International Journal of Electrical and Computer Engineering (IJECE)
Vol. 12, No. 3, June 2022, pp. 3013~3022
ISSN: 2088-8708, DOI: 10.11591/ijece.v12i3.pp3013-3022

Fake accounts detection on social media using stack ensemble system

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Article Info

Article history:

Received Mar 6, 2021
Revised Jan 4, 2022
Accepted Jan 21, 2022

Keywords:

Classification
Combining system
Feature selection techniques
Machine learning
Twitter accounts

ABSTRACT

In today's world, social media has spread widely, and the social life of people have become deeply associated with social media use. They use it to communicate with each other, share events and news, and even run businesses. The huge growth in social media and the massive number of users has lured attackers to distribute harmful content through fake accounts, leading to a large number of people falling victim to those accounts. In this work, we propose a mechanism for identifying fake accounts on the social media site Twitter by using two methods to preprocess data and extract the most effective features, they are the spearman correlation coefficient and the chi-square test. For classification, we used supervised machine learning algorithms based on the ensemble system (stack method) by using random forest, support vector machine, and naive Bayes algorithms in the first level of the stack, and the logistic regression algorithm as a meta classifier. The stack ensemble system was shown to be effective in achieving the best results when compared to the algorithms used with it, with data accuracy reaching 99%.

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1. INTRODUCTION

Social media use is becoming increasingly common, and it has become an essential part of daily life around the world. Besides being a means of communication, it is also considered a means of gaining fame and running a business. Social media sites are popular because of people's interests in making friends, posting pictures, tagging individuals in group photos, sharing their ideas and opinions on popular subjects, maintaining good working relationships, and having a general interest in others.

Twitter is one of the social media platforms used for cooperation and communication between users. It was initiated in 2006 [1], and in recent years, the number of users has reached millions. Users share short messages, called tweets, of 140 characters or less, as well as pictures and videos, as the primary forms of communication on the network. Regrettably, the emergence of social communication on Twitter has drawn the attention of cybercriminals who leverage the trust between users to spread malicious content on the network, resulting in a large number of victims. They create fake accounts [2] and use them to spread false news or steal users' accounts. Therefore, uncovering these accounts has become one of the major challenges faced by social media sites at present [3].

A variety of methods have been proposed by researchers to classify fake accounts [4]–[6], some using crowdsourcing [7] which rely on human effort to detect them, or using a graph [8], [9] by analyzing network contents or using machine learning algorithms to classify accounts depending on specific features. Ersahin *et al.* [10] introduce a method of detecting fake accounts from the Twitter dataset using a classification algorithm called Naive Bayes. The accuracy of the pre-processed dataset was increased by using a supervised discretization technique called entropy minimization discretization (EMD), to reach a 90.9% accurate result.

Previous research [11] implemented a machine learning pipeline for online social networks to identify fake accounts. The framework classified groups of fake accounts instead of creating a forecast for each individual account to determine if they were generated by the same person. Several classification algorithms have been proposed, such as support vector machine (SVM), random forest, and deep neural network.

A previous study [12] examined the identification of Twitter spam accounts to enhance the initial detection of spammer classes by incorporating both managed principal component analysis (PCA) and k-mean algorithms. To detect spam on social networks, several existing features were adopted, and new features were added to improve performance. Three classification algorithms, multi-layer perceptron (MLP), support vector machine, and random forest, were trained. The best results were found using the random forest algorithm, which had an accuracy of 96.30%.

Another previous study [13] identified fake Instagram accounts as a problem of binary classification and proposed a cost-sensitive technique for reducing required features. The technique was based on a genetic algorithm to pick the best attributes for automatic classification of computation, correct the variance using the synthetic minority over-sampling technique-nominal continuous (SMOTE-NC) algorithm in a false computation dataset, and evaluate multiple methods of pattern recognition on pooled datasets. Ultimately, with a rating of 86%, the support vector machine and neural network-based techniques achieved the highest F1 score for robotic computing detection, and the neural network achieved the best F1 rating at 95%. In this paper, spearman's correlation coefficient and the chi-square test were used to preprocess Twitter data to find the best qualities for distinguishing between fake and real accounts [14], and the min-max normalization method to scale the data between (0, 1). For data classification, we used machine learning algorithms based on the stack ensemble system to increase the predictive strength of the algorithms and achieve the highest accuracy in data classification.

2. RESEARCH METHOD

This section discusses the suggested method for detecting fake accounts on social media and contains six basic steps. They are; dataset collection, data cleaning, features extraction and selection, data scaling, a classification stage depending on the ensemble system (stack method), and an evaluation and comparison stage. Figure 1 shows the phases of the technique adopted.

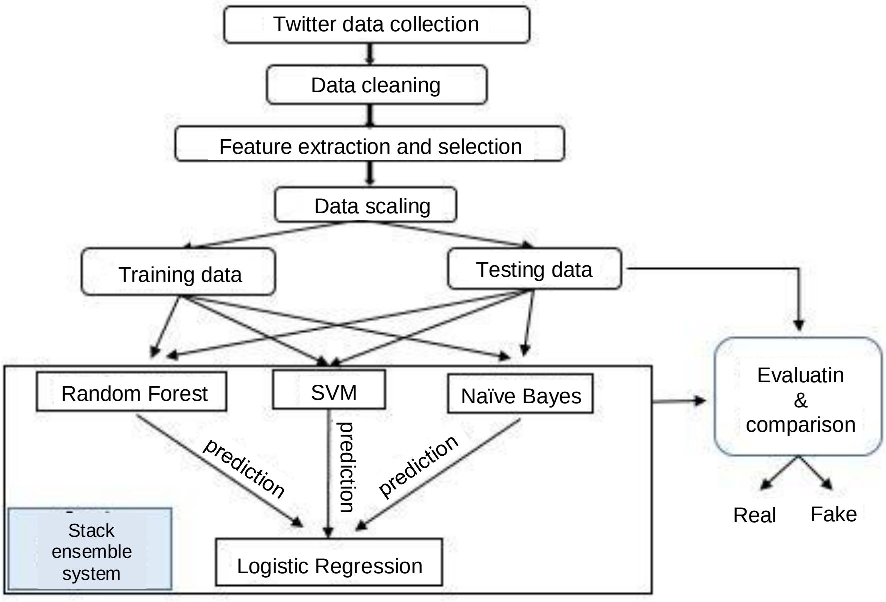


Figure 1. The steps of the technique adopted for the detection process

2.1. Twitter data collection

The Management Information Base "MIB" dataset [15] is used in this research, consisting of five datasets obtained from Twitter, two of them represent real accounts and three of them are fake accounts. The sum of all accounts is 5,301 with 29 features. They can be explained: i) the fake project (TFP) consists of 469 real accounts, ii) elections 2013 (E13) consist of 1,481 real accounts, iii) fastfollowerz dataset consist of 1,169 fake accounts, iv) InterTwitter dataset consist of 1,337 fake accounts, and v) Twitter technology dataset consist of 845 fake accounts.

2.2. Data cleaning

During the data collection process, some errors occur that lead to the loss of some data. This problem leads to a decrease in the quality of the data and thus leads to low-quality results when analyzing and exploring them. Our grouped data contains several blank fields, as shown in Figure 2, where the yellow color denotes the empty fields. Keeping these empty fields negatively affects the classification process and leads to inaccurate results, so this stage includes removing the columns of features that contain 30% or more blank fields [16].

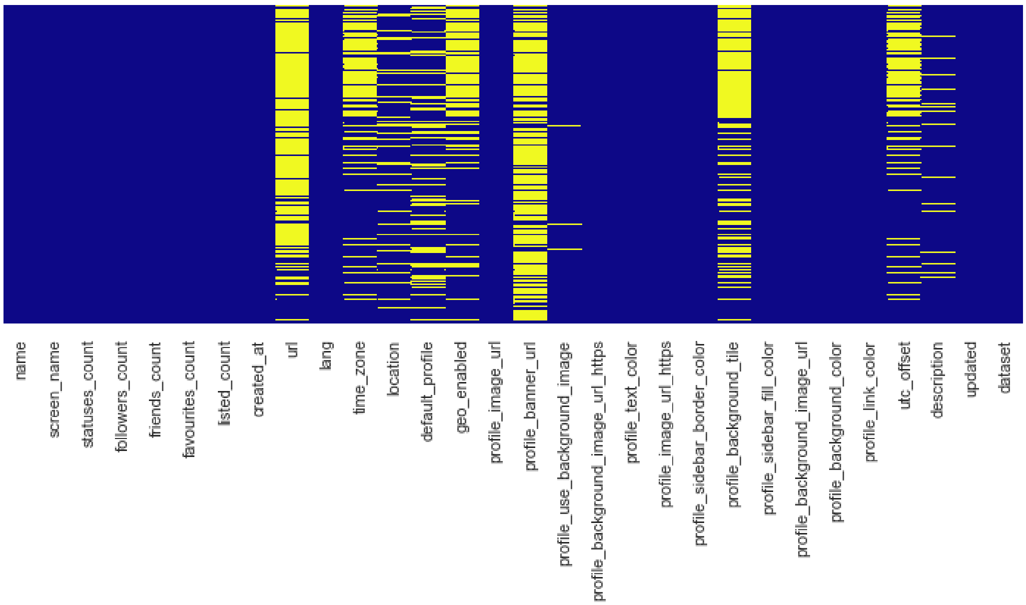


Figure 2. All features

2.3. Feature extraction and selection

Feature extraction is used to determine the optimal subset of features for model creation by eliminating inappropriate or redundant features, thereby concentrating only on necessary features. The purpose of this strategy is to minimize the training time for the prediction model by reducing over-processing, to improve the model's generalizability, and to help researchers interpret the model. In the proposed research, two methods are used to select the best features. These methods are:

2.3.1. Spearman rank correlation

Spearman correlation coefficient is one of the filtering methods used for feature selection [17], which tests the intensity and orientation of the monotonic association between two quantitative variables. They have values ranging from (-1) to (+1) to show the correlation degree. When the two variables are independent, each correlation measure is entirely zero. The result of spearman is a table that contains the correlation coefficients that link each variable in the dataset to the other variables. The following formula is employed to calculate the spearman rank correlation:

$$S = 1 - \left(\frac{6\sum \mathrm{d}is^2}{\mathrm{m}(\mathrm{m}^2-1)}\right) \quad (1)$$

where S=spearman rank correlation, dis=represents the distinction between the respective variable ranks, m=number of observations.

2.3.2. Chi-square test

The chi-square test is one of the statistical methods used to verify the independence of two events [18]. Whenever the two features are independent, the calculated chi-value is small compared to the critical chi value, meaning a large calculated chi-square value disproves the hypothesis of independence. A large chi-square value indicates which feature is dependent on the response and can be used for model training. The chi square formula is:

$$x^2{}_e = \sum \frac{(O_i - E_i)^2}{E_i} \tag{2}$$

where e=degree of freedom**,** O=observed value(s)**,** E=expected value(s).

First, the spearman correlation coefficient is used to find the correlation between all the features, whether numerical or qualitative, depending on the data rank, and extract only the correlated features. After applying spearman's correlation coefficient, two features of the remaining dataset contain empty fields. They are; default_profile and background_image. These features must be configured to use the statistical chi-square test. To fill in these fields, the number of current values for the columns is calculated, and the most common value was chosen to fill in the empty fields [19]. Then a chi-square test is implemented on spearman's output to find the correlation between the features and the target (output), to choose the best features that affect whether the account is fake or real to use in the classification process. The flow chart in Figure 3 explains the feature extraction process.

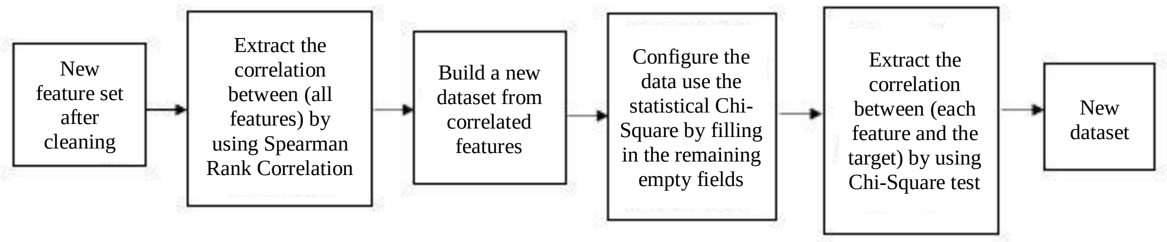


Figure 3. Feature extraction flow chart

2.4. Data scaling (normalization)

Scaling of features is a technique used to normalize the range of individual data variables or features. In this section, all numeric values in the selected features are listed between zero and one by using Min-Max normalization to increase the processing speed. In Min-Max normalization, the minimum value of the variable is converted to zero and the maximum value is converted to one, while the rest of the values are converted to a decimal number between zero and one. The general formula is:

$$v' = \frac{v - \min_a}{\max_a - \min_a}(new\_max_a - new\_min_a) + new\_min_a \tag{3}$$

whereas v= is an original value and v'=is the normalized value.

2.5. Detection model

We used the ensemble system by inserting features extracted from the datasets after normalizing them into a stacking. Stacking is an ensemble learning method that combines several classifiers or regression models through the meta-classifier or meta-regressor to improve predictive strength [20]. As shown in Figure 4, based on a full training group, the basic-level models are trained, and then the meta-model is trained on the model-like features of the basic level outputs. The algorithm below summarizes stacking.

Stacking Algorithm

```
Input: training data D={xi, yi}i m=1
Output: ensemble classifier H
Step 1: learn first-level classifiers
for t = 1 to T do
learn ht based on D
end for
Step 2: create a new prediction data set
```

```
for i=1 to m do
Dh={x'i, yi}, where x'i={h1 (xi),…., hT (xi)}
end for
Step 3: learn a meta-classifier
learn H based on Dh
return H
```

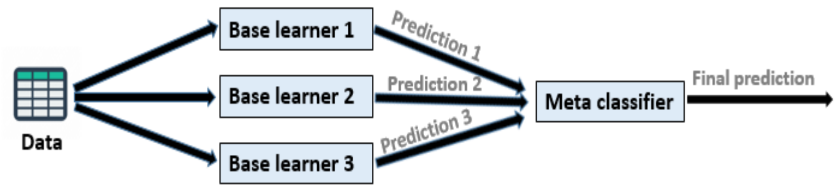


Figure 4. Stack ensemble system

The most important characteristic of the stack method is that it can benefit from the performance of a group of well-performing models in a classification or regression task and can provide better predictions than any individual model in the group. In our research, a group of the most common algorithms are used, four different learning techniques are trained and tested depending on the stack method. These algorithms are:

2.5.1. Random forest algorithm

Random forest (RF) is a powerful machine learning algorithm that performs the tasks of classification and regression [21], [22]. The basic building block of a random forest is derived from the decision tree. The model is obtained by dividing the data into bootstrapping samples depending on the number of trees that we want to perform, building a simple prediction model within each section, and combining their outputs based on the bagging ensemble learning technique to get to the final prediction.

2.5.2. Support vector machine algorithm

Support vector machine (SVM) is one of the most popular supervised learning algorithms that finds the optimal hyperplane, which separates the data points into two-component by maximizing the margin, which represents the distance from the decision surface to the closest data point [23], [24]. SVM is effective in cases where the number of dimensions is greater than the number of samples given.

2.5.3. Naïve Bayes algorithm

Naive Bayes (NB) is a type of classifier of probabilities. It works on the theory of Bayes and deals with both categorical variables and continuous variables [25], [26]. NB assumes that each pair of labeled-value features is independent of each other, meaning that the presence of any particular feature in a class is unrelated to the presence of other features. The NB equation is:

$$P\ (A\backslash B) = \frac{\mathrm{P\ (A)\ P(B\backslash A)}}{P(\mathrm{B})} \tag{4}$$

2.5.4. Logistic regression algorithm

Logistic regression (LR) is one of the machine learning algorithms used in binary classification [27]. It is a simple and commonly used algorithm that measures the relationship between one variable and many dependent variables (which we want to predict). As it uses its logistic function to estimate probabilities, to make a prediction, these probabilities must be converted into binary values, a task known as the sigmoid function. The sigmoid function is a curve in the form of an S that takes any number of real values and places them in the range between zero and one.

In the proposed method, the first level algorithms of the stack, including random forest, SVM, and naive Bayes, are trained on the training set, a k-fold validation is performed on each of these learners [28], and the validated expected values are collected from all the first level algorithms to use them as inputs to the meta classifier (logistic regression). The same steps are used to generate predictions on the test set. The accounts in the test suite are classified into real and fake accounts based on the training suite that is provided. The data was divided into a training and test group by choosing 75% as training data and 25% as testing data using stratified sampling [29] to ensure an equal division and maintain the same proportion of classes.

Default classifier parameters have been used, just the random state parameter is changed to (one) for each of the train-test-split and for the random forest algorithm to have steady and acceptable results. A prediction for each of the three basic algorithms is made using the dataset. The classifiers are implemented with 10-fold validation, where the data is divided into ten parts, such that every time the classifier is trained for nine parts and tested on the basis of the tenth part, the training and testing process are replicated ten times. Then, these predictions are fed into the meta-learner (logistic regression) to create the group prediction.

2.6. Evaluation and comparison

A confusion matrix is used as the main source of assessment in this research to evaluate false detection models. The result of the confusion matrix of the stack is evaluated and compared with the results of the algorithms that were used with it. Table 1 explains the confusion matrix in more detail. A confusion matrix is a technique used to describe the performance of classification algorithms, and which gives a better understanding of the classification model and the types of errors it can cause. All the results of the algorithms are plotted in a confusion matrix to determine where the error occurred.

- Accuracy: reflects the number of correctly classified instances in both groups over the overall number of all instances within a dataset.

$$Accuracy\ rate = \frac{\mathrm{TP+TN}}{\mathrm{TP+FN+FP+TN}} \tag{5}$$

- Precision: is the proportion of accurate positive predictions to the total number of positive predictions.

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \tag{6}$$

- Recall: is the ratio of accurate positive predictions to the total number of positive examples in the set of tests.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \tag{7}$$

- F_measure: is the measure of model efficiency, a weighted average of model precision and recall.

$$F\ Measure = 2 \times \frac{\mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision+Recall}} \tag{8}$$

Table 1. Confusion matrix

Actual Class	Predicted Class	
	Positive	Negative
Positive	TP correctly classified as positives	FN incorrectly classified as negatives
Negative	FP incorrectly classified as positives	TN correctly classified as negatives

3. RESULTS AND DISCUSSION

3.1. Pre-processing of dataset

This stage includes the results of data cleaning, followed by feature extraction and selection methods, and normalization method. In data cleaning, the columns containing 30% empty fields were deleted, and the features were reduced from 29 to 23. Feature extraction and selection involved using two filtering methods. First, the spearman correlation coefficient was used to find the correlation between all data, where the features were reduced to 7 in the dataset. Table 2 represents the result of spearman's correlation coefficient.

Then, the chi-square test was implemented on spearman's output. Where the number of features has reached five, they are as follows: (Statuses_count, Followers_count, Friends_count, Favourites_count, and Listed_count) the values of these features are shown in Figure 5, where Figure 5 (a) is Statuses_count, which represents the total number of tweets sent by the account. Figure 5(b) Followers_count is the number of followers who follow the user. Figure 5(c) Friends_count is the number of friends who follow the account holder. Figure 5(d) Favourites_count describe how many times each user account's tweets have been liked over the course of the account's existence, and Figure 5(e) is Listed_count, which is the number of people who have added the user to their list. The last stage of the data preprocessing process is applying Min-Max normalization to put all the data values on one level. All data values were converted into values between zero and one.

Table 2. The result of Spearman rank correlation

	Statuses Count	Followers Count	Friends Count	Favorites Count	Listed Count	Default Profile	Background Image	Dataset (output)
Statuses Count	1	0.84432	0.1598	0.7461	0.60878	0.00815	-0.0002	-0.7338
Followers Count	0.84432	1	0.233297	0.67047	0.63751	-0.0261	-0.00568	-0.6914
Friends Count	0.1598	0.233297	1	0.03005	0.15653	-0.2801	-0.04419	0.21315
Favorites Count	0.7461	0.67047	0.03005	1	0.60688	-0.1314	-0.0067	-0.7081
Listed Count	0.60878	0.63751	0.15653	0.60688	1	-0.1088	-0.0018	-0.5987
Default Profile	0.00815	-0.0261	-0.2801	-0.1314	-0.1088	1	0.16169	-0.1207
Background Image	-0.0002	-0.00568	-0.04419	-0.0067	-0.0018	0.16169	1	-0.0310
Dataset (output)	-0.7338	-0.6914	0.21315	-0.7081	-0.5987	-0.1207	-0.0310	1

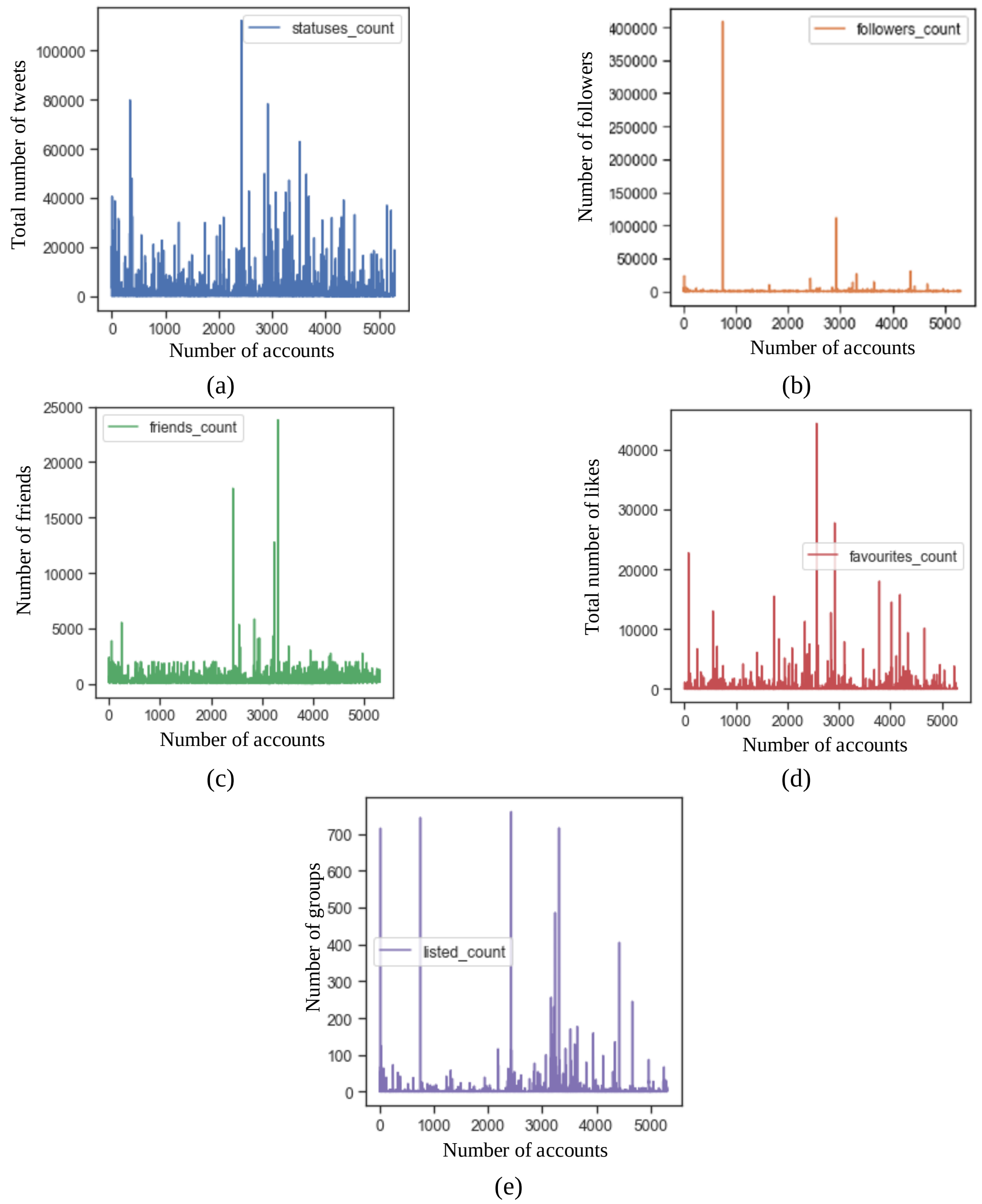


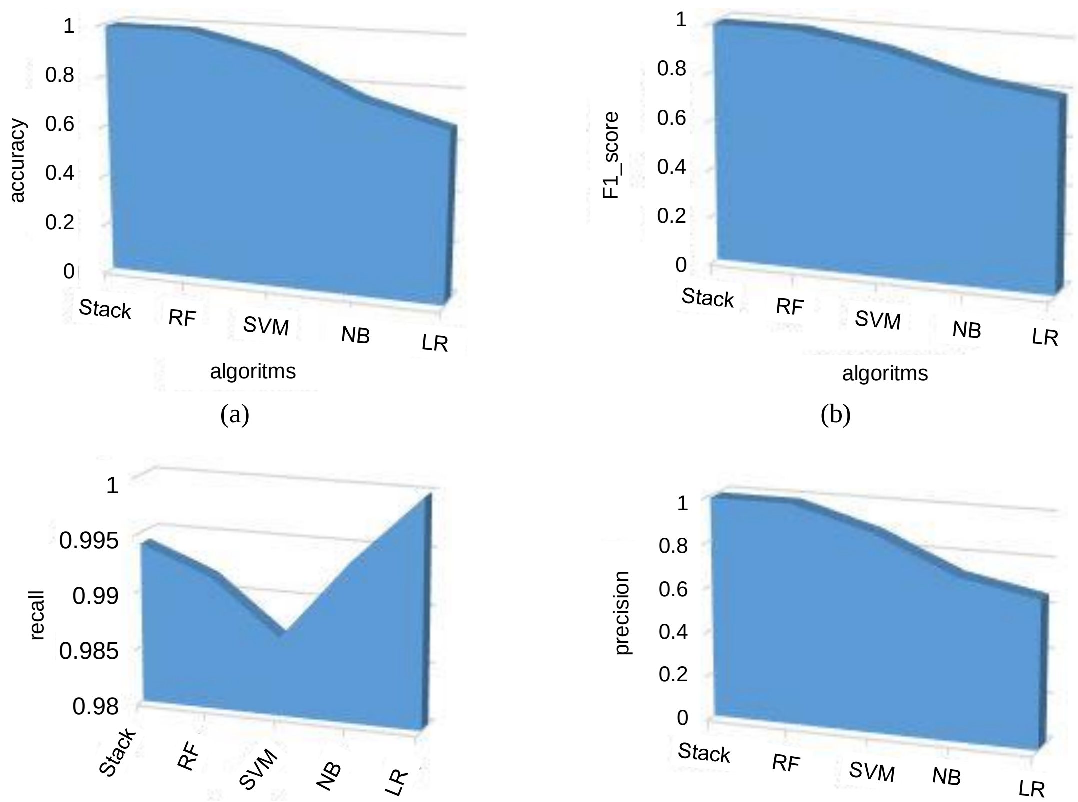
Figure 5. Values of the selected account features (a) statuses_count, (b) followers_count, (c) friends_count, (d) favourites_count, and (e) listed_count

3.2. Detecting of fake accounts

This stage includes the result of the confusion matrix of the stack method and the algorithms that were used with it. As shown in Table 3, based on the entire set of suggested features, the stack method achieved a high evaluation rate in terms of accuracy, precision, and F1_score, compared with using each algorithm separately. The accuracy of the stack method was 99%, the precision was 99%, and the F1_score was 99.2%. Figure 6 shows the visualization of the confusion matrix between the stack method and the algorithms. Where Figure 6(a) is the accuracy, Figure 6(b) is the F1_score, Figure 6(c) is the recall, and Figure 6(d) is the precision.

Table 3. A comparison between the stack system and the algorithms used

Name	Accuracy	F1_score	Recall	Precision
Stack	0.990196	0.992257	0.994033	0.990488
Random forest	0.988688	0.991055	0.991647	0.990465
SVM	0.913273	0.934992	0.986874	0.888292
Naïve Bayes	0.763952	0.841839	0.994033	0.730061
Logistic regression	0.674962	0.795444	1	0.660362



(a) (b) (c) (d)

Figure 6. Visualization of the confusion matrix between the stack method and the algorithms: (a) accuracy, (b) F1_score, (c) recall, (d) precision

4. CONCLUSION

In this paper, we proposed a model for fake accounts detection based on a collection of basic Twitter features that are publicly accessible. These feature sets were derived from the profile details available in the Tweets of users. To improve the detection model, the stack ensemble method based on four machine learning algorithms was used, and two feature selection methods were implemented to determine which features in the detection process were most influential. Initial work results show that successful results can be achieved in a stack ensemble method by using random forest, SVM, and naive Bayes classification algorithms as base level classifiers, and by using logistic regression as a meta classifier. By implementing this methodology, the accuracy of the data reached 99%. The results also revealed that the ensemble system has a significantly higher impact on the accuracy of the detection process over using each algorithm separately. For future work, much larger data could be collected using the same methodology as this work but using other machine learning algorithms.

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