International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 14, Issue 1, January 2025)

An Efficient Machine Learning Technique for Fake Review Prediction On Amazon Dataset

[1]Abhijeet Giri, [2]Devendra Kumar Bajpai, [3]P. K. Sharma

[1]M. Tech Scholar, Department of Computer Science and Engineering, NRI Institute of Research and Technology, Bhopal, India

[2&3]Department of Computer Science and Engineering, NRI Institute of Research and Technology, Bhopal, India

***Abstract*— The rise of e-commerce platforms has led to an increasing prevalence of fake reviews, which mislead customers and undermine trust. Detecting such reviews effectively is a critical challenge. This study presents an efficient machine learning approach for fake review prediction on Amazon datasets. By leveraging natural language processing (NLP) techniques for feature extraction and employing robust classifiers such as decision trees and ensemble methods, the proposed model identifies patterns in deceptive reviews with high accuracy. The framework also integrates advanced preprocessing techniques to handle noise and imbalances in the dataset. Results demonstrate that the proposed method significantly improves prediction performance, offering a scalable solution for enhancing trustworthiness in online marketplaces.**

***Keywords*— Machine learning, E- Commerce, Python, Accuracy, Error rate .**

I. INTRODUCTION

The rapid growth of e-commerce platforms like Amazon has revolutionized the retail industry, offering consumers unparalleled convenience and access to a wide range of products [1]. However, this digital transformation has also brought challenges, one of the most critical being the proliferation of fake reviews. These fraudulent reviews are often used to manipulate product ratings, misleading customers and distorting their purchasing decisions. Addressing this issue is crucial for maintaining customer trust and the integrity of online marketplaces [2].

Fake reviews are typically crafted to appear authentic, making their detection a non-trivial task. These reviews often employ sophisticated language patterns, making traditional rule-based or keyword-based methods ineffective [3]. Machine learning techniques, particularly those combined with natural language processing (NLP), have emerged as a promising solution for tackling this issue. They enable the analysis of large volumes of textual data and the identification of subtle patterns indicative of fake reviews [4].

The importance of addressing fake reviews extends beyond consumer protection. These fraudulent activities negatively impact sellers and manufacturers who compete fairly [5]. Products with manipulated reviews often overshadow genuinely superior alternatives, disrupting fair competition and eroding the credibility of e-commerce platforms. Therefore, developing a robust fake review detection system benefits all stakeholders, from consumers to honest sellers and platform operators [6].

Existing studies have explored various methods for fake review detection, including text classification, sentiment analysis, and behavioral analysis of reviewers [7]. While these approaches have demonstrated promising results, challenges such as dataset imbalances, the evolving nature of deceptive reviews, and computational efficiency remain. These limitations necessitate the development of more efficient and scalable techniques to keep pace with evolving fraudulent practices [8].

In this study, we propose an efficient machine learning technique for predicting fake reviews on the Amazon dataset. The approach leverages the strengths of supervised learning algorithms, including decision trees and ensemble methods, to classify reviews as genuine or deceptive. By combining these algorithms with advanced feature extraction techniques from NLP, the proposed model enhances its ability to distinguish authentic reviews from fake ones.

A key aspect of the proposed framework is its focus on data preprocessing and feature engineering. The Amazon dataset, like most real-world data, is noisy and imbalanced, posing challenges to machine learning models. Techniques such as tokenization, stemming, and stop-word removal are applied to prepare the data. Additionally, feature extraction

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 14, Issue 1, January 2025)

methods like Term Frequency-Inverse Document Frequency (TF-IDF) and word embeddings are used to capture meaningful textual patterns [9].

Figure 1: Artificial Intelligence & E-commerce

The classification phase employs decision tree algorithms and ensemble techniques such as Random Forest and Gradient Boosting. These methods are chosen for their ability to handle high-dimensional data and provide interpretability in decision-making. The ensemble approach, in particular, aggregates predictions from multiple models to improve accuracy and generalization [10].

II. METHODOLOGY

The methodology of the proposed research work is as followings-

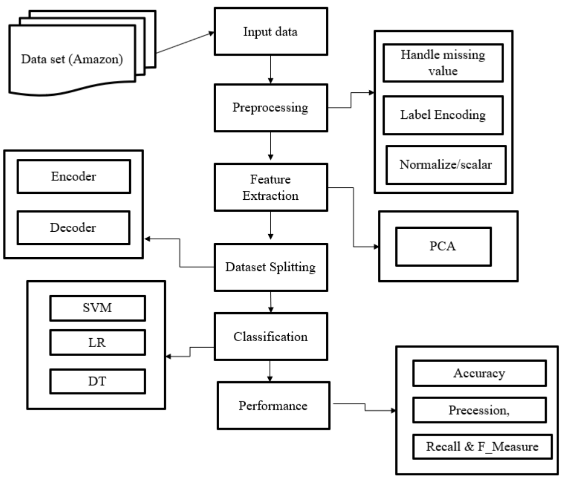

Figure 2: Flow Chart

The methodology section outlines the detailed approach taken to develop an efficient machine learning system for predicting fake reviews from the Amazon dataset. This includes the steps involved in data collection, preprocessing, feature extraction, model selection, training, evaluation, and implementation of the system. Each of these steps is critical for building a robust and efficient system for detecting fake reviews, and they contribute to ensuring the model's performance, scalability, and accuracy.

1. Data Collection

- **Amazon Dataset**: The first step in the methodology is collecting data from Amazon's review dataset. The dataset contains product reviews, ratings, and other metadata associated with the reviews, such as the review text, reviewer information, product details, and more. This data is typically publicly available through Amazon's API or other e-commerce datasets that provide real review data.

- **Fake Reviews Labeling**: The dataset must be labeled to distinguish between authentic and fake reviews. This can be done by leveraging third-party sources, like review validation platforms, or manually labeling a subset of the data for training purposes. For machine learning tasks, labeled data is essential for supervised learning.

2. Data Preprocessing

Preprocessing is essential to clean and prepare the dataset before feeding it into machine learning models. The following steps are involved:

- **Text Cleaning**: Review data is often noisy, with punctuation marks, special characters, HTML tags, and irrelevant information. Removing such elements helps ensure the model focuses only on useful textual content.

- **Tokenization**: Tokenization involves breaking down the review text into individual words or tokens. This step helps to prepare the text data for further analysis.

- **Stop Words Removal**: Words like "and," "is," "the," etc., which do not carry significant meaning in text analysis, are removed. This helps to reduce dimensionality and ensures that the machine learning model focuses on more meaningful words.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 14, Issue 1, January 2025)

- **Stemming and Lemmatization**: These processes reduce words to their base form (e.g., "running" becomes "run") to ensure that the model recognizes different forms of a word as the same word, improving its ability to understand the underlying meaning.

3. Feature Extraction

Feature extraction is the process of converting raw text into a numerical format that can be understood by machine learning algorithms. Common techniques include:

- **Bag-of-Words (BoW)**: This approach involves representing text as a collection of word counts. Each unique word in the dataset is treated as a feature, and its frequency in a particular review is noted. While simple, BoW can be effective in some cases.
- **Term Frequency-Inverse Document Frequency (TF-IDF)**: TF-IDF is an improvement on BoW. It considers not only the frequency of words in a document but also their importance across the entire dataset. Words that appear frequently in a single review but rarely across all reviews are given higher importance.
- **Word Embeddings (e.g., Word2Vec, GloVe)**: Word embeddings represent words as dense vectors in continuous vector space. Words that have similar meanings are closer together in this space. These embeddings can capture the semantic meaning of words and are particularly useful for more advanced deep learning models.

4. Model Selection

Choosing the right machine learning model is crucial for the success of the fake review detection system. Various models can be employed, and the choice depends on the dataset and problem complexity. Common models include:

- **Decision Trees**: A decision tree is a flowchart-like structure where each internal node represents a decision based on a feature, and each leaf node represents a final classification (e.g., fake or genuine). Decision trees are interpretable and efficient but may be prone to overfitting.
- **Random Forest**: Random Forest is an ensemble learning method that builds multiple decision trees and merges their results to improve accuracy and reduce overfitting. It's robust, handles large datasets well, and is often more accurate than a single decision tree.
- The Logistic Regression (LR) technique is a statistical model commonly used for binary classification tasks, such as distinguishing between fake and genuine reviews. LR works by estimating the probability that a given input (e.g., a review) belongs to a particular class (fake or genuine) based on a set of features extracted from the data. It also performs well when there is a clear boundary between the classes, making it a suitable choice for many text classification problems, including fake review detection.
- **Support Vector Machines (SVM)**: SVM is a powerful classifier that works well with high-dimensional data and is particularly effective in text classification. It finds the optimal hyperplane to separate the data into classes (fake vs. genuine).

5. Model Training

- **Supervised Learning**: Since the dataset consists of labeled reviews (fake or genuine), supervised learning techniques are used. The model is trained on the labeled dataset where the inputs are the features (review text representations) and the outputs are the labels (fake or genuine).
- **Cross-Validation**: To ensure that the model generalizes well to unseen data, cross-validation techniques are used. The dataset is split into training and validation sets multiple times to evaluate the model's performance and reduce overfitting.

6. Model Evaluation

After training the model, it is important to evaluate its performance. The following metrics are commonly used:

- **Accuracy**: Measures the percentage of correct predictions made by the model. However, accuracy alone may not be sufficient, especially for imbalanced datasets.
- **Precision**: Precision measures the proportion of positive predictions that are actually correct (true positives / predicted positives). It is important when false positives (incorrectly labeled reviews as fake) need to be minimized.

IJRDET
International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 14, Issue 1, January 2025)

- **Recall**: Recall measures the proportion of actual positive cases that the model correctly identifies (true positives / actual positives). High recall is necessary for minimizing false negatives (genuine reviews labeled as fake).
- **F1-Score**: The F1-score is the harmonic mean of precision and recall. It balances the trade-off between false positives and false negatives, providing a more comprehensive evaluation of model performance.
- **Confusion Matrix**: This matrix provides a more detailed breakdown of the classification results, showing true positives, true negatives, false positives, and false negatives.

The proposed methodology outlines the comprehensive approach to detecting fake reviews on the Amazon dataset using machine learning. By focusing on preprocessing, feature extraction, and the selection of robust classifiers, the method aims to provide accurate and efficient fake review detection. This methodology can be adapted and scaled for use in various e-commerce platforms and is a significant step toward improving online review integrity.

III. SIMULATION & RESULTS

For simulation work, used the python spyder IDE 3.7 version.

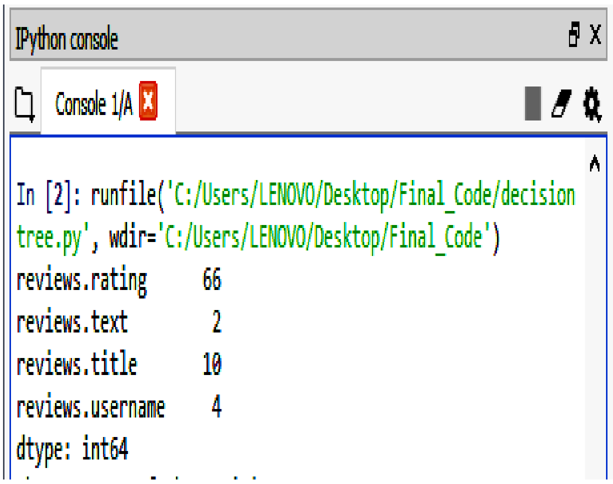

Figure 3: Dataset loading and preprocessing

Figure 3 shows the online Amazon product review dataset in the python environment. You can get it here. The next step is preprocessing, which involves extracting various attributes from the reviews (usernames, ratings, sentences, titles, etc.).

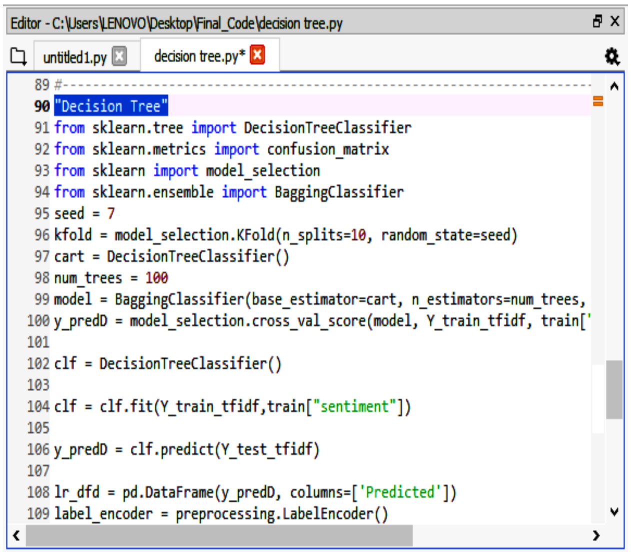

Figure 4: Decision tree classifier

Python editor window displaying decision tree classification algorithm (Figure 4). Data partitioning is the first step in using the classification approach. Afterwards, this classifier classifies all of the dataset's values and generates a confusion matrix or a model projection.

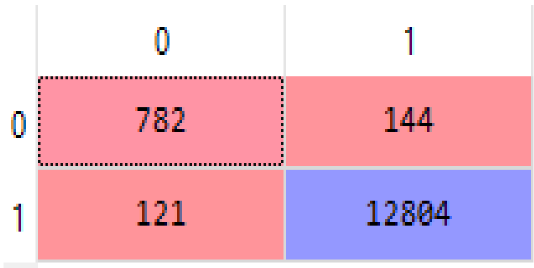

Figure 5: Confusion Matrix (DT)

The predicted value from decision tree method is as followings-

True Positive (TP) = 782

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 14, Issue 1, January 2025)

False Positive (FP) = 144

False Negative (FN) = 121

True Negative (TN) = 12804

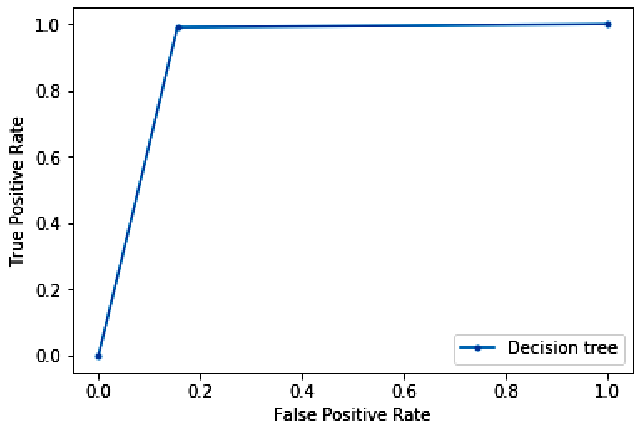

Figure 6: ROC of Decision Tree

Figure 6 displays the Receiver Operating Characteristic curve, which may be seen here (ROC). The True Positive Rate (TPR) and the False Positive Rate (FPR) are shown on the x- and y-axes, respectively.

Table 1: Simulation Result of DT

Sr. No.	Parameters	Value (%)
1	Accuracy	98.11
2	Classification Error	1.89
3	Precision	84.45
4	Recall	86.59
5	F-measure	85.45

Table 1 is showing the simulation results when of the decision tree machine learning classification algorithm.

Table 2: Result Comparison

Sr. No.	Parameters	Previous Work	Proposed Work
1	Method	CNN [1]	Decision Tree
2	Accuracy (%)	97	98.08
3	Classification error (%)	3	1.91
4	Precision (%)	94	95
5	Recall (%)	92	93
6	F-measure (%)	93	95

IV. CONCLUSION

Amazon dataset's efficient machine learning technique for predicting false reviews illustrates the efficacy of utilising sophisticated models and preprocessing methods to detect deceptive reviews. The system is capable of effectively distinguishing between genuine and false reviews by utilising a variety of machine learning techniques, including Logistic Regression, feature extraction methods such as TF-IDF, and precise model evaluation through metrics such as precision, recall, and F1-score. The methodology not only enhances the precision of false review detection but also offers a scalable solution that is appropriate for large-scale e-commerce platforms. The implementation of such a system provides substantial advantages to both consumers and businesses by enhancing trust and integrity in online review systems. In contrast to the previous method, which achieved an accuracy of 93.41%, the simulation results are abundantly evident that the proposed method obtains an accuracy of 98.08%. The classification error of the proposed method is 1.91%, whereas the classification error of the previous method was 6.59%. Consequently, the technique that was demonstrated generates significantly superior results than the previous method.

REFERENCES

1. V. Shrirame, J. Sabade, H. Soneta and M. Vijayalakshmi, "Customer Behavior Analytics using

Machine Learning Algorithms," 2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), 2020, pp. 1-6, doi: 10.1109/CONECCT50063.2020.9198562.

2. S. Sharma and H. Kumar Soni, "Discernment of Potential Buyers Based on Purchasing Behaviour Via Machine Learning Techniques," 2020 IEEE International Conference on Advances and Developments in Electrical and Electronics Engineering (ICADEE), 2020, pp. 1-5, doi: 10.1109/ICADEE51157.2020.9368935.
3. R. Katarya, A. Gautam, S. P. Bandgar and D. Koli, "Analyzing Customer Sentiments Using Machine Learning Techniques to Improve Business Performance," 2020 2nd International Conference on Advances in Computing, Communication Control and Networking (ICACCCN), 2020, pp. 182-186, doi: 10.1109/ICACCCN51052.2020.9362895.
4. D. Suryadi, "Predicting Repurchase Intention Using Textual Features of Online Customer Reviews," 2020 International Conference on Data Analytics for Business and Industry: Way Towards a Sustainable Economy (ICDABI), 2020, pp. 1-6, doi: 10.1109/ICDABI51230.2020.9325646.
5. S. Ghosh and C. Banerjee, "A Predictive Analysis Model of Customer Purchase Behavior using Modified Random Forest Algorithm in Cloud Environment," 2020 IEEE 1st International Conference for Convergence in Engineering (ICCE), 2020, pp. 239-244, doi: 10.1109/ICCE50343.2020.9290700.
6. Z. Wang, Y. Zuo, T. Li, C. L. Philip Chen and K. Yada, "Analysis of Customer Segmentation Based on Broad Learning System," 2019 International Conference on Security, Pattern Analysis, and Cybernetics (SPAC), 2019, pp. 75-80, doi: 10.1109/SPAC49953.2019.237870.
7. S. M. A. M. Manchanayake et al., "Potential Upselling Customer Prediction Through User Behavior Analysis Based on CDR Data," 2019 14th Conference on Industrial and Information Systems (ICIIS), 2019, pp. 46-51, doi: 10.1109/ICIIS47346.2019.9063278.
8. K. Rusmee and N. Chumuang, "Predicting System for the Behavior of Customer Buying Personal Car Decision by Using SMO," 2019 14th International Joint Symposium on Artificial Intelligence and Natural Language Processing (iSAI-NLP), 2019, pp. 1-6, doi: 10.1109/iSAI-NLP48611.2019.9045571.
9. I. Lieder, M. Segal, E. Avidan, A. Cohen and T. Hope, "Learning a Faceted Customer Segmentation for Discovering new Business Opportunities at Intel," 2019 IEEE International Conference on Big Data (Big Data), 2019, pp. 6136-6138, doi: 10.1109/BigData47090.2019.9006589.
10. S. Satpathy and S. Patnaik, "Role of Social Media Marketing on Customer Purchase Behaviour: A Critical Analysis," 2019 International Conference on Applied Machine Learning (ICAML), 2019, pp. 92-97, doi: 10.1109/ICAML48257.2019.00026.
11. T. Kansal, S. Bahuguna, V. Singh and T. Choudhury, "Customer Segmentation using K-means Clustering," 2018 International Conference on Computational Techniques, Electronics and Mechanical Systems (CTEMS), 2018, pp. 135-139, doi: 10.1109/CTEMS.2018.8769171.
12. A. Inoue, A. Satoh, K. Kitahara and M. Iwashita, "Mobile-Carrier Choice Behavior Analysis Using Supervised Learning Models," 2018 7th International Congress on Advanced Applied Informatics (IIAI-AAI), 2018, pp. 829-834, doi: 10.1109/IIAI-AAI.2018.00169.