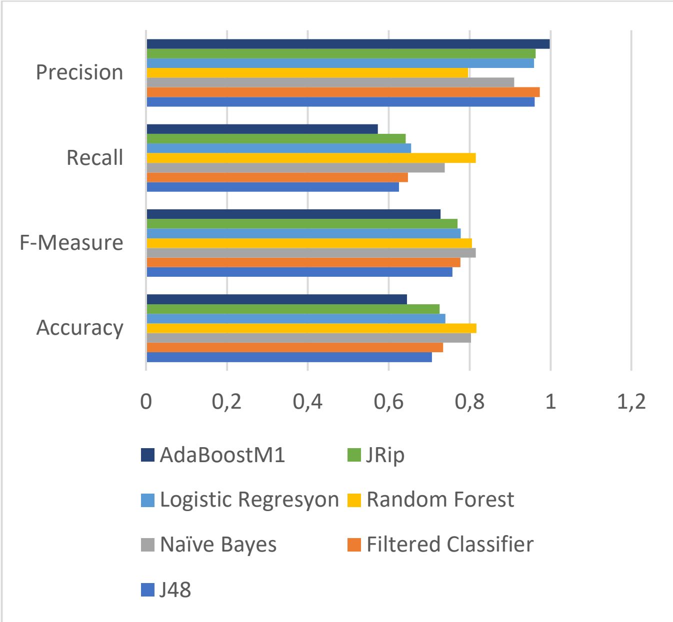

Figure 5. Performance results of algorithms (5-fold Cross Validation)

The dataset was tested on seven different machine learning algorithms for sarcastic word detection. The dataset cross-validation is set as 10-fold cross-validation and tests on algorithms. Standard versions of machine learning algorithms were used during the experiments. The results of this application are shown in Table 7. The graph of the values given in Table 7 is given in Figure 6.

Table 7. Performance values of machine learning algorithms (10-fold Cross Validation).

	Machine Learning Algorithms						
	J48	Filtered Classifier	Naïve Bayes	Random Forest	Logistic Regression	JRip	AdaBoostM1
Accuracy	0.811	0.812	**0.852**	0.822	0.742	0.731	0.642
F-Measure	0.817	0.806	**0.850**	0.814	0.779	0.773	0.726
Recall	0.758	**0.878**	0.822	0.811	0.659	0.646	0.571
Precision	0.886	0.744	0.879	0.816	0.952	0.961	**0.998**

When Table 7 is examined, it is seen that the Naive Bayes algorithm gives the highest accuracy value with 85.2%. The naive Bayes algorithm gave better results than other algorithms in terms of the F_measure metric. In addition, the Filtered Classifiers algorithm showed the highest performance in terms of the Sensitivity metric. The precision metric is higher in the AdaBoostM1 algorithm than in all other machine learning methods.

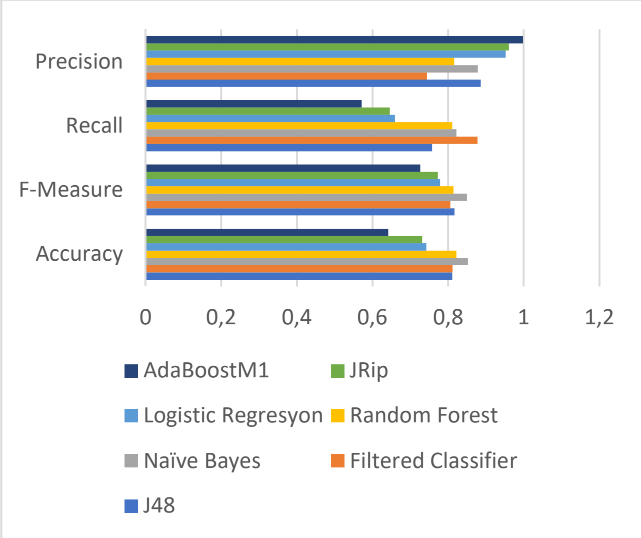

Figure 6. Performance results of algorithms (10-fold Cross Validation)

5. CONCLUSION

Since the internet is an integral part of our lives, people using this technology have increased rapidly. In addition, many positive and negative reflections of the internet on human life appear as an inevitable reality. In this study, using text mining techniques, which is a sub-branch of data mining, a method is proposed to detect sarcastic words in online social networks with machine learning methods on the public dataset. In this study, the detection of sarcastic words is considered a classification problem. The performances of machine learning methods were evaluated using four experiments in terms of accuracy, precision, precision, and F_measure metrics.

Considering the observations of the 4 experiments we have made for the proposed method, the highest accuracy values have been obtained with the Random Forest algorithm. After the Random Forest algorithm, the highest accuracy values were obtained with the Naive Bayes algorithm. The highest percentage values were observed in all experiments where the AdaBoostM1 algorithm was received in precision metrics. It is known that the performance of the algorithms used in the experiments varies according to the problem and dataset to be determined. Regarding future studies, the model's performance can be increased by discovering new algorithms, integrating metaheuristic optimization methods, or producing chaotic, adaptive, or hybrid versions of existing algorithms for more efficient results. Different feature extraction techniques can also be applied to improve the performance of the sarcastic word detection system in terms of many important metrics.

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Declaration of Competing Interest
There is no conflict of interest.

Author Contribution
Harun BİNGÖL and Muhammed YILDIRIM contributed equally at every stage of the article.

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