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ARTICLE

Deep Learning Approaches for Fake Review Detection: A Comprehensive Survey

Abordagens de Deep Learning para Detecção de Avaliações Falsas: Uma Revisão Abrangente

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ABSTRACT | **Purpose:** This study presents a comprehensive survey of methodologies and datasets used for *fake review detection* in e-commerce platforms. As online reviews increasingly influence consumer purchasing behavior, the proliferation of deceptive content poses serious threats to trust and market integrity. **Design/Methodology/Approach:** The paper systematically reviews machine learning and deep learning techniques for detecting fake reviews. It categorizes major approaches—supervised, unsupervised, and semi-supervised learning—highlighting feature extraction strategies (linguistic, behavioral, and network-based) and evaluating benchmark datasets such as Deceptive Opinion Spam Corpus, Amazon, and Yelp. The analysis compares conventional algorithms (Naïve Bayes, Random Forest, SVM) with modern deep learning models (LSTM, CNN, BERT, RoBERTa, and GNNs). **Findings:** Results demonstrate that deep learning models outperform traditional machine learning techniques in accuracy, scalability, and contextual understanding. Hybrid and ensemble approaches integrating multiple classifiers enhance precision, recall, and robustness. Despite significant progress, challenges persist, including high similarity between fake and genuine reviews, data scarcity, domain transferability, and evolving spammer tactics. **Research Limitations/Implications:** Deep learning models, while powerful, require large annotated datasets and significant computational resources. The study emphasizes the need for explainable AI and privacy-preserving models to strengthen consumer trust and platform integrity. **Originality/Value:** This survey provides an up-to-date synthesis of fake review detection research, emphasizing the transition toward deep learning and hybrid models. It contributes to future research directions aimed at developing real-time, cross-domain, and transparent detection systems for sustainable digital ecosystems.

Key Terms | Fake reviews, Deep learning, Machine learning, E-commerce, Review spam detection

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RESUMO | Objetivo: Analisar de forma sistemática e crítica as principais abordagens baseadas em *machine learning* e *deep learning* utilizadas na detecção de avaliações falsas (*fake reviews*) em plataformas digitais, destacando avanços metodológicos, limitações e direções futuras de pesquisa. **Método:** O estudo caracteriza-se como uma revisão de literatura abrangente, com análise comparativa de pesquisas que empregam técnicas tradicionais de aprendizado de máquina — como Naïve Bayes, Support Vector Machines (SVM) e Random Forest — e modelos avançados de *deep learning*, incluindo Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) e arquiteturas baseadas em *Transformers*, como BERT e RoBERTa. Foram examinados datasets amplamente utilizados na literatura, como Deceptive Opinion Spam Corpus, Amazon Reviews e Yelp Reviews, bem como estratégias de coleta, rotulagem e extração de características linguísticas, comportamentais e de rede. **Resultados:** Os resultados indicam que modelos de *deep learning* apresentam desempenho superior em termos de precisão, revocação e acurácia quando comparados às abordagens tradicionais, sobretudo em cenários com grandes volumes de dados textuais e alta similaridade entre avaliações genuínas e fraudulentas. Modelos baseados em *Transformers* demonstram maior capacidade de capturar contexto semântico e padrões complexos de linguagem. Entretanto, persistem desafios relevantes, como dependência de grandes bases rotuladas, alto custo computacional, dificuldades de generalização entre domínios e adaptação a estratégias evolutivas de spammers. **Conclusão:** Conclui-se que as abordagens de *deep learning* representam o estado da arte na detecção de avaliações falsas, embora pesquisas futuras devam priorizar modelos mais genéricos, interpretáveis e aplicáveis em tempo real, a fim de aumentar a confiabilidade dos sistemas de avaliação online.

Palavras-chave | Avaliações falsas; Deep learning; Aprendizado de máquina; Processamento de linguagem natural; Detecção de spam; Plataformas digitais.

1 INTRODUCTION

In today's online environment, online reviews are influencing consumer behaviour and business houses. Customers, nowadays, depend on these reviews in order to make fruitful purchasing decisions about products and services. These reviews help consumers in assessing the quality of a product. It also serves as valuable feedback for businesses to improve their offerings. However, it has given rise to misleading practices such as fake reviews, which misguide consumers and influence market trends. Fake reviews[7], also known as spam reviews, refer to misguiding or misleading reviews intended to promote or downgrade a product, service, or brand. The presence of fake reviews risks the credibility of online platforms and also creates distrust in consumers.The spammers have targeted social media platforms, online marketplaces, and review websites such as Amazon, Yelp, TripAdvisor[32] to influence public perception. Spammers[49] are those people who generate fake reviews.

The purpose why fake reviews have become prevalent varies—some businesses use them to increase their ratings, while others use them to decrease competitors rating. Due to their prospective economic impact, detecting and justifying fake reviews has become a critical challenge for researchers as well as industry professionals. The identification of fake reviews using manual process is incompetent and unrealistic due to the enormous volume of online content generated by user. As a result, automated detection techniques using natural language processing (NLP), artificial intelligence (AI), and deep learning have gained reputation. Fake review detection identifies distinction between genuine and misleading reviews using deep learning and machine learning techniques. Conventional machine learning techniques depend heavily on manual features such as linguistic cues, metadata, and reviewer behavior. But, deep learning techniques have emerged as more effective alternatives. This is because they have the ability of extracting features from text data. Advanced deep learning architectures, including Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), transformer-based models such as BERT, and Long Short-Term Memory (LSTM) networks, have depicted significant accuracy in detecting fake reviews.

The main objective of this survey is to provide a complete review of the previous methods and researches on fake review detection, with a particular focus on deep learning models. The survey gives overview of fake review detection methods, publicly available datasets, and methods and methodologies used in previous research. Moreover, it highlights the advantages and limitations of both traditional machine learning and advanced deep learning approaches. It also provides insight towards key research challenges and future scope in this field.

The rest of the paper is structured as follows: Section 2 describes overview of fake review detection. Section 3 provides summary of methods and methodologies used in previous research in detecting fake reviews. Section 4 describes the various kinds of datasets used in previous research. Section 5 presents survey of recent research on fake reviews detection. Finally, Section 6 gives the conclusion of the survey. The objective of this paper is to give a valuable insight to researchers and practitioners about advanced deep learning methodologies being used for fake reviews detection.

2 OVERVIEW OF FAKE REVIEW DETECTION

Deceptive opinions[44], spam reviews[4], or opinion spam[47], are some names used in place of fake reviews. Fake reviews refer to malicious, misguiding, or misleading reviews which are intentionally posted to influence consumer view or opinion.

A. Classification of Fake Reviews

Fake reviews can be categorized into three types:

1. **Untruthful Opinions**[**8**]: Untruthful opinions are those reviews which are either highlighting the positives of a product or deliberately criticizing it. Their main objective is to manipulate public conception regarding a product. Untruthful opinions either increase the reputation of a product or decrease the credibility of a competitor. These reviews are very hard to detect as they look very similar to genuine reviews.
2. **Brand Only Reviews**[**8**]: Brand reviews are general reviews about a brand. They do not comprise reviews of a specific product. While all brand reviews might not be fake, they are not often relevant to individual product analysis. Such brand reviews are considered as review spam.
3. **Non Reviews**[**8**]: Non reviews comprises of unrelated or unnecessary content, advertisements related to promotions, or very general statements that does not give a genuine opinion about a service or product.

Figure 1. Classification of Fake Reviews

Both brand-only reviews and non-reviews lack specific product related content, so they are relatively easy to detect. Untruthful opinions closely resemble genuine reviews so they pose a significant challenge in its detection.

Let us now take example from the Yelp Chicago dataset[37].

- **Genuine Review**: "I love this hotel. The staff is very cooperative. You will feel at home. Awesome location, excellent hotel to spend the night!"[8]
- **Fake Review**: "What an amazing place to stay. The staff is wonderful and so welcoming. The facilities, such as free bike on rent, are good. The architecture of the building is really remarkable. Thanks for making my stay extraordinary."[8]

At first instance, both reviews seem genuine. Based on manual annotation alone, it is hard to differentiate between fake and genuine reviews as both reviews are written in same style. It has also been observed in researches that manual annotation by experts often results in only about 60% accuracy in distinguishing fake from genuine reviews. For better results and accuracy, automated detection techniques are required.

B. Fake Review Detection Tasks

Fake review detection[8] is a classification problem. Here labeling of a review is done as either fake or genuine. Various deep learning and machine learning techniques are used by researchers for detection of fake reviews. The key tasks in fake review detection include:

1. **Supervised Learning Approaches**: These methods depend on labeled datasets. Here each review is labeled as fake or genuine. In order to make predictions supervised models learn patterns in linguistic, behavioral, and metadata-based features.
2. **Unsupervised and Semi-Supervised Learning**: These methods do not require labeled data. They cluster similar reviews based on statistical patterns. When large labeled datasets are unavailable then in that case unsupervised learning models are useful.
3. **Spammer and Group Detection**[49]: By analyzing user behavior, such as repeated postings, similar writing styles, and review burstiness individual spammers or groups of spammers can be identified. These spammers coordinate fake review campaigns.
4. **Cross-Domain and Multi-Domain Detection**[44]: Fake reviews often showcase different characteristics across different platforms and industries. The objective of cross-domain detection models is to generalize fake review detection across multiple domains.

C. Challenges in Fake Review Detection

There are several challenges that obstruct the effectiveness of fake review detection algorithms:

- **High Similarity Between Fake and Genuine Reviews**: As seen in the above example, fake reviews and genuine reviews look quite similar. So traditional rule-based detection are ineffective in discriminating fake and genuine reviews.
- **Evolving Deceptive Tactics**: Spammers are continuously changing their strategies of writing fake reviews. So dependency on static detection methods is quite difficult.
- **Data Scarcity and Annotation Issues**: Creating labeled datasets using human annotation is costly and subjective. This makes labeled datasets limited. So training supervised models with labeled datasets becomes difficult.
- **Domain-Specific Differences**: Generally a model trained on one dataset (e.g., electronics reviews) may not work well on another dataset (e.g., hotel reviews).

The deep learning models address most of these challenges. These models automatically extract high-level patterns and features from large volumes of text data.

3 METHODS AND METHODOLOGIES USED IN PREVIOUS RESEARCH

In fake review detection research, various methods and methodologies have been used. Based on various research papers in this area, the following table gives the summary of employed methods and methodologies that have been used in fake review detection research.

Table 1. Summary of Methods and Methodologies used for Fake Review Detection

References	Approach	Methodology	Dataset	Key Observations
Khurshid et al. [5]	Machine Learning	Ensemble Learning (Naive Bayes, AdaBoost, Random Forest, JRip, J48)	Real-life dataset	73.4% accuracy achieved using AdaBoost; same accuracy was not achieved on uneven data
Guo et al. [11]	Deep Learning	Graph Neural Networks (GNN)	Two Real-world Datasets	GNN gave better results than CNN, MLP, SVM, and LSTM
Sánchez-Junquera et al. [16]	Machine Learning	SVM & Naive Bayes with character n-gram features	Death penalty, Abortion, Best Friend	SVM & NB with character n-gram features gave better results than SVM with LIWC, LDA, Deep Syntax & Words but were not better than other methods
Hai et al. [20]	Semi-Supervised Learning	SMTL-LLR (Laplacian Logistic Regression)	AMT Dataset	85.4%-88.7% accuracy was achieved, but did not consider reviewer-based information
Nilizadeh et al. [32]	Machine Learning	OneReview Model (Textual and Metadata Features) + Change Point Analysis	Yelp Data Challenge, TripAdvisor	97% accuracy was achieved with combined features, 86% accuracy was achieved with textual features
Mani et al. [36]	Machine Learning	Unigram & Bigram Features with Naïve Bayes, Random Forest, SVM and Stacking Ensemble	Gold Standard Dataset	Stacking ensemble gave 87.68% accuracy, which outperformed single classifiers
Yilmaz & Durahim [37]	Semi-Supervised Learning	SPR2EP (Doc2Vec and Node2Vec)	Yelp Dataset	SPR2EP gave better results than baseline methods but could not compare neural network

References	Approach	Methodology	Dataset	Key Observations
Noekhah et al. [38]	Deep Learning	Multi-Iteration Network Structure (Behavioral and Structural Features)	Amazon Dataset	98% accuracy was achieved with combined features
Sedighi et al. [40]	Machine Learning	Decision Tree with Feature Selection	Yelp Dataset	Showed improved accuracy using feature correlation, but could not give better results on uneven data
Li et al. [43]	Machine Learning	Hidden Markov Model and Co-bursting Method for Spam Detection	Dianping Dataset	Spam patterns were identified based on when reviewer posted the review but could not perform well on evaluation metrics

Flowchart General Methodology for Fake Review Detection

The following flowchart represents the step-by-step process used in fake review detection:

- **Step-1: Review data collection** – Reviews are extracted from datasets like Yelp, Amazon, TripAdvisor, etc.
- **Step-2: Preprocessing and Feature Extraction** – Text cleaning, noise removal, and linguistic and behavioral features extraction.
- **Step-3: Fake Review Detection Model** – An appropriate classification method is selected based on the problem and available dataset amongst Machine Learning (SVM[17], RF[24], Naïve Bayes, HMM), Deep Learning (CNN, LSTM, BERT, RoBERTa) or Hybrid Approaches (Stacking, Graph Neural Networks)
- **Step-4: Evaluation and Performance Metrics** – Accurate prediction using Recall, Precision, F1-score, and AUC-ROC performance metrics measure.

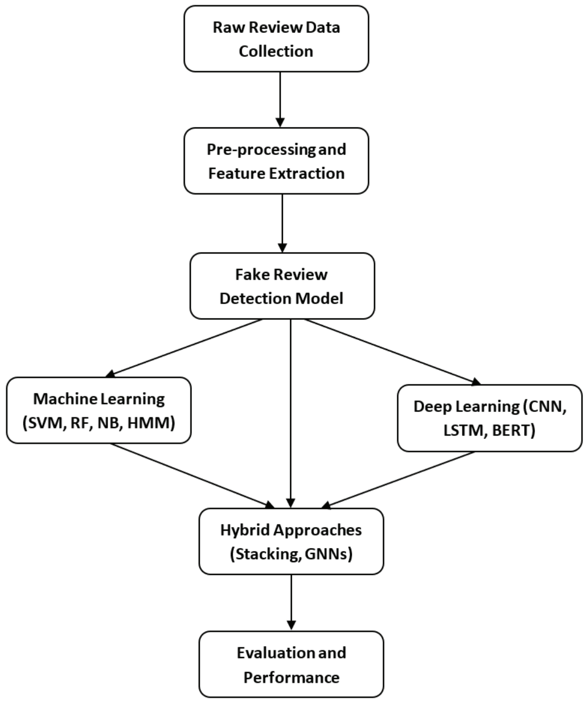

Figure 2. General methodology for fake review detection

4 DATASET DESCRIPTION USED IN PREVIOUS RESEARCH

Various datasets having several features are available publicly. The following table gives the summary of publicly available datasets. These datasets are generally used in fake review detection research.

Table 2. Summary of Publicly Available Datasets for Fake Review Detection

Dataset Name	Size	Source	Labeling Method	Domain
Amazon Reviews [38]	5.8M reviews	Amazon	Rule-based Filtering (Jaccard Distance)	Products
Yelp ZIP [32], [37], [40]	608,598 reviews	Yelp (2004-2015)	Filtering Algorithm	Mixed Categories
Yelp NYC [32], [37], [40]	359,052 reviews	Yelp (2004-2015)	Filtering Algorithm	Mixed Categories
Gold Standard [36]	100K reviews	Multiple sources	Naïve Bayes Classifiers	Multiple Domains
Yelp CHI [32], [37], [40]	67,365 reviews	Yelp (2004-2012)	Filtering Algorithm	Hotels, Restaurants
JD.com	50K reviews	JD.com (China)	Text and Metadata Features	Electronics
DeRev, OpSpam, and Opinions	20K reviews	Multiple sources	LIWC, LDA, WSM	Politics, Social Issues
Dianping [43]	9,765 reviews	Dianping (China)	Filtering Algorithm	Restaurants
Deceptive Opinion Spam	1,600 reviews	AMT (Amazon Mechanical Turk)	Crowdsourcing (Expert Review)	Hotels
TripAdvisor [32]	800 reviews	TripAdvisor	AMT Crowdsourcing	Hotels

5 SURVEY OF RECENT RESEARCH ON FAKE REVIEWS DETECTION

In current years, research in fake review detection has significantly increased. The application of deep learning models, machine learning models, and hybrid approaches has greatly improved the fake review detection system. Nowadays reviews are generated in such a way that it has become quite difficult to differentiate between fake and genuine reviews. This has led to the development of more stronger automated detection techniques. This section gives a detailed survey of machine learning based, deep learning based and hybrid based approaches.

A. Machine Learning-Based Approaches

In fake review detection, machine learning algorithms are widely used. This is because on small to medium-sized datasets these techniques are interpretable and efficient. Machine learning methods depend on feature engineering. In this process, experts extract textual, behavioral and other significant features. Based on these features, reviews are classified as genuine or fake.

Table 3. Machine Learning Based Approaches

References	Approach	Methodology	Dataset Used	Accuracy (%)	Key Observations
Desai & Rao (2022) [17]	Machine Learning	One-Class SVM	Yelp, AMT	74.37%-92.3%	Effective but did not do well for state-of-the-art models
Hai et al. (2021) [20]	Semi-Supervised Learning	SMTL-LLR (Laplacian Logistic Regression)	AMT, Doctor, Hotel, Restaurant	85.4%-88.7%	Gave good accuracy but reviewer-based information was ignored
Li et al. (2021) [24]	Machine Learning	Feature-Based Random Forest	Dianping, Yelp	82.6%	Effective on structured reviews but on free-text data it is limited
Yilmaz & Durahim (2020) [27]	Semi-Supervised Learning	SPR2EP (Doc2Vec & Node2Vec)	Yelp	80.71%-83.18% AUC	For improved detection textual and network features were combined

Limitations of Machine Learning Approaches

In fake review detection, algorithms of machine learning are quite efficient and explainable but still few limitations lie in this approach. Depending heavily on feature engineering is one of the major limitations where the experts have to extract meaningful features. Other limitations include scalability issues and limited generalization. In scalability issues, ML models does not work properly with large scale data processing whereas in limited generalization ML models trained on one dataset quite often fails on another domain dataset.

B. Deep Learning-Based Approaches

The limitations of machine learning methods have given researchers the scope to use deep learning models. Manual feature extraction is a major issue in machine learning techniques. The deep learning techniques eliminate this issue by automatically learning features from text. Thus with advancement in NLP (natural language processing), researchers have preferred deep learning models for fake review detection.

Table 4. Deep Learning Based Approaches

References	Approach	Methodology	Dataset Used	Accuracy (%)	Key Observations
Alsaad & Joshi (2024) [6]	Deep Learning	CNN, LSTM	Amazon, Yelp	88.1%	Excellent performance on long reviews but poor performance on short reviews
Mohawesh et al. (2024) [7]	Deep Learning	Transformer (RoBERTa)	Deceptive Opinion Spam	91.2%	In mixed-domain scenarios other models were outperformed
Kanmani & Balasubramanian (2023) [12]	Deep Learning	Transformer (BERT)	Yelp, Deceptive Opinion Spam	89.5%	Review classification was improved by contextual embeddings
He & Xu et al. (2022) [18]	Deep Learning	GNN for Review-User Interaction	Two real-world datasets	87.9%	For enhanced detection reviewer behavior was captured

Advantages of Deep Learning Approaches

In comparison to ML models, deep learning models have better advantages in contextual understanding, scalability and generalization. Transformer models are quite useful in detecting accurately due to contextual understanding of sentence structure and semantics. For large scale datasets, deep learning models are well suited. Even deep learning models applied on one dataset can generalize better across other domain datasets.

Limitations of Deep Learning Approaches

With so many advantages of using deep learning models in fake review detection, it still has several limitations such as high computational cost, data dependency and vulnerability to malicious attacks. For training deep learning models, it requires powerful GPUs/TPUs which are quite expensive. Also large annotated datasets are required for better performance in deep learning approach. Even being a suitable choice for fake review detection by researchers, deep learning models can be manipulated by malicious fake reviews.

C. Hybrid Approaches & Emerging Trends

In order to overcome the problems that deep learning and machine learning methods possess in detection of fake reviews, researchers have started using hybrid models[8]. Hybrid models combine multiple detection techniques to ensure more accuracy in prediction of fake reviews. Some emerging trends in fake review detection are multimodal learning, adversarial training, blockchain for review authentication and few shot and zero shot learning.

Emerging Trends in Fake Review Detection

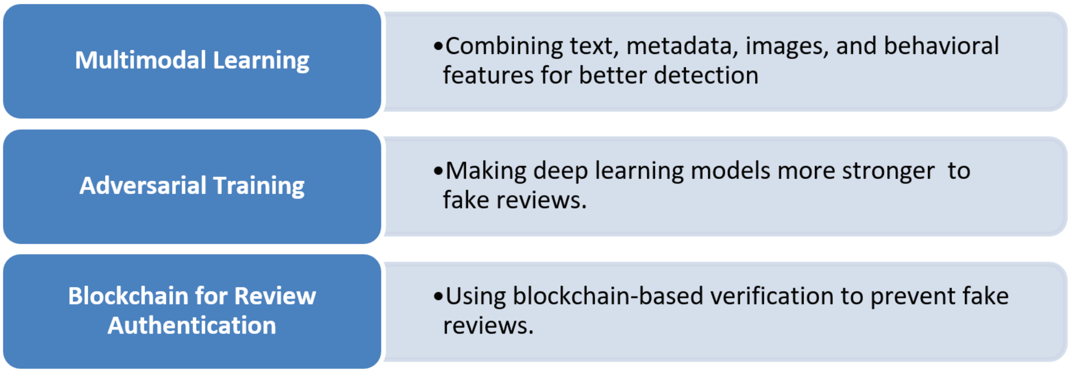

Figure 3. Emerging Trends in Fake Review Detection

6 CONCLUSION

Fake reviews are causing a significant threat to the trustworthiness of online platforms review system. While traditional methods such as machine learning techniques are useful in detecting fake reviews but it has limitations. With the use of RNNs, LSTMs, CNNs, transformer models (such as BERT and GPT), and graph-based approaches deep learning techniques have emerged as powerful tools for automated fake review detection. These approaches have improved the accuracy of detecting and predicting fake reviews to a great extent. However, deep learning techniques being formidable in detecting fake reviews, still several challenges such as data unevenness, malicious attacks and computational costs continue to exist.

In future research, areas of improvement can be on enhancing model explainability, developing privacy-preserving detection techniques, and integrating multimodal data sources for improved fake review detection system. As fake review detection is continuously evolving, so deep learning models will play an important role in ensuring fair, transparent, and reliable online review systems.

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