An Empirical Study on Detecting Fake Reviews Using Machine Learning Techniques

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Abstract— **Reputation systems in E-commerce (EC) play a substantial role that allows various parties to achieve mutual benefits by establishing relationships. The reputation systems aim at helping consumers in deciding whether to negotiate with a given party. Many factors negatively influence the sight of the customers and the vendors in terms of the reputation system. For instance, lack of honesty or effort in providing the feedback reviews, by which users might create phantom feedback from fake reviews to support their reputation. Moreover, the opinions obtained from users can be classified into positive or negative which can be used by a consumer to select a product. In this paper, we study online movie reviews using Sentiment Analysis (SA) methods in order to detect fake reviews. Text classification and SA methods are applied on a real conducted dataset of movie reviews. Specifically, we compare four supervised machine learning algorithms: Naïve Bayes (NB), Support Vector Machine (SVM), K-Nearest Neighbors (KNN-IBK), and Decision Tree (DT-J48) for sentiment classification of reviews in two different situations without stopwords and with stopwords methods are employed. The measured results show that for both methods the SVM algorithm outperforms other algorithms, and it reaches the highest accuracy not only in text classification but also to detect fake reviews.**

Keywords— Reputation systems; Sentiment Analysis; Naïve Bayes; Support Vector Machine; k-Nearest Neighbor; Decision Tree -J48; Fake Reviews.

I. INTRODUCTION

Sentiment Analysis (SA), also known as Opinion Mining (OM), is the domain of study that analyzes people's opinions, evaluations, sentiments, attitudes, appraisals, and emotions towards entities such as services, individuals, issues, topics, and their attributes [1].

In this study, we sometimes consider the time is more valuable than money, therefore instead of spending times in reading and figuring out the positivity or negativity of review we can use automated techniques for sentiment analysis.

The basic of Sentiment Analysis is classifying the polarity (positive & negative) of a given text at the levels of document, sentence, and aspect whether the expressed opinion in three levels is positive or negative.

The aim of sentiment analysis is to find opinions from reviews and then classify these opinions based upon polarity. According to [7], in Sentiment Analysis there are three major classification levels: the first level is document level, the second level is sentence level, and the third level is aspect level. The document level Sentiment Analysis aims to classify an opinion document as a negative or positive opinion. It regards the whole record as a basic information unit. The sentence level using Sentiment Analysis aims to setup opinion stated in every sentence. The aspect level using Sentiment Analysis goals to categorize the sentiment on the specific aspects of entities.

The document is obtained from a dataset of movie reviews [2], and then a sentiment analysis technique is applied to classify the documents resultant as real positive and real negative reviews or fake positive and fake negative reviews. Real negative and fake positive reviews can lead to financial gains. This, unfortunately, gives strong incentives to write fake reviews that attempt to intentionally mislead readers by providing unfair reviews to several goods for the purpose of damaging their reputations. Detecting such fake reviews is a significant challenge. For example, fake consumer reviews in the e-commerce sector are not only affecting individual consumers but also corrupt purchaser's confidence in the online shopping [3]. Machine learning techniques and Sentiment Analysis methods will have a major positively effect on reputation systems, and especially to detection processes of fake reviews in an e-commerce and social commerce environments.

In machine learning-based techniques, algorithms such as SVM, NB, and DT-J48 are applied for the classification [4]. SVM is a type of learning algorithm that represents supervised machine learning approaches [5], and it is an excellent successful prediction approach. The SVM also is a robust classifier approach [6]. One of the recent researchers has presented in [7] that introduce a survey on different applications and algorithms for Sentiment Analysis but it focused on algorithms used in various languages with stopwords and did not focus on without stopwords and the results are not accurate when without stopwords are considered. Also, the researchers did not focus on detecting fake reviews [8] [9]. This paper presents four supervised machine learning approaches to classifying sentiment of our dataset which is compared with stopwords and without stopwords methods. We have also detected fake positive reviews and fake negative reviews by using these methods.

The main goal of our study is to classify movie reviews as a real review or fake review using Sentiment Analysis algorithms with supervised learning techniques.

The conducted experiments have shown the accuracy of results through sentiment classification algorithms, and we have found that SVM in both cases without stopwords and with stopwords is more accurate than other methods such as NB, KNN-IBK, and DT-J48.

The main contributions of this study are detailed in the Conclusion and Future Work section, but can be briefly summarized as follows: We compared different sentiment classification algorithms for labeling movie reviews as fake or real, and ranked the algorithms according to accuracy. We also found that the use of stopwords proved more efficient in the classification task.

The rest of this paper is organized as follows. Section 2 presents the related works. Section 3 shows the methodology, section 4 explains the experiment results, and finally, section 5 presents the conclusion and future work.

II. RELATED WORKS

This work belongs to the set of studies on reputation systems evaluation vulnerability. This study employs statistical methods to evaluate the performance of detection mechanism for fake reviews and evaluate the accuracy of this detection; here we emphasize our literature review on studies that applied statistical methods to this issue.

A. Sentiment analysis issues

There are several issues accounted in conducting of Sentiment analysis [10]. In the first major issue, the viewpoint (or opinion) observed as negative in a situation possibly be considered positive in another situation. In the second major issue, the people don't always have same express views in a similar approach. Most common text processing employed the fact the minor changes between the two text fragments don't change the actual sense, accurately [10].

B. Textual reviews to provide detailed opinion about the product

Most of the available reputation models depend on numeric data available in different fields; an example is ratings in e-commerce. Also, most of the reputation models focused only on the overall ratings of products without considering reviews which provided by customers [11]. On the other hand, most websites allow consumers to add textual reviews to provide a detailed opinion about the product [12], [13]. These reviews are available for customers' to read, and customers' now depend increasingly on reviews rather than on ratings. Through the Reputation models that could use SA methods to extract users' opinions and use this data in the reputation system. This information may include consumers' opinions about different features [14] [15].

C. Detecting Fake Reviews Using Machine Learning

Filter and identification of fake reviews have substantial significance [16]. In [17] authors proposed a technique for categorizing a single topic textual review. A sentiment classified document level is applied for stating a negative or positive sentiment. Supervised learning techniques comprise of two phases, selection, and extraction of reviews categorization utilizing learning models such as SVM.

Extract the best and accurate approach, and simultaneously categorize the customers' written reviews text into negative or positive opinions. It has attracted attention as a major research field. Although it is still in an introductory phase, there has been a lot of work related to several languages [18] [19] [20] [21]. Our work used several supervised learning algorithms such as SVM, NB, KNN-IBK, and DT-J48 for Sentiment Classification of text to detect fake reviews.

D. Comparative Study of different Classification algorithms

Table I shows comparative studies on classification algorithms to prove the best method for detecting fake reviews using different dataset such as News Group dataset, Text documents, Movie Reviews dataset proves [23,24] that NB and DKV (Distributed Keyword Vector) are accurate without stopwords while [22] finds that NB is accurate for stopwords. Using same data sets [8] finds that SVM is accurate for with stopwords while [9] finds that SVM is only accurate without stopwords. However, in our empirical study results prove that SVM is robust and accurate for both with and without stopwords, and also for detecting fake reviews.

TABLE I. A Comparison of different studies of classification algorithms.

Reference	Data Source	Size of dataset	Using Supervised Learning	Using Unsupervised learning	Languag e	Classification algorithms	without stopwords	With stopwords	The best method
[22]	News Group dataset	20 categories with 1000 documents	Yes	No	English	NB, SVM	No	Yes	NB
[8]	Movie Reviews dataset	2000 Movie Reviews	Yes	No	English	NB,SVM,IBK ,DT	No	Yes	SVM
[23]	Movie Reviews dataset	4000 movie reviews	Yes	No	Chinese	NB, SVM, K-NN LLR, Delta TFIDF, LDA-SVM, TFIDF, DKV	Yes	No	NB and DKV
[24]	Movie Reviews dataset	1400 Movie Reviews, 2000 Movie Reviews	Yes	No	English	NB, SVM	Yes	No	NB
[9]	Movie Reviews dataset	2000 Movie Reviews	Yes	No	English	NB, SVM	Yes	No	SVM
This work	Movie Reviews dataset	2000 Movie Reviews	Yes	No	English	NB,SVM, KNN-IBK,DT-J48	Yes	Yes	SVM Robust and very accurate

III. METHODOLOGY

To accomplish our goal, we analyze a dataset of movie reviews using Weka tool for text classification. In the proposed methodology as shown in figure 2 we will follow some steps that are involved in Sentiment Analysis using the approaches are described below:

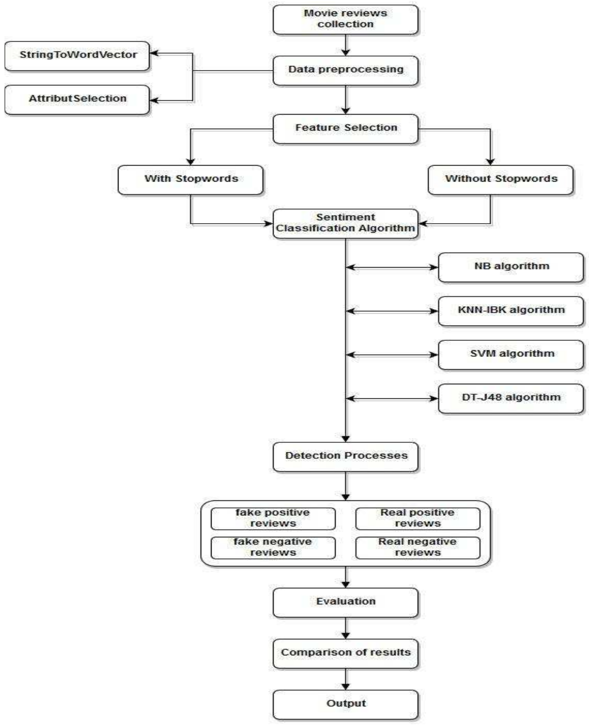

Fig. 1. Proposed Scheme

Step 1: Movie reviews collection

To provide an exhaustive study of machine learning algorithms, the experiment based on analyzing the sentiment value of the standard dataset. We use the original data set of the movie review to test our methods of reviews classification. This dataset is available and has been used in [9]. The dataset of movie reviews is available and collected through [2], and this dataset consists of 2000 reviews, and are uniform in 1000 positive and 1000 negative.

Step 2: Data pre-processing

The pre-processing phase includes preliminary operations which help in transforming the data before the actual SA task. To demonstrate the effect of pre-processing on the classification models data preprocessing plays a very significant in many supervised learning, through our proposed scheme we divided data preprocessing as the following:

A. StringToWordVector

To preparing our data for learning, which involves transforming it by using the StringToWordVector filter, and which is the main tool for text analysis in WEKA. This filter allows configuring the different steps of the term extraction. Indeed, we should be able to see something such as the following:

- Configure the tokenizer

  We need to do Feature extraction using machine learning technique that is converting the normal text to a set of features to make the provided document classifiable.

- Specify a stopwords list

  Stop words list are the words we want to filter out before training the classifier. Several of the most commonly used stop words in English, they could be "a," "the," "of," "I," "you," "it," and." These are usually high-frequency words that aren't giving any additional information to our labeling, but rather they actually confuse our classifier. In this study, we used a 630 English stopwords list. Stop word removal can help us in reducing the memory requirement while classifying the reviews.

B. Attribute Selection

Removing the poorly describing attributes can be valuable to get improved classification accuracy. Because not all attributes are relevant to the classification work, and irrelevant attributes can even decrease the performance of some algorithms. We should perform attribute selection before training the classifier.Attribute selection with supervised learning differs from unsupervised learning, where in the latter case, data have no goal attribute.

Step 3: Feature Selection

In this study, we implemented four feature selection methods widely used for the classification task of Sentiment Analysis with Stopwords and without Stopwords methods. The results differ from one method to another.

Step 4: Sentiment Classification algorithms

In this step, we will use sentiment classification algorithms, and they have been applied in many domains such as commerce, medicine, media, biology, etc. There are many different techniques in classification method like NB, DT-J48, SVM, K-NN, Neural Networks, and Genetic Algorithm. In this study, we will use four popular supervised classifiers: NB, DT-J48, SVM, K-NN, algorithms.

1) Naïve Bayes(NB)

The NB classifier is a basic probabilistic classifier based on applying Bayes' theorem. The NB calculates a set of probabilities by combinations of values in a given data set. Also, the NB classifier has fast decisions making process.

2) Support Vector Machine(SVM)

SVM in machine learning is supervised learning models with the related learning algorithm, which examines data and identify patterns, used for regression and classification analysis [25]. Recently, many classification algorithms have been proposed, but SVM is still one of the most widely and most popular used classifiers.

3) K-Nearest Neighbor (K-NN)

K-NN is a type of lazy learning and is a non-parametric approach for categorizing objects based on closest training. The k-NN algorithm is a very simple algorithm for all machine learning. The performance of the k-NN algorithm depends on several different key factors, such as a suitable distance measure, similarity measure for voting, and, k parameter [26], [27], [28], [29].

A set of vectors and class labels which are related with each vector constitute each of the training data. In the simplest way; it will be either positive or negative class. In this study, we are using a single number ''k'' with values of k=1, k=3, k=5, k=7. These numbers decide how many neighbors influence the classification.

4) Decision Tree (DT-J48)

The DT-J48 approach is useful in the classification problem. In the testing option, we are using percentage split as preferred method.

Step 5: Detection Processes

After training, the next step is to predict the output of the model on the testing dataset, and a confusion matrix generated which classifies the review as positive or negative. We are defining as Fake the set of reviews that are found to be False (False Positive or False Negative) and defining as Real the set of reviews that are found to be True (True positive and True Negative). The Fake and Real reviews are determined according to equations a trough d. The results involve the following attributes:

- True Positive: Real Positive Reviews in the testing data, which are correctly classified by the model as Positive (P).
- False Positive: Fake Positive Reviews in the testing data, which are incorrectly classified by the model as Positive (P).
- True Negative: Real Negative Reviews in the testing data, which are correctly classified by the model as Negative (N).
- False Negative: Fake Negative Reviews in the testing data, which are incorrectly classified by the model as Negative (N).

True negative (TN) is events which are Real and is effectively labeled as Real, true positive(TP) is events which are fake and are effectively labeled as fake. Respectively, False Positives (FP) refer to Real events being classified as fakes; False Negatives (FN) are fake events incorrectly classified as Real events. According to the confusion matrix, (a) -(f) shows numerical parameters that apply following measures to evaluate the Detection Process (DP) performance. In Table II the confusion matrix shows the counts of real and fake predictions obtained with known data, and for each algorithm used in this study is different performance evaluation and confusion matrix.

TABLE II. The confusion matrix

	Real	**Fake**
Real	True negative reviews (TN)	False positive reviews (FP)
Fake	False negative reviews (FN)	True positive reviews (TP)

$$\text{Fake Positive Reviews Rate} = \frac{FP}{FP+TN} \quad \text{(a)}$$

$$\text{Fake negative Reviews Rate} = \frac{FN}{TP+FN} \quad \text{(b)}$$

$$\text{Real Positive Reviews Rate} = \frac{TP}{TP+FN} \quad \text{(c)}$$

$$\text{Real negative Reviews Rate} = \frac{TN}{TN+FP} \quad \text{(d)}$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FN+FP} \quad \text{(e)}$$

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

For each algorithm different Performance evaluation and confusion matrix.

Step 6: Comparison of results

In this step, we compared the different accuracy provided by the dataset of movie reviews with various classification algorithms and identified the significant classification algorithm for detecting Fake positive and negative Reviews.

IV. EXPERIMENTAL RESULTS

In this section, we present experimental results from four different supervised machine learning approaches to classifying sentiment of our dataset which is compared with stopwords and without stopwords methods. Also, we have used the same techniques at the same time to detect fake reviews.

A. Without stopwords

1) Confusion matrix for all methods

The number of real and fake predictions made by the classification model compared with the actual results in the test data is shown in the confusion matrix. The confusion matrix is obtained after implementing NB, SVM, K-NN, DT-J48 algorithms. Table III displays confusion matrix for respectively Movie review dataset. The columns represent the number of predicted classifications made by the model. The rows display the number of real classifications in the test data.

TABLE III. Confusion matrix for all methods

Classification algorithms	SA	Real	Fake
NB	Real	806	194
	Fake	177	823
KNN-IBK (K=1)	Real	766	234
	Fake	426	574
KNN-IBK (K=3)	Real	800	200
	Fake	382	618
KNN-IBK (K=5)	Real	817	183
	Fake	370	630
KNN-IBK (K=7)	Real	824	176
	Fake	366	634
SVM	Real	**812**	**188**
	Fake	**177**	**823**
(DT-J48)	Real	743	257
	Fake	286	714

2) Evaluation parameters and accuracy for all methods

Four main performance evaluation measures have been introduced for Classification algorithms. These include Fake Positive Reviews predictive value, Fake Negative Reviews predictive value, Real Positive Reviews predictive value, Real Negative Reviews predictive value, accuracy and Precision. Table IV shows the results of evaluation parameters for all methods and provides a summary of recordings obtained from the experiment. Where, SVM surpasses for best accuracy among the other classification algorithms with 81.75%. The tabulated observations list the readings as well as accuracies obtained for a specific supervised learning algorithm on a dataset of a movie review.

TABLE IV. An evaluation of all methods using different parameters: without stopwords

Classification algorithms	Fake Positive Reviews %	Fake negative Reviews %	Real Positive Reviews %	Real negative Reviews %	Precision %	Accuracy %
NB	19.4	17.7	82.3	80.6	80.9	81.45
K-NN-IBK (K=1)	23.4	42.6	57.4	76.6	71	67
K-NN-IBK (K=3)	20	38.2	61.8	80	75.6	70.9
K-NN-IBK (K=5)	18.3	37	63	81.7	77.5	72.35
K-NN-IBK (K=7)	17.6	36.6	63.4	82.4	78.3	72.9
SVM	18.8	17.7	82.3	81.2	81.4	**81.75**
DT-J48	25.7	28.6	71.4	74.3	73.5	72.85

The graph in figure 2 shows a rate of Fake Positive Reviews, Fake negative Reviews, Real Positive Reviews, Real negative Reviews, Accuracy, and Precision for comparative analysis of all different algorithms.

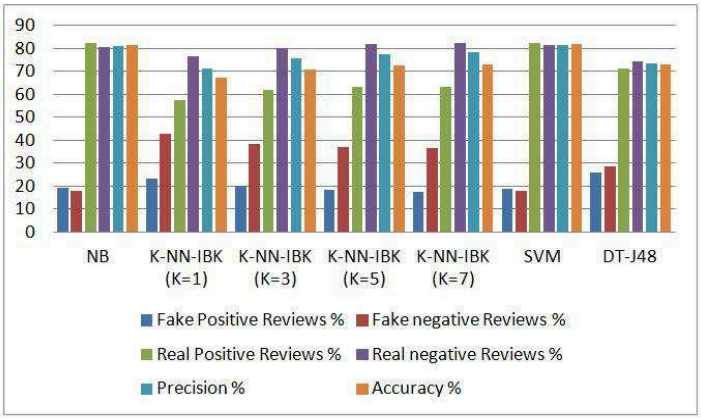

Fig. 2. Comparative analysis of all methods

The comparison in Table V indicates that the classification accuracy of SVM algorithm was better than NB, KNN-IBK, and DT-J48 algorithms.

TABLE V. A Comparison of the accuracy of classifiers

Classification algorithms	Accuracy %
NB	81.45
KNN-IBK (K=1)	67
KNN-IBK (K=3)	70.9
KNN-IBK (K=5)	72.35
KNN-IBK (K=7)	72.9
SVM	**81.75**
DT-J48	72.85

The graph in Figure 3 shows accuracy rate of NB, SVM, (K-NN, k=1, k=3, k=5, k=7), DT-J48 algorithms. We obtained a high accuracy of SVM algorithm than other algorithms.

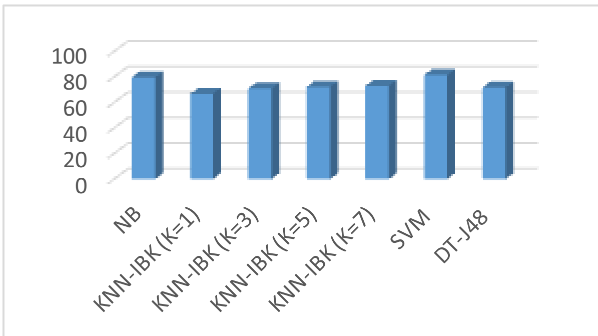

Fig. 3. The accuracy of different algorithms

Table VI shows the time taken to build prediction model by each algorithm. As evident from the table, K-NN takes the shortest amount of time of 0 seconds to create a model and SVM takes the longest amount of time of 1.58 seconds to build a model.

TABLE VI. Time taken to build model: without stopwords

Classification algorithms	Time taken to build model (Seconds)
NB	0.05
KNN-IBK (K=1)	0
KNN-IBK (K=3)	0.01
KNN-IBK (K=5)	0
KNN-IBK (K=7)	0
SVM	**1.58**
DT-J48	0.93

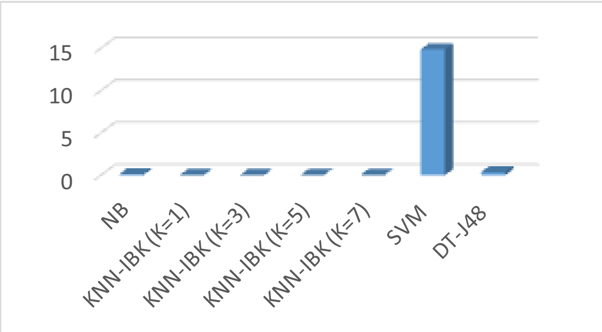

Fig. 4. Time taken to build model (Seconds): without stopwords

B. *With stopwords*

1. *Confusion matrix for all methods*

The previous section compared different algorithms without the usage of stopwords. In this section, the algorithms were made to do a sentimental analysis on data with stopwords. From the results (refer table VII) the confusion matrix displays for respectively Movie review dataset.

TABLE VII. Confusion matrix for all methods

Classification algorithms	SA	Real	Fake
NB	Real	781	219
	Fake	187	813
KNN-IBK (K=1)	Real	771	229
	Fake	435	565
KNN-IBK (K=3)	Real	804	196
	Fake	387	613
KNN-IBK (K=5)	Real	816	184
	Fake	372	628
KNN-IBK (K=7)	Real	824	176
	Fake	366	634
SVM	Real	**809**	**191**
	Fake	**182**	**818**
DT-J48	Real	762	238
	Fake	330	670

2. *Evaluation parameters and accuracy for all methods*

Four main performance evaluation measures have been introduced for Classification algorithms. These include Fake Positive Reviews predictive value, Fake Negative Reviews predictive value, Real Positive Reviews predictive value, Real Negative Reviews predictive value, accuracy and Precision. Table VIII displays the results of evaluation parameters for all methods and provides a summary of recordings obtained from the experiment. As a results, SVM surpasses for best accuracy among the other classification algorithms with 81.35%.

TABLE VIII. An evaluation of all methods using different parameters: with stopwords

Classification algorithms	Fake Positive Reviews %	Fake negative Reviews %	Real Positive Reviews %	Real negative Reviews %	Precision %	Accuracy %
NB	21.9	18.7	81.3	78.1	78.8	79.7
K-NN-IBK (K=1)	22.9	43.5	56.5	77.1	71.1	66.8
K-NN-IBK (K=3)	19.6	38.7	61.3	80.4	75.8	70.85
K-NN-IBK (K=5)	18.4	37.2	62.8	81.6	77.3	72.2
K-NN-IBK (K=7)	17.6	36.6	63.4	82.4	78.3	72.9
SVM	19.1	18.2	81.8	80.9	81.1	**81.35**
DT-J48	23.8	33	67	76.2	73.8	71.6

The graph in figure 5 displays a rate of Fake Positive Reviews, Fake negative Reviews, Real Positive Reviews, Real negative Reviews, Accuracy, and Precision for comparative analysis of all different algorithms.

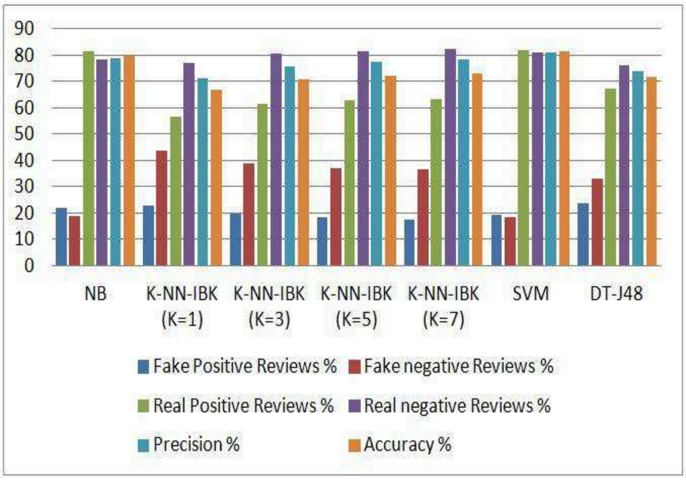

Fig. 5. Comparative analysis of all methods

The comparison in Table IX indicates that the classification accuracy of SVM algorithm was better than NB, KNN-IBK, and DT-J48 algorithms.

TABLE IX. Comparison of Accuracy of classifiers

Classification algorithms	Accuracy %
NB	79.7
KNN-IBK (K=1)	66.8
KNN-IBK (K=3)	70.85
KNN-IBK (K=5)	72.2
KNN-IBK (K=7)	72.9
SVM	**81.35**
DT-J48	71.6

The graph in Figure 6 displays accuracy rate of NB, SVM, (K-NN, k=1, k=3, k=5, k=7), DT-J48 algorithms. We obtained a high accuracy of SVM algorithm than other algorithms.

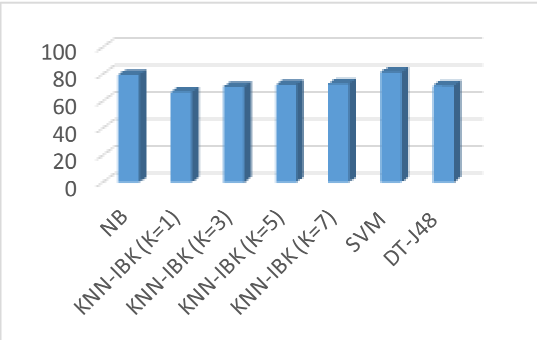

Fig. 6. The accuracy of different algorithms

TABLE X. Time taken to build model: with stopwords

Classification algorithms	Time taken to build model (Seconds)
NB	0.11
KNN-IBK (K=1)	0
KNN-IBK (K=3)	0.01
KNN-IBK (K=5)	0
KNN-IBK (K=7)	0
SVM	**14.84**
DT-J48	0.34

Table X displays the time taken to build prediction model by each algorithm. As evident from the table, K-NN takes the shortest amount of time of 0 seconds to create a model and SVM takes the longest amount of time of 14.84 seconds to build a model.

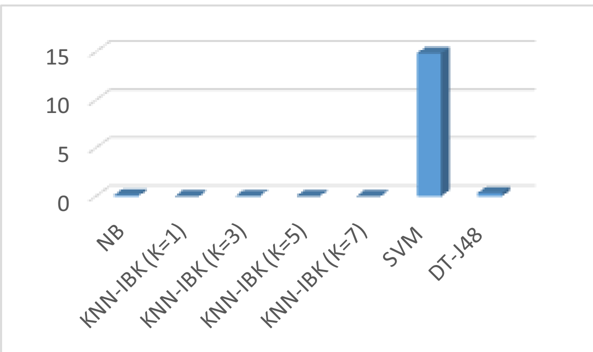

Fig. 7. Time taken to build model (Seconds): with stopwords

C. The summary of our experiments

Table XI and figure 8 present the summary of the experiments, where SVM is the best algorithm by accuracy for all tests with stopwords and without stopwords. It can be inferred that SVM does not agree with other algorithms. SVM tends to be more accurate than other methods in comparison. The presented study emphasizes that the accuracy of SVM tends to be higher when using the without stopwords feature. However, the detection process of Fake Positive Reviews and Fake Negative Reviews offers less promising results when compared to using the with stopwords feature.

TABLE XI. The best result of our experiments by accuracy

Features and Parameters	Fake Positive Reviews of SVM %	Fake Negative Reviews of SVM %	Precision of SVM %	Accuracy of SVM %
without stopwords	**18.8**	**17.7**	81.4	**81.75**
with stopwords	**19.1**	**18.2**	81.1	**81.35**

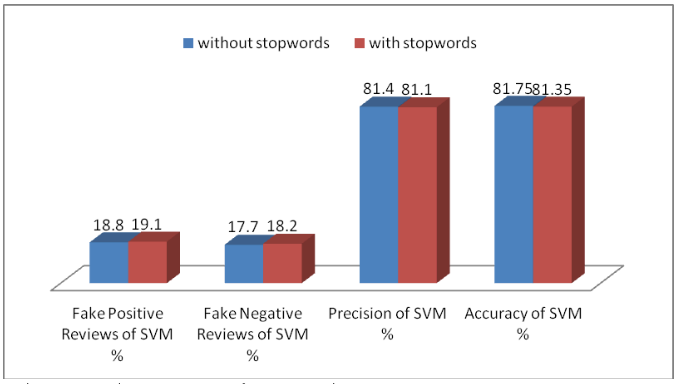

Fig. 8. The summary of our experiments

V. CONCLUSION AND FUTURE WORK

In this paper, we proposed several methods to analyze a dataset of movie reviews and presented sentiment classification algorithms and supervised learning used in our work with stopwords and without stopwords methods. Our experimental approaches studied the accuracy of all sentiment classification algorithms, and how to determine which algorithm is more accurate. Furthermore, we were able to detect fake positive review, and fake negative review through detection processes are shown in our results.

Four supervised learning algorithms to classifying sentiment of our dataset have been compared in this paper with stopwords and without stopwords. The first algorithm is NB, the second algorithm is SVM, and the third algorithm is K-NN, and the fourth algorithm is DT-J48. Through all of these algorithms also we have detected fake positive reviews and fake negative reviews. In this paper, our experiments have shown the accuracy of results through sentiment classification algorithms, and we have found that SVM algorithm in both cases stopwords and without stopwords are more accurate than other methods. Also, detection processes for fake positive reviews and fake negative reviews depend on the best and more accurate method that used in this study.

The main contributions of this study are summarized as follows:

- This study compares different sentiment classification algorithms in Weka tool, which are used to classify movie reviews dataset into fake and real reviews.
- This study applies the sentiment classification algorithms using without-stopwords and with-stopwords methods. We realized that with stopwords method is more efficient not only in text categorization but also to detect fake reviews.
- This study performs several analysis and tests to find the best-supervised learning algorithm in terms of accuracy.

Finally, in our future work, we would like to extend this work to use other datasets such as Amazon dataset or eBay dataset or different dataset of a movie review and use different feature selection methods. Furthermore, we may apply sentiment classification algorithms to detect fake reviews for other aspects in the same area such as collusion and manipulation issues.

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