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## Semi Supervised and Supervised Learning Technics to Detect Fake Online Reviews

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### Abstract

Online reviews have great impact on today's business and commerce. Decision making for purchase of online products mostly depends on reviews given by the users. In recent times in the E-commerce world, people rely on reviews of the products to make an opinion for purchasing the product. In an E-commerce application, anyone can post reviews of the products, due to this loophole spam postings are increasing day by day. The Spammers post the reviews in two different agendas, like posting reviews with positive opinions and with negative opinions. This project introduces some semi-supervised and supervised text mining models to detect fake online reviews as well as compares the efficiency of both techniques on dataset. It has two parts; one is the identification of spam reviews and second is analysis of the sentiment classification models and predicts the sentiment of the reviews. In spam reviews detection, three features are used, these three features depend on two concepts like feature-based, and text-based. On the other hand, for analysis of the classification and for sentiment calculation of the reviews, five (5) algorithms are used. Of the algorithms implemented is calculated and accuracy score for identification of best algorithm is also shown. Sentiment of the reviews is calculated and represented in the form of graphs.

Keywords: - classifications, reviews, Performance, accuracy score.

### 1. INTRODUCTION

#### Overview

The popularity of online commerce applications is increasing day by day, parallely spreading the spam reviews also increasing with high growth. Online product reviews are not only useful to the E-commerce users also will be useful to the startup clients to increase their sales or improve quality, etc. To change the product opinions, the promotion of products spammers publish the reviews into e-commerce applications [1]. In previous studies [4] [5], spam detection models

are only depending on Behavioral-based data (context data) like location, IP address, etc. In this project, few parameters are taken into account for predicting the spam reviews, namely Review Burstiness (RB), Average Reviews Text (ART), and Negative Rating Ratio (NRR). These features depend on the context and content behaviors. The RB and NRR depend on context data like dates of the reviews and ratings. The ART model depends on content data like the text of the reviews. By considering the content and context data, the spam detection model in this project is proposed. The

sentiment prediction is a process of predicting the opinion of the reviews like positive or negative or neutral review. In this project, Sentiment prediction model is implemented, which is used for displaying the sentiment view (Positive or Negative or Neutral) of the reviews. For the prediction of sentiment reviews, this project has taken the Sentiment dataset [2] for building the best classification model.

## 2. Objectives of the project

In this project, detection of spam reviews and predicting the sentiment of the reviews are the main objectives. For spam detection, it is required to review the best possible features which predict spam reviews effectively.

Following are the main objectives of the proposed system:

- Identify the spam features, which can cover both content and context-based data types. In this project, three spam models are used which are listed as:
  - Review Burstiness (RB) (Context data type)
  - Average Reviews Text (ART) (Content data type)
  - Negative Rating Ratio (NRR) (Context data type)
- In this project, to demonstrate detection of spam reviews and sentiment prediction, Amazon review dataset [3] is taken.
- For prediction of the sentiment of the reviews, sentiment reviews dataset [2] is used for training and testing.

- For classifying the sentiment dataset, following classification models are used for training and comparing the performance:

- Random Forest (RF)
- K-Nearest Neighbor (KNN)
- Neural Network (NN)
- Support Vector Machine (SVM)
- Logistic Regression (LR)

## 3. IMPLEMENTATION

### System Architecture

In this section, the methodology of the system with architecture is described. This architecture is designed with two stakeholders flow, namely, admin and users. Sentiment classification model and Spam detection model are the two phases of the project. the methodology of the system is discussed in the following sections.

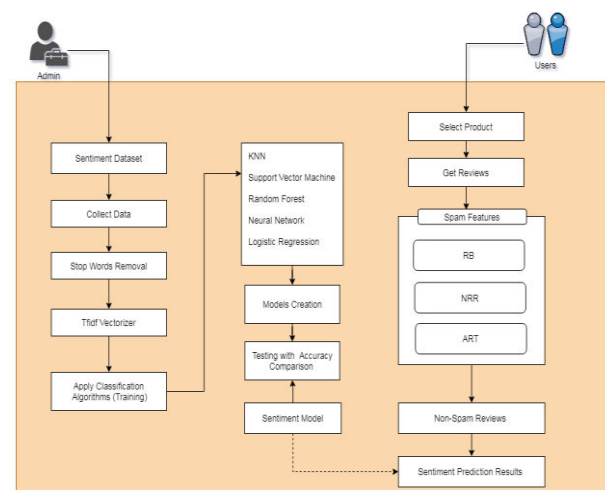


Fig 2.1: System Architecture

### Spam Detection Model

In this proposed system, the spam detection process model is the main module. This model is processed at the user side of the application. After the selection of the product name, the system loads reviews of the product and applies spam

models to predict the spam reviews. In spam detection, three models of context and content-based are taken. Let's discuss each model in this section.

## Review Burstiness (RB)

The RB model is context-based, this depends on the dates of the review of posts by the user. Generally, normal users post a review for a product only one time or after a long time they will post. This model calculation will identify the spammers who post the reviews within a short period of time. In the following, the calculation of the RB with an example is mentioned.

```
Score = 1 - (Last Review of item Date - First Review of item Date) / 28;
Threshold value = 0.5
Score > 0.5 → spam
Score < 0.5 → not spam
For Ex:
1 - [(14/09/17) - (13/09/17)]/28;
1 - (1/28) => 0.96 > 0.5 == Spam
```

## Negative Rating Ratio (NRR)

The NRR model is context-based, this depends on ratings of review posts of user for each product. Generally, normal users post a negative rating for a product only once, if any user posts multiple reviews frequently with a negative rating (less rating), then these ratings are considered to be spam reviews. In the following, the calculation of the NRR with an example is mentioned.

```
Mean of ratings <= 2.5 is spam;
else: Not Spam

2 & 1 & 1 => 2+1+1 / 3 => 1.33 which is less than 2.50 it is spam.
Note: minimum 2 or more than 2 attempts are required.
```

## Average Reviews Text (ART)

The ART model is content-based, this depends on the text of review posts of user for a product. Generally, normal users post reviews with different opinions and with different words. Spammers post multiple reviews with similar content either with negative opinion or positive opinion. In this model, for string comparison 'fuzzywuzzy' API is used, which internally implements Levenshtein distance algorithm. In the following, the calculation of the ART with an example is described.

```
if StringCompare( $\gamma_n$ ) >  $\phi$ : r = Spam
else: r = Not Spam

Where, 1 is spam and 0 is legitimate
 $\phi$  threshold value = 0.5
```

## Sentiment Analysis

Prediction of sentiment of the product reviews is an important task, because reviewing opinions can affect sales of the product. For the prediction of product reviews sentiment, supervised algorithms are used. training and testing for identifying suitable algorithms for prediction review sentiment with high accuracy are performed. For classification analysis, five supervised machine learning algorithms are taken which are listed as follows:

1. Random Forest (RF)
2. K-Nearest Neighbor (KNN)
3. Neural Network (NN)
4. Support Vector Machine (SVM)
5. Logistic Regression (LR)



In machine learning algorithm, as machine takes input only as numerical data. These algorithms are implemented in mathematical equations as it cannot handle the string data. In pre-processing, TfidfVectorizer is implemented to convert the string data to numerical data.

## TFidfVectorizer

Generally, to convert string data to numerical data we have two models, CountVectorizer and TfidfVectorizer. In these, the CountVectorizer model depends on word count and which is not consider the weightage of words in text. But in TfidfVectorizer, it depends on the weightage of words intext. This weightage is calculated with TF-IDF score. In this project, for all ML algorithms TfidfVectorizer is implemented.

$$TF = \frac{\text{Count of a word } w \text{ in a document}}{\text{Total No. of words in a document}}$$

$$IDF = \frac{\text{Total Documents Count}}{\text{Document Frequency of word present}}$$

$$TF-IDF = TF * IDF$$

For example,

Documents are 'President of Britain', 'Britain queen', 'India president'

## TfidfVectorizer

Doc	Britain	India	Of	President	queen
0	0.517	0.000	0.680	0.517	0.000
1	0.605	0.000	0.000	0.000	0.795
2	0.000	0.795	0.000	0.605	0.000

## Build Models

After completion of training, predicting the data require a trained classification object. Based on

the trained object only, the prediction process will take place. But for multiple predictions iteration, this process is not suitable. In this case, we need to save the trained object in a physical file and that file is used to load and predict the data number of times. For creating and loading the training object, the 'pickle' API is used. This API is able to store the trained object in the '.sav' file format. In Fig 2.4, model files of the ML algorithms are shown.

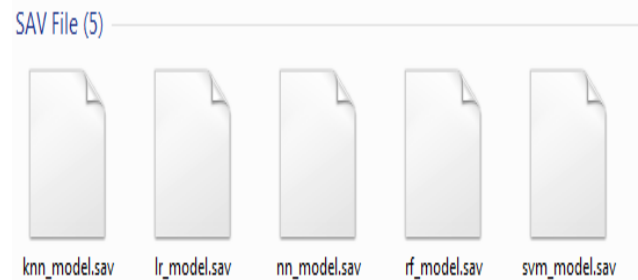


Fig 2.4 Model files

## Performance Measure

For calculating the performance of all five algorithms, for comparing the performance between them, Accuracy Score calculation is used. For training and testing, the data is split in the ratio of 70:30. After predicting the results for 30% of testing data, based on the returned results and actual results the accuracy score is calculated, following, is the accuracy equation.

## Accuracy:

$$\text{Accuracy} = \frac{\text{Correctly Predicted}}{\text{Total inputs}}$$

## 4. RESULTS

### Project Homepage

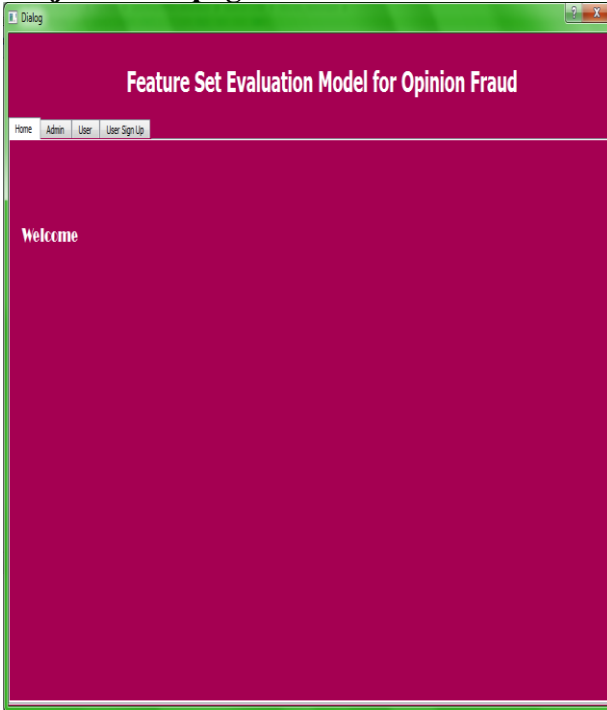


Fig 4.1: Homepage

This is the homepage screen where we can see all the tabs available for both Users and Admin.

### Training classification layout

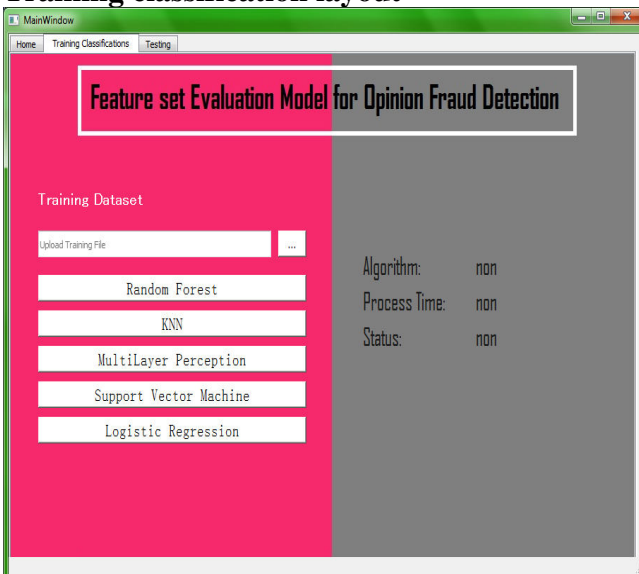


Fig 4.2: Training page layout

Here we calculate the Training data set using 5 Algorithms mentioned.

### Training page result

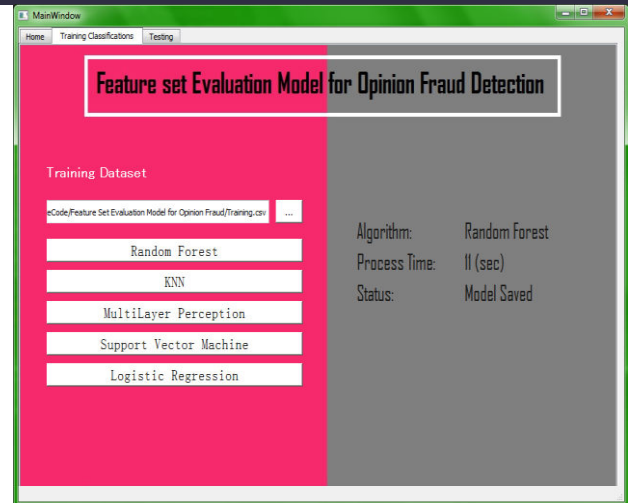


Fig 4.3: Training page result

This webpage shows the result of each algorithm running time and status

### Testing page result

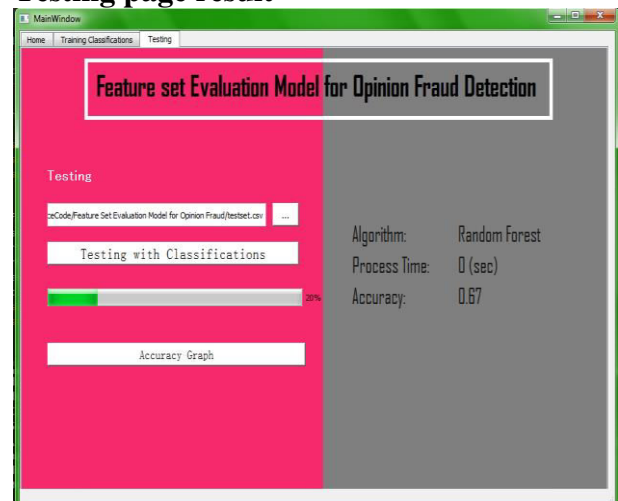


Fig4.4: Testing page result

The above-mentioned screenshot is for testing, it shows the progress of testing data and also shows the accuracies of each algorithm.

### View Accuracies

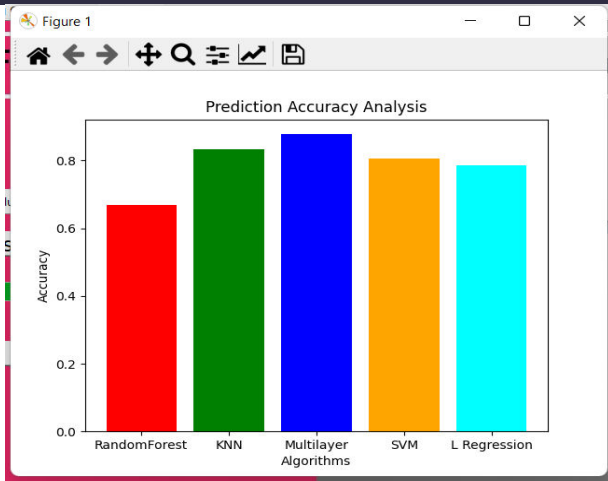


Fig 4.5: View Accuracies

### View Product List

Product	Review Count
1 Microsoft Surface Pro 4 Type Cover with Fingerprint ID	512
2 Boytone - Z500W 2.1-Ch. Home Theater System - Black Diamond	91
3 Sanus VLF410BL 10-Inch Super Slim Full-Motion Mount for 37 - 84 Inches TV's	162
5 Ultimate Ears MEGABLAST Portable Wi-Fi/Bluetooth Speaker with hands-free Amazon Alexa.	100
6 Flipside 300 Backpack (Black)	143
7 Corsair CMSA8GX3M2A1066C7	114
8 iHome Rechargeable Splash Proof Stereo Bluetooth Speaker - Black (BT33BC)	154
9 Verizon MFJ6620L Jetpack 4G LTE Mobile Hotspot (Verizon Wireless)	148
10 JVC KD-X320BTS Apple iPod and Android Digital Media Receiver with Bluetooth	142
11 JBL Coaxial	97
12 Lenovo - AC Adapter for Select Lenovo Yoga Laptops - Black	39
13 SiriusXM SXEZR1V1 XM Onyx EZR Satellite Radio Receiver with Vehicle Kit	90
14 PNY Anarchy 16GB Kit (2x8GB) DDR4 2400MHz (PC4-19200) CL15 Desktop Memory (BLUE) ...	191
15 Slingbox M2	342

Fig 4.6: View Product List

It is how a product list page looks like, it shows all the products available in the database.

### Spam results

Reviews	Spam	Sentiment	Rating
2 This keyboard is very easy to type on, but the fingerprint reader is the best feature. It is very accurate...	Not Spam	positive	5.0
3 It's thin and light. I can type pretty easily on it.	Not Spam	neutral	4.0
4 I love the new design the keys are spaced well no more mis types. The finger print recognition work...	Not Spam	neutral	4.0
5 Attached easily and firmly. Has a nice feel. A must with the Surface Pro.	Not Spam	positive	5.0
6 Our original keyboard was okay, but did not have a laptop feel to it, a bit floppy. The new one has a ...	Not Spam	positive	5.0
7 purchased to replace original surface pro 3 keyboard. much better feel and fingerprint reader is hand...	Not Spam	neutral	5.0
8 I find it very comfortable to type with it but i rarely use the fingerprint ID	Not Spam	neutral	4.0
9 Good Keyboard and addition to the Surface Pro platform if you desire fingerprint scanner access. For...	Not Spam	positive	3.0
10 tough getting it to work on surface pro 3, but once it worked the bugs out I love the spacing and larg...	Not Spam	neutral	4.0
11 I can now quickly and hassle free log into my surface with finger print scanner. It works every time an...	Not Spam	neutral	5.0
12 A must have accessory for the surface pro computer	Not Spam	neutral	5.0
13 Fingerprint scanner for that price is not worth it. It's a very good keyboard, but the fp scanner should...	Not Spam	positive	4.0
14 The keyboard feels surprisingly good considering how thin it is. The keys have satisfying tactile...	Not Spam	positive	4.0
15 I really like the fingerprint ID makes login in very easy and fast. The fact on the keyboard is very...	Not Spam	positive	4.0

Fig 4.7: Spam Results

This is the end results page where a user can know which of the reviews are spam and which are not, based on this a user can take a decision of buying a product.

### Sentiment results

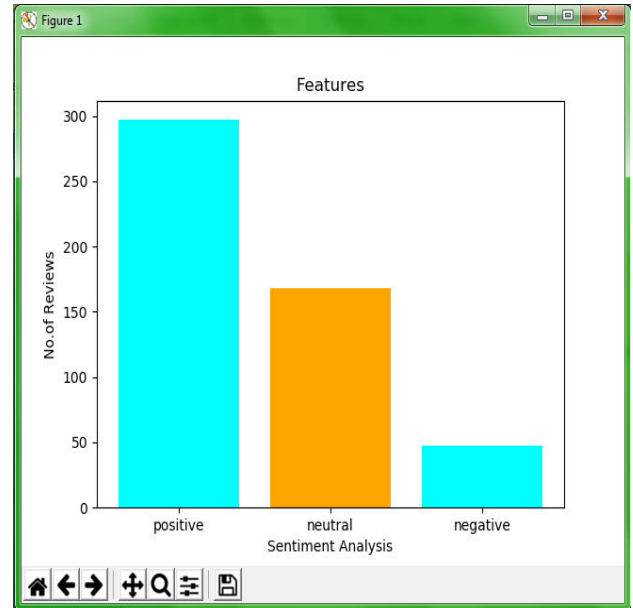


Fig 4.8: Sentiment Results

Here is the screenshot of sentiment results of a product, where a user can see what is the major opinion of a product amongst the users of the database.

## 5. CONCLUSION

In all E-commerce applications users are depend on the public reviews for making an opinion for purchasing the product. Due to public portals in E-commerce applications, anyone can post reviews. Based on this disadvantage propagation spam reviews of the products are increasing, due to this loophole spam postings are increasing day by day. In spam reviews detection, have implemented three models, namely, Review Burstiness (RB), Average Reviews Text (ART), and Negative Rating Ratio (NRR). With these models, detected spam reviews from the dataset is

successful. Also, have performed analysis of the classification models for sentiment calculation of the reviews. Random Forest (RF), K-Nearest Neighbor (KNN), Neural Network (NN), Support Vector Machine (SVM), and Logistic Regression (LR) algorithms are used. From these algorithms, NN algorithm has got highest accuracy in performance evaluation. Future Scope In future, preference to improve the spam features is required and useful. In this project three models are used; preference should be given to identify more models and implement those features in both content-based and context-based.

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