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Detection of Fake Review

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ABSTRACT

The rapid growth of online reviews has revolutionized how consumers make purchasing decisions. However, this digital landscape has also birthed a pervasive problem. It will have the challenges associated with counterfeit online reviews. It is often generated by individuals with vested interests, who aim to manipulate public perception, boost sales or train the competitors/ reputations. Their prevalence is alarming with countless businesses resorting to this deceptive tactic. It will explore the multifaceted impact of fake reviews on consumers, businesses, and online platforms. Online platforms grapple with the task of policy and removing fake online reviews from their platforms. There are many varieties of online review fraud one of the most prevalent, which comes with the highest risk to your business, is playing for disingenuous and fraudulent customers feedback it can encompass any feedback that is not a genuine opinion or experience related to a product, service or business they can either positive, neutral or negative depending on whether the intent is to help a business or hurt a competitor. There will be a lot of legal consequences will happen. There are several algorithms used in this abstract are text generation, sentiment analysis, context duplication, review posting timing, and user profiting algorithms. It also summarizes and analyses the existing techniques critically to identify gaps based on two groups: traditional statistical machine learning and deep learning methods.

Keywords: Fake review, fake review detection, feature engineering, machine learning, deeplearning.

1. INTRODUCTION

In this era of the internet, customers can post their reviews or opinions on several websites. Detection of fake online reviews has become a crucial endeavor in the age of ecommerce and digital marketing. These reviews are helpful for organizations and for future consumers, who get an idea about products or services before making a selection. As the influence of online reviews on consumer behavior continues to grow, the practice of posting fraudulent or misleading reviews has also proliferated. These fake reviews Detection can mislead consumers, harm businesses, and undermine the trustworthiness of online platforms. To combat this issue, various techniques and technologies have been developed to identify and mitigate fake online reviews. The detection of fake online reviews involves the application of data analysis, machine learning, and Natural Language processing (NLP) techniques to scrutinize the content, behavior, and characteristics associated with reviews. In recent years, the World Wide Web has drastically changed the way of sharing the opinions. Online reviews are comments, tweets, and posts, opinions on different online platforms like review sites, news sites, e-commerce sites or any other social networking sites. Sharing reviews is one of the ways to write a review about services or products Reviews are considered as an individual's personal thought or experience about products or services Customer analyzes available reviews and takes decision whether to purchase the product or not. Therefore online reviews are valuable source of information about customer opinions. Fake or spam review refers to any unsolicited and irrelevant information about the product or service. Spammer writes fake reviews about the competitors' product and promotes own products. The reviews written by spammers are known as fake reviews or spam reviews. Thus fake reviews detection has become critical issue for customers to make better decision on products trustworthy as well as the vendors to make their purchase. The linguistic feature [4] is one of main features to detect fake reviews that depend on writing styles and languages. Linguistic and textual features include N-gram feature, POS feature, LIWC features and stylistic feature. N-gram feature contains unigram, bigram and trigram. In POS tag, each word of review, POS tagger use syntactic deception clues about review spamming. Most of the spammer writes imaginative reviews using pronouns or adverbs, verbs, while normal users write informative reviews using more adjective or noun. LIWC (Linguistic Inquiry and Word Count) is also used to identify the fake reviews. LIWC feature likes score of affective positive and negative feelings, score of punctuation marks. The stylistic based feature depends on word similarity measure (for example, cosine similarity) semantic similarity between objects and review (like product, news articles etc. The stylistic based feature also includes percentage of repeated words, percentage of personal pronouns, percentage of emotional words, percentage of capitalized words, frequency of passive voices etc. The detection of fake reviews has become an increasingly critical aspect in maintaining the trustworthiness of online platforms. As the volume of user-generated content continues to rise, so does the risk of deceptive reviews that can mislead consumers and tarnish the reputation of products or services. In response to this challenge, sophisticated techniques in artificial intelligence and machine learning have been developed to identify and filter out fake reviews effectively. The goal of fake review detection systems is to distinguish between genuine and manipulated reviews by leveraging advanced algorithms and linguistic analysis. These systems analyze various aspects of the reviews, including sentiment, writing style, and contextual information, to uncover patterns indicative of deceptive behavior. With the continuous evolution of tactics employed by individuals generating fake reviews, these detection systems are designed to adapt and stay ahead of new deceptive strategies. In this context, an effective fake review detection system is crucial for ensuring the authenticity of user-generated content and fostering a trustworthy online environment. This introduction sets the stage for understanding the importance of fake review detection and the subsequent paragraphs can delve into specific methodologies, technologies, and strategies employed in building robust systems for identifying and mitigating the impact offake reviews.

II. LITERATURE SURVEY

Supervised learning techniques are used to predict if reviews are fake or not. This sub-section shall sum up the existing supervised learning techniques in the literature shown For example, Jindal and Liu [1] introduced a supervised learning algorithm to detect fake reviews by studying duplicate reviews. The proposed model consisted of two phases. The first phase used unigram and bigram as features, with Naïve Bayes, Random forest, and support vector machine utilized as a classification algorithm. The second phase used two ensemble methods (stacking and voting) enhance the classification methods performance. The results on theAMTdataset showed that the ensemble techniques gave better results than the Naïve Bayes random forest and SVM classification algorithms. Using the simple feature and ensemble methods can enhance the accuracy in detecting fake reviews. However, it can be unreliable if duplicate reviews are considered to be fake reviews. In the study by Cardoso *et al.* [2], the authors performed a comparison analysis of distinctive content-based classification models to investigate if the data characteristics change over time or not. The experimental results on real-world datasets from Yelp [3] showed that the models' performance dropped significantly over time. This is because the spammers continuously tried to avoid the spam. Further, in the real-world application, most recent reviews contain features not demonstrated by a model trained with past reviews. Furthermore, they discovered that the performance of the models dropped significantly over-time. Hence, the need for new models that can work with dynamic changes of fake review characteristics over time. Moreover, the performance of the methods was affected by the polarity of the reviews. So, they recommended using a specialised method for each type of polarity. Further, they found that the techniques' performance could be affected by the diversity of products and services. They recommended using a specific model for each type of product and service. Similarly, Lin *et al.* [4] introduced a classi_cation model to detect fake reviews in a cross domain environment based on a Sparse Additive Generative Model (SAGE), which is created based on the Bayesian generative model [5]. The model is a combination of a generalized additive model and topic modelling [6]. They used linguistic query and word account (LIWC), POS, and unigram techniques as features to detect fake reviews in cross-domains. The proposed model could capture different aspects such as fake vs. truthful and positive vs. negative. They used the AMT dataset [7] which consisting of three domain reviews (Hotels, Doctors, and Restaurants) to evaluate the proposed model. The experimental results showed that the accuracy of the classification using unigram was 65%. The accuracy of two class classifications (Turkey and Employee reviews) using unigram was 76.1%. The accuracy on cross-domain using unigram, POS, and LIWC separately were 77%, 74.6%, and 74.2%, respectively, on the restaurant domain. The accuracy on cross-domain using unigram, POS, and LIWC separately using Doctor domain were: 52%, 63.4%, and 64.7%. However, the proposed model failed in capturing the semantic information of the sentence. In related work, Hernández-Castaneda *et al.*

[4] investigated the efficiency of using SVN (Support Vector Network) in classi_cation tasks to detect fake reviews in one, mixed and cross-domains. They used the LIWC, Word space model (WSM), and latent Dirichlet Allocation (LDA) techniques as a feature extraction method. They evaluated the proposed model on three datasets; the DeRev dataset [89], Spam dataset [7] and Opinions dataset [9]. The results compared to the previous works [7], [8], [9] showed that a combination of WSM and LDA achieved the best results in one domain with an accuracy of 90.9% on the spam dataset, 94.9% on DeRev dataset, 87.5% on Abortion dataset, 87% on Best Friend dataset and 80% on Death Penalty dataset. There was also an accuracy of 76.3% in a mixed domain compared to the Naïve Bayes classier. However, the proposed model did not achieve the best results on cross-domain compared to state-of the-art methods. The performance was good in one domain and mix domain and poor in cross-domain because they used the dataset for testing and combined the remaining dataset for training. This suggests that a deep neural network is probably more appropriate to improve fake review detection in a cross-domain by improving the learning presentation. From their part, Sleigh *et al.* proposed a decision tree method to detect fake reviews. They used traditional feature selection techniques to select suitable features and evaluate them. The proposed model can be improved by taking into account the data correlation in choosing the appropriate features. In the study by.Khurshid *et al.* [10], the authors proposed a supervised machine learning model to detect fake reviews based on content features and primal features. The proposed model used classifiers to classify the reviews: Naive Bayes, Random forest, JRip, AdaBoost, and J48. The results on a real-life dataset [8], showed that the AdaBoost with combined features performed better than other classifiers with an accuracy of 73.4%. Further, using Primal features has a significant impact on improving performance. However, the proposed model did not perform well with an imbalanced dataset. The proposed model was evaluated based onYelpNYC and Yelp Zip data set. The proposed model achieved better results than SVM with linguistic features and behavioural features [3]. Similarly, Li *et al.* extended their previous work and proposed an unsupervised model to address the cold start problem in fake reviews detection. Instead of reviewing content and social relations between users with

other existing users, they considered behaviour representation by dynamic links re-weighting. The proposed model was evaluated based on Yelp NYC and Yelp Zip datasets of. The proposed model achieved poor results with a 60% F1 score on the hotel domain and a 70% F1 score on the restaurant domain. However, the proposed model did not outperform the stateof the-art method and ignored the review text features that could boost the classi_cation model performance. More recently, the authors proposed an aspect-rating local outlier factor in order to identify fake reviews. They considered fake review detection as outlier detection. First, they utilize the lexicon based method to compute the aspect rating of the review. Then tensor factorization method was used for completeness. After that, the local outlier factor (LOF) algorithm was used to classify the reviews. The experimental results on a dataset from TripAdvisor.com show that aspect rating improved the performance for fake review detection. However, integrating more reviewer's features can boost performance.

III. PROPOSED SYSTEM

The introduction of a proposed system for addressing fake online reviews would typically provide an overview of the problem of fake reviews, explain its impact on businesses and consumers, and introduce the solution that the proposed system aims to provide. It might include information about the growing significance of online reviews, the prevalence of fake reviews, and the challenges they pose. Additionally, it could briefly outline the key features or methods the proposed system will employ to detect and mitigate fake reviews effectively. Train machine learning models like Random Forest, Support Vector Machines, or deep learning models such as LSTM or BERT. Use labelled data to teach the system to differentiate between genuine and fake reviews. These models determine the sentiment expressed in reviews to gauge whether the sentiment is genuine or artificially manipulated. Fake reviews might exhibit extreme sentiments or unrelated emotions to deceive readers. Random Forest is an ensemble learning algorithm that combines multiple decision trees to make predictions. It's commonly used for detecting fake reviews by analyzing various features and attributes of reviews. SVM is a supervised machine learning algorithm used for classification tasks. It can be employed to classify reviews as genuine or fake by finding a hyper plane that best separates the two classes. Algorithms like Page Rank can be adapted to analyze review graphs to identify spam reviewers or products that receive an unusually high number of fake reviews. Detecting fake reviews is a critical aspect of maintaining the integrity of online platforms. A proposed system for fake review detection can be designed using various machine learning and natural language processing techniques. “In the proposed fake review detection system, we leverage advanced machine learning algorithms and natural language processing techniques to sift through user-generated content and identify potentially fraudulent reviews. The system employs sentiment analysis to assess the overall sentiment expressed in the reviews, flagging anomalies that may indicate fake or manipulated content. Additionally, feature engineering is utilized to extract relevant attributes from the textual data, enabling the system to discern patterns associated with deceptive reviews . The model is trained on a diverse dataset encompassing genuine and fabricated reviews, ensuring robustness and adaptability. Through continuous learning and updates, the system stays ahead of evolving tactics employed by malicious actors, providing a reliable tool for maintaining the authenticity of online reviews. To enhance the accuracy of the system, it incorporates natural language processing techniques such as part-of-speech tagging and named entity recognition. By analyzing the syntactic an semantic structure of the reviews, the system can identify suspicious patterns or inconsistencies that may indicate the presence of fake content. Furthermore, the model takes into account the historical behavior of users, considering factors such as review frequency, writing style, and review consistency over time. In order to address the challenge of evolving strategies used by individuals generating fake reviews, the system implements an ensemble of machine learning models. This ensemble approach combines the strengths of multiple algorithms, improving overall detection performance and robustness. Regular model updates and retraining mechanisms are integrated to ensure the system stays effective against emerging patterns of deception. User feedback is also incorporated into the system's learning process, allowing it to adapt to new forms of manipulation and continuously improve its performance. The proposed fake review detection system represents a comprehensive and dynamic solution to the growing challenge of maintaining the authenticity of online reviews in an ever-changing digital landscape. At the core of the system is a deep learning architecture, leveraging recurrent neural networks (RNNs) or transformers, which excel at capturing sequential dependencies in textual data. The model is trained on a vast corpus of reviews, both genuine and fraudulent, enabling it to learn intricate patterns indicative of deceptive content. Transfer learning techniques may also be employed, leveraging pre-trained language models like BERT or GPT-3 to extract high-level features and nuances from the reviews. To augment the model's understanding of context, the system incorporates metadata analysis, considering factors such as the timing and frequency of reviews, user engagement patterns, and the product/service lifecycle. This holistic approach ensures that the system not only identifies suspicious linguistic patterns but also considers the broader context in which reviews are generated. For real-time processing and scalability, the proposed system can be deployed on cloud-based platforms, utilizing serverless computing for efficient and cost-effective operations. Additionally, a user-friendly interface can be developed, allowing platform administrators to visualize and interpret the results, and take appropriate actions based on the flagged reviews. Continuous monitoring and periodic model updates are essential to keep the system resilient against emerging tactics employed by malicious entities. The integration of explainable AI techniques further enhances transparency, enabling users and platform administrators to understand how the system arrives at its conclusions. Overall, the proposed fake review detection system [1] represents a sophisticated and adaptive solution to theongoing challenge of maintaining trust in online review systems.

IV. SYSTEM ARCHITECTURE

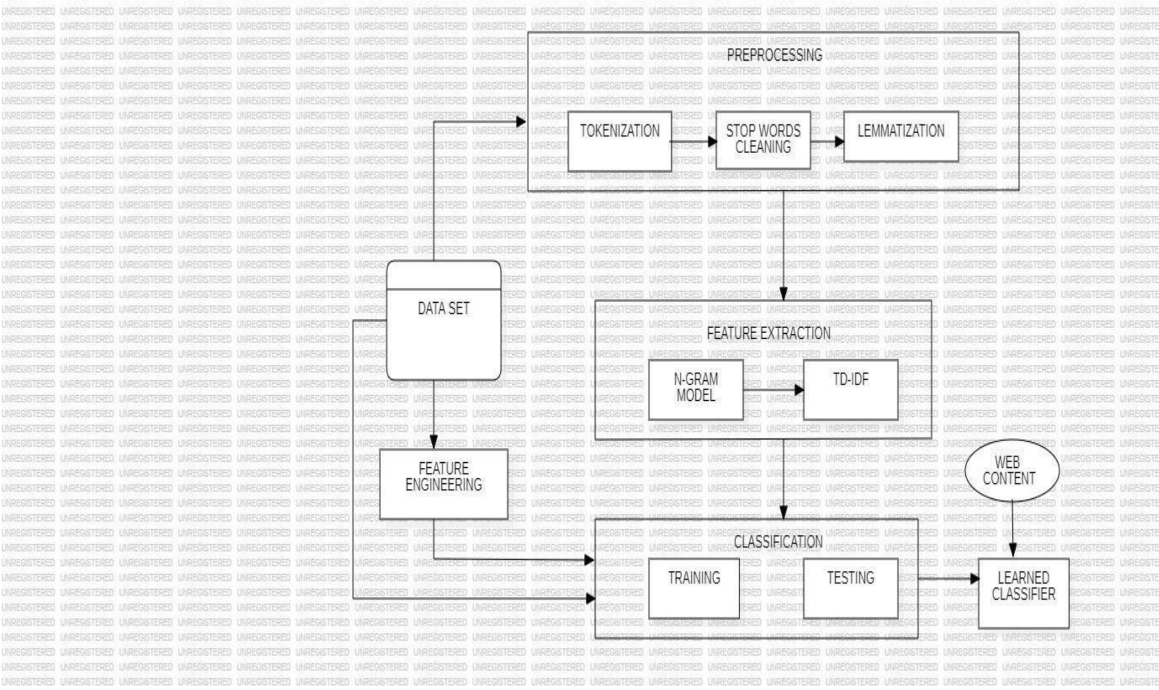

Fig 1: The Proposed Framework

This section explains the details of the proposed approach. The proposed approach consists of three basic phases in order to get the best model that will be used for fake reviews detection. These phases are explained in the Following:

A. Data Pre-processing

The first step in the proposed approach is data pre-processing one of the essential steps in machine learning approaches. Data pre-processing is a critical activity as the world data is never appropriate to be used. A sequence of pre-processing steps have been used in this work to prepare the raw data of the Yelp dataset for computational activities. This can be summarized as follows:

1) Tokenization:

Tokenization is one of the most common natural language processing techniques. It is a basic step before applying any other pre-processing techniques. The text is divided into individual words called tokens. For example, if we have a sentence (“wearing helmets is a must for pedal cyclists”), tokenization will divide it into the following tokens (“wearing”, “helmets”, “is” , “a”, “must”, “for”

, “pedal” , “cyclists”).

2) Stop Words Cleaning:

Stop words are the words which are used the most yet they hold no value. Common examples of the stop words are (an, a, the, this). In this paper, all data are cleaned from stop words before going forward in the fake reviews detection process.

3) Lemmatization:

Lemmatization method is used to convert the plural format to a singular one. It is aiming to remove inflectional endings only and to return the base or dictionary form of the word. For example: converting the word (“plays”) to (“play”).

B. Feature Extraction

Feature extraction is a step which aims to increase the performance either for a pattern recognition or machine learning system. Feature extraction represents a reduction phase of the data to its important features which yields in feeding machine and deep learning models with more valuable data. It is mainly a procedure of removing the unneeded attributes from data that may actually reduce the accuracy of the model Several approaches have been developed in the literature to extract features for fake reviews detection. Textual features is one popular approach It contains sentiment classification which depends on getting the percent of positive and negative words in the review; e.g. “good”, “weak”. Also, the Cosine similarity is considered. The Cosine similarity is the cosine of the angle between two n-dimensional vectors in an n-dimensional space and the dot product of the two vectors divided by the product of the two vectors’ lengths (or magnitudes). TF-IDF is another textual feature method that gets the frequency of both true and false (TF) and the inverse document (IDF). Each word has a respective TF and IDF score and the product of the TF and IDF scores of a term is called the TF-IDF weight of that term. A confusion matrix is used to classify the reviews into four results; True Negative (TN): Real events are classified as real events, True Positive (TP): Fake events are classified as fake, False Positive (FP): Real events are classified as fake events, and False Negative (FN): Fake events are classified as real. Second there are user personal profile and behavioural features. These features are the two ways used to identify spammers Whether by using time-stamp of user’s comment frequent and unique than other normal users or if the user posts a redundant review and has no relation to domain of target. In this paper, We apply TF-IDF to extract the features of the contents in two languages models; mainly bi-gram and tri-gram. In both language models, we apply also the extended dataset after extracting the features representing the users behaviours.

C. Feature Engineering

Fake reviews are known to have other descriptive features related to behaviours of the reviewers during writing their reviews. In this paper, we consider some of these feature and their impact on the performance of the fake reviews detection process. We consider caps-count, punt-count, and emoji behavioural features. caps-count represents the total capital character a reviewer use when writing the review, punt-count represents the total number of punctuation that found in each review, and emoji counts the total number of emoji in each review. Also, we have used statistical analysis on reviewers' behaviours by applying "group by" function, that gets the number of fake or real reviews by each reviewer that are written on a certain date and on each hotel. All these features are taken into consideration to see the effect of the users behaviours on the performance of the classifiers.

V. RESULTS

We evaluated our proposed system on Yelp dataset .This dataset includes 5853 reviews of 201 hotels in Chicag written by 38; 063 reviewers. The reviews are classified into 4; 709 review labelled as real and 1; 144 reviews labelled fake. Yelp has classified the reviews into genuine and fake Each instance of the review in the dataset contains the review date, review ID, reviewer ID, product ID, review label and star rating. The statistics of dataset is summarized in Table I. The maximum review length in the data contains 875 word, the minimum review length contains 4 words, the average length of all the reviews is 439:5 word, the total number of tokens of the data is 103052 word, and the number of unique words is 102739 word.

SUMMARY OF DATA SET	
Total number of reviews	5853
Number of fake reviews	1144
Number of real reviews	4709
Number of distinct words	102739
Total number of tokens	103052
The maximum review length	875
The minimum review length	4
The Average review length	436.5

Table 1. Summary of the Dataset

In addition to the dataset and its statistics, we extracted other features representing the behaviours of reviewers during writing their reviews. These features include caps-count which represents the total capital character a reviewer use when writing the review, punt-count which represents the total number of punctuation that found in each review, and emoji which counts the total number of emoji in each review. We will take all these features into consideration to see the effect of the users behaviours on the performance of the classifiers. In this part, we present the results for several experiments and their evaluation using five different machine learning classifiers. We first apply TF-IDF to extract the features of the contents in two languages models; mainly bi-gram and trigram. In both language models, we apply also the extended dataset after extracting the features representing the users behaviours mentioned in the last section. Since the dataset is unbalanced in terms of positive and negative labels, we take into consideration the precision and the recall, and hence and hence f1-score is considered as a performance measure in addition to accuracy. 70% of the dataset is used for training while 30% is used for testing. The classifiers are first evaluated in the absence of extracted features behaviors of users and then in the presence of the extracted behaviors. In each case, we compare the performance of classifiers in Bi-gram and Trigram language models.

In this part, we present the results for several experiments and their evaluation using five different machine learning classifiers. We first apply TF-IDF to extract the features of the contents in two languages models; mainly bi-gram and trigram. In both language models, we apply also the extended dataset after extracting the features representing the users behaviours' mentioned in the last section. Since the dataset is unbalanced in terms of positive and negative labels, we take into consideration the precision and the recall, and hence and hence f1-score is considered as a performance measure in addition to accuracy. 70% of the dataset is used for training while 30% is used for testing. The classifiers are first evaluated in the absence of extracted features behaviours' of users and then in the presence of the extracted behaviours'. In each case, we compare the performance of classifiers in Bi-gram and Trigram language models.

Table II Summarizes the results of accuracy in the absence of extracted features behaviours' of users in the two language models. The average accuracy for each classifier of the two language models is shown. It is found that the logistic regression classifier gives the highest accuracy of 87.87% in Bi-gram model. SVM and Random forest classifiers have relatively close accuracy to logistic regression. In Tri-gram model, KNN and Logistic regression are the best with accuracy of 87.87%. SVM and Random forest have relatively close accuracy with score of 87.82%. In order to evaluate the overall performance, we take into consideration the average accuracy of each classifier in both language models. It is found that the highest average accuracy is achieved in logistic regression with 87.87%.

Classification Algorithm	Accuracy Bigram %	Accuracy Trigram %	Average Accuracy %
Logistic Regression	87.87%	87.87%	87.87%
Naïve Bayes	86.76%	87.30%	87.03%
KNN	86.34%	87.87%	87.82%
SVM	87.82%	87.82%	87.82%
Random Forest	87.82%	87.82%	87.82%

Table 2. Accuracy of bi-gram and tri-gram in the absence of Extracted features Behaviours

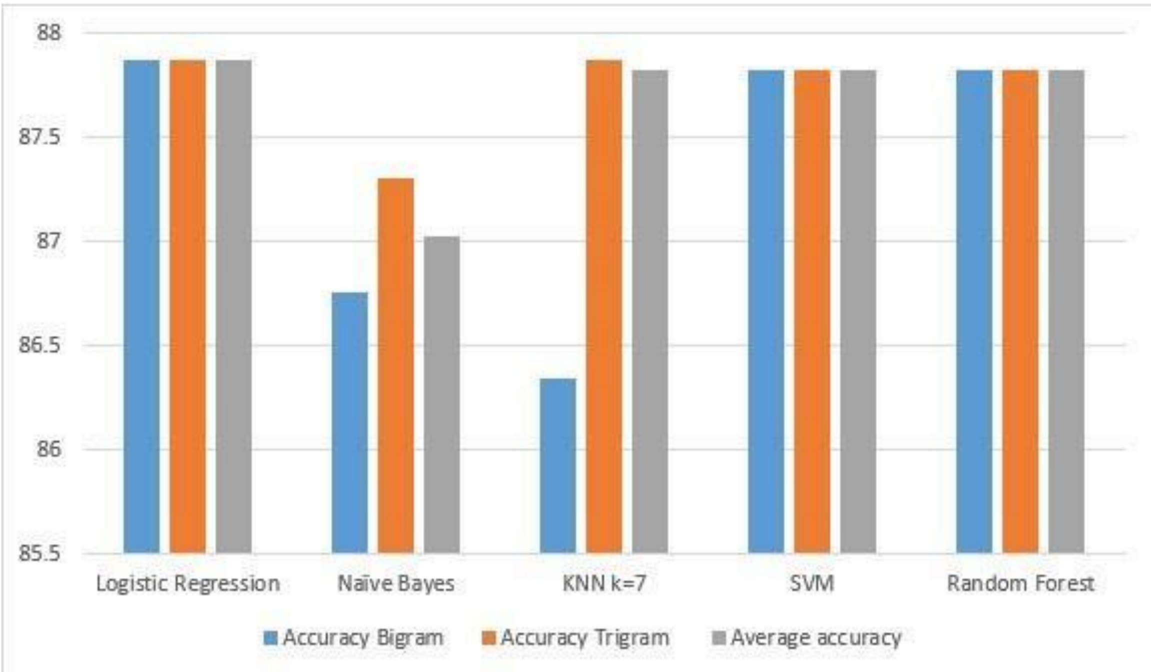

Fig. 2. Accuracy, and Average Accuracy in Absence of Extracted Behavioural Features.

On the other hand, Table III summarizes the accuracy of the classifiers in the presence of the extracted features behaviours' of the users in the two language models. The results reveal that the classifiers that give the highest accuracy in Bi-gram is SVM with score of 86.9%. Logistic regression and Random forest have relativity close accuracy with score of 86.89% and 86.85%, respectively. While in Tri-gram model, both SVM, and logistic regression give the best accuracy with score of 86.9%. The Random forest gives a close score of 86.8%. The summary of the results are illustrated in Fig. 3. Also, it is found that the highest average accuracy is obtained with SVMclassifier with score of 86.9%.

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Classification Algorithm	Accuracy Bigram %	Accuracy Trigram %	Average Accuracy %
Logistic Regression	86.80%	86.89%	86.89%
Naïve Bayes	85.82%	86.34%	86.08%
KNN	86.56%	85.09%	86.23%
SVM	86.09%	86.09%	86.09%
Random Forest	86.85%	86.08%	86.82%

Table 3. Accuracy of bi-gram and tri-gram in the presence of extracted features behaviours.

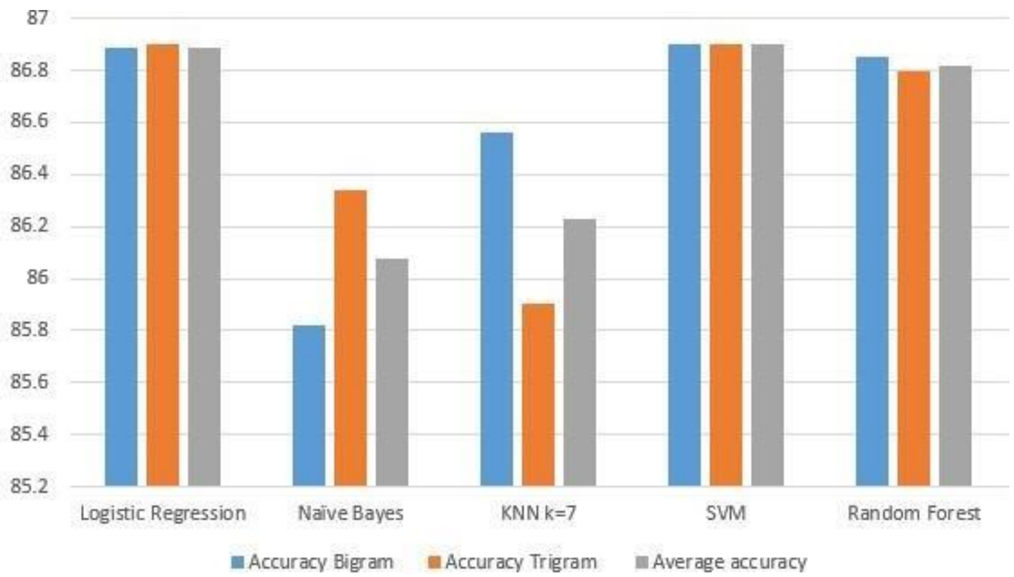

Fig 3. The Accuracy, and the Average Accuracy after Applying Feature Engineering.

Table IV summarizes the recall, precision, and f1- score in the presence of the extracted features behaviours' of the users in the two language models. It is found that, the highest f1-score value is achieved by Logistic regression with f1-score value of 82% in case of Bi-gram. While the highest f1-score value in Tri-gram is achieved in KNN with f1-score value of 86.20%. Fig. 5 illustrates the performance of all classifiers. The KNN classifier outperforms all classifiers in terms of the overall average f1-score with value of 83.73%. The results reveal that KNN(K=7) outperforms the rest of classifiers in terms of f-score with the best achieving fscore 82.40%. The result is raised by 3.80% when taking the extracted features into consideration giving best f-score value of 86.20%.

	Recall	Precision	F-Score	Recall	Precision	F-Score	Average Score
Logistic Regression	87.87%	77.22%	82.20%	87.87%	77.20%	82.20%	82.20%
Naïve Bayes	86.79%	78.23%	81.86%	87.33%	78.97%	82.12%	81.99%
KNN(K=7)	86.34%	80.20%	82.40%	87.87%	77.22%	82.20%	82.30%
SVM	87.82%	77.21%	82.17%	87.82%	77.21%	82.17%	82.17%
Random Forest	87.82%	81.29%	82.28%	87.82%	77.21%	82.17%	82.22%

Table 4. Recall, precision, and f1-score in presence of extracted behavioural features.

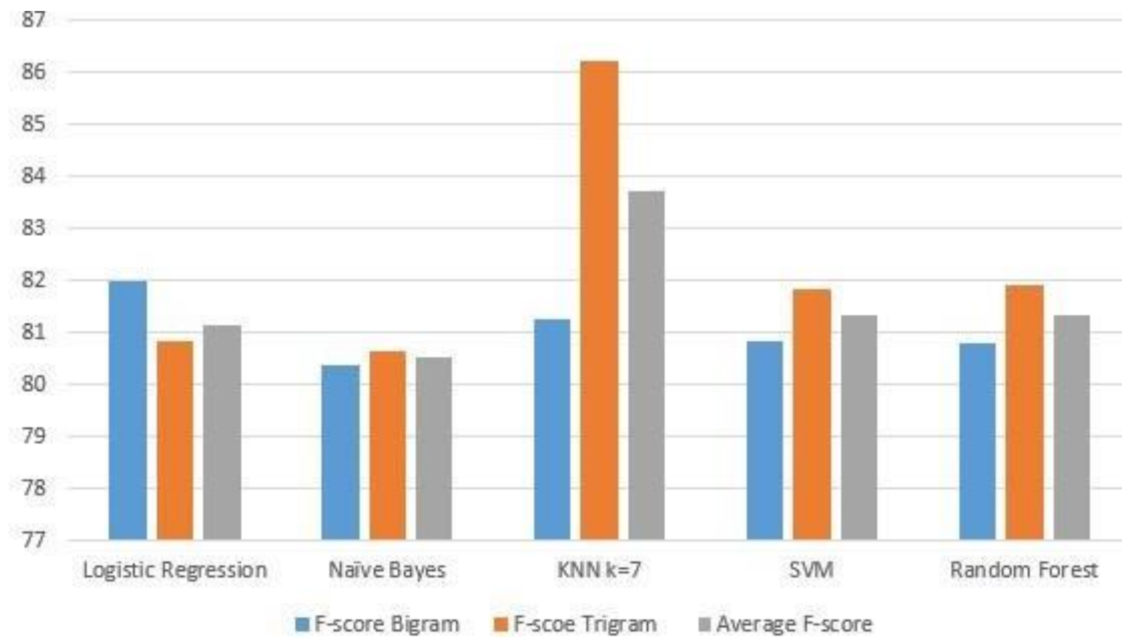

Fig 4.f-score, and Average f-score in Presence of Extracted Behavioural Features.

VI .CONCLUSION

It is obvious that reviews play a crucial role in people's decision. Thus, fake reviews detection is a vivid and ongoing research area. In this paper, a machine learning fake reviews detection approach is presented. In the proposed approach, both the features of the reviews and the behavioural features of the reviewers are considered. The Yelp dataset is used to evaluate the proposed approach. Different classifiers are implemented in the developed approach. The Bi-gram and Trigram language models are used and compared in the developed approach. The results reveal that KNN(with K=7) classifier outperforms the rest of classifiers in the fake reviews detection process. Also, the results show that considering the behavioural features of the reviewers increase the f-score by 3.80%. Not all reviewers behavioural features have been taken into consideration in the current work. Future work may consider including other behavioural features such as features that depend on the frequent times the reviewers do the reviews, the time reviewers take to complete reviews, and how frequent they are submitting positive or negative reviews. It is highly expected that considering more behavioural features will enhance the performance of the presented fake reviews detection approach.

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