

Sentiment Analysis for Product Reviews: Fake Reviews Detection Using Sentiment Analysis

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Abstract- The emergence of e-commerce platforms has resulted in increased reliance on customer reviews while making purchasing decisions. In this regard, there is a high risk of fake and deceptive reviews since they may lead to the wrong choice for consumers. Therefore, this study aims to analyze the use of sentiment analysis with machine learning and deep learning approaches for detecting fake product reviews. Analyzing the current state of research, it is possible to say that sentiment-only approaches are ineffective in detecting deceptive patterns. Thus, the proposed approach combines sentiment analysis with linguistic and behavioral aspects as well as a CNN-LSTM model for improving efficiency. The process of working with data involves several steps, including collecting data from relevant sources, cleaning and preprocessing data, extracting features, creating the model, and evaluating performance. From the experimental results, it is possible to conclude that hybrid models demonstrate greater efficiency compared to other traditional classifiers like Naive Bayes and Support Vector Machine. For example, the model designed during the research reaches an accuracy level of 95%. Nonetheless, the problem of data imbalance and fake reviews generated by artificial intelligence algorithms should be taken into account when developing new approaches.

Keywords:- Fake Reviews, Sentiment Analysis, Machine Learning, Deep Learning, CNN, LSTM, Review Spam Detection.

I. INTRODUCTION

Online reviews have become one of the most significant factors that influence decision-making of customers in today's world. Sites like Amazon, Flipkart, and Yelp depend on users' content for reviewing their products and services. Nonetheless, there have been an alarming rise in fake reviews or review spam. These kinds of reviews may be

generated artificially to market their goods or services or to harm other competitors, hence misleading consumers. Sentiment analysis categorizes online reviews into three groups – positive, negative, or

neutral; nevertheless, it cannot identify if the review is fake because traditional algorithms focus only on the text rather than the deceptive intention. Researchers have been experimenting with different approaches for detecting fake online reviews through the use of sentiment analysis in conjunction with machine learning, natural language processing, and deep learning. This study will review existing

approaches to determine the most effective way to detect fake reviews by analyzing the features utilized by each technique.

II. LITERATURE REVIEW

The development of ecommerce platforms made customers rely more on reviews in their buying choices. In response to this, the problem of fake and deceptive reviews arose, leading researchers to develop multiple fake review detection methods based on the application of sentiment analysis, machine learning, behavioral analysis, and deep learning.

Initial research concentrated on the distinction between genuine and fake reviews by means of text classification and review patterns. Thus, Mukherjee et al. [1] utilized classification techniques to analyze authentic and pseudo reviews, whereas Xie et al. [16] researched the temporal patterns in review activities as means of distinguishing spam behaviors.

Sentiment analysis techniques are often utilized in fake review detection. For example, Chang et al. [2] suggested sentiment analysis methods for detecting fake comments. Ravi [12] emphasizes the importance of opinion mining and sentiment analysis in this matter, and Yousif and Buckley [5] mention the significance of sentiment inconsistency for better detection results.

In addition, linguistic, semantic, and behavioral aspects were studied for their influence on fake reviews. Abri et al. [3] investigated the writing style and lexical patterns of reviews, while Kumar [4] emphasized the behavior aspect. Chen et al. [17] introduced rating-sentiment inconsistency in their detection model.

Modern studies emphasize transformer-based models and AI models. Mohawesh et al. [7] presented an enhanced transformer-based model, while Liu et al. [8] applied RoBERTa models in identifying fake reviews. Sun et al. [9] used the review content and user behavior characteristics for detecting fake reviews.

In summary, there have been advancements in the area of fake reviews detection from using conventional ML models to deep learning and transformer-based models. While modern approaches have proven to be more accurate, some issues like multi-language reviews, spam evolution, and class imbalances still exist.

III. PROBLEM STATEMENT

Although considerable progress has been made in the field of detecting fake online reviews, a number of issues remain unsolved regarding the reliability of the outcomes. Firstly, most of the reviewed techniques are based on using single-

feature detection, such as sentiment or language-based detection, making it less efficient in identifying the required patterns. Moreover, traditional sentiment analysis techniques pay too much attention to polarity classification and do not take into account the real meaning expressed by the reviewed text. The absence of properly labeled data is also one of the challenges in this area. Most of the datasets are not well-balanced since legitimate reviews exceed the number of fake ones. In addition, with AI-generated content becoming more widespread nowadays, the problem of fake reviews became more complicated. The currently used techniques cannot cope with advanced deception techniques. That is why there is a need to apply an integrated approach to detecting the required patterns using multiple features and advanced deep learning models.

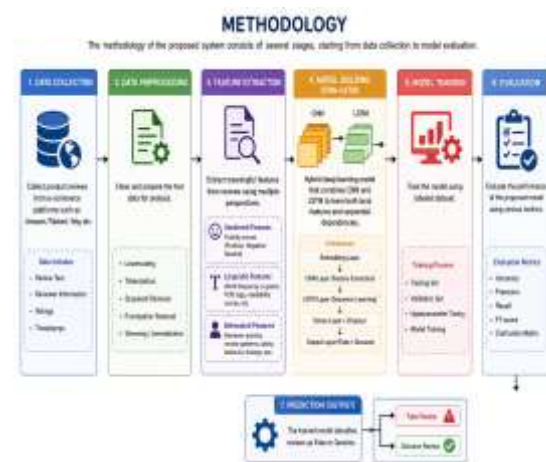
IV. PROPOSED SYSTEM

The hybrid system uses sentiment analysis, language-based attributes, and behavior-based attributes with deep learning algorithms to detect fake reviews. The first stage in the process involves data collection through e-commerce sites, Amazon and Yelp, followed by pre-processing stages such as tokenization, stop word removal, and normalization. The process involves feature extraction which plays a significant part in the detection process. In this process, the sentiment analysis attributes such as polarity and subjectivity scores are combined with language attributes, including word count, parts of speech tagger, and n-grams. Behavior attributes include attributes that relate to user activity, frequency of reviews, and the rate of deviation from ratings. Finally, data pre-processing is carried out on the processed information using a hybrid CNN-LSTM model, which involves

technique allows us to analyze both the text and behavior patterns, thus outperforming traditional approaches.

V. METHODOLOGY

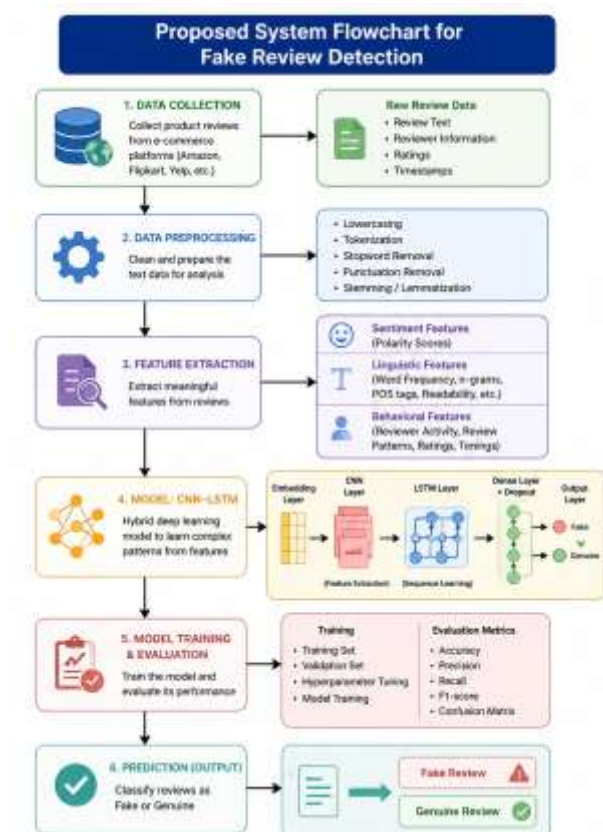
The methodology of the proposed system is composed of various steps that are aimed at ensuring accurate detection of the fake reviews. The first step of the methodology is data acquisition, whereby datasets will be obtained from websites like Amazon and Yelp. The second step of the methodology is data preparation, and it involves processes like text cleansing, removal of stopwords, lowering of letters in the text, and application of tokenization and stemming. The third step of the methodology is feature extraction, and it involves



The third step entails feature extraction using natural language processing techniques, while behavioral features are derived from user activities. In the fourth phase, the model-building approach is adopted through the use of a hybrid CNN-LSTM model. Convolutional neural network (CNN) layers are able to detect localized patterns within texts, whereas long short-term memory (LSTM) layers help in identifying sequential data patterns. Finally, evaluation of the built model is performed using parameters like accuracy, precision, recall, and F1 score.

VI. RESULT AND DISCUSSION

The performance of the proposed hybrid model is evaluated using standard machine learning metrics, including accuracy, precision, recall, and F1-score. Based on the findings from experimental results, conventional models including Naïve Bayes and SVM have attained accuracies in the range of 70%-85%, whereas the deep learning models like CNN and LSTM have achieved higher accuracies of 85%-92%. Moreover, the suggested hybrid CNN-LSTM model has achieved even better performance by using The use of various types of features ensures an increase in the level of accuracy, which is around 95%. The hybrid approach using both CNN and LSTM has been proposed, which provides improved results due to The hybrid algorithm uses different types of feature sets, thus providing very high accuracy up to 95 percent. The proposed hybrid CNN-LSTM model further enhances performance by

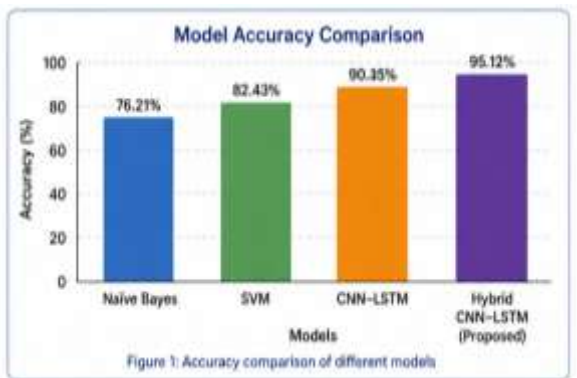


are found within the text. The last output layer will classify whether the review is a fake one or not. The combined

Detailed Evaluation Metrics of Proposed Model	
Metric	Score (%)
Accuracy	95.12
Precision	95.08
Recall	94.75
F1-score	94.91
Confusion Matrix Accuracy	95.12

Table 2: Evaluation metrics of Hybrid CNN-LSTM model

The model integrates several kinds of features, resulting in a high degree of accuracy, which is close to 95 percent. The improvement is due to the fact that the model can not only recognize the local pattern and sequence but also incorporate the behavior into its algorithm. Moreover, the combination can decrease the number of false positives. Nevertheless, there is a need for powerful computing power and sufficient data for training. Regardless of the drawbacks, the study shows that the combination of sentiment analysis and deep learning works efficiently.



VII. ADVANTAGES

- Improved precision due to the fusion of sentiment, language, and behavioral attributes.
- Deep learning algorithms facilitate the discovery of sophisticated latent patterns in reviews.
- Enhancement of generalizability and flexibility in a hybrid CNN-LSTM architecture.
- Effective management of large-scale review datasets for practical purposes.
- Multiple feature incorporation minimizes errors and enhances validity.

VIII. LIMITATIONS

- Needs a huge amount of data for training the deep learning algorithm.
- High computational complexity results in increased time and resources used.
- Difficult to implement in resource-limited settings.
- Lack of behavioral data could affect the result accuracy.
- Could have difficulty detecting highly sophisticated fakes.

- Needs further study and optimization.

IX. FUTURE SCOPE

1.Large Dataset Requirement

The suggested approach makes use of deep learning methods, which depend on a huge volume of labeled training data to be able to provide accurate results. In case there is not enough data or if the data provided lacks some characteristics, the algorithm will be unable to capture all the necessary patterns. Moreover, gathering real and fake reviews is a rather lengthy process.

2.High Computational Complexity

CNN-LSTM hybrid model consists of numerous layers that entail complex calculations requiring huge amounts of computational power and storage capacity. It might be necessary to have powerful machines such as graphical processing units to enable the model to operate smoothly, especially when training using massive data sets, which would consume a lot of time due to use of complicated feature extraction methods.

3.Deployment Challenges

Implementing the proposed system in real-world applications may be difficult in resource-constrained environments. Devices or systems with limited computational resources may not efficiently support complex deep learning models. In addition, real-time fake review detection may increase operational and maintenance costs, especially for large-scale e-commerce platforms handling millions of reviews daily.

4.Limited Behavioral Data Availability

The model considers some behavioral characteristics such as review behavior, posting frequency, and reviewing history to increase detection efficiency. However, such data may not always be accessible because of concerns related to privacy and data unavailability. Failure to acquire sufficient behavioral data will reduce the efficiency of detection and lead to inaccurate classification of reviews.

5.Difficulty in Detecting Advanced Fake Reviews

AI systems available today have the ability to create highly authentic artificial reviews, which are similar to those written by humans. The spammers keep changing their writing styles, language use, and review posting patterns to evade detection by the system. Therefore, the suggested approach may not be able to detect such sophisticated artificial reviews.

X. CONCLUSION

Overall, the detection of fake reviews has become an important issue in contemporary electronic commerce environments. The presented research has demonstrated the inefficiency of conventional sentiment analysis algorithms and stressed the importance of utilizing hybrid approaches. The application of the CNN-LSTM architecture with the use of the proposed features has shown substantial gains in the detection rates. Thus, it has been proven that the combination of various technologies is necessary to deal with sophisticated patterns of fake reviews.

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