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Proposed framework to improve fake review detection

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***Abstract**: In recent years, people have increasingly turned to e-commerce for purchasing products and accessing services, moving away from traditional methods. Online platforms allow customers to share their feedback through reviews, which help companies understand customer needs and assist other consumers in making informed decisions. However, these reviews can be either genuine or fraudulent, making Fake Review Detection (FRD) a crucial research area.*

This study presents a systematic review of existing literature on FRD and extends previous research to enhance detection methods. The paper serves two main purposes. First, it aims to support research by identifying future directions in FRD and facilitating access to relevant studies. The findings provide a taxonomy of research directions in fake review detection, highlighting the advantages and limitations of existing approaches in preprocessing, feature selection, and detection techniques.

Second, the paper proposes a theoretical framework for improving fake review detection. This framework consists of six phases: data collection, preprocessing, feature extraction and selection, handling data imbalance, future prediction (using a hybrid approach combining deep learning, machine learning, and time series analysis), and performance evaluation.
. By outlining these phases, this research aims to enhance the effectiveness of fake review detection and contribute to the ongoing development of FRD methodologies.
***Key Word**: Fake Review, Fake review detection, Machine learning, Ensemble classifiers, deep learning, time series*

I. Introduction

In recent years, online shopping platforms such as Amazon have dramatically expanded. These platforms allow users to post reviews and ratings about the quality of products and services. Reading reviews before making a purchase has become a common habit, particularly among potential buyers who rely on them as a valuable resource for making informed decisions. When a product or service receives mostly positive reviews, the likelihood of purchase increases. Conversely, predominantly negative reviews often deter customers, leading them to seek alternative options. According to Heidary et al. (2015), positive customer reviews can generate significant economic benefits for businesses and individuals while also serving as valuable input for product and service design. However, the growing influence of reviews has led fraudsters to exploit this system by posting fake reviews to either promote or discredit a product or service. According to Ott et al., fake reviews include any misleading or irrelevant information about a product or service. Detecting such fraudulent activity is a critical challenge. Wahyuni, Eka Dyar, and Arif Djunaidy (2016) categorize different types of spam, as illustrated in Figure 1. These include web spam, email spam, and review spam. Among these, detecting review spam is particularly challenging. There are two approaches to detecting fake reviews: manual and automated. The manual approach has several limitations, including being time-consuming, costly, and prone to inaccuracies. In contrast, fake reviews can be detected automatically using various techniques, such as machine learning and deep learning, which will be discussed in the next section. Identifying whether a review is spam or not can be framed as a binary classification problem.

The rest of this paper is organized as follows. Section 2 provides the methodology. Section 3 presents the analysis and discussion of related work, identifying research gaps, techniques, future research directions, and our critique. Section 4 presents the findings. Section 5 proposes a framework to improve fake review detection. Finally, Section 6 concludes the paper and suggests possible future research directions.

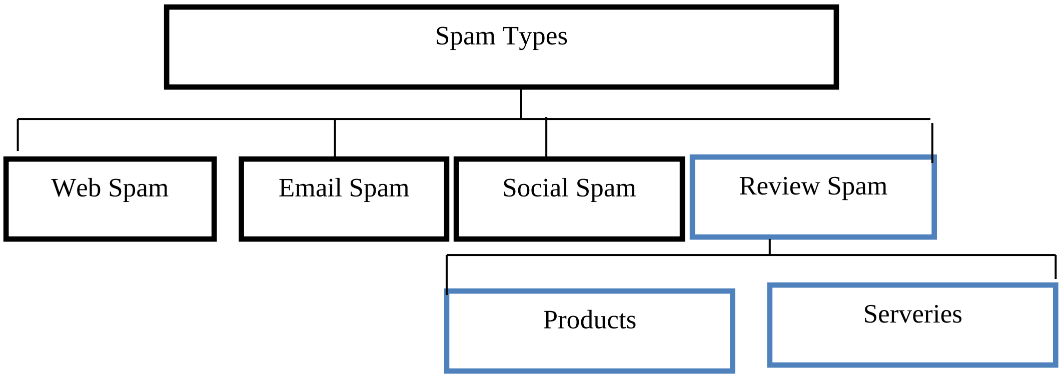


Figure 1: The most area of spam detection

II. Research Methodology

In this paper, we discuss various techniques/ features/ approaches that are used to detect fake reviews. A systematic review is executed using a systematic, explicit, and rigid, standard that aims not only to recap, current research in this topic but also to cover an element of analytical criticism as shown in Table (1). This paper followed eight guidelines of (Okoli, Chitu, 2015) [1] to conduct a systematic literature review.

2.1 Research Questions

Identifying research questions is the first step in conducting a systematic review. This step must be concise and clear to ensure a structured approach to the study. In the context of this research, the key questions are as follows:

Q1: What are the current research trends, and who has published relevant studies? When were they published?
Q2: What are the major gaps and limitations in the reviewed literature?
Q3: What are the key research directions in fake review detection?
Q4: What are the most effective techniques and methods used to detect fake reviews?
Q5: How can fake review detection be improved?

III. Related Work

While examining recent research in the field of fake review detection, as shown in Figure (2), four key areas of study have been identified: preprocessing strategies, dataset-related work, feature selection, and fake review detection algorithms. Several studies have been carried out to enhance fake review detection. This research will discuss these studies from different perspectives, including preprocessing techniques, feature selection and weighting, and classification methods, as follows:

Preprocessing Of Fake Reviews

Preprocessing is a crucial step in fake review detection, as it enhances the quality of text data before feature extraction. Various studies have employed different preprocessing techniques to refine datasets and improve detection accuracy. Many researchers have applied standard preprocessing steps, including removing stop words, lemmatization, stemming, tokenization, spell correction, removing special characters, and lowercasing text. Several studies, such as those conducted by Ahmed and Muhammad (2019) and Hussain et al. (2020), have adopted combinations of these methods to clean review datasets and improve the quality of input data.Some studies have implemented advanced techniques, such as n-gram models and word embedding methods. For instance, Barushka and Hajek (2019) used a skip-gram model to enhance feature extraction. Similarly, Pandey and Rajpoot (2019) employed a multi-phase preprocessing approach, where the first phase involved removing unwanted elements such as numbers, white spaces, and special symbols, followed by tokenization and lemmatization in the second phase.In addition to these common approaches, some researchers introduced unique preprocessing strategies to improve fake review detection. Soni and Prabakar (2018) attempted to build graphs from datasets to analyze relationships between data points. Shahariar et al. (2019) emphasized punctuation removal and stemming to refine textual input, while Chauhan et al. (2017) focused on removing malicious curse words and repetitive letters to eliminate irrelevant content. Hajek et al. (2020) utilized spell checking and part-of-speech tagging to improve textual consistency. Additionally, Furia (2020) used the NLTK toolkit for automated preprocessing, which demonstrated the effectiveness of leveraging pre-built natural language processing tools. Despite the progress in preprocessing techniques, some gaps and limitations remain. While most studies detail their preprocessing strategies, others, such as Ghai et al. (2019), do not provide a clear explanation of how their data was preprocessed. Some researchers relied on pre-labeled datasets without elaborating on their preprocessing steps, as seen in the work of Ren and Ji (2017). This lack of consistency in reporting preprocessing methods highlights the need for a standardized framework in future research. Preprocessing plays a vital role in fake review detection by improving text quality and facilitating effective feature extraction. Researchers have adopted various methods, ranging from basic text cleaning to advanced NLP-based approaches. However, inconsistencies in documentation across studies suggest that more standardized preprocessing frameworks should be developed to ensure reproducibility and comparability of results in future research.

Feature Selection

Features are essential for detecting customer opinions, whether genuine or fake. According to Asghar, Muhammad Zubair (2020), these features can be categorized into opinion spam detection (review-based), opinion spammer detection (reviewer-based), item spam detection (product-based), and hybrid approaches. A detailed overview of these features is provided in Table (2).Eldin, Sarah Saad (2019) [1] focused on review-based features, using seven linguistic and heuristic Arabic patterns with fourteen rules to extract explicit features and assign weights. Elmurngi, Elshrif, and Abdelouahed Gherbi (2018) [2] applied a feature selection method combining BestFirst + CfsSubsetEval and Genetic Search. Pandey, Avinash Chandra, and Dharmveer Singh Rajpoot (2019) [3] extracted features using Linguistic Inquiry and Word Count. Barushka, Aliaksandr, and Petr Hajek (2019) [4] did not specify their feature selection strategy. (2018) [6] did not discuss data preprocessing but extracted features using term frequency, Latent Dirichlet Allocation, and word2vec. Shahariar, G. M., et al. (2019) [7] employed TF-IDF, N-grams, and word embedding (word2vec). Soni, Jayesh, and Nagarajan Prabakar (2018) [8] applied word2vec (skip-gram) and random walk for feature extraction.Hussain, Naveed, et al. (2020) [9] used Information Gain (IG) for feature selection. Ahmed, Sifat, and Faisal Muhammad (2019) [10] utilized TF-IDF and Chi-Square (Chi^2) for feature extraction. Ren, Yafeng, and Donghong Ji (2017) [11] extracted features using word embedding and a look-up matrix. Mani, Shwet, et al. (2018) [12] employed simple N-gram (unigram + bigram) features. Rout, Jitendra Kumar, Amiya Kumar Dash, and Niranjan Kumar Ray (2018) [13] incorporated product, review, and reviewer-based features, using N-grams, part-of-speech (POS) tags, opinion polarity, and LIWC output. Zeng, Zhi-Yuan, et al. (2019) [14] encoded entire reviews into vectors using BiLSTM. Algur, Siddu P., N. H. Ayachit, and Jyoti G. Biradar (2017) [15] examined review and reviewer-based features but did not specify their selection method. Furia, Ruchit (2020) [16] applied multiple techniques, including LIWC + bigrams, POS + unigram, and N-gram. Danti, Ajit (2019) [17] used six features: Response (R1), Profile Usefulness (R2), Template (R3), Stars (R4), Reply (R5), and Thickness (R6). Chauhan, Shashank Kumar, et al. (2017) [18] focused on product features like display, camera, battery life, and speakers. Ahsan, MN Istiaq, et al. (2016) [19] extracted unigram, bigram, and trigram features. Saumya, Sunil, and Jyoti Prakash Singh (2018) [20] employed features such as review sentiment, comment sentiment, content-based factors, and rating deviation. Hajek, Petr, and Aliaksandr Barushka (2020) [21] incorporated three feature types: word embedding, emotional indicators, and bag-of-words representation (N-gram). Hajek, Petr, Aliaksandr Barushka, and Michal Munk (2020) [22] used reviewer-based, product-based, and hybrid feature selection approaches.

Fake Reviews Approach and Detection Techniques

Researchers have developed various fake review detection approaches using multiple techniques to enhance opinion mining accuracy, support factual customers, and ensure truthful stores.Eldin (2019) [1] proposed an enhanced opinion retrieval method for Arabic text, consisting of eight phases, including customer requirement analysis, feature extraction, classification, and evaluation, using Conditional Random Fields (CRF) for fake review detection. Elmurngi and Gherbi (2018) [2] employed five supervised learning algorithms (NB, K-NN, K*, SVM, DT-J48) for sentiment classification. Pandey and Rajpoot (2019) [3] introduced a spiral cuckoo search-based clustering method to optimize fake review detection. Barushka and Hajek (2019) [4] utilized n-gram and skip-gram models for preprocessing, followed by a deep feed-forward neural network (DNN) for classification. Ghai et al. (2019) [5] proposed a review processing method involving rating variation, gap count, and reviewer count. Jia et al. (2018) [6] extracted features and applied SVM, Logistic Regression, and Multi-layer Perceptron models. Shahariar et al. (2019) [7] developed a spam review detection model with four phases: preprocessing, labeling (using active learning), feature selection, and classification (deep learning and machine learning). Soni and Prabakar (2018) [8] employed a deep-walk approach to detect fake reviewer groups, using supervised and unsupervised machine learning. Hussain et al. (2020) [9] presented two methods: (1) a behavioral approach using 13 spammer features and (2) a linguistic method analyzing review content. Ahmed and Muhammad (2019) [10] used boosting algorithms and active learning for spam review classification. Ren and Ji (2017) [11] developed a neural network model integrating CNN and a gated recurrent neural network. Mani et al. (2018) [12] employed SVM, NB, and RF classifiers, followed by ensemble techniques. Rout et al. (2018) [13] proposed a framework using preprocessing, feature selection, and machine learning models (supervised, unsupervised, and semi-supervised). Zeng et al. (2019) [14] designed an integrated model splitting reviews into three segments, processed with bidirectional LSTM models and a fully connected neural network.. (2017) [18] applied sentiment analysis and a dictionary-based sentiment scoring method. Ahsan et al. (2016) [19] developed a model with three phases: duplicate review detection, feature selection and supervised learning, and classification via ensemble techniques. Saumya and Singh (2018) [20] proposed a robust spam review detection system. Hajek and Barushka (2020) [21] introduced two models—CNN and DFNN—for fake review classification. Hajek, Barushka, and Munk (2020) [22] developed a seven-step detection system, including preprocessing, feature selection, and spamicity detection. Tables (1) and (2) summarize the techniques used for fake review detection, identifying their limitations and future directions.

IV. Findings

In this section introduces the findings of the fake review and contributes to answering the two first research questions as follow:

Prepossessing fake review

Figure (3) showed information about the most preprocessing strategies used in the fake review. In general, it clearly noticed that most research used through the preprocessing phase including stop words removal, tokenization, and lemmatization and stemming. It found 35% of the papers considered stop words removal as an important step. Meanwhile, tokenization, lemmatization, and stemming were used in 19%, 13%, and 13% respectively.

Common Features in fake review

Figure (4), reveals the most frequent features that are used in fake review detection. It showed that, per the features used in the paper, n-gram models are the highest and chip-square, and information gains the lowest.

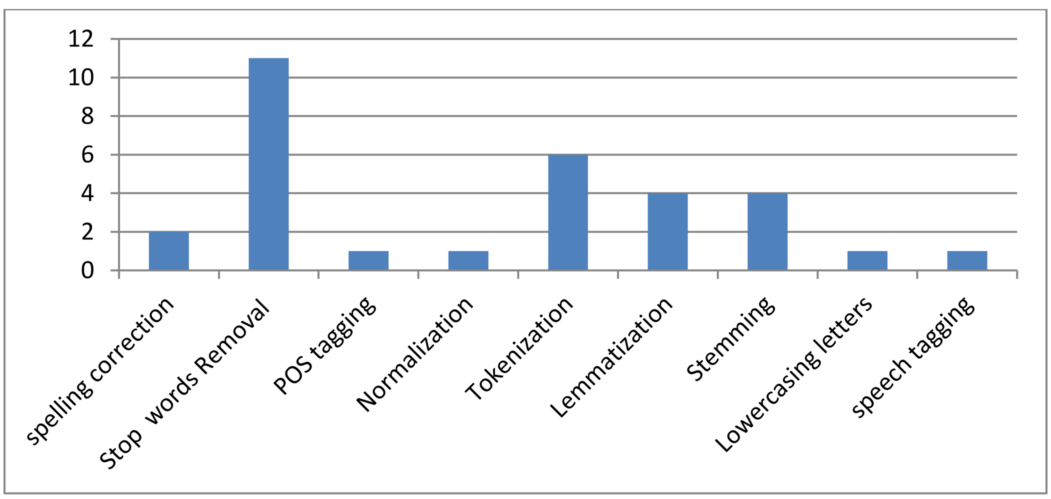


Figure 3: The most preprocessing strategies used in fake review

The analysis clearly indicates that **N-gram models** are the most widely used feature in fake review detection, accounting for **33.33%** of studies. This is followed by **Word Embedding**, which is utilized in **23.80%** of cases. Meanwhile, **TF-IDF**, **Part-of-Speech (POS) tagging**, and **Emotional Indicators** are employed in **14.28%**, **9.52%**, and **9.52%** of studies, respectively. Lastly, **Information Gain** and **Chi-Square** are the least used methods, each appearing in **4.76%** of studies.

Methods Used in fake review

Reviewed studies have introduced a wide set of methods and techniques to detect fake reviews. Figure (5) illustrates the most methods used in fake reviews. It is clearly noticed that SVM is highly used methods in articles followed by RF, NB, CNN, and ensemble. It found 17% of the papers considered SVM as an important method. Meanwhile by RF, NB, CNN, and ensemble are used in 8% to each one.

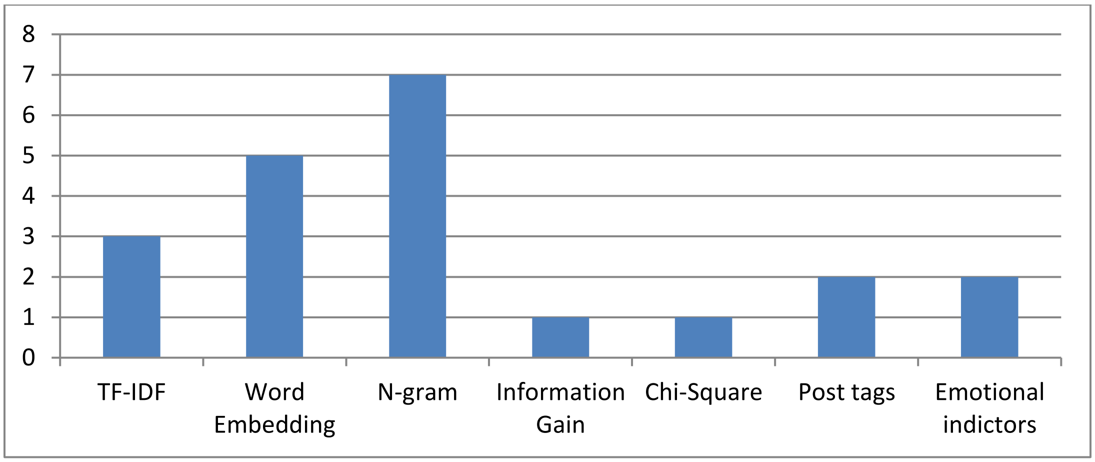


Figure 4: The most frequent features used in fake review

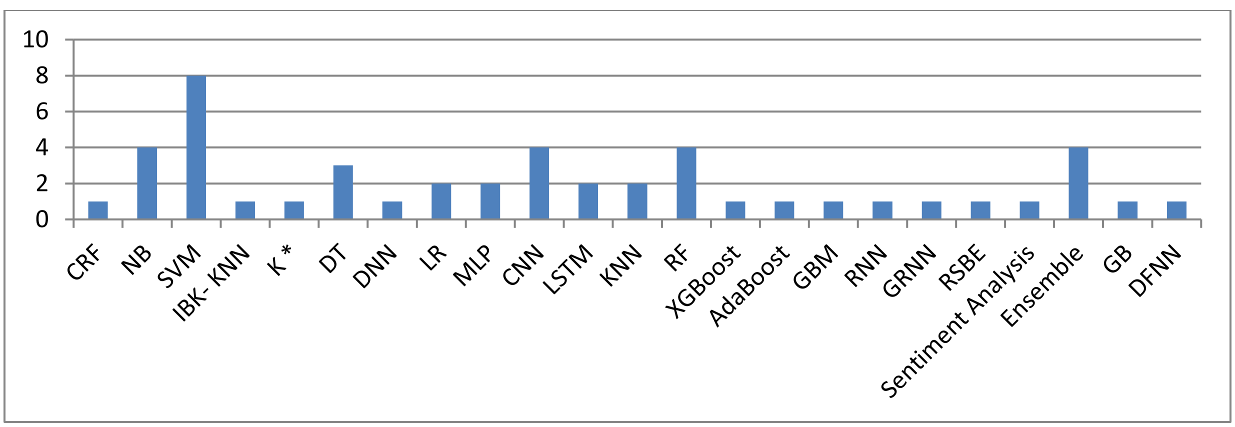


Figure 5: The most methods used in reviews classification

Fake review domains

Figure (6) showed the most domains were targeted to apply deceptive review spam. It is clearly noticed in figure (6) that several researchers inclined to use product datasets (35%), hotel datasets (32%), and resultants (19%).

Performance fake review tool

Figure (7) reveals the most frequent performance techniques that are used to validate fake review detection. . It is clearly noticed that the accuracy (41%) is high performance techniques used followed by precision (17%) and recall (17%).

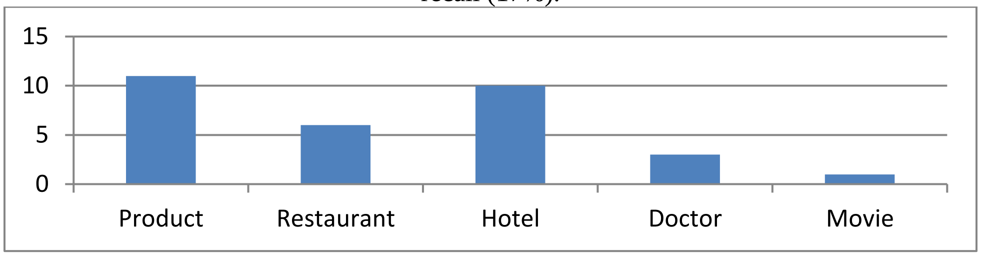


Figure 6: domain of dataset used detect fake review

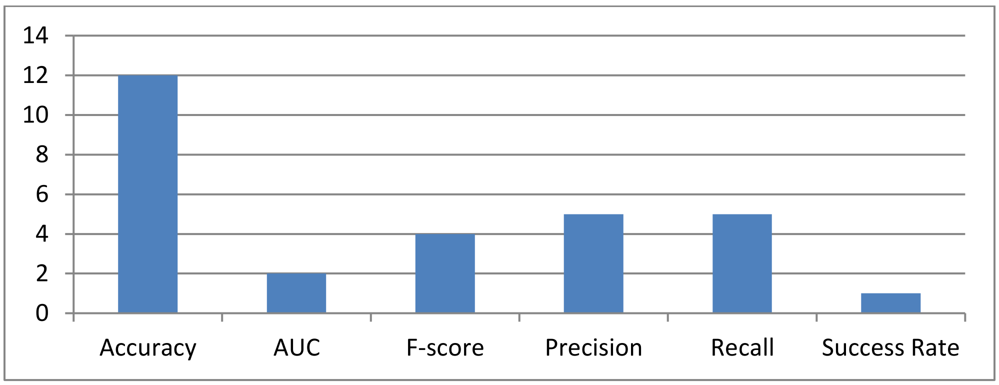


Figure 7: The most performance of fake review tool

V. Proposed Framework

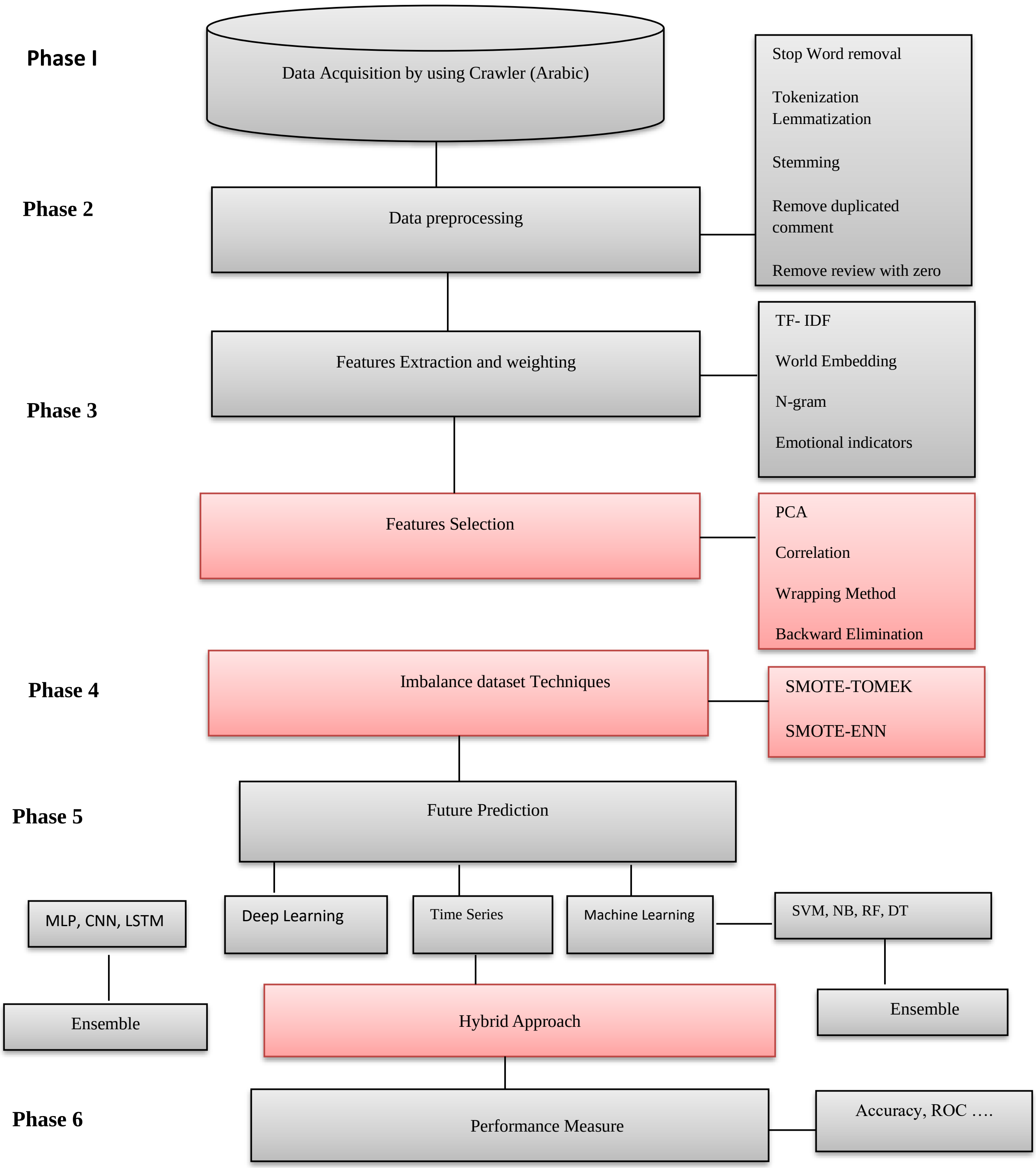
Our approach for fake review detection follows a structured methodology, as outlined in Figure (8). The process begins with data collection, where reviews are gathered from Arabic sources, specifically souq.com. In the second phase, the collected dataset undergoes preprocessing using several techniques, including stop word removal, stemming, tokenization, and duplicate review removal. These steps enhance the quality of the data and prepare it for further analysis.

The third phase involves feature extraction and selection. The extracted features from the text include n-gram, TF-IDF, word embedding, and emotional indicators. To optimize model performance and accuracy, feature selection techniques such as Principal Component Analysis (PCA), the Wrapping Method, and Backward Elimination are applied.

Following feature extraction and selection, the fourth phase focuses on data labeling. In this study, we propose an automatic labeling approach that classifies reviews as spam or non-spam based on [22]. Since imbalanced datasets can negatively impact classification performance, the fifth phase addresses this issue using techniques like SMOTE-TOMEK and SMOTE-ENN, which balance the dataset within each cluster group.

For future prediction, a hybrid approach is implemented by integrating different methodologies. This includes deep learning, where an ensemble of the most effective techniques identified in our survey is utilized, machine learning, which also employs an ensemble of the most successful approaches, and time series analysis, which is used to predict future trends. By combining these methods, we aim to enhance the accuracy and reliability of the detection system.

The final phase is dedicated to evaluating the output results. Various performance metrics are applied to assess the effectiveness of the proposed approach. Through this comprehensive methodology, our system ensures a robust and efficient framework for detecting fake reviews.



VI. Conclusion

Fake reviews have become a rapidly growing problem, making Fake Review Detection (FRD) a crucial yet challenging task. Differentiating fake reviews from genuine ones is complex, requiring systematic approaches. This research systematically reviewed existing literature on FRD, analyzing 22 research papers to provide insights into key contributions and address research questions. The study offers a structured overview of FRD research and proposes a framework to overcome gaps identified in previous studies.

FRD has emerged as a critical issue encompassing multiple aspects, including data collection, preprocessing, feature extraction and selection, and classification models. The state-of-the-art research in FRD reflects diverse approaches and perspectives. This study highlights frequent preprocessing strategies and the most commonly used techniques in feature selection, presenting an overview of the most effective methods in FRD. Additionally, it introduces a taxonomy of research directions and provides a comparative analysis of different techniques, algorithms, and feature types used in fake review detection.

Despite the progress in FRD, the review underscores the need for further research. Key limitations in previous studies include challenges related to imbalanced datasets and prediction accuracy. Furthermore, there is a significant gap in research focusing on fake review detection in the Arabic language. To address this, we propose a framework specifically designed to detect fake reviews in Arabic.

The proposed framework consists of six phases. The first phase involves data collection using a web crawler. The second phase focuses on preprocessing data using various techniques, including stemming. The third phase is dedicated to feature extraction and selection. The fourth phase addresses the issue of imbalanced data. The fifth phase introduces a hybrid approach combining deep learning, machine learning, and time series analysis to enhance fake review detection. Finally, the sixth phase is responsible for evaluating performance.

By implementing this framework, we aim to improve the accuracy and effectiveness of fake review detection, particularly for Arabic-language reviews, and contribute to advancing research in this domain.

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Appendix

Table (1) Contribution /advantages /limitations /future work and Criticism

Reference/Year	Proposed approach	Advantages	Limitations / Future work	Criticism
[1],2019	They proposed a novel approach to determine product requirement based on the opinion of customers	This work combines between information retrieval and opinion of customers	This approach can't be applied to other languages because the features extract based language on syntax. In the future work on implicit product features. The implicit features of identification and comparative opinions are not covered in the study. In future work, they want to improve results by using implicit features.	1.They didn't detect fake reviews as well as they used review-based features only to capture opinion of customers 2. They didn’t use methods to select features 3. They only used CRF technique. I think that not enough.
[2],2018	They used sentiment classification algorithms to detect fake reviews on Movie Reviews	They used three datasets with a balance between fake and normal reviews. They used five supervised learning algorithms to classifying sentiment.	For future work, they would like to extend this study to use other datasets such as the Amazon dataset. Furthermore, we may apply sentiment classification algorithms with stop words removal and stemming methods	1. Only used for labeled data. Not suitable for Unlabeled dataset. 2. The accuracy of the result is very low (66.5). 3. Not assign a weighting to each feature
[3],2019	They proposed a novel variant of the cuckoo search based clustering method has been introduced to discover fake reviews.	This approach finds the optimal solution in a smaller number of iterations. This proposed spiral CS method has been used to detect spam reviews.	Therefore, future work involves exploring more feature selection techniques and optimization algorithms for better accuracy.	1. Not assign a weighting to each feature. 2. The accuracy of results is very low in Hotel, Restaurant dataset
[4],2019	They propose a novel content-based approach that considers both bag-of-words and word context to enhance performance	The proposed detection system outperforms other popular algorithms for review spam detection	Different languages represent another challenge for future research	They only used review-based features
[5],2019	Review processing method is proposed	Some parameters have been suggested to find the usefulness of reviews. These parameters show the variation of a particular review from others, thus increasing the probability of it being spam.	---	They didn't use methods to select features. They didn't discuss how to preprocessing their data (not shown in their approach)

Table (1) Contribution /advantages /limitations /future work and Criticism

Reference/ Year	Proposed approach	Advantages	Limitations / Future work	Criticism
[6],2018	They proposed a method to extract features based on Latent Dirichlet Allocation (LDA)	They used traditional machine learning (SVM and LR) and deep learning (Multi-layer Perceptron) The study proved the effectiveness of features extracted based on LDA.	Possible directions for future work is to explore why Logistic Regression and Multilayer Perceptron have high accuracy, SVM is not.	1. The accuracy result need improvement (81.3) 2. Two datasets that have been used imbalance
[7],2019	They proposed deep learning methods for spam review detection which includes (MLP), (CNN) and LSTM	They used several deep learning methods as well as compared them with traditional machine learning.	The data labeling process can be improved by introducing Deep Learning methods. The number of reviews from Yelp Dataset can be increased. Hybrid CNN-RNN model can be introduced	They used a small amount of data, that lead to appear Overfitting problem an effect on the detection accuracy
[8],2018	They proposed a method that focuses on finding such a group of fake reviewers.	Detect Groups of Fake Reviewers.	The scope of the work can be expanded in the future to include text-based modeling using review text, star rating.	The accuracy result need improvement (87.3 in SVM)
[9],2020	They proposed methods based on Linguistic and Spammer Behavioral Methods to detect fake (spam) review	The evaluations show that both proposed models have significantly improved the detection process of spam reviews.	They want to use extra features to improve accuracy. These may include an IP address of the spammer, registered an email address, and signed-in location of the reviewer.	They used a traditional approach (machine learning) to detect fake review but I think they need to use deep learning because the size of data that used is huge
[10],2019	They used Boosting Approaches to Detect Spam Reviews	They employee XGBoost to improve performance	They want to improve the dataset more and look forward to taking other aspects of the boosting algorithms to observe the change in results.	They label some data Manually this is time consuming and expensive
[11],2017	They proposed a model based on Neural networks to detect opinion spam detection	They used several deep learning methods such as CNN ,RNN	--	They used RNN to been used for recurrent semantic composition. As we know the RNN is short memory so I think they need to use LSTM to improve accuracy (83.6)
[12],2018	They used Ensemble Machine Learning to Detect Spam Reviews	They Ensemble technique performed better than classification algorithms	The proposed method emphasizes only on detecting fake reviews. So, a mechanism can be proposed for reducing the fake reviews in the future	Only used for labeled data. Not suitable for Unlabeled dataset.
[13],2018	They proposed a framework to deal with fake reviews.	They used several machine learning algorithms. They used review, reviewer and product features	As a huge amount of data (data stream) are generated by review site, big data techniques need to be explored	When they used semi supervised algorithms the accuracy of the result is low (need improvement). They didn't say which algorithms use to select features

Table (1) Contribution /advantages /limitations /future work and Criticism

Reference/Year	Proposed approach	Advantages	Limitations / Future work	Criticism
[14],2019	They proposed an integrated model based on the structure of the review for deceptive review detection.	They used an attention mechanism to focus on important features. They used neural network models to represent a document.	Their model failed to perform well in the cross-domain experiment. In the next study, we may try two approaches to the mentioned problems.	They didn't deal with imbalanced data
[15],2017	They proposed an approach that integrates content and usage information to detect fake product reviews.	The proposed model exploits both product reviews and reviewers' behavioral traits interlinked by specific spam indicators.	As future work, they plan to modify the introduced methodology to better account for singleton spam reviews.	The best result achieved by precision (75.2) is very low so I think they need to improve results.
[16],2020	They worked towards developing a tool which will classify the reviews as fake or genuine	Experimental results show that the proposed ensemble classifier is efficient in the fake review detection task.	The future scope may encompass features like LIWC, POS in addition to the Bigrams and Lemmatization which have been considered	They didn't weight select features
[17],2019	They proposed a method based on decision tree and information gain	The efficiency of the proposed approach has achieved 96 % success rate.	NA	They didn't weight select features and didn't handle imbalanced data
[18],2017	They incorporated a sentiment analysis of review techniques into spam review detection.	They used shallow dependency parser to calculate the sentiment score	They would also try to update our dictionary containing sentiment words. They would try to add more words in our dictionary and	The accuracy result is very low (57.2%)
[19],2016	They proposed an ensemble methodology for detecting Review spam	They deal with duplicated reviews. They used cross validation to overcome of Overfitting	In the future they want to use a large dataset from different domains of different languages as well as use new features	They label some data Manually this is time consuming and expensive
[20],2018	They proposed a novel sentiment mining approach for detecting spam reviews	They handle imbalance data by using SMOTE and ADASYN algorithms (oversampling)	The future experiments can include Products from other categories and from another e-commerce websites to make a generalize system.	They used text features only.
[21],2020	They proposed an approach based on integration word embedding and emotion mining to detect fake review	They used to deep learning techniques to improve performance	For future works, they also plan to use the advantages of both the DFFNN and the CNN models and develop a hybrid deep NN structure.	The proposed model is that in contrast to the CNN model sentence weights were ignored due to their domain specific nature.
[22],2020	They proposed Opinion spam detection framework using a hybrid classification scheme	They used a hybrid approach of features	Integration of user accounts on existing review sites, such as Amazon, with social media sites (Facebook, Twitter, etc.). They also want to perform an experiment on other datasets.	Feature selection is performed manually, however, automated feature selection may yield improved results

Table (2): A comparative study of different classification algorithms

Reference/ Year	Data Source	Domain	Feature type	Language	Techniques	Algorithms	Detect fake review	Measures	Performance %	The best Method
[1],2019	souq.com	Mobile application stores and products opinions	Review based	Arabic	Classification	Conditional Ransdom Fields (CRF)	No	F1 score Precision Recall	95.7 64.6 77.2	---
[2],2018	Movie Reviews dataset	Movie	Review based	English	Classification	NB SVM IBK- KNN K * DT-j48	Yes	Accuracy	61.2 66.5 59.6 63.5 62.5	SVM
[3], 2019	TripAdvisor Dataset	Twitter, Hotel, Restaurant	Review based	English	Hybrid (clustering then classification)	Spiral	Yes	Precision Recall(to each data set in optimal feature case)	**96**.13 95.07 72.13 69.64 72.56 70.21	Spiral
[4],2019	Cornell University	Positive Hotel Negative Hotel	Review based	English	n-gram + skip-gram n-gram	Deep feed-forward neural network (DNN)	Yes	AUC FP Rate FN Rate	0.956 ,0.950 0.956, 0.946 0.103, 0.128 0.11, 0.123 0.103 ,0.128 0.140, 0.115	DNN
[5],2019	Amazon.com	Lenovo K5 note Oppo F1S dataset	Review based and Reviewer features	English	Rating and Review Processing Method	Rating and Review Processing Method	Yes	Accuracy	94.60 91.15	Proposed method
[6],2018	Yelp.com	Hotel and Restaurant	Review based and Reviewer features	English	Classification	LDA+Word2Vec+SVM LDA+ Logistic Regression LDA+ Multi-layer Perceptron	Yes	Accuracy	61.3 81.3 81.3	LAD with Multi-layer and with Logistic Regression
[7],2019	Yelp Dataset OTT DATASET	Chicago hotels.	Review based	English	word2vec Nigram+Bigrams+Trigrams	CNN LSTM MLP	Yes	Accuracy	95.56 96.75 93.19	LSTM
[8],2018	Google	640 apps for Play Store	Reviewer features	English	Hybrid(classification then clustering)	SVM KNN RF	Yes	Accuracy	87 81 85	SVM
[9],2020	Amazon	Products	Review based and Reviewer features	English	SRD-LM	NB LR SVM RF	Yes	Accuracy	85.8 88.5 86.52 84.03	LR

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Reference/ Year	Data Source	Domain	Feature type	Language	Techniques	Algorithms	Detect fake review	Measures	Performance %	The best Method
[10],2019	Amazon	Products	Review based	English	Boosting Classifiers	XGBoost AdaBoost GBM	Yes	Accuracy Precision Recall	0.958 0.951 0.898 0.942 0.911 0.887 0.952 0.939 0.906	XGBoost
[11],2017	Amazon	Hotel Restauran t Doctor	Review based	English	classification	CNN RNN Average GRNN Bi-directional average GRNN	Yes	Accuracy	75 .9 63 .2 80 .1 83 .6	Bi-directiona l average GRNN
[12],2018	Ott et al	Hotels in Chicago	Review based	English	classification :spam /non spam	SVM NB RF Voting/Stackin g Ensemble	Yes	Accuracy	83.0 87.12 84.87 87.43/87.68	Stacking Ensemble
[13],2018	OTT dataset	Chicago hotels.	Review, Reviewer an product	English	Supervised, semi supervised And un supervised	SVM NB DT	Yes	Accuracy	88.67 90.19 90.02	NB
[14],2019	Amazon	Restauran t Doctor Hotel	NA	English	Classification	Basic CNN SWNN Hier-LSTM RSBE	yes	Accuracy Precision Recall F1	71,69,88,78 81,80,87,83 62,61,95,74 83,82,82,82	Hier-LSTM is the best in recall and f1 while the RSBE is the best in accuracy and recall
[15],2017	Amazon	Product	Reviews and Reviewers features	English	Basic Basic + burst pattern Basic + burst pattern + reviewer reputation	NA	Yes	Precision Recall F1	67.6 ,66,65 66.9 ,65.2 ,64 75 ,75 ,74.9	Basic + burst pattern + reviewer reputation
[16],2020	Amazon	Product	Star Rating, Review Text, and Verified Purchase.	English	Classification	SVM KNN NB Weighted ensemble	Yes	AUC	0.86 0.63 0.71 0.84	Weighted ensemble
[17],2019	Amazon	Product	Reviews based	English	Classification	DT	Yes	Success rate	96	DT
[18],2017	Amazon	Product	Reviews based	English	Classification	sentiment analysis	Yes	Accuracy	57.2	sentiment analysis
[19],2016	OTT YELP	Hotel and restaurant	Reviews base	English	Classification	Ensemble method	Yes	Recall and precision Accuracy	>95 >88	Ensemble method

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Reference/ Year	Data Source	Domain	Feature type	Language	Techniques	Algorithms	Detect fake review	Measures	Performance %	The best Method
[20],2018	Amazon	Product	Reviews base	English	Classification	RF GB SVM	Yes	Precision, recall and F1Score	88,95,91 86,91,88 77,56,65	RF
[21],2020	Multiple source	1-Amazon 2-Doctor 3-Hotel 4-Restaurant	Reviewer-and product-based	English	Classification (Deep learning)	DFNN CNN	Yes	Accuracy AUC F-score	83,89,82, 88,94 ,91 90,95,90 90,96,90	DFNN in (1,4) and CNN in (2,3)
[22],2020	Amazon	Product	Reviewer, review product-based and hybrid approach	English	Classification	Proposed approach	Yes	Accuracy	98.2	Proposed approach