WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Comparative Analysis of Deep Learning-Based Approaches for Detecting False Reviews in E-Commerce Platforms

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DOI : https://doi.org/10.55248/gengpi.6.0325.1109

ABSTRACT—

The exponential growth of e-commerce has made online reviews a critical factor in consumer decision-making and brand reputation management. However, the growing prevalence of fake reviews has significantly eroded trust, creating problems for both platforms and users. This project addresses this issue by introducing a hybrid approach that integrates Bidirectional Encoder Representations from Transformers (BERT) with Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to improve the accuracy of fake review detection. The model combines the context understanding of BERT, the sequential analysis capabilities of LSTM, and the feature extraction capabilities of CNN to effectively classify reviews as real or fake. The proposed system is evaluated on a benchmark dataset, demonstrating its ability to capture subtle patterns in review data. The solution implements advanced deep learning techniques and focuses on aspect-oriented sentiment features to improve detection accuracy while reducing false positives. This approach improves reliability in identifying fraudulent reviews, enabling e-commerce platforms to maintain integrity and provide trustworthy information for users to make informed decisions.

Index Terms- E-Commerce, Fake Review Detection, Deep Learning, Aspect Features, BERT, CNN, LSTM, Sentiment Anal- ysis

I. Introduction

Online reviews have a significant impact on consumer purchasing decisions and brand reputation in the digital mar- ketplace. They provide essential information about product quality, user satisfaction, and service reliability, becoming important tools for making informed decisions. However, the growing problem of fake reviews is undermining trust in e-commerce platforms. Businesses may post fake positive reviews to promote their own products, or negative reviews to harm competitors by misleading consumers and undermining trust in the platform. Detecting fake reviews is a complex task that goes beyond basic text analysis: an effective solution must evaluate language patterns, user behavior, and contextual nuances that traditional rules and keyword-based systems cannot handle. The emergence of advanced neural network architectures has revolutionized detection capabilities: models such as Convolutional Neural Networks (CNNs), Long Short- Term Memory (LSTM) networks, and Bidirectional Encoding Representations from Transformers (BERT) have proven to be highly effective. They excel in identifying subtle linguistic cues, capturing semantic meanings, and analyzing sequential text dependencies.

Hybrid approaches combining multiple techniques have emerged as robust solutions, addressing the limitations of standalone models. These models leverage the feature extrac- tion power of CNN, the context awareness of BERT, and the strengths of continuous processing of LSTM to improve accuracy and adaptability in detecting abusive content. Along with the evolution of these methods, the paper explores challenges such as data scarcity, domain adaptation, and real- time implementation, highlighting the need for continued innovation to restore and maintain consumer trust in online platforms.

II. LITERATURE REVIEW

[1] The paper present a hybrid methodology that combines deep learning techniques with aspect-based sentiment analysis to improve detection accuracy. At the core of this approach is an aspect fusion network that uses a hierarchical attention mechanism to prioritize important aspect terms, and a cardinality fusion model to mitigate the impact of random weights.The system extracts complex text features using a Convolutional Neural Network (CNN) and integrates them with aspect-specific features derived from GloVe embeddings and part-of-speech (PoS) tagging. The fused features are used to train a classification layer. Extensive experiments on multiple datasets, including Amazon and Yelp Chi, demonstrate the robustness and adaptability of our model. This work highlights the importance of combining syntactic and semantic analysis to detect hidden fake reviews and promises to be a significant improvement over previous methods. Future directions include extending the model to include multi-modal data such as images, as well as exploring transfer learning for broader applications. This research provides a scalable and robust tool to combat fraudulent reviews and helps build trust in the digital marketplace.

[2] This paper presents a comprehensive methodology for extracting and analyzing customer feedback from mobile app reviews in the service industry, highlighting the important role that customer feedback plays in improving service quality and decision-making in organizations. The study considers the key space in the analysis of moods, focusing on implicit opinions that are not expressed directly, and introduces a two stage hybrid approach to analysis of moods based on aspects (ABSA).

The first step includes extracting the terms of opinions using a fundamental approach based on the rules in which part of the taging (POS) is used and dependence analysis. This step covers obvious and implicit opinions, simultaneously classifying them into predetermined categories of aspects oriented to service, such as maintenance quality, cost, payment, user application interface and customer support. The second step includes a deep learning model, which includes the pole (active or negative) of mood (aggressive or negative), to classify these opinions and the protein adjustment and Bert. Researchers have created a new dataset unique to the mobile application field, which has been noted under the opinions, side categories, and mood polarity conditions. Experiments show that the proposed hybrid model outperforms baseline methods, achieving an accuracy of 81.4 percentage for opinion term extraction and 79 percentage for sentiment classification. By using a pipelined approach, the model seamlessly integrates the results of each task, improving overall performance. The research contributions include the development of a new annotated dataset, the introduction of a combined rule-based and machine learning methodology for extracting implicit aspects, and the application of a fine-tuned BERT to the ABSA task. This book provides key insights for service-oriented businesses, enabling them to identify areas for improvement and make data-driven decisions to increase customer satisfaction. Future directions include extending the dataset to include evaluations in multiple languages and applying the methodology to other service-oriented domains.

[3] The paper Sentiment Analysis and Fake Amazon Re- views Classification Using SVM Supervised Machine Learn- ing Model,explores the application of machine learning in sentiment analysis and fake review detection, with a primary focus on Support Vector Machines (SVM). The study evaluates SVM's performance against other models, such as Na¨ıve Bayes, Logistic Regression, and Random Forest, demonstrating that SVM achieves superior results, particularly after hyperparameter tuning, with an accuracy of 93 percentage for sentiment classification. The analysis highlights the impact of review length on model performance, showing that shorter reviews increase accuracy due to reduced complexity of the sentiment data, while longer reviews containing more detailed information are more difficult to classify. The paper also explores fake review detection using a dataset of real and computer-generated reviews, showing that fake reviews tend to be shorter and less descriptive than real reviews. The SVM model distinguishes incorrect criticism, and proves its robustness.The study concludes that SVM is an effective tool for both sentiment analysis and opinion spam detection, but highlights the need for labeled datasets and suggests exploring semi-supervised or unsupervised approaches for future work.

[4] The paper presents a sentiment analysis model that uses a Bidirectional LSTM (Bi-LSTM) network to classify Amazon product reviews as positive or negative. The methodology involves preprocessing the dataset by tokenizing and case- folding to clean and standardize the text. Word vectors are generated using TensorFlow's 'TokenTextEncoder' and a Bi-LSTM model is designed with embedding, Bi-LSTM, dense, dropout and output layers and optimized using Adam optimizer and binary cross-entropy loss. However, the study has limitations, including a binary sentiment focus, domain- specific testing, and computational cost due to the complexity of Bi-LSTM architecture. Additionally, the limited number of training epochs may constrain model generalization. In the study, gaps such as the need for detailed emotional analysis, the generalization of domains, the incorporation of the overall method, and the explanation of predictions are specified, providing the direction of future work to improve the emotional analysis application.

[5] The paper presents an explainable ensemble deep learning model for fake review detection that leverages multi-view feature extraction to analyze review content, reviewer behavior, and product description. The method improves accuracy by integrating CNN, Bi-LSTM, and DNN classifiers, each dealing with a specific feature perspective, and combining their outputs using an ensemble approach. To ensure interpretability and trust, the model uses explainability methods such as SHAP (Shapley Additive Explanations) and attention mechanisms that provide insight into the classification process.this model faces limitations such as high computational costs, reliance on balanced datasets, and challenges in adapting to dynamic or cross-domain scenarios. Research gaps include the need for enhanced generalization across different domains, integration of additional features for multilingual or multi-domain detection, and addressing real-time processing challenges while maintaining model transparency and trustworthiness.

[6] The paper presents an multi-scale cascade domain (MCDB) approach to detect fake reviews in Arabic, which addresses the lack of high-quality Arabic datasets for this problem. It presents the Arabic Fake Review Detection (AFRD) dataset, a benchmark dataset covering the hospitality, restaurant, and product domains. The study uses Bi-LSTM, Bi-GRU, CNN+Bi-LSTM, and CNN+Bi-GRU models, integrating them into a cascade framework that transfers knowledge across domains to improve performance in low-resource environments.this work has limitations, such as the relatively small size of the AFRD dataset and its sensitivity to domain characteristics Furthermore, standardizing hyperparameters across models may not fully optimize performance for each domain. Research gaps include the need for a larger and more diverse Arabic dataset, improved cross-domain generalization techniques, and further exploration of domain-specific optimizations to improve the robustness and scalability of fake review detection across all platforms.

[7] The study proposes a method for analyzing online product reviews to identify detailed sub-features of products. It starts by collecting reviews through web scraping and cleaning the data using tools like NLTK. Then, we use BERT, an advanced language model, to understand the context of words in a sentence and use the Affinity Propagation (AP) algorithm to group similar meanings. A context word map is created to interpret these clusters, and sentiment analysis is performed using the fine-tuned BERT model to measure customer satisfaction for each sub-feature. However, the method has some limitations. It has only been tested on TVs and four features, so its use for

other products is unclear. It relies heavily on sentences containing specific feature names and may omit other relevant information, naming subfeatures requires manual effort, and some features such as ”cable” perform poorly due to clustering issues. The study highlights research gaps, including testing across a range of products, considering more types of words (not just nouns), automating the process of naming subfeatures, and creating a control dataset to better compare and evaluate methods. Resolving these issues will make the method more reliable and more widely applicable.

[8] The paper focuses on improving sentiment analysis methods to classify customer opinions about specific aspects of products more efficiently. While traditional sentiment analysis provides the overall sentiment for a review, ABSA aims to extract sentiments associated with individual aspects such as “price”, “comfort”, or “power”. The proposed model combines the strengths of convolutional neural networks (CNNs) and gated recurrent units (GRUs). CNN is utilized to extract local features, such as phrases or short text patterns, that highlight critical sentiment cues. These features are then processed by GRU, which captures the sequential and long-term dependencies in the data, ensuring that the context of the sentiment is preserved. The model architecture also incorporates bidirectional GRUs, analyzing both the input direction and the back, and incorporating a pooling layer for reducing dimensions, and a completely connected soft max output layer. Classes the polarity of ment as a positive, negative, neutral, or unmentioned. This architecture is tested in two Chinese review datasets (one is for hotels, the other is for automobiles), which is accurate compared to other models such as TextCnn, LSTM, SVM.The authors also highlight the importance of hyperparameter tuning, showing how factors such as embedding dimension, filter size, and GRU units affect performance. This hybrid approach fills the gap between local functions and understanding the global context, and provides a robust solution for analysis of fine grain emotions. By approaching the limits of the conventional method and the previous learning model, this article provides effective and adapted frameworks between fields. It allows businesses to accurately interpret consumer feedback and improve their products and services to meet customer expectations.

[9] [9] The paper addresses the growing issue of fake reviews in e commerce, emphasizing their role in misleading customers and artificially boosting product reputations. It proposes a machine learning-based approach to detect fake reviews by analyzing both the textual features of reviews and the behavioral patterns of reviewers. Using a real Yelp restaurant review dataset, the study evaluates multiple classifiers, including K-Nearest Neighbors(KNN), Naıve Bayes, Support Vector Machine(SVM), Logistic Regression, and Random Forest, along with n-gram models like bigram and tri-gram for text analysis.This research highlights the effectiveness of combining textual and behavioral features to improve the accuracy of fraud detection models, offering valuable insights for enhancing trust in e-commerce platforms.

[10] [10] In this paper, we address the problem of detecting and eliminating fake reviews in datasets using natural language processing (NLP) techniques and machine learning (ML) models. Fake reviews have become a major problem in the e-commerce industry and other platforms where customer trust heavily relies on online reviews. Companies like Flipkart and Amazon face challenges due to the increasing prevalence of fraudulent reviews, which can mislead consumers and damage trust in online shopping. The proposed solution involves training datasets using two ML models Naıve Bayes and Random Forest to predict the authenticity of reviews. These models aim to identify spam notifications and enable website or application administrators to take corrective action against spammers.The model helps maintain the platform’s reputation by instantly detecting spammy reviews. The paper notes that while small-scale implementations look promising, solving the problem comprehensively will require more complex models trained on millions of reviews.

III. CONCLUSION

Detection of fake reviews on the electronic business plat- form is important to maintain the trust and transparency of the digital market. In this survey, various advanced approaches, including deep learning hybrid models that use Bert, CNN, and LSTM methods, were studied. These models effectively address the problems of understanding complex language pat- terns and detecting fraudulent content by combining multiple processing methods. The integration of aspect-based sentiment analysis and multiple feature extraction has further improved the detection process, increasing the accuracy and adaptability of the model. However, issues such as lack of data, domain adaptation, and real-time implementation remain major obsta- cles. Closing these gaps will require further innovation and the development of scalable solutions that can adapt to the dynamic online environment. Future research should consider more comprehensive datasets, real-time processing methods, and better cross-domain generalization techniques to improve the accuracy and robustness of fake review detection systems. Overcoming these challenges will help e-commerce platforms ensure trustworthy reviews and increase consumer trust.

References

[1] Samia M Abd-Alhalem, Hesham A Ali, Naglaa F Soliman, Abeer D Algarni, and Hanaa Salem Marie. Advancing e-commerce authenticity: A novel fusion approach based on deep learning and aspect features for detecting false reviews. *IEEE Access*, 2024.

[2] Afsheen Maroof, Shaukat Wasi, Syed Imran Jami, and Muham- mad Shoaib Siddiqui. Aspect based sentiment analysis for service industry. *IEEE Access*, 2024.

[3] Myasar Tabany and Meriem Gueffal. Sentiment analysis and fake amazon reviews classification using svm supervised machine learning model. *Journal of Advances in Information Technology*, 15(1):49–58, 2024.

[4] UB Mahadevaswamy and P Swathi. Sentiment analysis using bidirec- tional lstm network. *Procedia Computer Science*, 218:45–56, 2023.

[5] Rami Mohawesh, Shuxiang Xu, Matthew Springer, Yaser Jararweh, Muna Al-Hawawreh, and Sumbal Maqsood. An explainable ensem- ble of multi-view deep learning model for fake review detection. *Journal of King Saud University-Computer and Information Sciences*, 35(8):101644, 2023.

[6] Nour Qandos, Ghadir Hamad, Maitha Alharbi, Shatha Alturki, Waad Alharbi, and Arwa A Albelaihi. Multiscale cascaded domain-based approach for arabic fake reviews detection in e-commerce platforms. *Journal of King Saud University-Computer and Information Sciences*, 36(2):101926, 2024.

[7] Kyunghoon Park, Seyoung Park, and Junegak Joung. Contextual meaning-based approach to fine-grained online product review analysis for product design. *IEEE Access*, 2023.

[8] Narisa Zhao, Huan Gao, Xin Wen, and Hui Li. Combination of convolutional neural network and gated recurrent unit for aspect-based sentiment analysis. *IEEE Access*, 9:15561–15569, 2021.

[9] Ahmed M Elmogy, Usman Tariq, Mohammed Ammar, and Atef Ibrahim. Fake reviews detection using supervised machine learning. *International Journal of Advanced Computer Science and Applications*, 12(1), 2021.

[10] Syed Mohammed Anas and Santoshi Kumari. Opinion mining based fake product review monitoring and removal system. In *2021 6th International Conference on Inventive Computation Technologies (ICICT)*, pages 985–988. IEEE, 2021.