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# A Survey on Feature Selection Based Spam Review Detection using Deep Learning Techniques

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**Abstract:** In recent times, online shoppers are technically knowledgeable and open to product reviews. They usually read the buyer reviews and ratings before purchasing any product from e-commerce website. For the better understanding of products or services, reviews provided by the customers gives the vital source of information. In order to buy the right products for the individuals and to make the business decisions for the Organization online reviews are very important. These reviews or opinions in turn, allow us to find out the strength and weakness of the products. Spam reviews are written in order to falsely promote or demote a few target products or services. Also, detecting the spam reviews has also become more critical issue for the customer to make good decision during the purchase of the product. A major problem in identifying the fake review detection is high dimensionality of the feature space. Therefore, feature selection is an essential step in the fake review detection to reduce dimensionality of the feature space and to improve the classification accuracy. Hence it is important to detect the spam reviews but the major issues in spam review detection are the high dimensionality of feature space which contains redundant, noisy and irrelevant features. To resolve this, Deep Learning Techniques for selecting features is necessary. To classify the features, classifiers such as Naive Bayes, K Nearest Neighbor are used. An analysis of the various techniques employed to identify false and genuine reviews has been surveyed.

**Keywords -** Fake review detection; Machine learning; Feature selection and classification; Deep learning.

## 1. Introduction

The Commercial website is also a main venue for individuals to articulate themselves. Clients can share their perspectives on products and ventures effectively with the utilization of internet business pages, blogs, forums and e-commerce websites. Prior to getting them, most customers read feedback about the product and services. Everybody on the webpage likewise knows the estimation of these online feedbacks for different clients just as for vendors. Contingent upon these reviews, sellers/vendors are likewise ready to design their particular promoting methodologies. For instance, if multiple consumers purchase a similar laptop model and write complaints about problems related to its screen resolution, the manufacturer can become aware of this problem and fix it to improve customer satisfaction. [11].

The spam-attack pattern has as of late created, as anybody can rapidly compose spam reviews and post them to web based business sites with no limitations. Any business may enroll people for their merchandise and ventures to compose false reviews; these individuals are named as spammers. Spam comments are usually written in order to receive a commission to advertise the products or services they provide. These practices are classified as spamming feedback. A portion of the main complaints regarding opinion sharing platforms are that spammers will, without much of a break, create a conversation about the actual company by writing spam comments. These spam scores may expect a key activity in bringing competition up in products or services. For e.g., at whatever point a purchaser needs to buy an item on the web, they normally go to the comment segment and look at specific customers' feedback. When the comments are mainly favorable, the consumer will purchase the particular product, otherwise they will not purchase it. All of this shows that negative reviews have been the biggest concern of online shopping and can result in a loss for both the buyer and the supplier. Reviewing spam may have a significant effect on businesses, causing a sense of distrust in the general public, and this subject has recently gained media and political interest due to its relevance. [11]

The following procedures are commonly used to identify spam analysis approaches. The principal essential advance


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step is to gather the review dataset; since the survey datasets comprise for the most part of unstructured text and can contain uproarious information, it is quite often imperative to pre-process the data sets. The next move is to select a method for software creation, such as a linguistic n-gram method or an algorithm strategy focused on specific spammers. Eventually, various spam recognition testing techniques, such as machine learning , deep learning, and Lexicon-based approaches, are implemented to determine can comments are spam. This survey paper has shared views on different methodologies tailored for the identification of fraudulent reviews by using various machine learning techniques. The accuracy level for each technique is also discussed in the succeeding sections
.

*1.1 Characteristics of Fake Reviews*

Spam reviews anyway bit extraordinary and are essentially found in product review sites. The goal is to give positive surveys with respect to a particular item for benefit and advancement and give ridiculous negative ones to downgrade the contending brand or items. The review spam is first planned by Jindal and Liu in the year 2007 with regards to product reviews and consequently accepted to be the principal reported examination in this domain. There has been an impressive development of misleading fraudulent reviews in additional time, beginning from singular spammers to gather spammers both are on rise. Except if recognized or expelled, it will harm the online business by and large and the web based life which is accepted to be a believed wellspring of popular supposition may lost its brilliance. Regardless of that, the issue is as yet colossal and needs critical examination progression. Some of the characteristics of fake reviews are as follows:

*Less Reviewer Information*

Clients with less informal communities and no information about records are typically impostors, and are probably going to post only few reviews that are fake. [2]

*Duplicating the feedbacks frequently*

Spammers, who additionally take feedback from their own or from others, will post frequently duplicate feedbacks. These reviews may have spam reviews. [2]

*Short & Quick Reviews*

Since spammers are keen on bringing in income, they incline toward composing exceptionally short reviews with bunches of syntactic mistakes and unnecessarily use rates, numerals, and certain capital words. [2]

*Abrupt posting of feedback in a similar time period*

Perhaps the most ideal approaches to identify false feedback is to take a gander at the timestamp ratings and whether a gathering of remarks is composed at a similar date, at that point this is an indication of spam reviews. [2]

*Exorbitant utilization of positive and negative terms*

In analysis, spammers additionally utilize a great deal of idealistic and negative terms that probably won't be required in a practical setting. They some of the time compose proclamations that depend on product titles and not on their data of using the product. [2]

## 2. Literature review

They classified spam reviews into three types: Type 1, Type 2 and Type 3. [10] Here Type 1 Spam surveys are untruthful opinions that look to delude clients or opinion mining algorithms by giving untruthful feedback on certain objective product for their own benefit. Type 2 Spam surveys are simply business appraisals, those that focus absolutely on the brand and not the products. Type 3 spam reviews are not so much reviews, they are for the most part either advertisements or insignificant reviews that don't contain any perspectives about the product. [1]

*Active Learning based Spam Detection: (2016)*

Mr. N. Istiaq Ahsan [3] et al., used the TF-IDF features of the review material to incorporate active learning approach to identify review spam. His model makes remarkable changes in efficiency measurements, based on nearly 3600 feedback from various fields. In the best case, in most cases, it achieves accuracy and precision of up to 88 per cent, recall and f-scores are above 85 per cent. In addition, during the process about 2000 comments were labelled manually. To perform the experiment, they used 1600 labelled reviews (both positive and negative), and 2000 unlabeled reviews (total 3600). Throughout the active learning method, manually labelling 1000 + unlabeled statements. The feature vectors were built using analytical content TF-IDF values, and the classification method used 3 classifiers-Linear SVM, SGD, and Perceptron. The sufficiency of the proposed model was assessed using the Recall (R), Precision (P),Accuracy (A) and F1-score (F) measures. With great exactness (87.0) and f-score (88.0), the Linear SVM played out the best with up to 88.2 percent precision.

*Fake Review Detection using Classification: (2018)*

Neha S. Chowdhary[4] et al., proposes two new feature types: the frequency of user review on the same product and the frequency of word. Here the identification of fake reviews was seen as a binary classification issue with the two classes being: fake and genuine. The author focuses primarily on identifying the fake reviews from a sample of product reviews by simulating spam reviews combining numerous sorts of opinion spam review options and generating a training set, and so classifying them using the Naïve Thomas Bayes classification and ensemble classification algorithm like random forest to check model accuracy. Experiments show that the established pattern and technique are effective in the classification of fake and genuine reviews. Experimental results point to the conclusion that Random Forest does better than Naïve Bayes and may be used to distinguish true as well as fake feedback. With excellent precision (99.94) and f-score (99.02), the Random Forest performed the best with up to 99.5 per cent accuracy.

*Generative Adversarial Networks based Deceptive Reviews (2018)*

Hojjat Aghakhani [5] et al., proposed FakeGAN a program that increments and receives Generative Adversarial Networks (GANs) for text classification function for the first time, especially to detect deceptive comments. Testing was done on a dataset of 800 reviews from TripAdvisor's 20 Chicago hotels reveals that FakeGAN with 89.1 percent accuracy operated on a comparison with state-of - the-art models. FakeGAN utilizes GAN for text classification tasks.

*Deep Learning baed Spam Review Detection: (2019)*

G. M. Shahariar[6] et al. experimented on both classified and unlabeled data and suggested deep learning approaches to identify spam feedback that involve the Recurrent Neural Network (RNN)[20] model Multi-Layer Perceptron (MLP), the Convolutional Neural Network (CNN), and the Long Short-Term Memory (LSTM). They additionally applied a few ordinary AI classifiers, for example, Nave Bayes (NB), K Nearest Neighbor (KNN), and Support Vector Machine (SVM) to recognize spam reviews and used correlation for both regular and deep learning classifiers. Here they took 2000 reviews and 1600 reviews respectively from Yelp dataset and Ott data sets. LSTM gives the best accuracy of 96.75% for "Yelp Dataset" and 94.565% for "Ott Dataset".

*Detecion of Spam Reviewsusing Boosting Approaches : (2019)*

Sifat Ahmed [7] et al., suggested a boosting method to identify the fraudulent Amazon Review Dataset reviews. With the aid of active learning they have created a labeled dataset from real-life data in this paper. Most researchers have used typical classifiers of machine learning. However with regards to accurately distinguishing the genuine fake reviews it has not had a major impact. They have presented boosting algorithms like, the Gradient Boosting System (GBM) , Adaptive Boosting (AdaBoost) and Extreme Gradient Boosting (XGBoost) in false review detection among conventional machine algorithms. By using this approach, they have obtained a substantial improvement in performance. An accuracy of 93% was achieved when attempting to detect fake reviews using boosting approach whereas conventional machine learning algorithms achieved an accuracy of only 89%.

*Fake Reviews Detection Based on Text Feature and Behavior Feature (2019)*

A PU learning algorithm was introduced by Yin Shuqin [9], to classify the text of false reviews. Based on conventional PU learning algorithm analysis, this paper proposes a mixed population and individuality dependent PU learning model (MPINPUL). The MPINPUL model is divided into four steps: selection of accurate negative samples, measurement of representative samples, and description of the spy sample category mark and confirmation of the final classifier. Through three arrangements of near investigations, the significance of the activities of the basic in recognizing counterfeit audits and the plausibility and viability of MPINPUL were checked from both capacity and grouping model viewpoints. Two major LELC and SPUL learning algorithms are introduced, respectively. Simultaneously, it contrasted the MPINPUL model and the most recent work on the Yelp site dataset, specifically SVM and XGBoost. Trial tests on genuine informational indexes show that the MPINPUL model's recognition rate (Accuracy – 87.54 percent) is higher than that of other single usefulness under combination future fusion conditions.

*Temporal feature based detection of fake reviews and comments(2019)*

Wenquain Liu [12] et al., proposed the isolation forest algorithm which initially dissects the attributes of review information in Amazon china dataset. The review records of items are first concentrated to a temporal feature vector and afterwards an isolation forest algorithm is built by concentrating on the contrasts between the examples of product reviews to recognize false reviews. Experimental tests on Amazon china dataset show that the isolation forest algorithm accuracy rate is (83 percent) is higher than SVM, ARIMA and LOF techniques.

*Deep neural networks integrated word embeddings and emotion mining for detecting fake consumer reviews (2020)*

Petr Hajek [8] et al., Proposed two models of neural networks which incorporate typical bag of word meaning and user emotions. In particular, the models learn to reflect at the text level by using three sets of features: (1) ngrams, (2) skip gram word embedding, and (3) various lexicon- emotion indicators. He contrasts their detection output with other state-of-the-art methods for detecting fake feedback to demonstrate the efficacy of the recognition frameworks offered. The model proposed is doing well on all datasets, irrespective of the polarity of their feelings and the type of product.

*Review Spam Detection in the Persian Language using sSupervised ramework (2019)*

In a recent study, Mohammad Ehsan [13] et al. model the problem of spam review detection using a supervised framework in the Persian language. They collected the reviews of cellphone and identified the as fake reviews and reviews written only for brands. Digikala.com is designated as the source for creating the Persian dataset. Naive Bayes, SVM and Decision tree techniques are used to classify the Balanced and Unbalanced Data. Reviewer-based, Metadata features were used in this study to classify the spam reviews.

*Fake online reviews idenification using semi-supervised and supervised learning (2019)*

Rakibul Hassan [14] et al., has used order methods for identifying fraudulent online reviews, some of which are supervised and semi-supervised. The Expectation-Maximization Algorithm is used for semi-supervised learning. The Statistical Naive Bayes classifier and Support Vector Machines (SVM) are used as classifiers to improve grouping the reviews. Word recurrence test, sentiment polarity and survey duration as spotlight are used. A precision of 85.21 percent and 84.87 percent respectively for a split ratio of 80:20 and 75:25 for semi-supervised structure of Naive Bayes classifier was achieved.

*Detecting Fake News in Online Text using deep learning techniques(2018)*

Eslam Amer [15]et al., uses a classifier that can anticipate whether a bit of news is counterfeit or not based just its content, along these lines drawing nearer the issue from an absolutely profound learning point of view by RNN procedure models (vanilla, GRU) and LSTMs. The dataset used is LAIR. The outcome using GRU(Gated Recurrent Unit) is the best of the outcomes that came to (0.217) followed by LSTM (0.2166) finally vanilla (0.215). More precision can be obtained by a hybrid model between the GRU and CNN techniques on the same LAIR dataset. [16]

*long short-term memory and recurrent neural network for detection of spamming reviews (2018)*

Chih-Chien Wang, et al. [19] endeavored to utilize Long Short Memory (LSTM) and Recurrent Neural Network (RNN) system to distinguish spam and original reviews. Strategies utilized System: long short memory (LSTM).The authors discovered that, LSTM is more accurate than SVM and other customary strategies.

*Ontology based Pervasive Online Spam Review Detection using Naive Bayesian(2018)*

Alok Katiyar [21] et al., concentrated on dissecting spam review based on their content. Ontology based model can be used for recognizing false feedback and comments. False comments/feedbacks were divided into four categories by the authors: non-review, brand-only review, off-subject review and untruthful review. They reuse three kinds of spam survey from past studies and include off-point analysis in that. Two datasets were collected, each with 800 surveys, to test the presentation of the system they manufactured. Those two sets are categorized and labeled in relation to the spam review and truthful analysis of four kinds. The system delivers a relatively good classification result with two data sets which shows that system output reached over 75 percent (Precision). For each identification module, the non-review identification module produces the classification result that reached more than 90%, while the three rests have lower results.

Table 1. Comparison of fake review methods

| S. No. | Paper title | Dataset used | Type of review spam | Techniques used | Accuracy rate |
|---|---|---|---|---|---|
| 1 | Using Boosting Approaches to Detect Spam Reviews | Amazon Review Dataset | I,II,III | The Gradient Boosting System (GBM),Adaptive Boosting (AdaBoost) and Gradient Boosting (XGBoost), | Accuracy:<br>XGBoost:93%<br>AdaBoost:90%<br>GBM:91% |
| 2 | Deep Learning based Spam Review Detection | Ott Dataset and Yelp Dataset | I,II | Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM) and Multi-Layer Perceptron (MLP) | Accuracy:<br>For Ott Dataset:<br>MLP: 92.25%<br>CNN: 91.583%<br>LSTM: 94.565%<br>ForYelp Dataset:<br>MLP: 93.19%<br>CNN: 95.56%<br>LSTM: 96.75% |

| | | | | | |
|---|---|---|---|---|---|
| 3 | Review Spam Detection using Active Learning | Ott Dataset and Yelp Dataset | I,II | Active learning approaches for feature classification: Stochastic Gradient Descent classifier (SGD), Perceptron classifier, Linear SVM classifier | Accuracy: LinearSVM:**88.20 %** SGD: 86.30% Perceptron: 84.30% |
| 4 | Fake Review Detection using Classification | Amazon review Dataset(Sennheiser CX 180 Headphone) | I,II,III | Naïve Bayes and Random Forest | Accuracy: Naïve Bayes: 98.15 % Random Forest: 99.55 % |
| 5 | Detecting Deceptive Reviews using Generative Adversarial Networks | TripAdvisor(800 reviews from 20 Chicago hotels) | I,II,III | FakeGAN model | Accuracy: 89.1% |
| 6 | Fake consumer review detection using deep neural networks integrating word embeddings and emotion mining | Amazon,Doctor, Hotel,Restrauant | I,II,III | DFFNN and CNN models : Skip-Gram word embeddings, n-gram model, lexicon-based emotions model | Accuracy: DFFNN model:88% CNN:89% |
| 7 | A method for detection of fake reviews based on temporal features of reviews and comments | China Amazon Dataset | I,II | Isolation Forest Algorithm, LOF(Local Outlier Factor), SVM (Support Vector Machine), ARIMA(Auto Regressive Integrated Moving Average) | Accuracy: ARIMA:77% LOF:80% SVM:79% |
| 8 | Fake Reviews Detection Based on Text Feature and Behavior Feature | Yelp Dataset | I,II | MPINPUL model | Accuracy: Unigram :77.31% POS :76.45% LDA: 76.82% Behavioral :83.84% Behavioral+Relational: 82.65% fusion feature: 87.51% |
| 9 | A Supervised Framework for Review Spam Detection in the Persian Language | Cellphone review dataset from Digikala.com | I,II | Naive Bayes , SVM and Decision tree | Accuracy: Decision Tree-Balanced data: 95% Unbalanced data: 80% |

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|---|---|---|---|---|---|
| 10 | Detection of fake online reviews using semi supervised and supervised learning | Ott.dataset-1600 hotel reviews | I,III | NB, SVM | Accuracy: Semi Supervised SVM: 81.34% NB: 85.21% Supervised SVM: 82.28% NB: 86.32% |
| 11 | Deep Learning Algorithms for Detecting Fake News in Online Text | LAIR dataset | I,III | Vanilla-RNN (Recurrent Neural Network),LSTM (long short-term memories),GRU(Gated Recurrent Unit),CNN (Convolution Neural Networks ) | Accuracy: GRU: 0.217 Vanilla: .215 SVM:025 LSTM: 0.216 CNN: .270 |
| 12 | Pervasive Online Spam Review Detection based on Ontology using Naive Bayesian | Amazon Dataset | I,II,III | Naïve Bayes | Accuracy: 90% |

From table 1, it is identified that the most generally utilized ML algorithms are Naïve Bayes, SVM classifier and Random Forest. The model functions admirably in classifying both genuine and false feedback on account of a Random Forest classification. Chowdary et al. explicitly reasoned that if just features F1 to F6 are considered, the Random Forest classifier performs better than the Naïve Bayes. When testing features F1 to F10, both the Random Forest and the Naïve Bayes classifiers are on an equivalent balance regarding exactness, yet when taking a gander at the f-measure, it is discovered that the Random Forest has an addition of about 43%. Random Forest are a more noteworthy measure of an equilibrated classifier. Nonetheless, among these machine learning techniques used by the various writers of the different research papers, the accuracy in considering features F1 to F10 is 98 percent for Naïve Bayes and 99 percent for Chowdary's Random Forest[4]. The most well known Deep Learning strategies utilized by M. Shahariar[6] and Sherry Girgis[15] are the different RNN models, for example, LSTM, GRU, MLP and CNN, where the best among the numerous deep learning strategies is the bidirectional LSTM model with the most elevated precision of 96.75 percent in the filtering word model.

## 3. Discussion

This paper analyzed current literature on methods conducted between 2016 and 2020 for the spam review identification. An endeavor has been made to furnish analysts with a similar investigation of the different strategies for spam review distinguishing and their detailed precision. In common, Detection techniques for the spam review analysis are partitioned into two gatherings. The first is machine-learning-based approaches that involve XGBoost, Gradient Boosting System, Naïve Bayes, Stochastic Gradient Descent Classification, Perceptron Classification, Random Forest and SVM techniques. Table 1 shows the performance of various machine learning approaches. It uncovers that Random Forest, Support Vector Machine and Naïve Bayes show improvement over different procedures of ML. The second technique is deep learning methods that involve Multi-Layer Perceptron, Convolutional Neural Network, Long Short-Term Memory. Table 1 shows the performance of various machine learning approaches. Precise usage of deep learning techniques is better than using machine learning techniques.

## 4. Conclusion

Deceptive reviews available on the Internet that is quickly affecting organizations and clients, as well. It is thusly imperative to distinguish and take out such fake reviews from the sites on the web. This paper uncovers various methodologies used to spam review recognition and performance measures have been distinguished. This paper identified Type I, Type II and Type III reviews. This identification and removal of such fake reviews will ensure that all online customers can safely purchase products and business based manipulations can be prevented.

## References

[1] Kolli Shivagangadhar, Sagar H, Sohan Sathyan, Vanipriya C.H, "Fraud Detection in Online Reviews using Machine Learning Techniques" 2015 (IJCER) International Journal of Computational Engineering Research , ISSN (e): 2250 – 3005, Volume, 05, Issue, 05.

[2] A.Lakshmi Holla, Dr Kavitha K.S, "A Comparative Study on Fake Review Detection Techniques" 2018, International Journal of Engineering Research in Computer Science and Engineering (IJERCSE) , Vol 5, Issue 4.

[3] M. N. I. Ahsan, T. Nahian, A. A. Kafi, M. I. Hossain and F. M. Shah, "Review spam detection using active learning," 2016 IEEE 7th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), Vancouver, BC, 2016, pp. 1-7.

[4] Chowdhary, N., & Pandit, A.A. (2018). Fake Review Detection using Classification. International Journal of Computer Applications, 180, 16-21.

[5] H. Aghakhani, A. Machiry, S. Nilizadeh, C. Kruegel and G. Vigna, "Detecting Deceptive Reviews Using Generative Adversarial Networks," 2018 IEEE Security and Privacy Workshops (SPW), San Francisco, CA, 2018, pp. 89-95.

[6] G. M. Shahariar, S. Biswas, F. Omar, F. M. Shah and S. Binte Hassan, "Spam Review Detection Using Deep Learning," 2019 IEEE 10th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), Vancouver, BC, Canada, 2019, pp. 0027-0033.

[7] S. Ahmed and F. Muhammad, "Using Boosting Approaches to Detect Spam Reviews," 2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT), Dhaka, Bangladesh,2019,pp.1-6.

[8] Hajek, Barushka, Munk, "Fake consumer review detection using deep neural networks integrating word embeddings and emotion mining" 2020 NEURAL COMPUTING & APPLICATIONS, DOI: 10.1007/s00521-020-04757-2.

[9] Y. Shuqin and F. Jing, "Fake Reviews Detection Based on Text Feature and Behavior Feature," 2019 IEEE 21st International Conference on High Performance Computing and Communications; IEEE 17th International Conference on Smart City; IEEE 5th International Conference on Data Science and Systems (HPCC/SmartCity/DSS), Zhangjiajie, China, 2019, pp. 2007-2012.

[10] S. P. Rajamohana, K. Umamaheswari, M. Dharani and R. Vedackshya, "A survey on online review SPAM detection techniques," 2017 International Conference on Innovations in Green Energy and Healthcare Technologies (IGEHT), Coimbatore, 2017, pp. 1-5.

[11] Hussain, N.; Turab Mirza, H.; Rasool, G.; Hussain, I.; Kaleem, M. Spam Review Detection Techniques: A Systematic Literature Review. Appl. Sci. 2019, 9, 987.

[12] W. Liu, J. He, S. Han, F. Cai, Z. Yang and N. Zhu, "A Method for the Detection of Fake Reviews Based on Temporal Features of Reviews and Comments," in IEEE Engineering Management Review, vol. 47, no. 4, pp. 67-79, 1 Fourthquarter,Dec. 2019, doi: 10.1109/EMR.2019.2928964.

[13] M. E. Basiri, N. Safarian and H. K. Farsani, "A Supervised Framework for Review Spam Detection in the Persian Language," 2019 5th International Conference on Web Research (ICWR), Tehran, Iran, 2019, pp. 203-207, doi: 10.1109/ICWR.2019.8765275.

[14] R. Hassan and M. R. Islam, "Detection of fake online reviews using semi-supervised and supervised learning," 2019 International Conference on Electrical, Computer and Communication Engineering (ECCE), Cox'sBazar, Bangladesh, 2019, pp. 1-5, doi: 10.1109/ECACE.2019.8679186.

[15] S. Girgis, E. Amer and M. Gadallah, "Deep Learning Algorithms for Detecting Fake News in Online Text," 2018 13th International Conference on Computer Engineering and Systems (ICCES), Cairo, Egypt, 2018, pp. 93-97, doi: 10.1109/ICCES.2018.8639198.

[16] J. C. Rodrigues, J. T. Rodrigues, V. L. K. Gonsalves, A. U. Naik, P. Shetgaonkar and S. Aswale, "Machine & Deep Learning Techniques for Detection of Fake Reviews: A Survey," 2020 International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE), Vellore, India, 2020, pp. 1-8, doi: 10.1109/ic-ETITE47903.2020.063.

[17] R. Pawade and P. Gupta, "A Survey on Spam Review Detection and Recommendation of Superior Results in Netspam Framework," 2019 2nd International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT), Kannur,Kerala, India, 2019, pp. 18-21, doi: 10.1109/ICICICT46008.2019.8993340.

[18] J. K. Rout, A. K. Dash and N. K. Ray, "A Framework for Fake Review Detection: Issues and Challenges," 2018 International Conference on Information Technology (ICIT), Bhubaneswar, India, 2018, pp. 7-10, doi: 10.1109/ICIT.2018.00014.

[19] Chih-Chien Wang, Min-Yuh Day, Chien-Chang Chen, and Jia-Wei Liou. 2018. Detecting spamming reviews using long short-term memory recurrent neural network framework. In Proceedings of the 2nd International Conference on E-commerce, E-Business and E-Government (ICEEG ’18). Association for Computing Machinery, New York, NY, USA, 16–20. DOI:https://doi.org/10.1145/3234781.3234794

[20] S. P. Rajamohana, K. Umamaheswari and S. V. Keerthana, "An effective hybrid Cuckoo Search with Harmony search for review spam detection," 2017 Third International Conference on Advances in Electrical, Electronics, Information, Communication and Bio-Informatics (AEEICB), Chennai, 2017, pp. 524-527, doi: 10.1109/AEEICB.2017.7972369.

[21] A. Katiyar, R. Kumar, S. Kant and Y. D. S. Arya, "Pervasive Online Spam Review Detection based on Ontology using Naive Bayesian," 2018 International Conference on Advances in Computing, Communication Control and Networking (ICACCCN), Greater Noida (UP), India, 2018, pp. 883-888, doi: 10.1109/ICACCCN.2018.8748781.