Fake Review Detection Using Ensemble Techniques by the Fusion of Chronology, Aspect and Sentiment of Reviews and Oversampling by Smote

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Abstract: To proposing a system for classification of fraud reviews on products by generating novel features on user-review behaviour, user-review chronology as well as linguistic text features. In this research the utilization of a comprehensive and wide-ranging dataset obtained from the Yelp.com review platform, which is accessible to the public, has been taken into account. From the dataset, we chose the data for Hotels/Restaurants in the state New York City. This research work is divided into 4 parts 1. Pre-processing raw data by using NLTK libraries. 2. Analysis and design of novel features. 3. Building an ensemble supervised machine-learning model over features generated in the previous steps for the detection of ham and fabricated reviews. New features were drawn by considering the combination of user-review (UR) aspect, user-review-product (URP), and the review-review (RR) context. In the 4-part, the comparison with previous research is presented in a tabular format. Additionally, a graph has been generated to depict the performance metrics of precision, recall, F1-score, and accuracy. Extra Tree ensemble classifier outperformed others in accuracy (96%), precision (97%) and f1-score (96%).

Keywords: Ensemble learning, supervised, machine learning, Spam detection, SMOTE

1. Introduction

In the current context of the E-commerce market, the identification, detection, analysis, and prediction of automated fake reviews have become crucial aspects of sentiment analysis. There has been a significant increase in the demand for automatic systems that employ Machine Learning (ML) techniques [1] - [8], drawing upon the foundations of NLP, ML, and Artificial Intelligence (AI). While numerous predictors and analyzers have been created for industrial, corporate, and commercial domains, the need for a trustworthy and efficient system that can accurately predict fake reviews remains a prominent requirement.

Efforts to address the issue of detecting fake reviews have been ongoing since 2007. [9]. Studies to detect fake reviews leveraged two main categories of features, written and behavioural features. Text features pertain to the linguistic characteristics or attributes of the review content. In other words, the qualities of the text primarily rely on the substance of the review. Behavioural traits refer to non-verbal traits of appraisals. They mostly depend on reviewer behaviour such as writing style, emotional expression, and frequency of writing reviews. While textual features are difficult and important to deal with, the significance of behavioral features cannot be overlooked, as they play a pivotal role in enhancing The effectiveness of the process for identifying fake reviews. While text features are widely explored in various research papers on fake review detection, it is important to acknowledge that behavioral features also hold substantial importance.

In the study mentioned, SpEagle [10] was developed specifically for detecting fake spam by utilizing metadata from reviews, users, and businesses. It establishes a network among reviews, users, and businesses. For this research, three datasets consisting of real reviews from actual users in practical scenarios were obtained from Yelp.com, consisting of both filtered (fake) and recommended (genuine) reviews.

The n-grams technique for feature development of the review text on the Trip Advisor website dataset and sentiment scores provided by the reviewer were used to construct a false review detection system [11] on e-commerce platforms. The classification experiments conducted in the study demonstrated the performance of various algorithms in terms of testing accuracy and F1-score. The results showed that Naïve Bayes (NB) achieved an accuracy of 88%, Support Vector Machine (SVM) achieved an accuracy of 93%, and Adaptive boosting (AB) achieved an accuracy of 94%. Lastly, random forest (RF) achieved an accuracy of 95%. Only 1600 reviews of the hotels were involved in the study.

Reviews [12] of "teeth whitening" products were taken for spam detection. This study worked on both supervised and unsupervised models in their experiment. In the study, several unsupervised learning techniques, namely DBSCAN, K-means, Hierarchical clustering, and Spectral Cluster, were employed. Additionally, supervised learning models such as Logistic Regression, SVC, LGBM (Light GBM), K Neighbors, Gradient Boosting, Random Forest, XGB Classifier (Extreme Gradient Boosting), Gaussian NB (Naive Bayes), Extra Trees Classifier, and Decision Tree Classifier were utilized., the accuracy ranged from 81–85%.

In the mentioned research [13], bigram and trigram language models were utilized for feature extraction techniques. Various classifiers were employed, and among them, KNN (K=7) exhibited superior performance in terms of the F-score. It achieved the highest F-score of 82.40%, outperforming the other classifiers in the study.

The study [14] on spam detection in Arabic tweets. The authors created a labelled dataset of Arabic tweets up to 2020 and utilized Word2Vec and N-gram for feature engineering. They evaluated the performance of different algorithms and found that in terms of accuracy, the Random Forest algorithm demonstrated superior performance when compared to alternative algorithms. It attained the utmost level of accuracy among the evaluated algorithms.

The authors [15] compare Word2Vec, BERT, and a newly developed model called BSTC in the context of spam detection. The authors highlight that Word2Vec struggles with capturing multiple meanings of a word, while BERT does not incorporate sentiment knowledge during its pre-training stage. As a solution, they propose the BSTC model, which combines a language model that has undergone pre-training with a CNN. In order to assess the effectiveness of the models, the authors used three gold-standard datasets related to hotels, restaurants, and doctors. The highest accuracy rates were achieved on these datasets, with percentages of 93.44% for hotels, 91.25% for restaurants, and 92.86% for doctors.

FRD-LSTM [16] a fake review detection approach based on deep learning was developed. Deep features of the text review was generated by the Contextualized Deep Word Representation (DCWR) technique. PCA was used for feature pruning and Bi-LSTM classifier was trained on the features for finding fraud review from the Amazon product reviews dataset. 97.21% average accuracy they got.

This study [17] attempts to identify legitimate tweets and doing sentiment analysis on archived tweets as well as real-time live tweets. The suggested approach made use of two distinct datasets, one for spam identification and one for sentiment analysis. Several vectorization, machine learning and deep learning techniques were used for result comparison. A 97.78% accuracy was achieved with multinomial naive Bayes classifier and the deep learning model, LSTM, earned a validation accuracy of 98.74%.

We identified from the existing research that need for larger and more diverse datasets, generalizability of the proposed approaches, comprehensive evaluation with multiple evaluation metrics, and exploring more sophisticated algorithms or techniques for improving the accuracy and effectiveness of spam detection in various domains and contexts.

2. Methodology

This section describes the methodology adopted for conduction of the research. Figure 10 shows the proposed system.

2.1 Data Collection and Dataset

The work presented here is based on the supervised ensemble machine learning approaches, for that dataset with labels is required but availing large scale gold standard labelled dataset not possible so that the dataset used in the research [10] is used here. These datasets are currently the most extensive, comprehensive, and versatile labelled datasets available to the public for fake review detection, considering their size and the breadth of information they encompass. These datasets have been labelled based on Yelp's classification, where recommended reviews are considered as 'genuine' and not recommended reviews are considered as 'fake.' The classification provided by Yelp serves as a reliable ground truth and has been utilized in numerous studies. Table I provides an overview of the datasets, including a condensed overview of the information they contain. The figures presented in the table 1 represent the proportion of (filtered) deceptive opinions (and corresponding users) within each dataset. These datasets contain the reviews of time span 2004-2015. Figure 1 showing the reviews distribution year wise. No of words in entire dataset is 21116319. Number of unique words in the entire dataset is 644909.

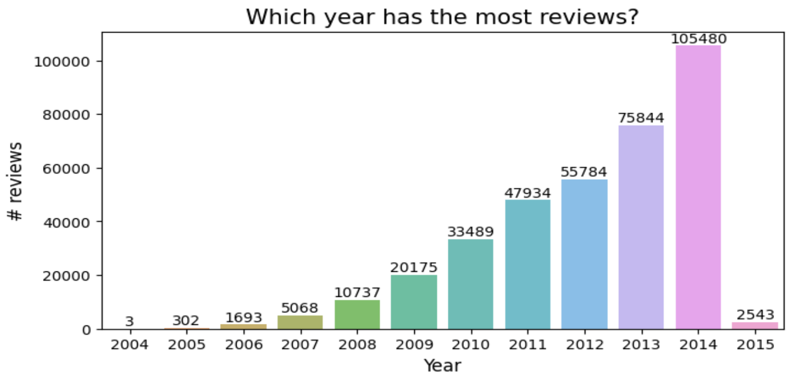

Figure 1: Depicting year wise reviews distribution.

Table 1: Overview of the information contained within the datasets under consideration.

Dataset	Posts	Users	Businesses
YelpNYC	359,052 (10.27%)	160,225 (17.79%)	923

The YelpNYC dataset comprises reviews pertaining to restaurants located in New York City. This databases' advantages include: • Since the number of reviews per user is large, it becomes possible to consider the behavioral characteristics of each user. • Different types of companies were surveyed. Hotels and restaurants • More importantly, each record only contains basic information such as a user ID, review text, product ID, rating, and date of review.

Table 2: Snapshot of the yelp dataset

user_id	prod_id	review_date	review_text	rating	label
3433	603	11-06-2013	Can my friends have more birthdays so we can celebrate here more often? The food here is always exceeds my expectations. The menu is always interesting and it's hard not to choose everything.	5	1
68668	202	22-09-2012	Really phenomenal and so crazy charming! I've walked by this place for years never having gone in. Me and the boyfriend went in on a whim the other day because (we both had a craving for Muscles) and it was insanely	5	1

			good.		
161021	921	25-11-2012	I used to really enjoy the place for the relaxed vibe and good cocktails. However, I've had a few recent terrible experiences with the service that have led to me give a bad review.	2	-1
39968	542	02-01-2011	Delicious pizza - fresh mozzarella, sauce and toppings, simply perfect in taste. One addition I would make is - they should add some type of spice to the crust. Maybe bake in some oregano or something. Service was eh. And the diet coke tasted questionable. But I'd definitely go back for the pizza.	3	1

2.2. Data Pre-processing

During the process of training machine learning models using datasets, we often come across the phrase "trash in, trash out." Essentially, this means that if we utilize poor or "dirty" data to train a model, the resulting model will be of low quality and unsuitable for meaningful analysis.

Data pre-processing step involved eight sub-steps like the case lowercasing, special character removal, removing emoji's, punctuation removal, alphanumeric character removal, stop words removal and at last stemming the review text. An example of review-text is shown in the figure 2 before and after pre-processing.

```
dataset['text_clean']=dataset['text_clean'].apply(lowering_text)
dataset['text_clean']=dataset['text_clean'].apply(special_char_removal)
dataset['text_clean']=dataset['text_clean'].apply(encoding_text)
dataset['text_clean']=dataset['text_clean'].apply(remove_punctuations)
dataset['text_clean']=dataset['text_clean'].apply(remove_alnum_text)
dataset['text_clean']=dataset['text_clean'].apply(remove_stopwords)
dataset['text_clean']=dataset['text_clean'].apply(steming_text)
```

text	review_text_clean
The food at snack is a selection of popular Greek dishes. The appetizer tray is good as is the Greek salad. We were underwhelmed with the main courses. There are 4-5 tables here so it's sometimes hard to get seated.	food snack select popular greek dish appet tray good greek salad underwhelm main cours tabl sometim hard get seat

Figure 2: Depicting review text before and after pre-processing

2.3. Feature Engineering

Considering domain-specific knowledge, it is possible that a dataset of reviews may include additional features related to consumers that could be relevant for fake review detection. These additional features could provide valuable insights into the behavior, preferences, or characteristics of the reviewers. Furthermore, from the existing features in the dataset, it is also possible to derive additional features. Feature engineering techniques can be employed to extract more meaningful information from the available data. For example, from the review text, additional features such as text sentiment or topic modeling can be performed to capture deeper insights. By incorporating these domain-specific features and derived features, the effectiveness of the fake review detection system can be enhanced. It allows for a more comprehensive analysis and understanding of the reviews, thereby improving the accuracy and reliability of the classification models. These features can be categorized as follows.

A. Review's Text centric features

Text-centric features of a review refer to the characteristics or attributes of the textual content itself. These features capture various aspects of the review text, such as its length, language complexity, sentiment, lexical diversity, and syntactic structures. Text-centric features play a crucial role in analyzing and understanding the content, sentiment, and quality of reviews in tasks like sentiment analysis, fake review detection. Table-3 illustrating the review centric those are derived in this research.

Table 3: review-text centric features

text	AMAZING!!!!!!!Excellent customer service, the food was beyond DELISH! I LOVE this place, it's one of my favourite restaurants. Can't wait to go back!
text_clean	amaz excel custom servic food beyond delish love place one favorit restaur ca wait go back
words_count	16
numbers_count	0
hashtags_count	0
url_count	0
mean_words_length	4.7
characters_count	90
caps_count	0
puncs_count	0
emojis_count	0
wrong_word_count	5
sent_count	4

B. User-review centric features

F1: **Very first review [VFR]** The time elapsed between the user's initial review and the first review of the same item. Spam reviews are typically issued early in order to have the most possible impact. Can be calculated as
min(All review timestamps on a product P_j by user U_i)-min(All review timestamps on a product P_j)

F2: User account age (UAA) [21] is the duration of timestamps in which user starts uploading reviews to the end of the last review posted by the reviewer. Since fraudsters are not genuine users, their accounts are younger, which suggests that they have less reviews since they aren't actually interested in writing reviews but rather in promoting particular brands. Can be calculated as
max(All review timestamps by a U_i)-min(All review timestamps by a user U_i)

F3: User activity period (UAP) [new] is the count of months in which user uploaded a review. If the user posted more than one review in a month, it counts one. On the basis of this UAP feature we can supposed to draw a new feature that is Reviews per month. Can be calculated as

$$\mathrm{UAP}(U_i) = \sum_{j,k=1}^{N} \text{normalize}[0,1]\ (\text{all reviews given by a user } \mathrm{U}_i \text{ in a month } M_{jk})$$

F4: User maximum number of reviews per day (maxRPD) [new] is the maximum value of the reviews posted by the reviewer in a day of all the reviews posted by him/her. This feature is calculated by taking the maximum number of values generated by grouping the reviews of a user date wise.

F5: User review count per month (URPM) [new] is the numerical calculation of the total reviews authored by the user within a one-month period. RPM is calculated as total reviews by a reviewer /UAP

F6: User review count on a product in a time slot (URPT)[**new**] Total reviews published by the author in a specific time interval (∂t) on a product. This time interval can be set as a week, a month or some other value for a specific restaurant.

F7: Number of users rated a product (ProdRCount)[New]=A product reviewed by number of users is calculates as

$$\text{ProdUserCount}(P_j) = \sum_{i=1}^{N} u_i \quad \textit{Where } j = 1,2,\ldots\ldots,M$$

Where u represents a user and P_j represents j^{th} product

F8: Number of reviews given by all users on a product in a specific time interval

$$ReviewCount(P_j) = \sum_{R_i=1}^{N} u_1 + \sum_{R_i=1}^{N} u_2 + \sum_{R_i=1}^{N} u_3 + \cdots\ldots\ldots + \sum_{R_i=1}^{N} u_N \quad \textit{Where } i = 1,2,\ldots\ldots,N$$

Where Ri indicates number of reviews

$$\text{ReviewCount}(P_j, \partial t) = \sum_{i=1}^{N} RC(\partial t, u_i) \textit{ Where } i \in \{1,2,\ldots,N\} \textit{ and } j \in \{1,2,\ldots,M\}$$

∂t is a specific time interval it can be a month, a week etc. u_i represents the i^{th} user in the dataset. For the specific product if the rating having drastic changes either positive or negative, product need to be further engineering for finding the specific user(s) which are responsible for the changes.

Once the user-review centric features (F1-F8) were applied, the relationship between fake and real reviews was examined based on two factors: user_review_count and user_account_age. The corresponding relationships are illustrated in separate figures 3 and 4 respectively. Additionally, Table 4 presents the results obtained for a user having user_id 12471 when the features (F1-F8) were applied to their reviews. The table showcases the outcomes and findings related to the user specific analysis using these features.

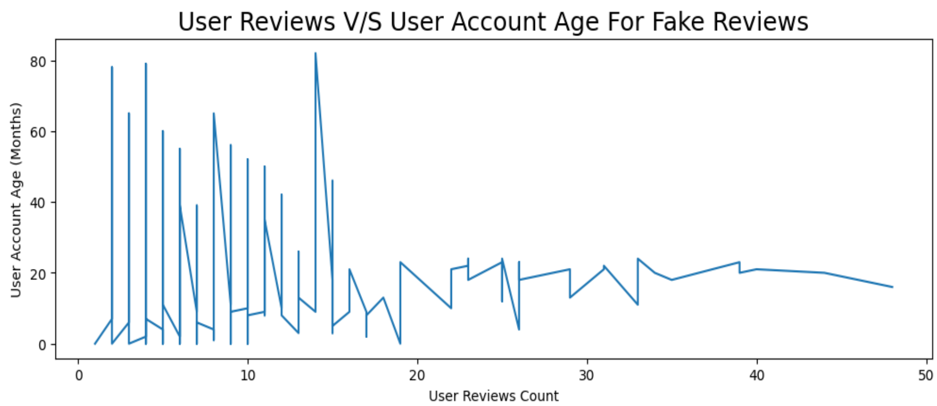

Figure 3: Relation between user account age v/s user reviews count for fake reviews

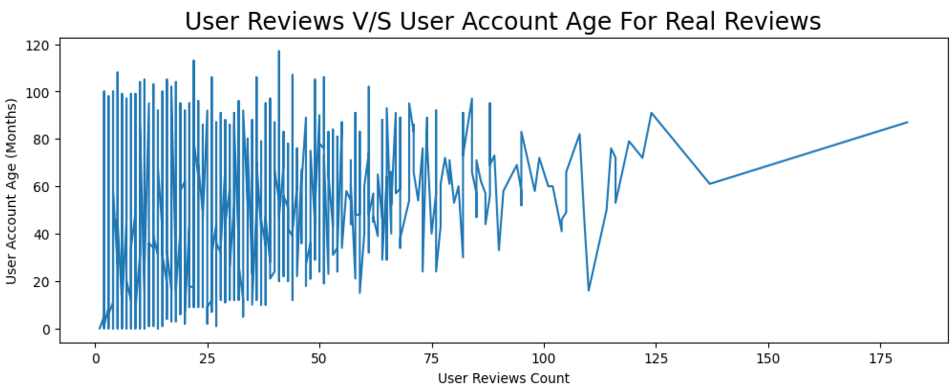

Figure 4: Relation between user account age v/s user reviews count for real reviews

Table 4: User-Review centric features

user_id	12471
prod_id	40
rating	5
label	1
URC	9
rating_avg	3.777777778
maxRPD	5
rating_std	0.833333333
rating_var	0.694444444
UAP	5
UAA	18
RPM	1.8

C. Review's Text centric syntactic and contextual features

Sentiment is a type of feature derived from text. It refers to the overall emotional tone or attitude expressed in a piece of text, such as a review or a sentence. Sentiment analysis is a widely used NLP technique employed to ascertain whether a given text expresses a neutral, positive, or negative sentiment. This feature can be useful in various applications, including fake review detection, customer feedback analysis, and opinion mining.

After calculating the sentiment of the text authored by the user's, figure 5 shows the proportion of positive and negative review for the entire dataset. Table-5 shows the values for features generated by sentiment analysis and POS tagging a text review. Figure 6 and 7 depict the relation between the mean_word_length and the target values of reviews, both for reviews without any analytical thinking applied (Figure 6) and for reviews with analytical thinking applied (Figure 7). By analyzing these figures, it can be inferred that the target values derived through the application of analytical thinking closely align with the provided labels. Figure 8 and 9 display the relationship between the character count and labels. It is observed that the target values calculated through the application of analytical thinking are consistent and identical in both figures.

Table 5: Review text sentiment analysis and POS Tagging.

text	Good pizza but not worth the 45-minute line or the additional 45-minute wait to get our pizza served. However, the pepperoni is amazing and so is the cheese and the crust
Sentiment	0.5
Subjectivity	0.35
Neg_Count	0
Pos_Count	3
Word_Count	33
Unique_words	24
Noun_Count	6
Adj_Count	4
Verb_Count	3
Adv_Count	3
Pro_Count	1
Pre_Count	1

Con_Count	3
Art_Count	1
Nega_Count	1
Aux_Count	1

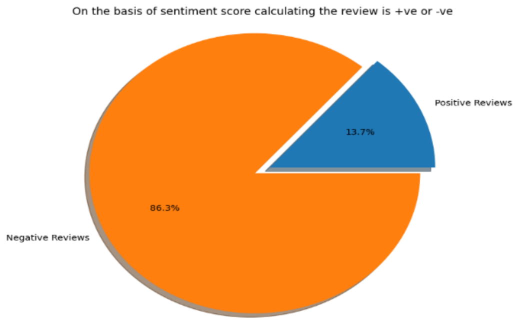

Figure 5: **Illustrating the relationship between +ve and -ve review**

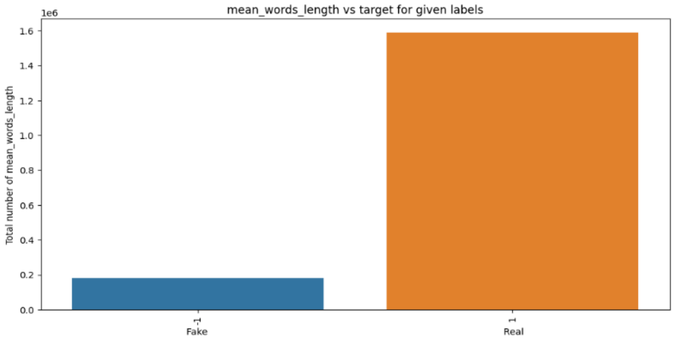

Figure 6: **The relation between the mean_word_length and the target values without analytical thinking**

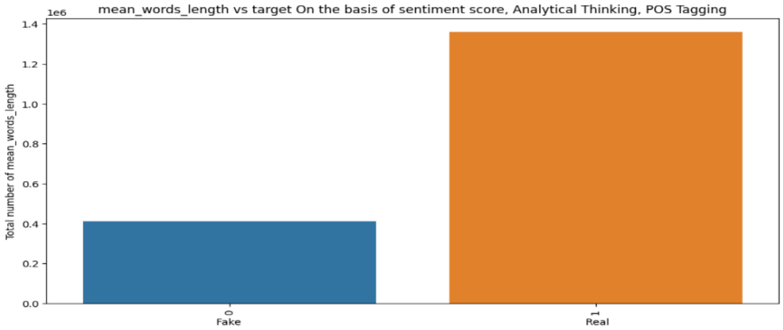

Figure 7: Illustrating the relation between the mean_word_length and the target values with analytical thinking

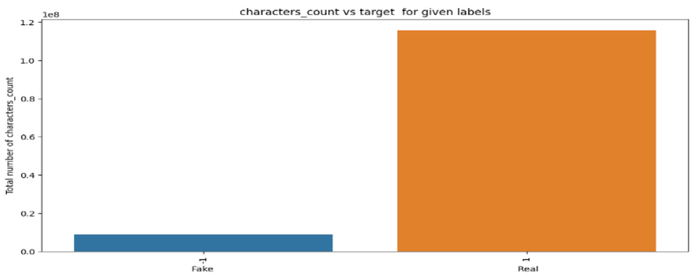

Figure 8: Illustrating the correlation between the char_count and the target values without analytical thinking

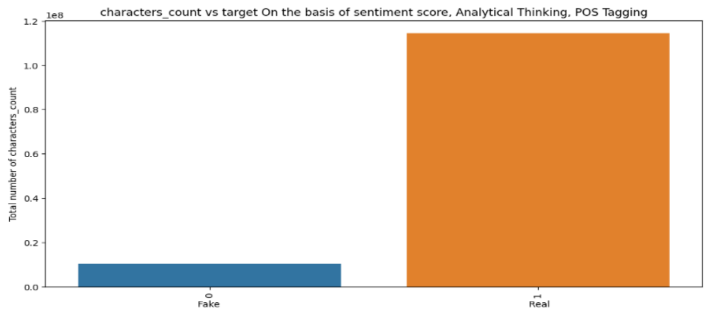

Figure 9: Illustrating the correlation between char_count and target values with analytical thinking

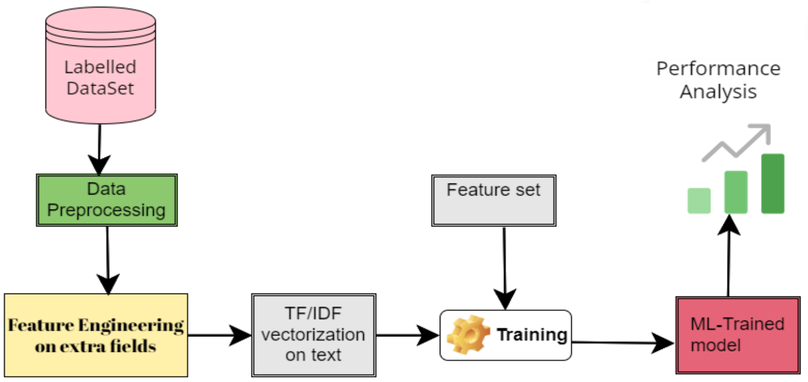

Figure 10: **Proposed Architecture**

3. Results and discussion

In this section, a comprehensive evaluation of the fake review detection model is conducted by considering all the features, including user-review centric, user-centric, text sentiment analysis, text-centric, and text POS tagging. The classifier's performance is evaluated on various matrices like f1-score, recall, accuracy, and precision using the combined feature set. The outcomes are presented in Table 6, and the performance of all classifiers is visualized in Figure 11. It is worth noting that the dataset used for evaluation is imbalanced, consisting of 36,874 fake reviews out of a total of 359,052 reviews (10.27%).

Table 6: Performances of different ML algorithm before resampling.

Algorithm	Accuracy	Precision	recall	F1score
DTC	0.89	0.89	0.99	0.94
RFC	0.89	0.89	0.99	0.94
AdaBoost	0.89	0.89	0.99	0.94
Extra Tree	0.89	0.89	0.99	0.94
GradientBoosting	0.89	0.89	0.99	0.94
XGBClassifier	0.89	0.89	0.99	0.94
GaussianNB	0.46	0.96	0.41	0.58
MultinomialNB	0.89	0.89	1	0.94
BernoulliNB	0.75	0.94	0.77	0.85

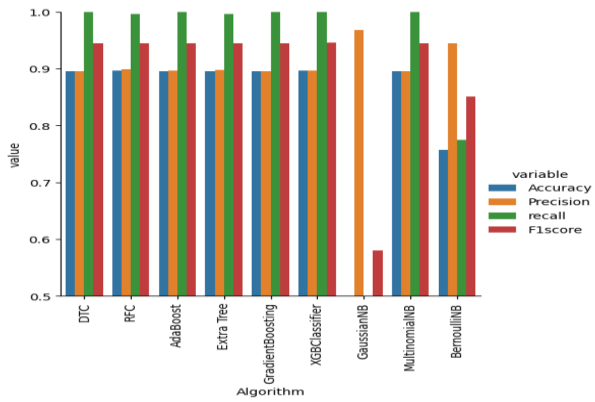

Figure 11: Performances evaluation of different ML algorithm before resampling.

In order to address the issue of imbalanced dataset in this research, the SMOTE (Synthetic Minority Over-sampling Technique) oversampling method is employed. Through this technique, the dataset is balanced by generating synthetic samples. Specifically, 322,100 fake reviews and 322,100 real reviews are created using the oversampling technique. The results of this approach are presented in both a figure 12 and a over performance of the model.With the help of figure and table we can see that the Extra treeensemble ML classifier outperform others in accuracy, precision and f1-score

Table- 7, showcasing the influence of balancing the dataset

Algorithm	Accuracy	Precision	recall	F1score
BernoulliNB	0.67	0.65	0.71	0.68
GaussianNB	0.67	0.77	0.49	0.60
MultinomialNB	0.71	0.77	0.59	0.67
DTC	0.79	0.83	0.73	0.78
AdaBoost	0.83	0.87	0.79	0.83
GradientBoosting	0.86	0.90	0.80	0.85
XGBClassifier	0.92	0.90	0.95	0.92
RFC	0.94	0.91	0.98	0.95
Extra Tree	**0.96**	**0.97**	**0.95**	**0.96**

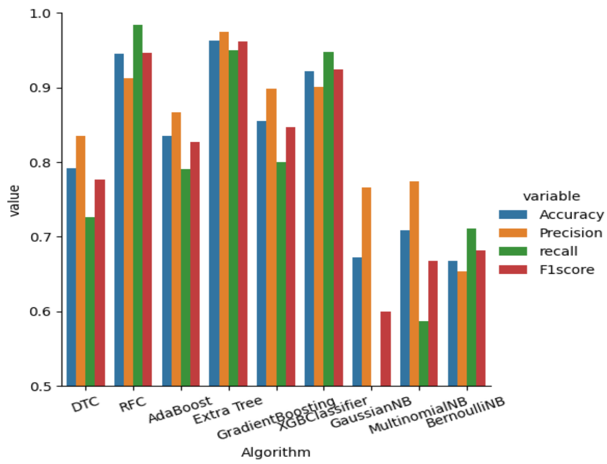

Figure 12: Performances of different ML algo. After resampling dataset

As mentioned in the introduction, various methods have been suggested in previous studies to identify fake reviews using supervised classifiers. One particularly influential study by Julien Fontanarava et al. [18] is frequently referenced as a starting point for evaluating labeled datasets that utilize Yelp's classification system to distinguish between recommended and non-recommended reviews. Table 8 and figure 13 illustrates the comparison of performance between the current study and previous research. Additionally, it highlights how the Extra Tree classifier surpasses the random forest algorithm with regard to f1-score, accuracy and precision.

Table 8: Comparison between current work and proposed in [18].

Algorithm	Precision	Recall	F1-score	Accuracy
Current work (RF)	91	98	95	94
Julien Fontanarava et al. in [18]	77.6	86.1	81.6	80.6
Current work (Extra Tree)	97	95	96	96

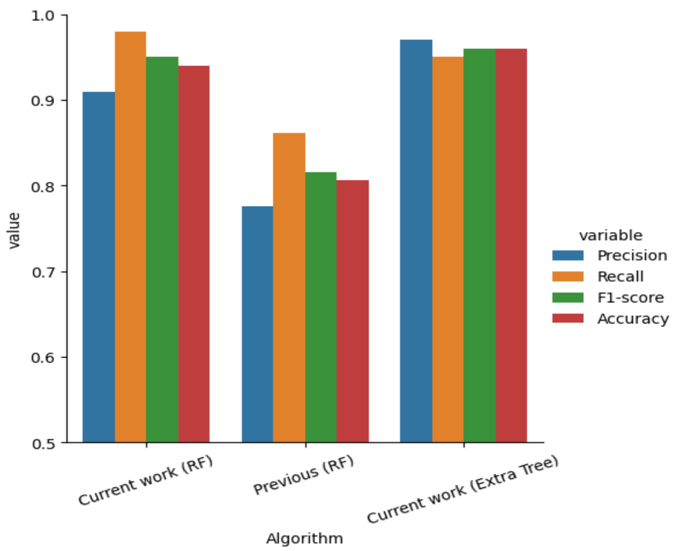

Figure 13: Comparison between current work and proposed in [18].

4. Conclusion and Future work

The primary emphasis of this research work is on evaluating the effectiveness of supervised ensemble classification for detecting fake reviews. The study includes a feature analysis that incorporates various aspects such as review-text centric, user-review centric, user centric, text sentiment, and text pos-tagging features. To address the issue of imbalanced data, the researchers utilize an oversampling technique called SMOTE.

The impact of these features is evaluated using several supervised classifiers, including BernoulliNB, GaussianNB, MultinomialNB, and DTC. Additionally, ensemble classifiers such as AdaBoost, GradientBoosting, XGBClassifier, RFC, and Extra Tree are developed. The evaluation is conducted using a publicly accessible extensive and comprehensive labeled dataset.

Among the classifiers, the Extra Tree ensemble classifier performs the best, achieving high accuracy (96%), precision (97%), and f1-score (96%). The results suggest that this classifier is particularly effective for detecting fake reviews.

The article concludes by mentioning potential directions for future research, such as extending the study with larger datasets and exploring the use of unsupervised classifiers in this context.

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